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## **Federal State Differentials in the Efficiency of Health Production in Germany: An Artifact of Spatial Dependence?\***

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July 20, 2011

**Abstract:** Due to regional competition and patient migration, the efficiency of health care provision at the regional level is subject to spatial dependence. We address this issue by applying a spatial autoregressive model to longitudinal data from Germany at the district ('Kreis') level. The empirical model is specified to explain efficiency scores, which we derive through non-parametric order-m efficiency analysis of regional health production. The focus is on the role of health policy of federal states ('Bundesländer') for district efficiency. Regression results reveal significant spatial spillover effects. Notably, accounting for spatial dependence does not decrease but increases the estimated effect of federal states on district efficiency. It appears that genuinely more efficient states are less affected by positive efficiency spillovers, so that taking into account spatial dependence clarifies the importance of health policy at the state level.

**Keywords:** health production, order-m efficiency, spatial autoregressive model

**JEL Classification:** I12, R10

**Acknowledgements:** \* Correspondence to Harald Tauchmann, Rheinisch-Westfälisches Institut für Wirtschaftsforschung (RWI), Hohenzollernstraße 1-3, D-45128 Essen, E-mail: [harald.tauchmann@rwi-essen.de](mailto:harald.tauchmann@rwi-essen.de). The authors are grateful to Rüdiger Budde for generating the regional distance matrix used in the empirical analysis, to Peter Grösche for helpful comments, Simon Decker and Adam Pilny for research assistance, and to Miriam Krieger for editorial assistance. Data provision by the Federal Association of Statutory Health Insurance Physicians (Kassenärztliche Bundesvereinigung) is gratefully acknowledged.

# 1 Introduction

The efficiency of health care provision has become a major topic in health policy and applied economics. In a recent survey Hollingsworth (2008) lists as many as 317 pertinent articles published before mid-2006. These papers mostly analyze efficiency differentials at the level of individual health care providers, foremost hospitals (e.g. Sloan, 2000; Street, 2003; Chen et al., 2005; Harrison et al., 2004; Staat, 2006; Herr, 2008; Pilyavsky & Staat, 2008; Herr et al., 2011), but also nursing homes (e.g. Anderson et al., 1999; Crivelli et al., 2002 Björkgreen et al., 2004;), general practitioners and primary care facilities (e.g. Staat, 2003; Puig-Junoy & Ortun, 2004; Collier, 2006).<sup>1</sup> Poor coordination e.g. between out- and in-patient care rather than the inefficiency of individual providers, however, might in fact present a major source of technical and economic inefficiency. This applies in particular to Germany, where a rigid separation of health care sectors, free and direct access to medical specialists, and generous coverage by social health insurance are frequently blamed for generating inefficiencies such as the over-use of services, redundant medical treatments, and medical malpractice due to insufficient exchange of information. These potential sources of inefficiency, which are located at the level of the health system rather than the individual provider level, can hardly be addressed using individual provider data.

A second set of papers analyses the efficiency of health systems based on aggregated cross-country data (e.g. Afonso & St. Aubyn, 2005; Bhat, 2005; Grosskopf et al., 2006). However, cross-country comparisons are of limited value for measuring efficiency due to fundamental structural and institutional differences across countries, which cannot easily be controlled for. Few analyses use intra-country regional variation (e.g. Thanassoulis et al., 1996; Kathuria & Sankar, 2005), where the units of observation are more homogeneous, and hence more comparable, albeit at a level, which is still aggregated. The present paper takes the latter path by using data at the district level for the efficiency analysis. Districts ('Kreise') seem to be the appropriate regional production unit for an efficiency analysis, as they are typically the subject of public planning in Germany (Kopetsch, 2007).

Recent studies have already followed this approach by investigating quality, effectiveness, and efficiency of health care provision in Germany using district-level data (e.g. Schwierz & Wübker, 2010; Augurzky et al., 2009b; Sundmacher & Busse, 2009). However, the implicit assumption – inherent in conventional regression analyses of regionally aggregated data – of statistically independent observation units becomes almost indefensible.<sup>2</sup> As regional health care systems are not strictly separated, the shape of regional health care efficiencies is subject to different sources of spatial interdependence. On the one hand, spatial efficiency spillovers from competition for patients result in positive cross-border effects on quality and efficiency. Moreover, regional distribution of labor in health care provision also contributes

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<sup>1</sup> See Hollingsworth (2003, 2008) and Hollingsworth et al. (1999) for comprehensive surveys. Pilyavsky & Staat (2008) is most relevant for the present analysis as it also employs the order-m efficiency approach; see section 4.1. Key references include Staat (2006), Herr (2008), and Herr et al. (2011) as they address the German health care system.

<sup>2</sup> To some degree, Schwierz & Wübker (2010) allow for inter-regional correlation by carrying out a 'multi-level analysis'. But in fact they account for correlation at the state level rather than spatial dependence.

to cross-border interdependence. Medical specialists and specialized hospital departments not available everywhere will provide services to neighboring regions. On the other hand, spatial error correlation also matters. Unobserved net patient migration – that is patients provided with services in regions other than the one they reside in – generate a spatial pattern of error correlation, as districts exhibiting net patient inflows provide services to their neighbors which are not accounted for in efficiency measures based on outputs such as reductions in mortality or morbidity. While little is known about patient flows in outpatient care in Germany, Augurzky et al. (2009b) provide detailed figures on flows for the hospital sector. Indeed, in some regions the share of patients treated locally is substantially lower than 50%.

Ignoring spatial interdependence will thus result in misleading empirical evidence on the quality and efficiency of health care provision at the regional level. Conventionally computed standard errors will be incorrect in the presence of spatial error correlation (Anselin, 1988, 59). Even worse, results on the determinants of regional efficiency will suffer from omitted variables bias if the endogenous variable following a spatial autoregressive process is ignored (LeSage & Pace, 2009: 65). For instance, spatial dependence not properly addressed at the district level will affect estimates of differentials in the efficiency of health care provision at higher geographic levels, e.g. at federal state ('Bundesland') level.

In Germany, the question of potential differentials in the efficiency of health care provision at the state level has recently attracted much interest, as health inequality is a controversial issue in the public debate. Institutional factors do suggest the existence of such differentials: Firstly, the states are responsible for investments in inpatient care, such as the construction and closure of hospitals. Secondly, public planning at the state level determines the number of hospitals and hospital beds. Thirdly, state-level associations of Statutory Health Insurance-accredited physicians regulate the regional provision of outpatient care. Although nationwide guidelines exist for the required number of resident physicians, the state-level physicians' associations exert substantial influence on the supply of physicians. Moreover, empirical analyses (cf. Augurzky et al. 2009a) report substantial differentials in state-level efficiency.

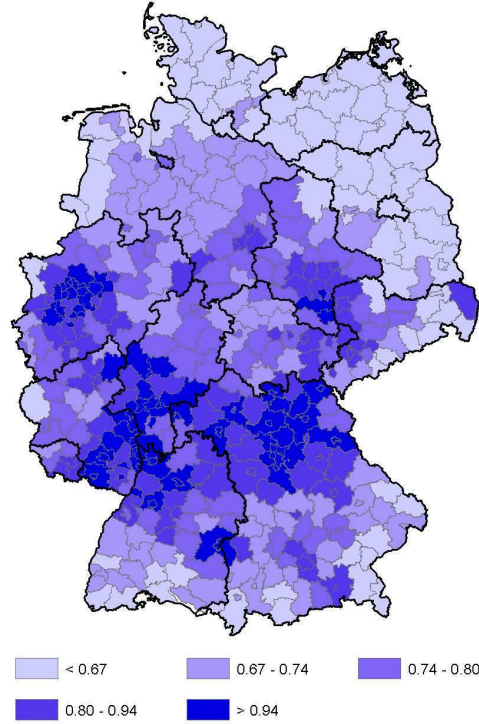
This paper investigates the spatial dependence of health production efficiency at the district level in Germany. It addresses the question whether estimated state efficiency differentials reported in the literature to date are possibly due to ignored spatial dependence. The paper brings together two previously unconnected strands of literature on efficiency measurement of health production as discussed above and a recent literature on spatial dependence in the health care sector. As an early example for the latter, Mobley (2003) employs a spatial autoregressive regression model to analyze interactive pricing behavior in California's hospital market. Taking into account possible interaction between authorities as well as unobserved heterogeneity, Costa-Font & Moscone (2008) identify some degree of interdependence in the health spending decisions of neighboring regions in Spain. Similarly, Moscone et al. (2007) as well as Moscone & Knapp (2005) analyze mental health spending in

England and find evidence of spatial autocorrelation in local government expenditure decisions. In analyzing the long-run economic relationship between health care expenditures and income in the OECD countries, Baltagi & Moscone (2010) consider spatial dependence. They find income elasticities much smaller than those estimated in earlier studies. Moscone & Tosetti (2010) is a similar investigation for states in the US. More closely related to the topic of the present analysis, but based on a different modeling approach, Cohen & Morrison Paul (2008) find a positive agglomeration effect on the cost efficiency of Washington state hospitals by including spatially weighted characteristics of other hospitals as explanatory variables. The papers by Moscone & Knapp (2005), Moscone et al. (2007), and Costa-Font & Moscone (2008) are of particular relevance, as they address intra-country regional interdependence.

The remainder of the paper is organized as follows: section 2 illustrates the possible bias in regression results if spatial dependence is not controlled for, section 3 introduces the data, section 4 discusses our two-step empirical approach of conducting a non-parametric efficiency analysis and subsequently explaining district-level efficiency using a Cliff-Ord modeling framework (Cliff & Ord, 1973), section 5 presents and discusses the estimation results, and section 6 concludes.

