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Ownership and Financial Performance in the German Hospital Sector

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Abstract
This paper considers the role of ownership form for the financial performance of German acute care hospitals and its development over time. We measure financial performance by a hospital-specific yearly probability of default (PD). Using a panel of hospital data, our models allow for state dependence in the PD as well as unobserved individual heterogeneity. We find that private ownership is more likely to be associated with sound levels in financial performance than public ownership. Moreover, state dependence in the PD is substantial, albeit not ownership-specific. Finally, our evidence suggests that overall efficiency may be enhanced most by closing down some loss-making public hospitals rather than by their restructuring, especially because the German hospital market has substantial excess capacities.

JEL Classification: I11, I18

Keywords: Hospitals ownership, financial performance, state dependence

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1. Introduction

Due to demographic change and medical progress demand for health care rises substantially faster than other aspects of economic activity and, correspondingly, health care expenditures. Thus, economic efficiency in health care delivery is an issue of vital concern for all industrialized economies. Specifically, the financial performance of acute care hospitals which account for roughly a quarter of total health care expenditures (OECD 2007) is an important element of the overall financial viability of health systems. From the perspective of economic policy, the best approach to dealing with inefficiencies is not obvious. If financial performance of hospitals is persistent over time, short-term measures to reduce costs in existing hospitals may not be very successful. Rather, it might be advisable to close down loss-making hospitals. However, if such hospitals tend to improve their financial performance substantially over time, restructuring to increase their efficiency or selling them to experienced private restructurers can be reasonable alternatives.

To substantiate this debate, this paper assesses the dynamics of financial performance of German hospitals, based on their probability of default (PD), and investigates differences in the PD between ownership types. In the past, hospitals in Germany had only few incentives to increase their efficiency and achieve financial soundness: Until the 1990ies hospitals operated under a regime of full cost reimbursement. Together with community subsidies, this system insured them against any risk of default. Even today some communities regularly finance the annual deficits of their publicly owned community hospitals. However, recent reforms such as the introduction of a prospective payment system in 2004 have emphasized hospitals' responsibilities for their economic performance. Most importantly, economic defaults of hospitals have become a realistic contingency. Consequently, measures to reduce costs and increase efficiency, and even the privatization of publicly owned hospitals, are on the political agenda.

Already between 1991 and 2006 the market share of public hospitals (measured in terms of hospital beds) fell from 61.4% to 51.1% while that of for-profit hospitals increased from 4.0% to 13.6% (Destatis 2006). In this process, the share of private nonprofit hospitals remained relatively stable, increasing from 34.6% to 35.3%.[1] Since market entry barriers erected by regulatory requirements and high start-up costs are substantial, private for-

[1] A similar development can be observed within the US hospital market (Hansmann et al. 2003).

profits expanded their market share mainly via privatizations of public hospitals. Augurzky et al. (2008) report that privatization accounts for 73% of the gain in beds of for-profits between 1996 and 2005. And in order to avoid privatization more and more public owners change the legal status of their hospitals from being part of the community's balance sheets to independent limited liability corporations owned by the community. In 2003 30% out of 796 publicly owned hospitals were run as an independent limited liability corporation, in 2006 this was already the case for 51% (Destatis 2008).[2]

Many observers argue that private ownership tends to produce superior financial outcomes, thus advocating an increased emphasis, within the system of health care delivery, on private rather than public hospitals. We test this hypothesis in this paper. The key arguments are derived from theories of property rights, asymmetric information (Furubotn and Petrovich 1972, Danzon 1982, Easley, O'Hara 1983, Hansmann 1987, 1980) or bureaucracy theory (Eisinger 1993). However, due to a variety of data and methods used and the difficulty to test the theories directly, empirical results are mixed. In the setting of a meta-analysis Shen et al. (2005) find only a modest difference in profitability in favor of for-profit hospitals. Analyses that have sought to explain credit ratings find that private nonprofit, hospitals chains (Sloan et al. 1987), hospitals with a high market share, those located near urban markets and with high occupancy rates (McCue et al. 1990, 1996) receive good ratings, on average. Most studies have analyzed the financial performance of hospitals within the U.S. (e.g. McCue et al. 1990, 1996). To our knowledge, no empirical evidence exists for Europe, however.