## 2 An Illustrating Model

The key argument that ignored spatial interdependence results in spurious regression results on the impact of states on regional efficiency can be illustrated in a simple model. Here none of the exogenous determinants of efficiency – including state policies – vary across districts and states and can thus be captured by a single scalar  $\mu > 0$ . Assume that district efficiency follows a spatial autoregressive process according to  $y = \mu J + \lambda W y$ , where  $y$  denotes the vector of districts' efficiency scores,  $J$  is a vector of ones,  $W$  denotes a spatial weighting matrix that measures the distance between districts, and the scalar  $\lambda$  captures the direction and strength of spatial spillover effects. Efficiency in one district is thus affected by the efficiency of any other district, depending on the distance between them.  $y = \mu(I - \lambda W)^{-1} J$  then holds for the equilibrium efficiency score at the district level. In consequence, for  $\lambda \neq 0$ , the efficiency scores exhibit heterogeneity across districts because of spatial spillover and feedback effects, unless the overall level of spatial interdependence is the same for all districts. Moreover, as the distance in space is the sole source of efficiency differentials, the distribution of efficiency scores will exhibit a distinct spatial pattern.



**Figure 1:** Spatial distribution of artificial efficiency scores ( $\mu = 0.5$ ,  $\lambda = 0.5$ , i.e. positive spillover effects)  
**Source:** Own calculations

Figure 1 maps the districts in Germany. It displays the pattern of efficiency scores for  $\lambda = 0.5$ , i.e. positive spillover effects, and for real distances between districts in Germany entering the matrix  $W$  (we chose inverse squared travel time as the measure of adjacency and applied eigenvalue normalization to  $W$ , see section 4.2). In the absence of spatial dependence, i.e.  $\lambda = 0$ , all districts would exhibit a uniform artificial efficiency of  $\mu = 0.5$ . With positive spillover-effects, all artificial efficiency scores exceed this value, the minimum is 0.57, and the maximum is 1.63. This implies a factor of 16 between the minimal and the maximal gain in artificial efficiency due to spillovers.<sup>3</sup> In other words, positive spillover-effects are heterogeneous and heterogeneity exhibits a distinct spatial pattern. Districts in the center of the country are clearly subject to much stronger spillover effects than their counterparts at the periphery. This pattern carries over to the states, marked by thick border lines. The average efficiency in states at the periphery, e.g. Mecklenburg-Vorpommern located in the remote north-east of the country, is less strongly affected by spatial interdependence than the average efficiency in more centrally located states.

Indeed, naively regressing the artificial efficiency scores on a set of state dummies yields distinct state differentials. These spurious state effects cannot be explained by state policies, which are absent by assumption in this model. Consequently, any health policy proposal based on this model would be misleading at the state level. Evidently, reality is far more complex. For instance, genuinely more efficient states might be located in remote areas and

<sup>3</sup>  $(1.63 - 0.5)(0.57 - 0.5)^{-1} \approx 16$ . The absolute values have no economic meaning as the value 0.5 is arbitrarily assigned to the parameter  $\mu$ .

benefit less from positive spillovers. In this case, the corresponding effects might cancel out in an empirical analysis that ignores spatial dependence. Moreover, the spatial distribution of covariates will play an important role, and the data generating process will be stochastic rather than deterministic. Nevertheless, the above example reveals that not taking into account spatial dependence may overestimate state differentials and bias the effect of state policies on district level efficiency.

### 3 The Data

The empirical analysis is based on German district-level data for the years 2004-2006. During this time Germany was sectioned into 439 districts with an average of 190,000 inhabitants and 800 km<sup>2</sup> in area. Districts exhibit pronounced heterogeneity with respect to both population and territory. This is partly due to the typical pattern of large and medium-size, sometimes even small, cities and towns constituting one district (urban district, 'Stadtkreis') and their surrounding countryside constituting another (rural district, 'Landkreis'). Thus, large rural districts often border directly on densely populated urban districts. The two largest German cities, Berlin and Hamburg, constitute urban districts as well. District populations hence range from less than 35,000 to almost 3.5 million people.

Comprehensive district-level data is provided by the Federal Statistical Office (dataset 'Statistik Regional') as well as by the Federal Office for Building and Regional Planning (dataset 'INKAR'). We added information from two additional sources: the German Hospital Register from the Federal Statistical Office and resident physician data provided on request by the Federal Association of Statutory Health Insurance Physicians (Kassenärztliche Bundesvereinigung). Specifically, we use (i) demographic information, i.e. population and deaths by gender and age, (ii) the number of hospital beds by medical specialty, (iii) the number of physicians by medical specialty, and (iv) territory, from which we calculate population density, (v) per capita income, (vi) district unemployment rates, (vii) the share of hospital beds by type of ownership (private, public, non-profit), and (viii) a dummy indicating urban districts. The data for (i)-(iii) serve to derive inputs and outputs of health production for the efficiency analysis. The remaining variables, along with the demographic information, enter the subsequent spatial regression model as explanatory variables.

The state within which a district is located is also included in the regression analysis. Here the city states Berlin, Hamburg and Bremen – each single districts in their own right, except for Bremen which is divided into two urban districts ('City of Bremen' and 'Bremerhaven') – establish a joint category. Data are available for the years 2004 to 2006.<sup>4</sup> A few districts were excluded due to missing data, giving rise to a slightly unbalanced panel data set of 1286

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<sup>4</sup> The observation period is restricted to three years for several reasons. First, there are missing values in the data, e.g. the 'INKAR' data base did not release an issue every year. Second, a major district reform in East Germany in 2007 and 2008 impedes the construction of a consistent district-level panel for a longer period of time.

district-year-observations altogether (2004: 436, 2005 and 2006: 425 observations). Table 1 displays descriptive statistics for the variables included in the empirical analyses.

**Table 1: Descriptive statistics (pooled sample)**

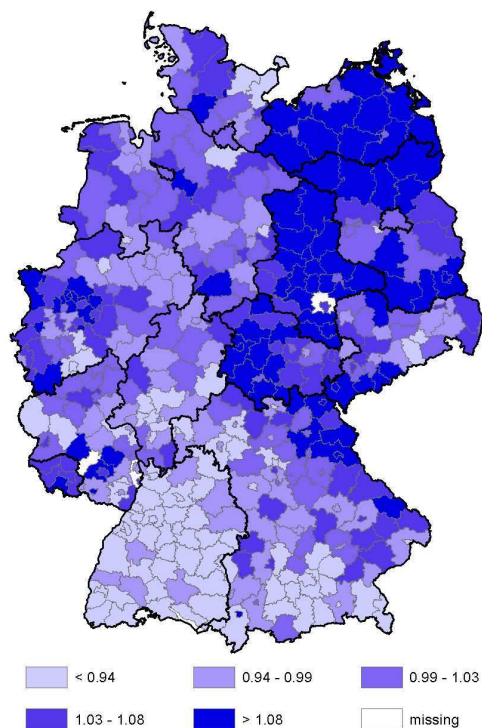
Variable	Mean	S.D.	Median	Min	Max
standardized mortality	1.014	0.085	1.012	0.787	1.264
hospital beds (per 10,000 inhabitants)	66.60	38.45	57.64	1.75	235.08
general practitioners <sup>a</sup> (per 100,000 inhabitants)	72.14	9.60	70.70	48.52	111.42
resident medical specialists (per 100,000 inhabitants)	83.67	46.98	65.45	13.75	302.83
input-oriented order-m efficiency ( $m = 100$ ) <sup>b</sup>	0.850	0.149	0.856	0.484	2.457
population (million people)	0.190	0.222	0.135	0.035	3.404
females (share in population)	0.510	0.007	0.509	0.488	0.540
aged 21 to 40 (share in population)	0.252	0.024	0.247	0.202	0.362
aged 41 to 60 (share in population)	0.293	0.016	0.291	0.250	0.358
aged 61 to 80 (share in population)	0.208	0.022	0.207	0.153	0.300
aged above 80 (share in population)	0.046	0.007	0.045	0.026	0.077
population density (1,000 people per km <sup>2</sup> )	0.515	0.661	0.201	0.039	4.171
per capita disposable income (100,000 € per year)	0.172	0.023	0.172	0.126	0.280
unemployment rate	0.113	0.052	0.098	0.034	0.293
non-profit hospital ownership (share in beds)	0.281	0.329	0.161	0	1
private hospital ownership (share in beds)	0.155	0.273	0.011	0	1
urban district (indicator)	0.271	0.444	0	0	1

Notes: <sup>a</sup> including paediatrician and internists operating as general practitioners and; <sup>b</sup> see section 4; descriptive statistics are reported for the pooled sample, i.e. 1286 district-year observations; years 2004, 2005, and 2006 considered.

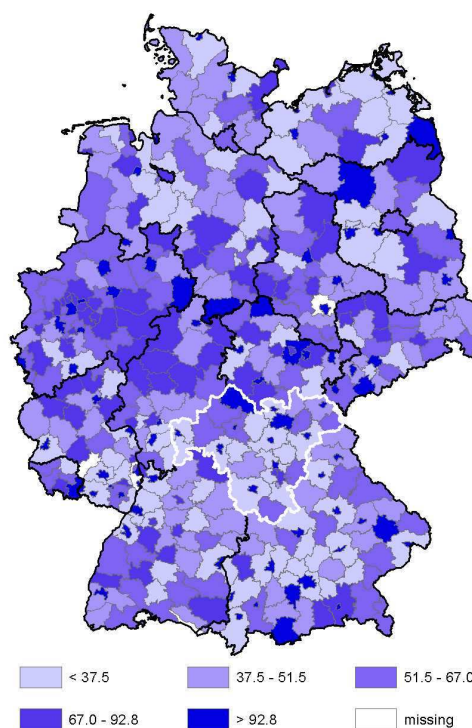
As district populations differ substantially in size and demographic composition, we use national gender- and age-specific death rates to standardize the raw regional numbers of deaths. That is, for each district and year we divide the actual number of deaths by the corresponding, yet hypothetical number that one would observe if national gender and age specific death rates did uniformly apply to all districts. Figure 2 indicates substantial heterogeneity of standardized mortality across districts in Germany. While in some districts mortality is 22% lower than expected on the basis of demographic structure alone, others exhibit mortality rates as far as 26% above the expected level. Standardized mortality is highest in the northeast of the country – the former GDR – and lowest in the south-west – the state of Baden-Wurttemberg and southern Bavaria.

Figures 3 and 5 show the typical pattern of hospitals and medical specialists located in cities or towns, with a much weaker supply of medical infrastructure in the countryside. This pattern is particularly distinct in Franconia (marked by a white boundary in Figure 3) and some bordering regions, where the arrangement of districts adheres closely to the 'Stadtkreis-Landkreis' scheme. Though the distribution of general practitioners (Figure 4) exhibits some interesting regional features – e.g. remarkably low numbers for the western states of North Rhine-Westphalia and Lower Saxony – the difference between urban and rural districts is slightly less distinct. Moreover, high densities of physicians are frequently observed in districts close to faculties of medicine, e.g. Gottingen and Heidelberg. This might be due to limited mobility among graduates.

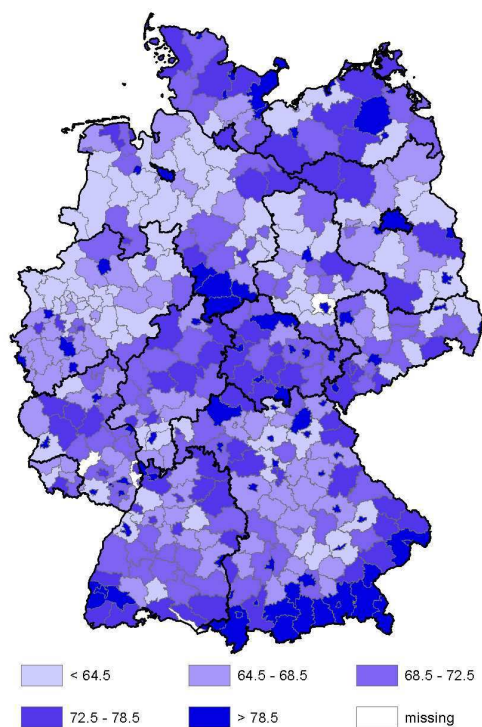




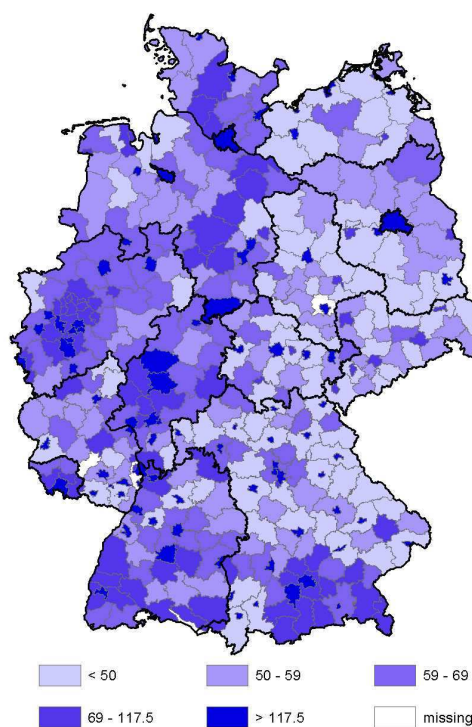
**Figure 2:** Standardized mortality, 2004  
**Source:** Statistisches Bundesamt, own calculations



**Figure 3:** Hospital beds per 10,000 inhabitants, 2004  
**Source:** Statistisches Bundesamt (Statistik Regional)



**Figure 4:** General practitioners per 100,000 inhabitants, 2004  
**Source:** Kassenärztliche Bundesvereinigung



**Figure 5:** Resident medical specialists per 100,000 inhabitants, 2004  
**Source:** Kassenärztliche Bundesvereinigung

## 4 The Empirical Approach

### 4.1 Order- $m$ Efficiency Analysis

The first step of our empirical analysis is to perform a ‘conventional’ efficiency analysis without taking spatial interdependence into account. The purpose is to calculate descriptive district-specific performance figures (efficiency scores) rather than to identify structural parameters of the underlying production technology. For this reason, we prefer a non-parametric approach to a structural stochastic frontier model. Data envelopment analysis (DEA) is the most common tool for non-parametric efficiency analysis. However, our two-step framework – using efficiency scores as dependent variable in a subsequent regression analysis – requires special attention to the following points: (i) efficiency scores obtained from DEA are sensitive to outliers and measurement errors; (ii) DEA generates a complex and generally unknown correlation pattern among estimated efficiency scores (Simar & Wilson, 2007), which might result in misleading inference in the subsequent regression analysis; (iii) estimated scores are bounded from above at one, requiring a generalized regression model to take this feature of the data into account (cf. McDonald, 2009). For ordinary least squares, Simar & Wilson (2007) developed a truncated regression-based bootstrap that considers the latter two problems. But this procedure cannot be applied directly to conventional spatial regression analysis. We therefore employ the concept of order- $m$  efficiency (Cazals et al., 2002). Also a non-parametric approach, it is less sensitive to outliers and measurement errors since efficiency estimates are obtained from a partial frontier that does not envelop all data points. The order- $m$  approach is based on enveloping artificial subsamples (of size  $m$ ) that are randomly drawn from the original data. This procedure attenuates the impact of extreme observations on the estimated efficiency scores. Compared to DEA, the correlation among estimated efficiencies is therefore reduced, rendering misleading inference in a subsequent regression analysis only a minor problem (Binder & Broekel, 2008). Moreover, as a partial frontier approach, order- $m$  efficiency naturally allows for super-efficient observations located beyond the estimated efficiency frontier, implying that efficiency scores may exceed the value of one.<sup>5</sup> The subsequent regression analysis thus requires no truncated regression or fractional response (Papke & Wooldridge, 1996), allowing for the application of a standard spatial regression model.

We employ an input-orientation approach to order- $m$  efficiency, where the efficiency scores indicate the factor by which input consumption may be reduced while leaving outputs unchanged.<sup>6</sup> This appears adequate, given that inefficiency of health care provision is typically discussed in terms of excessive cost in the current policy debate in Germany. Each observation year is analyzed separately.

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<sup>5</sup> Allowing for super efficient units has great appeal with our data, as they are presumably insufficient for comprehensively describing the physical process of health production. Hence, super-efficiency may capture unobserved yet relevant information (cf. Daraio & Simar, 2007, 81).

<sup>6</sup> For order- $m$  efficiency, the distinction between input- and output-oriented efficiency is even more essential than for DEA. Input- and output-orientations do not only differ with respect to the direction in which the distance from the production frontier is measured, but also with respect to the frontiers themselves.

In the order- $m$  approach, input-oriented efficiency scores  $y^m(u_0, v_0)$  are estimated as follows:

$$\hat{y}^m(u_0, v_0) = \frac{1}{B} \sum_{b=1}^B \min_{i=1, \dots, m \mid v_{is} \geq v_{0s} \forall s} \left\{ \max_{r=1, \dots, R} \left( \frac{u_{ir}^b}{u_{0r}} \right) \right\}, \quad (1)$$

where  $u_{ir}$  with  $r=1, \dots, R$  and  $v_{is}$  with  $s=1, \dots, S$  respectively denote inputs and outputs of the analysed production process, and  $u_0$  and  $v_0$  represent the respective vectors of inputs and outputs of the unit under consideration.  $i=1, \dots, m$  indexes the observations in an artificial sub-sample of size  $m$ , drawn with replacement from the original data set. Finally,  $b=1, \dots, B$  denotes re-sampling repetitions. Calculating (1) involves the following four steps:

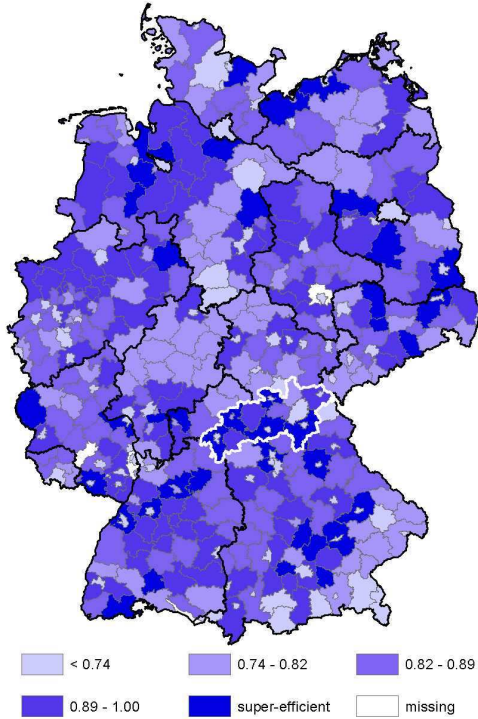
1. For any production unit with a given output vector  $v_0$ , a random sample of size  $m$  is drawn with replacement among those units of the original data set, for which  $v_{is} \geq v_{0s} \forall s$  holds. The corresponding input vectors are denoted by  $u_i^b$ ,  $i=1, \dots, m$ .
2.  $\hat{y}^{mb}(u_0, v_0) = \min_{i=1, \dots, m} \left\{ \max_{r=1, \dots, R} \left( \frac{u_{ir}^b}{u_{0r}} \right) \right\}$  is calculated using the artificial sample.
3. Steps 1 and 2 are carried out  $B$  times, with  $b=1, \dots, B$ .
4.  $\hat{y}^m(u_0, v_0)$  is calculated as the mean  $\frac{1}{B} \sum_{b=1}^B \hat{y}^{mb}(u_0, v_0)$ .

It is important to note that order- $m$  efficiency represents an outlier-robust variation of the ‘free disposal hull’ (FDH) approach (Deprins et al., 1984), which relaxes the convexity-assumption inherent in DEA. More precisely, carrying out step 2 just once with the entire sample leads to FDH-based efficiency scores. The measure has intuitive appeal, since the observed production unit is compared to those that produce at least the same amount of output, and the best-practice unit is the one with minimal input use. As all production units that are not dominated by any other unit span the efficiency frontier, the FDH approach rests on the principle of weak dominance.

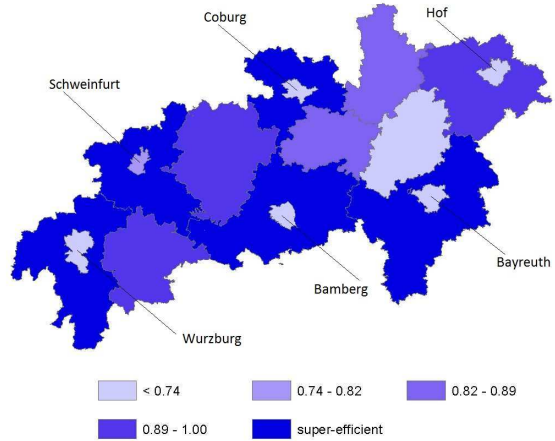
This measure would be very sensitive to outliers if it depended solely on one sample of observations. For this reason, order- $m$  efficiency estimates the expected best practice among a fixed number of  $m$  peer units producing at least the same amount of output; see Cazals et al. (2002) and Daraio & Simar (2007) for a detailed and formal discussion and Pilyavsky & Staat (2008) for an application to health production.

The choice of  $m$  becomes relevant for practical applications. For  $m \rightarrow \infty$ , order- $m$  efficiency coincides with FDH. Hence, robustness to outliers calls for a relatively small value of  $m$ , so comparing the observed unit to just a few peers. However, as  $m$  gets smaller the share of super-efficient units increases, rendering the estimated scores an increasingly degenerated measure of efficiency. Bonaccorsi et al. (2006) suggest choosing  $m$  such that the share of super-efficient observations is 10%. Following this suggestion, we end up with roughly  $m =$

100.<sup>7</sup> Robustness checks carried out with respect to this choice revealed only limited impact of the value of  $m$  on estimation results in the second-stage regression analysis (see Tables 4 and 6 in Appendix B for a selection). For the number of re-sampling iterations we choose  $B = 2,000$ .<sup>8</sup>



**Figure 6:** order- $m$  efficiency scores, 2004  
Source: Own calculations



**Figure 7:** order- $m$  efficiency scores, 2004 (detail)  
Source: Own calculations

Unfortunately, the limited availability of data at the district level restricts the opportunities for formulating a rich model of efficiency that includes measures of morbidity as outcome variables. Instead, we use the standardized mortality (see section 3) as a single output variable of health production.<sup>9</sup> In order to base the analysis on a desired good rather than an unwanted 'bad', we use the inverse of standardized deaths as output variable  $v$ .<sup>10</sup> We consider three inputs to health production at district level: hospital beds, general practitioners, and resident medical specialists each measured on a per inhabitant basis (see section 3 for detailed description).

Figure 7 displays the corresponding order- $m$  results ( $m = 100$ ) in terms of input-oriented technical efficiency  $y$ . Considering all three years, the districts reach an average efficiency level of 0.850, which almost coincides with the median value 0.856. The lowest score is

<sup>7</sup>  $m = 100$  is a large value compared to other applications (e.g. Binder & Broekel, 2008; Pilyavsky & Staat, 2008). But as the present analysis considers one output only, the share of observations satisfying  $v_{is} \geq v_{0s}$  for  $s = 1, \dots, S$  is typically larger than for multi-output applications. Hence, when a large number of potential benchmark observations is available, a relatively large sample of actual observations can be drawn.

<sup>8</sup> Daraio & Simar (2007) suggest that the substantially smaller value of  $B = 200$  is sufficient. But with our data, increasing the number of iterations to  $B \gg 200$  markedly changes at least some estimated scores.

<sup>9</sup> This is not uncommon in applied health economics; see Hall and Jones (2007) for a recent example.

<sup>10</sup> While DEA would necessarily require such a transformation (cf. Scheel, 2000), order- $m$  analysis allows the use of the original variable – with no effect on estimated efficiencies – if the condition  $v_{is} \leq v_{0s}$  is used in (1) instead of  $v_{is} \geq v_{0s}$ .

0.484 while the highest is 2.457. The share of districts classified as super-efficient (efficiency score > 1) is 10.7%. Generally, order-m efficiency scores do not exhibit an obvious regional pattern. Nevertheless, we still find substantial heterogeneity at the state level. State means range from 0.715 (city states) to 0.889 (Baden-Wurttemberg).

Moreover, for some regions, most prominently those in Franconia<sup>11</sup>, the estimated efficiency measures exhibit a distinct local pattern of less efficient urban districts surrounded by highly efficient, in most cases even super-efficient, rural ones (see Figures 6 and 7 and Table 2).

**Table 2: Order-m efficiency scores for some Franconian urban and contiguous rural districts**

	Bamberg	Bayreuth	Cobourg	Hof	Schweinfurt	Wurzburg
urban district	0.537	0.627	0.647	0.548	0.798	0.576
rural district	1.118	1.367	1.147	0.910	1.054	1.012

This pattern corresponds to the regional distribution of hospitals and medical specialists and supports our original hypothesis of a strong influence of net patient flows on district-specific efficiency scores. Inhabitants of rural Franconia thus receive medical treatment in urban districts such as Bamberg, Bayreuth, Schweinfurt and Wurzburg, leading to poor efficiency scores there, while the rural contiguous neighbors seem highly efficient. Indeed, Moran's I test based on inverse squared distances indicates a highly significant spatial correlation, regardless of whether it is applied unconditionally to the raw efficiency scores or conditionally on covariates  $x$ .

## 4.2 A Spatial Regression Model

In order to account for spatial spillovers in the regression analysis explaining efficiency of health care provision at the district level we include the efficiency scores of neighboring districts as right-hand side variables. We allow for spatially correlated errors and regard net patient flows as the most likely source of this correlation pattern. This leads us to a spatial autoregressive model with autoregressive disturbances (see Anselin, 1988), which accommodates both types of spatial interdependence. The basic structure of the model is given by

$$y = X\beta + \lambda Wy + \xi \quad (2)$$

$$\xi = \rho M\xi + \varepsilon \quad (3)$$

$$\text{with } E(\varepsilon_{it}) = 0, \quad \text{var}(\varepsilon_{it}) = \sigma^2, \quad \text{and} \quad \text{cov}(\varepsilon_{it}, \varepsilon_{j\tau}) = 0.$$

$y$  indicates the  $N \times 1$  vector of the dependent variables (order-m efficiency scores), where  $N$  denotes the total number of district-year observations. Districts are indexed by  $i$  and  $j$  and years by  $t$  and  $\tau$ .  $\xi$  denotes the corresponding vector of error terms and  $X$  denotes

<sup>11</sup> A similar pattern is also found in regions other than Franconia, yet, due to the layout of districts, it is less obvious in our data. One may, nevertheless, find other examples than Franconia.

the  $N \times k$  matrix of regressors, where  $\beta$  is a vector of coefficients subject to estimation.  $W$  and  $M$  represent  $N \times N$  spatial weighting matrices, capturing the pattern of spatial dependence. As we consider a period of three years and since spatial interdependence is a matter of contemporaneity,  $W$  and  $M$  are block-diagonal in our application. These matrices are thus composed of three year-specific  $N_t \times N_t$  spatial weighting matrices. The endogenous variable  $y$  enters the right-hand side of the equation (2) via  $Wy$ . The latter represents a  $N \times 1$  vector of spatial lags of  $y_{it}$ , i.e. weighted sums of  $y_{j\tau}$ , with  $j \neq i$  and  $\tau = t$ . Hence, the efficiency of any district  $i$  potentially depends on the efficiency of any other district under consideration.

An appropriate spatial weighting matrix must satisfy certain requirements (see e.g. Kelejian & Prucha, 2008). In particular, the diagonal elements  $w_{ii}$  and  $m_{ii}$  must be zero and the intensity of spatial dependence must be restricted and decline sufficiently with increasing distance between two spatial units. Formally, each row and column sum must be uniformly bounded if the number of spatial units grows to infinity, and  $(I - \lambda W)$  as well as  $(I - \rho M)$  must be non-singular. Yet  $W$  and  $M$  need not be symmetric, allowing for different travel times between two districts depending on the direction of travel. The model further allows for the special case  $W = M$ , in which the same pattern of spatial dependence applies to the covariance structure among the error terms  $\xi_i$  and to the pattern of direct spillovers between the dependent variables  $y_i$ . In practical applications, both  $W$  and  $M$  are typically exogenously given and not subject to estimation, except for rare cases where panel data are available and the number of cross-sectional units is small compared to the number of periods.

In applied work, spatial weighting matrices are normalized in order to allow for a straightforward interpretation of the model parameters. The most common practice is to row-standardize the weighting matrices, where all matrix elements  $w_{ij}$  and  $m_{ij}$  are divided by the corresponding row sum. Other approaches are (i) minmax standardization, i.e. standardization by the minimum of the largest row and the largest column sum, and (ii) eigenvalue standardization, i.e. standardization by the modulus of the largest eigenvalue of the relevant matrix. The latter two approaches allow for spatial dependence being differently important across observations. In contrast, by using row standardization, one implicitly assumes that spatial interdependence is of equal relevance to all regions. Kelejian & Prucha (2008) and Baltagi et al. (2008) therefore argue against row-normalization unless its implicit assumption is clearly suggested by economic theory. This does not apply to the present case, as districts in Germany evidently vary with respect to remoteness and spatial interlinkage to the rest of the country. Hence we prefer eigenvalue normalization. Finally,  $\lambda$  and  $\rho$  are unknown scalar coefficients that are estimated along with  $\beta$ . For both, the unit-interval represents the relevant parameter space; see Kelejian & Prucha (2008) for a detailed

discussion. Clearly, no spatial autoregression, i.e. no direct spillover effect, is present for the case  $\lambda = 0$ , while for  $\rho = 0$  the errors are spatially uncorrelated.

The spatial autoregressive model exhibits a close analogy to well-known autoregressive time-series models. In fact, (2) and (3) allow for inversion, yielding a reduced form and moving average representation of the model

$$y = (I - \lambda W)^{-1} X \beta + (I - \lambda W)^{-1} (I - \rho M)^{-1} \varepsilon \quad (4)$$

from which the conditional mean  $E(y | X)$  is directly derived as

$$E(y | X) = (I - \lambda W)^{-1} X \beta. \quad (5)$$

Thus, in the spatial autoregressive model a change in an exogenous variable  $x_{kj}$  exerts an effect not only on region  $j$  but potentially on any other region  $i$  as well. Moreover, due to feedback effects from  $i$  to  $j$ ,  $\beta_k$  does not represent the total effect on region  $i$ . Rather, marginal effects of an explanatory variable  $x_k$  represent an  $N \times N$  matrix

$$\frac{\partial E(y | X)}{\partial x_k} = (I - \lambda W)^{-1} \beta_k, \quad (6)$$

where the  $ij$ -element captures the effect of a marginal change of  $x_k$  in district  $j$  on the efficiency in district  $i$ . Hence, if one is interested in the effect of an isolated change in  $x_{kj}$  on the efficiency of district  $j$ , one has to incorporate the diagonal elements of (6). If, however, one is interested in the aggregate effects of a uniform and simultaneous change in all districts, the row-sums of (6) are the relevant measures; see LeSage & Pace (2009) for a detailed discussion of marginal effects in spatial autoregressive models.

The spatial autoregressive model does not allow for a straightforward estimation of equation (2) by OLS as the endogenous variable  $y$  enters the right-hand side via the spatial lag, for which  $E(Wy' \xi) \neq 0$  holds. In order to avoid endogeneity bias, we follow the approach suggested by Kelejian & Prucha (1998).<sup>12</sup> The corresponding three-stage estimation proceeds as follows. First, equation (2) is estimated using a conventional instrumental variables approach, with  $X$ ,  $WX$ ,  $W^2X$ ,  $MX$ ,  $M^2X$ , and serving as instruments for the endogenous spatial lag  $Wy$ . Second, based on the residuals obtained from the initial two-stage least-squares (2SLS) regression, Kelejian & Prucha (1998) derive a set of moment restrictions that allow for estimating  $\rho$  and  $\sigma^2$  via GMM.<sup>13</sup> Finally, with an estimate for  $\rho$  in hand, a Cochrane-Orcutt transformation can be applied and a 2SLS estimation carried out again using the transformed data. Here, the transformed left-hand side variable is  $\tilde{y} \equiv y - \hat{\rho}My$ , while the transformed right-hand side variables are defined analogously.

<sup>12</sup> Maximum likelihood estimation represents an alternative approach. Arraiz et al. (2008) argue, however, that ML performs poorly even for small deviations from distributional assumptions and involves computational difficulties. We therefore prefer the Kelejian & Prucha (1998) estimator.

<sup>13</sup> All moment restrictions receive equal weight; hence a GMM technically coincides with non-linear least squares.



As a robust alternative, we also report the initial 2SLS results for which we calculated heteroscedasticity and autocorrelation consistent (HAC) standard errors, as proposed by Kelejian and Prucha (2007); see Appendix B, Table B.4.<sup>14</sup> We also checked whether the estimated standard errors were incorrect due to error correlation induced by efficiency measurement, applying a modified Simar & Wilson (2007) procedure; see Appendix A. This procedure yields standard errors that deviate only marginally from analytically derived ones, vindicating the argument of Binder & Broekel (2008) that order-m efficiency estimates are less vulnerable to misleading inference. Hence, we report analytically derived conventional standard errors.

### 4.3 Extension to Panel Data

Panel data call for taking into account the error terms most likely to be correlated over time. Applying a generalization of the Egger et al. (2005) approach to the original Kelejian & Prucha (1998) model, we allow for unobserved individual time-invariant heterogeneity. The error term then includes the district-specific component  $\mu_i$ , with

$$\varepsilon_{it} = \mu_i + \zeta_{it}, \quad \text{with} \quad \text{cov}(\zeta_{it}, \zeta_{j\tau}) = 0, \quad (6)$$

which captures unobserved time-invariant determinants of regional efficiency. The Egger et al. method accommodates both random and fixed effects, where for the former  $\mu_i$  is assumed to be uncorrelated with the regressors and the innovations  $\zeta_{it}$ . The estimation procedure for this generalized model closely resembles the original three-stage Kelejian & Prucha approach; see Egger et al. (2005) for a detailed discussion. Yet, the first stage – irrespective of whether fixed or random effects are considered – uses within-transformed data to remove the individual effects, where spatial lags of the within-transformed explanatory variables serve as instruments. Subsequently, the estimator employs a set of modified moment conditions in order to derive estimates for  $\rho$ ,  $\sigma_\mu^2$ , and  $\sigma_\zeta^2$  from the composite first-stage regression residuals  $(\hat{\mu}_i + \hat{\zeta}_{it})$  using GMM. Finally, the estimate for  $\rho$  is used to perform a Cochrane-Orcutt transformation on the data that is also within-transformed for the fixed effects model and quasi-within-transformed<sup>15</sup> for the random effects model. As in the original Kelejian & Prucha approach, 2SLS estimation is then applied to the transformed data where first- and second-order spatial lags of within- (respectively quasi-within-) transformed explanatory variables serve as instruments.

<sup>14</sup> Computation of HAC standard errors is based on: (i) a Parzen kernel, (ii) raw travel time as distance measure, (iii) travel time of 45 minutes as bandwidth. Point estimates obtained from initial 2SLS are close to the preferred three stage results. HAC standard errors estimated for 2SLS are somewhat larger than their conventional counterparts, computed for the three stage procedure. Nevertheless, in terms of significance, the majority of the qualitative findings still hold for the more robust model variant.

<sup>15</sup>  $\tilde{x}_{it} \equiv x_{it} - \hat{\theta}_i \bar{x}_i$  with  $\hat{\theta}_i = 1 - \hat{\sigma}_\zeta (T_i \hat{\sigma}_\mu^2 + \hat{\sigma}_\zeta^2)^{-0.5}$  holds for a quasi-within-transformed variable  $\tilde{x}_{it}$ , where  $T_i$  denotes the number of observations on district  $i$  and  $\bar{x}_i$  denotes the district mean of  $x_{it}$  (see e.g. Greene, 2000: 569). For the fixed effects model,  $\theta_i$  takes on the value 1.



As almost all variables in our data exhibit only small variations over time, a fixed effect approach which relies exclusively on within-group variation appears inappropriate. Unlike Egger et al. (2005), we therefore use a random effects variant that avoids the within-estimator at the first stage of the procedure.<sup>16</sup> Nevertheless, we also report results for the original Egger et al. (2005) fixed effects estimator.

#### 4.4 Model Specifications and Hypotheses

Our preferred specification for the spatial autoregressive model considers order- $m$  efficiency scores with  $m = 100$  as dependent variable. On the right-hand side we first consider total population and population density in order to capture rurality. On the basis of economies of scale, one may expect large districts to be more efficient than smaller ones. Rurality likely involves lower efficiency scores, as providing a sufficient level of health care in sparsely populated regions requires more resources. A further indicator captures the special status of urban districts which are expected to seem less efficient, as they typically provide health services to the populations of surrounding rural districts as well.

Although we already account for demographics in the district-specific mortality rates, we also consider district-level sex-age-structures in the regression analysis. Specifically, we distinguish between men and women and between five age classes (1-20, 21-40, 41-60, 61-80, 80+ years of age), each measured as shares in total population. Since demand for health care is higher in old age, we expect districts with older populations to be less efficient. Likewise, the higher demand observed among women should result in a negative correlation between a district's share of women and its efficiency in health production.

We also include two economic indicators in the regression, the district's unemployment rate and its average disposable household income. Since economic status and health are frequently found to be positively correlated, we expect a negative coefficient estimate for the former control and a positive coefficient for the latter. We further include hospital ownership as an explanatory variable for efficiency (for recent studies with mixed results, see Herr, 2008, and Herr et al., 2011). Ownership is measured in terms of share in total hospital beds, with public ownership serving as the reference. Private and (private) non-profit are then considered explicitly. Finally, we include sets of both year- and state-specific dummies, the latter being of particular interest to our analysis.

For the spatial weighting matrices, we consider average travel time by car between two districts' centroids. Travel time appears to be far more important for patient flows and efficiency spillovers than distance alone. An inverse-squared-distance matrix is our preferred specification. Alternatively, we use a contiguity matrix where 'contiguous' is defined as a travel time between two districts of less than 45 minutes. Estimated coefficients are similar (see Table B.3 in Appendix B). All reported results are based on eigenvalue-standardized

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<sup>16</sup> Instead, we employ a random effects estimator at the first stage. The moment restrictions (cf. Kapoor et al., 2006) exploited at the second stage are derived under general fixed effects conditions, and are also valid for the special case of random effects.

matrices (while minmax standardization yields similar results, row standardization provides substantially different patterns of estimated spatial dependence). The reported variants all consider the case where  $W = M$ , as we know of no theory in favor of a particular pattern of spatial dependence regarding spillovers and error correlation.

## 5 Estimation Results

Table 3 displays results from the spatial autoregressive regression model, explaining the efficiency scores derived by order- $m$  efficiency analysis. To begin with, the results for the pooled estimator (Kelejian & Prucha, 1998) do not indicate any importance of hospital ownership for the efficiency of health production at the district level. The same applies to income: its coefficient is also not significant. By contrast, the unemployment rate is a significant predictor of a district's efficiency and its coefficient exhibits the expected negative sign. It is unlikely that this estimate captures a pure causal effect; it probably also reflects the (unobserved) higher morbidity of unemployed individuals. From a spatial point of view, labor market status might serve as a proxy for mobility, as employees may need to travel long distances to their workplaces (unlike the unemployed). Commuters may in fact represent interregional patient flows, especially in outpatient care, if they tend to visit physicians near their place of work rather than their place of residence.

A district's demographic composition clearly matters for the efficiency of health care provision. As expected, a larger share of people beyond the age of 80 decreases the efficiency of regional health production. Somewhat surprisingly, this also holds for the age class 21 to 40. A possible explanation for this finding is that women of prime child bearing age fall into this age class. Pregnancy and birth involve health care consumption. Thus, in regions with many women of this age, one should expect an extra supply of – primarily gynecological – health care facilities. The share of women in a district's population is also negatively associated with efficiency, which is likely to capture a similar effect.

The urban district dummy variable is significantly negative, confirming the conjecture that urban districts provide health services to the populations of neighboring rural districts. Controlling for a district's type (urban or rural), population density exhibits a significant and positive impact on efficiency. This result is intuitively appealing, as a proportionately larger stock of health infrastructure is required to provide sufficient primary and emergency health care in sparsely populated regions. In contrast to population density, district population size has a negative effect on efficiency. This result contradicts the hypothesis that there are scale economies in the provision of healthcare services. However, it could well be that small districts benefit from services supplied only by adjacent large ones.

**Table 3: Results for the Spatial Autoregressive Model**

	Pooled		Random Effects		Fixed Effects	
	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
spatial lag ( $\lambda$ )	0.108***	0.014	0.093***	0.024	0.285**	0.119
Population	-0.046**	0.022	-0.044	0.035	0.398	1.219
population density	0.039***	0.011	0.032*	0.018	0.198	0.301
urban district	-0.127***	0.015	-0.158***	0.024	-	-
Women	-4.503***	0.671	-4.967***	1.025	-2.786	2.769
aged 21 to 40	-1.560***	0.324	-0.969**	0.468	1.786	1.099
aged 41 to 60	0.910**	0.398	0.414	0.530	0.116	1.013
aged 61 to 80	-0.756*	0.392	-0.890	0.550	1.976	1.490
aged above 80	-2.872***	0.739	-2.085**	1.037	9.909***	2.692
unemployment rate	-0.706***	0.156	-0.188	0.153	0.346	0.213
Income	0.161	0.229	0.338	0.321	-0.887	0.965
hospitals non-profit	0.011	0.012	0.008	0.017	-0.008	0.037
hospitals private	-0.006	0.012	0.005	0.012	0.009	0.015
year 2005	0.003	0.007	0.003	0.006	0.004	0.009
year 2006	-0.012	0.009	-0.002	0.009	0.007	0.016
state indicators (coefficients expressed as mean-deviations)						
Schleswig-Holstein	-0.010	0.016	-0.012	0.027	-	-
Lower Saxony	0.023**	0.011	0.022	0.018	-	-
North Rhine-Westphalia	-0.007	0.013	0.006	0.021	-	-
Hesse	-0.044***	0.014	-0.033	0.023	-	-
Rhineland-Palatinate	-0.052***	0.014	-0.025	0.022	-	-
Baden-Wuerttemberg	-0.006	0.014	0.008	0.023	-	-
Bavaria	-0.040***	0.013	-0.024	0.020	-	-
Saarland	-0.106***	0.023	-0.083**	0.040	-	-
Brandenburg	0.036*	0.020	0.025	0.032	-	-
Mecklenburg-West Pomerania	0.013	0.022	-0.009	0.034	-	-
Saxony	0.086***	0.015	0.068***	0.024	-	-
Saxony-Anhalt	0.068***	0.019	0.046	0.029	-	-
Thuringia	-0.019	0.017	-0.029	0.027	-	-
city states	0.057	0.038	0.040	0.061	-	-
Constant	3.639***	0.349	3.768***	0.541	0.677	1.751
$\rho$	-0.206		0.036		-0.334	
$\sigma_\mu$	-		0.096		0.404	
$\sigma_\varepsilon$	-		0.040		0.039	
$\sigma_\varepsilon$	0.103		-		-	
R <sup>2</sup> (overall)	0.518		0.508		-	
R <sup>2</sup> (within)	-		-		0.041	
joint significance (p-value):						
States	0.000		0.009		-	
hospital ownership	0.494		0.858		0.762	
Age	0.000		0.004		0.003	

**Notes:** \*, \*\*, and \*\*\* indicate significance at the 0.1, 0.05, and the 0.01 level, respectively; input oriented order-m ( $m = 100$ ) efficiency scores at the district level serve as dependent variable; regression results based on 1286 district-year observations; years 2004, 2005, and 2006 considered, spatial weighting matrix based on inverse squared distances.

We also examine the influence of states on the district-level efficiency of health production. The coefficients here represent mean deviations from the average value set at zero; see Haisken-DeNew & Schmidt (1997) on how to calculate appropriate standard errors. Clearly, the state indicators are jointly significant. Though state dummies capture any persistent

differentials in efficiency that are state-specific, this result still points towards a substantial impact of state-level health policy on regional efficiency. Individually, the estimated coefficients indicate that several East German states (Brandenburg, Saxony, Saxony-Anhalt) are among the most efficient – conditional on the control variables – while some West German states (notably Saarland, Rhineland-Palatinate, Bavaria and Hesse) display low efficiency figures. Moreover, the statistically significant east-west<sup>17</sup> differential in estimated average state effects is 0.067. This might reflect the fact that medical infrastructure was renewed in the East after the fall of the Berlin wall. As this process was not influenced strongly by district-level politics, the states were able to establish a fairly slim infrastructure. By contrast, the process of specialization in inpatient care, including mergers and closures of hospitals, has been slow in the West due to political opposition and vested interests.

Finally, estimation results for the parameters that capture spatial dependence indeed indicate that this is a relevant feature of the data. The coefficient  $\lambda$  attached to the spatial lag of efficiency scores is highly significant and positive, pointing to substantial positive spatial efficiency spillovers. The estimate for  $\rho$ , on the other hand, bears a negative sign, indicating negative spatial error correlation. By nature, the specific cause of the cross-section error correlation found in the data is unknown. Hence, one cannot rule out that sources of cross-section dependence other than genuine spatial dependence are captured by the estimate for  $\rho$ .<sup>18</sup> This applies, for instance, to global shocks exerting heterogeneous effects on districts that are not fully captured by the time-specific dummies (Moscone & Tosetti, 2010). Nevertheless, the negative sign of  $\rho$  corresponds well with our earlier reasoning on inter-district patient flows generating a pattern of spatially negatively correlated efficiency scores. Hence, we regard cross-border patient migration as the most likely explanation for the estimated error correlation pattern.

Given the empirical relevance of spatial dependence, we examine its impact on the estimated coefficients by comparing our results to those obtained from a simple OLS model which ignores both spatial spillovers and spatial error correlation; see Table 4. It turns out that the OLS model – though apparently misspecifying inter-district dependence – yields results similar to those from the spatial autoregressive model. We find the state effects jointly significant in both model variants. However, heterogeneity – including the east-west pattern for which the differential in average state effects is only half as big and statistically insignificant – is less distinct if spatial dependence is ignored. This is most likely due to a negative association between the estimated state effects and the state average level of spatial dependence (correlation 0.5). That is, on average states that are genuinely more efficient benefit less from positive spillover effects. Hence, in a regression that ignores spatial dependence and therefore does not disentangle genuine efficiency differentials and spillover effects, state effects seem to be smaller. In essence, rather than representing an

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<sup>17</sup> City-states are not taken into account. Berlin cannot be classified as either east or west.

<sup>18</sup> Results for tests on general cross-section dependence (cf. Baltagi & Moscone, 2010) – not necessarily spatial dependence – strongly argue in favor of the presence of cross-section dependence in the data.

artifact of ignored spatial dependence, state heterogeneity is even more prevalent in the efficiency of health production if spatial interdependence is accounted for.

Applying a random effects model yields similar results. The estimates for  $\sigma_\mu$  and  $\sigma_\xi$  indicate that roughly 86 percent of the error variance is district-specific.<sup>19</sup> Hence, unobserved district-specific heterogeneity is indeed an issue that should be accounted for. Nevertheless, the estimated coefficients are very close to our previous results from the pooled model. This applies in particular to  $\lambda$ , which is roughly 0.1 and highly significant here as well. Random effects estimation also yields a similar pattern of state effects on efficiency, though somewhat less distinct in terms of point estimates and statistical significance. With respect to the latter, one has to note that standard errors are generally larger for the random effects model. The east-west pattern also comes out more clearly here than in the model that ignores spatial dependence. Here the east-west differential in estimated average state effects is 0.037 for the former compared to 0.013 for the latter. On the other hand, the random effects model does not indicate relevant spatial error correlation, as the estimate for  $\rho$  is virtually zero. Generally, random effects estimation yields slightly larger standard errors and, in turn, fewer individually significant coefficients than the pooled model. As the latter does not take account of the panel structure of the data, standard errors for the random effects model would seem more reliable.

Finally, we examine results for a fixed effects specification that allows district effects to be correlated with the explanatory variables. Interestingly, fixed effects results indicate much stronger spatial dependence than our previous specifications. This holds for both  $\lambda$  and  $\rho$ , the former suggesting substantial positive spillover effects and the latter strong negative error correlation.<sup>20</sup> However, a very low within- $R^2$  value signals poor explanatory power of the within-estimator. And a highly significant and large positive effect of the share of elderly people – counter to intuition – raises further suspicion about these results. In general, a fixed effects approach seems ill-suited for our data, which display very little variation across periods. Hence, we prefer the random effects model to the fixed effects one.

All in all, our empirical analysis points to significant spatial dependence of health production efficiency at the district level. Firstly, the results indicate that net patient flows result in misleading district efficiency estimates. Secondly, spatial spillovers are clearly present in health production, as districts benefit from efficient service provision in neighboring districts. Thirdly, accounting for spatial spillovers does not remove state-specific heterogeneity in district efficiency. Rather, the variance in estimated state effects increases if spatial dependence between districts is considered. This increases confidence in state dummies indeed capturing the impact of state-level health policy on efficiency.

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<sup>19</sup>  $\sigma_\mu^2 / (\sigma_\mu^2 + \sigma_\xi^2) = 0.86$ .

<sup>20</sup> Fixed effects estimation does not allow for the inclusion of time-invariant explanatory variables. Hence, we cannot address state effects directly. But regressing estimates for  $\mu_i$  on the time-invariant regressors yields highly significant state effects.

**Table 4: Results for models not considering spatial dependence**

	Pooled		Random Effects		Fixed Effects	
	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
spatial lag ( $\lambda$ )	-	-	-	-	-	-
Population	-0.065***	0.022	-0.061*	0.036	0.212	1.258
population density	0.058***	0.011	0.051***	0.018	0.401	0.298
urban district	-0.127***	0.015	-0.157***	0.025	-	-
Women	-4.399***	0.692	-4.750***	1.055	-2.397	2.821
aged 21 to 40	-1.421***	0.335	-0.935*	0.481	0.984	1.112
aged 41 to 60	1.413***	0.407	0.724	0.536	-0.138	1.066
aged 61 to 80	-0.630	0.404	-0.924	0.565	0.477	1.445
aged above 80	-3.570***	0.760	-2.340**	1.059	9.254***	2.788
unemployment rate	-0.555***	0.161	-0.063	0.152	0.377*	0.224
Income	0.418*	0.237	0.527	0.325	-0.047	0.882
hospitals non-profit	0.006	0.012	0.004	0.018	-0.007	0.037
hospitals private	-0.007	0.012	0.003	0.012	0.009	0.015
year 2005	-0.003	0.008	-0.001	0.006	-0.003	0.009
year 2006	-0.018*	0.010	-0.007	0.009	-0.004	0.015
state indicators (coefficients expressed as mean-deviations)						
Schleswig-Holstein	-0.020	0.017	-0.024	0.028	-	-
Lower Saxony	0.033***	0.012	0.030	0.019	-	-
North Rhine-Westphalia	0.007	0.013	0.015	0.021	-	-
Hesse	-0.013	0.014	-0.010	0.023	-	-
Rhineland-Palatinate	-0.018	0.014	-0.001	0.022	-	-
Baden-Wuerttemberg	0.014	0.015	0.021	0.023	-	-
Bavaria	-0.015	0.013	-0.004	0.019	-	-
Saarland	-0.097***	0.025	-0.074*	0.041	-	-
Brandenburg	-0.002	0.020	-0.002	0.032	-	-
Mecklenburg-West Pomerania	-0.034	0.022	-0.043	0.034	-	-
Saxony	0.082***	0.015	0.065***	0.025	-	-
Saxony-Anhalt	0.060***	0.020	0.045	0.030	-	-
Thuringia	-0.026	0.018	-0.031	0.028	-	-
city states	0.030	0.039	0.013	0.063	-	-
Constant	3.373***	0.359	3.549***	0.555	1.065	1.777
$\rho$	-	-	-	-	-	-
$\sigma_\mu$	-	-	0.099	-	0.398	-
$\sigma_\xi$	-	-	0.040	-	0.040	-
$\sigma_\varepsilon$	0.106	-	-	-	-	-
R <sup>2</sup> (overall)	0.505	-	0.494	-	-	-
R <sup>2</sup> (within)	-	-	-	-	0.053	-
joint significance (p-value):						
States	0.000	-	0.015	-	-	-
hospital ownership	0.674	-	0.955	-	0.763	-
Age	0.000	-	0.001	-	0.011	-

**Notes:** \*, \*\*, and \*\*\* indicate significance at the 0.1, 0.05, and the 0.01 level, respectively; input oriented order-m ( $m = 100$ ) efficiency scores at the district level serve as dependent variable; regression results based on 1286 district-year observations; years 2004, 2005, and 2006 considered.

Accounting for spatial dependence yields fairly small effects on estimation results for the determinants of district-level efficiency. Nevertheless, this still substantially alters the structure of the model, in particular the marginal effects that exhibit substantial heterogeneity across districts due to spillover and feedback effects. If, for instance, health

policy in one state managed to initially increase efficiency within the state, spatial spillovers will make this effect carry over to neighboring regions in other states. Moreover, federal policies with a uniform effect of e.g. one percentage point on efficiency in all districts will result in heterogeneous equilibrium effects ranging from 1.02 to 1.23 percentage points in the districts, with regional heterogeneity exhibiting the pattern illustrated in Figure 1. Analyses ignoring spatial spillovers would miss both effects.

Our main results are robust to several variations of the specification of the model, in particular to the choice of the spatial weighting matrix as well as to the choice of  $m$  for estimating order- $m$  efficiencies. Even the use of DEA-efficiency scores – ignoring the shortcomings discussed earlier – yields similar results to those presented. Only if we employ an output-oriented efficiency measure rather than an input-oriented one do results not indicate strong spatial dependence in efficiency.

## 6 Conclusions

This paper investigates potential spatial dependence in the district-specific efficiency of health production in Germany. If spatial dependence applies – more specifically: if regional efficiency follows a spatial autoregressive process – regular empirical analyses might be biased and result in misleading policy advice. Our initial descriptive analysis of efficiency at the district level reveals patterns that indicate the presence of spatial error correlation and/or spatial spillovers. The subsequent regression analysis supports this conjecture, as we detect both significant spatial error correlation and spatial spillovers.

Estimation results indicate that federal state-specific heterogeneity does not vanish once spatial dependence is controlled for. Rather, state differentials are even more prominent in the model specifications considering spatial spillovers. This supports the notion that state indicators do indeed capture the effects of state policy on the efficiency of health production. Our spatial regression analysis hence confirms the important role of states which has been found in several empirical studies. In turn, state efficiency differentials do not represent an artifact of (ignored) spatial dependence. Inefficient states are, thus, well advised to review and adjust the regulation of health care provision.

We conclude that spatial dependence represents a major feature of district-level efficiency in health production in Germany. Empirical applications using regionally disaggregated health care data should therefore consider taking spatial dependence into account. This applies particularly if the focus is on quantitative effects of exogenous changes that are relevant not just to one but potentially to all districts.

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## Appendix A: A modified Simar & Wilson procedure

Following the estimation of  $\hat{\beta}$ ,  $\hat{\lambda}$ ,  $\hat{\rho}$ , and  $\hat{\sigma}$  obtained by the Kelejian & Prucha (1998) approach, we apply and attune the four-step procedure by Simar & Wilson (2007) to the spatial autoregressive model:

1. A vector  $\tilde{\varepsilon}^d$  of independent errors is drawn from the  $N(0, \hat{\sigma}^2)$  distribution and an artificial, spatially correlated error vector  $\tilde{\xi}^d$  is computed as  $(I - \hat{\rho}M)^{-1} \tilde{\varepsilon}^d$ .
2. From this, a vector of artificial bootstrap efficiency scores is derived as  $\tilde{y}^d = (I - \hat{\lambda}W)^{-1} (X\hat{\beta} + \tilde{\xi}^d)$ .
3.  $\tilde{y}^d$  is used as dependent variable to obtain bootstrap estimates  $\hat{\beta}^d$  and  $\hat{\lambda}^d$ , once again following the estimation procedure of Kelejian & Prucha (1998).
4. Steps 1 to 3 are repeated  $D$  times, with  $d=1, \dots, D$ , and standard errors for  $\hat{\beta}$  and  $\hat{\lambda}$  are computed from the bootstrap distribution of  $\hat{\beta}^d$  and  $\hat{\lambda}^d$ .

In contrast to the original Simar & Wilson (2007) procedure, neither drawing from the truncated normal distribution nor truncated regression is required, as order-m efficiencies – unlike DEA efficiency scores – are not bounded from above. In our application we choose  $D = 250$ . While the described procedure yields standard errors for  $\hat{\beta}$  and  $\hat{\lambda}$  that are robust to efficiency measurement-induced error correlation, this does not apply to  $\hat{\rho}$  and  $\hat{\sigma}$ , as these estimates enter the distribution from which the bootstrap error vector  $\tilde{\xi}^d$  is drawn. Moreover, the estimate for  $\rho$  will eventually capture efficiency measurement-induced error correlation along with spatial error correlation.

## Appendix B: Results for alternative model specifications

**Table B.1: Descriptive statistics for alternative efficiency measures (pooled)**

Efficiency Measure	Mean	S.D.	Median	Min	Max	Super-efficient (share)
DEA (var. returns, input-oriented)	0.746	0.107	0.741	0.448	1.000	0.000
FDH (input-oriented)	0.798	0.128	0.798	0.448	1.000	0.000
order-m ( $m = N$ , input-oriented)	0.808	0.126	0.812	0.452	1.106	0.059
order-m ( $m = 250$ , input-oriented)	0.819	0.127	0.826	0.460	1.371	0.073
order-m ( $m = 100$ , input-oriented) <sup>a</sup>	0.850	0.149	0.856	0.484	2.457	0.107
order-m ( $m = 50$ , input-oriented)	0.886	0.209	0.880	0.507	3.863	0.156
order-m ( $m = 25$ , input-oriented)	0.935	0.324	0.912	0.533	6.213	0.226
order-m ( $m = 10$ , output-oriented)	0.912	0.072	0.912	0.709	1.118	0.120

**Notes:** <sup>a</sup> preferred measure; descriptive statistics are reported for the pooled sample, i.e. 1286 district-year observations; years 2004, 2005, and 2006 considered; efficiency scores are estimated separately for each year.

**Table B.2: Regression results for alternative efficiency measures (pooled regression)**

	order-m (50)		order-m (250)		DEA	
	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
spatial lag ( $\lambda$ )	0.187***	0.019	0.051***	0.013	0.074***	0.014
population	-0.051	0.035	-0.040**	0.016	-0.038**	0.015
population density	0.028*	0.017	0.045***	0.008	0.035***	0.008
urban district	-0.123***	0.024	-0.127***	0.011	-0.084***	0.010
women	-4.730***	1.076	-4.595***	0.510	-3.465***	0.473
aged 21 to 40	-1.624***	0.518	-1.497***	0.247	-1.118***	0.229
aged 41 to 60	1.992***	0.636	0.291***	0.305	0.450	0.284
aged 61 to 80	-0.407	0.630	-0.992	0.297	-0.408	0.276
aged above 80	-3.689***	1.190	-2.293***	0.561	-3.639***	0.521
unemployment rate	-0.904***	0.248	-0.653***	0.121	-0.483***	0.113
income	-0.201	0.361	0.552***	0.179	0.629***	0.167
hospitals non-profit	0.020	0.019	0.000	0.009	0.005	0.008
hospitals private	-0.009	0.019	-0.008	0.009	-0.006	0.008
year 2005	-0.001	0.011	0.009	0.007	0.012*	0.007
year 2006	-0.024*	0.014	-0.004	0.008	0.015**	0.008
state indicators (coefficients expressed as mean-deviations)						
Schleswig-Holstein	0.021	0.025	-0.012	0.027	-0.029**	0.012
Lower Saxony	0.035**	0.017	0.022	0.018	0.018**	0.008
North Rhine-Westphalia	-0.009	0.020	0.006	0.021	-0.004	0.010
Hesse	-0.068***	0.021	-0.033	0.023	-0.017*	0.011
Rhineland-Palatinate	-0.069***	0.021	-0.025	0.022	-0.035***	0.011
Baden-Wuerttemberg	-0.023	0.022	0.008	0.023	0.009	0.011
Bavaria	-0.012	0.020	-0.024	0.020	-0.049***	0.009
Saarland	-0.129***	0.036	-0.083**	0.040	-0.065***	0.018
Brandenburg	0.023	0.032	0.025	0.032	0.032**	0.014
Mecklenburg-West Pomerania	0.028	0.034	-0.009	0.034	-0.004	0.016
Saxony	0.075***	0.023	0.068***	0.024	0.067***	0.011
Saxony-Anhalt	0.044	0.030	0.046	0.029	0.064***	0.014
Thuringia	-0.040	0.027	-0.029	0.027	-0.011	0.012
city states	0.125**	0.061	0.040	0.061	0.025	0.027
constant	3.561***	0.557	3.749***	0.267	2.857***	0.248
$\rho$	-0.470		0.198		0.266	
$\sigma_\varepsilon$	0.166		0.078		0.072	
$R^2$	0.345		0.625		0.547	
joint significance (p-value):						
states	0.000		0.000		0.000	
hospital ownership	0.440		0.638		0.561	
age	0.000		0.000		0.000	

**Notes:** \*, \*\*, and \*\*\* indicate significance at the 0.1, 0.05, and the 0.01 level, respectively; input oriented order-m efficiency ( $m = 100$ ,  $m = 250$ ) and DEA input oriented efficiency scores at the district level serve as dependent variables; regression results based on 1286 district-year observations; years 2004, 2005, and 2006 considered, spatial weighting matrix based on inverse squared distances.

**Table B.3: Results for the Model using contiguity spatial weighting matrix**

	Pooled		Random Effects		Fixed Effects	
	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
spatial lag ( $\lambda$ )	0.047***	0.018	0.085***	0.026	0.281***	0.097
population	-0.054**	0.022	-0.045	0.036	0.606	1.197
population density	0.042***	0.012	0.030	0.018	0.193	0.292
urban district	-0.127***	0.015	-0.152***	0.024	-	-
women	-4.644***	0.682	-4.956***	1.030	-2.329	2.739
aged 21 to 40	-1.257***	0.332	-0.913*	0.469	1.723	1.048
aged 41 to 60	1.253***	0.413	0.485	0.529	0.240	0.987
aged 61 to 80	-0.630	0.401	-0.991*	0.551	1.705	1.374
aged above 80	-3.186***	0.766	-1.763*	1.051	9.530***	2.604
unemployment rate	-0.568***	0.162	-0.130	0.151	0.343	0.211
income	0.449*	0.241	0.405	0.318	-0.684	0.881
hospitals non-profit	0.007	0.012	0.008	0.018	-0.012	0.037
hospitals private	-0.005	0.012	0.004	0.012	0.007	0.015
year 2005	0.000	0.009	0.001	0.006	0.001	0.009
year 2006	-0.017	0.011	-0.005	0.009	0.003	0.015
state indicators (coefficients expressed as mean-deviations)						
Schleswig-Holstein	-0.019	0.017	-0.021	0.027	-	-
Lower Saxony	0.026**	0.012	0.020	0.018	-	-
North Rhine-Westphalia	-0.003	0.015	0.001	0.021	-	-
Hesse	-0.022	0.015	-0.025	0.022	-	-
Rhineland-Palatinate	-0.021	0.015	-0.022	0.022	-	-
Baden-Wuerttemberg	0.010	0.015	0.018	0.022	-	-
Bavaria	-0.023*	0.013	-0.014	0.019	-	-
Saarland	-0.103***	0.026	-0.082**	0.040	-	-
Brandenburg	0.013	0.021	0.020	0.032	-	-
Mecklenburg-West Pomerania	-0.019	0.023	-0.019	0.033	-	-
Saxony	0.083***	0.016	0.069***	0.024	-	-
Saxony-Anhalt	0.064***	0.021	0.048*	0.029	-	-
Thuringia	-0.027	0.018	-0.025	0.027	-	-
city states	0.041	0.039	0.033	0.062	-	-
constant	3.485***	0.359	3.733***	0.543	0.493	1.741
$\rho$	0.334		-0.027		-0.480	
$\sigma_\mu$	-		0.097		0.420	
$\sigma_\zeta$	-		0.040		0.039	
$\sigma_\varepsilon$	0.104		-		-	
R <sup>2</sup> (overall)	0.510		0.501		-	
R <sup>2</sup> (within)	-		-		0.041	
joint significance (p-value):						
states	0.000		0.010		-	
hospital ownership	0.733		0.865		0.798	
age	0.000		0.007		0.003	

**Notes:** \*, \*\*, and \*\*\* indicate significance at the 0.1, 0.05, and the 0.01 level, respectively; input oriented order-m ( $m = 100$ ) efficiency scores at the district level serve as dependent variable; regression results based on 1286 district-year observations; years 2004, 2005, and 2006 considered.

**Table B.4: Initial 2SLS estimates (pooled model)**

	Estimate	HAC standard errors
spatial lag ( $\lambda$ )	0.098***	0.027
population	-0.048	0.039
population density	0.040**	0.016
urban district	-0.130***	0.033
women	-4.634***	1.794
aged 21 to 40	-1.439***	0.546
aged 41 to 60	0.982	0.706
aged 61 to 80	-0.604	1.103
aged above 80	-3.125**	1.458
unemployment rate	-0.729**	0.349
income	0.181	0.356
hospitals non-profit	0.011	0.031
hospitals private	-0.004	0.071
year 2005	0.004	0.011
year 2006	-0.011	0.017
state indicators (coefficients expressed as mean-deviations)		
Schleswig-Holstein	-0.011	0.018
Lower Saxony	0.023	0.018
North Rhine-Westphalia	-0.004	0.024
Hesse	-0.040*	0.024
Rhineland-Palatinate	-0.046*	0.025
Baden-Wuerttemberg	-0.003	0.030
Bavaria	-0.038	0.030
Saarland	-0.107***	0.024
Brandenburg	0.031	0.037
Mecklenburg-West Pomerania	0.007	0.053
Saxony	0.086***	0.026
Saxony-Anhalt	0.067*	0.038
Thuringia	-0.023	0.042
city states	0.059	0.057
constant	3.640***	0.901
R <sup>2</sup>		0.519
joint significance (p-value):		
states		0.000
hospital ownership		0.928
age		0.000

**Notes:** \*, \*\*, and \*\*\* indicate significance at the 0.1, 0.05, and the 0.01 level, respectively; computation of HAC standard errors based on (i) a Parzen kernel, (ii) raw travel time as distance measure, (iii) travel time of 45 minutes as bandwidth parameter; input oriented order-m ( $m = 100$ ) efficiency scores at the district level serve as dependent variable; regression results based on 1286 district-year observations; years 2004, 2005, and 2006 considered; the spatial lag is calculated using inverse squared distances.