In a market that is changing its efficiency so rapidly, taking a snapshot perspective does not suffice. Rather, our empirical contrasts between public, profit and nonprofit hospitals should also address the persistence in financial performance over time. In particular, many public hospitals in Germany are subsidized by their public owners, allowing them to exist with annual deficits for a protracted period. Furthermore, local politicians might be against the serious restructuring of a hospital because they may fear job losses in their community. Probably for these reasons public hospitals often retain capacity above cost-efficient capacity limits and adjust capacity more slowly in markets with changing demand (Steinwald and Neuhauser 1970; Hansmann 1987, Hansmann et al. 2003). Therefore, path dependence may be stronger for public hospitals, and yet after a while they might be able to achieve the same level of efficiency as privatized hospitals. The only study addressing financial performance of hospitals over time is Wilcox-Gök (2002) who finds for Florida between 1984 and 1987 that nonprofits neither

[2] This distinction according to legal form is not available before 2003.

perform better nor worse than for-profits. However, in her study no difference between public and private nonprofits is made.

In order to assess both long-term economic viability and the dynamics of financial performance of German hospitals, we first use a static model to explain the level of the PD and then consider a dynamic model specification to estimate its path dependence. For this purpose, we estimate an autoregressive distributed lag model via generalized methods of moments (GMM) and bias-corrected Least Squares Dummy Variables (LSDVC) estimators. We thereby draw on a unique data base, the hospital-level data underlying the annual hospital rating reports (*Krankenhaus-Rating Reports*) produced by a research consortium led by the *Rheinisch-Westfälisches Institut für Wirtschaftsforschung* (RWI). Most importantly this data contains information on hospitals' financial performance and on their ownership status.

In short, we find that in terms of their financial performance, hospitals are quite heterogeneous. Confirming the impression held by many participants in the current debate, private ownership is more likely to be associated with sound levels in financial performance than public ownership. Moreover, it seems that path dependence can be substantial, but is in general not ownership-specific. While those hospitals which already displayed a low probability of default in the past frequently even improve financial soundness over time, some hospitals with a particularly bad financial performance tend to remain in that state over time. This result suggests that closing down the worst low-performers is more promising as a strategy for economic policy than the decision to restructure all low-performers.

The paper is organized as follows: Section 2 presents the data and a descriptive analysis with a focus on the dynamics of the PD. Section 3 introduces the econometric model and estimation methods to explain the PD. Results are presented in section 4. The paper concludes with a summary and a discussion of the results in section 5.

2. Data and descriptive results

2.1 Data

Probability of default

Our main database is an unbalanced panel of 962 balance sheets from 331 hospitals covering the years 2001 to 2005.[3] Table 1 compares the sample with the population of acute care hospitals in Germany excluding purely psychiatric hospitals. Our sample slightly overrepresents hospitals of public and private nonprofit and underrepresents hospitals of for-profit ownership. On average the sample includes bigger hospitals. Some 18 percent of hospitals in the sample cover 24.4 percent of total bed capacity. This is due to the fact that balance sheets in our sample can comprise more than one hospital. This especially applies to for-profits whose size (in terms of beds) is more than double the average size in the universe of all hospitals.[4] In our sample, all public hospitals operate under the legal status of private law. This assures that they use the same accounting principles as private hospitals, facilitating sensible comparisons across ownership types. By contrast, balance sheet data of hospitals operating under public law is hardly available, because these hospitals are not obliged by law to publish their balance sheet data.

Our measure of financial performance is the probability with which an enterprise is predicted to default within one year (probability of default, PD). The PD is a comprehensive indicator of financial soundness and often preferred by institutional creditors to simple alternative measures such as profits or costs. And indeed, for the purpose of investments, hospitals increasingly rely on external capital such as bank loans. Against the background of the new financial regulation "Basle II" which raises credit costs for borrowers displaying a high risk of default, we expect higher risk premiums for financially instable hospitals. As our focus lies on financial performance, we do not take into account explicit or implicit guarantees, e.g. those given by public owners such as municipalities: From the perspective of a creditor these guarantees would reduce the risk of default, but our assessment asks how financially sound is a hospital without the luxury of tapping public funds. The PD is not only comparable across hospitals, it also indicates the risk to the tax payer who usually has to pay for guarantees.

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[3] The data are extracted from the Dafne database. Dafne is a product of the largest German credit rating agency (Creditreform), distributed by the leading company in electronic publishing of business information (Bureau van Dijk). It is updated monthly. In 2007 it contained accounting data for over 105,000 German firms. Accounting data is collected centrally at Creditreform headquarters and the quality of the data should be high.

[4] Unfortunately, our data set does not provide any information on the year of mergers.

Table 1
Acute care hospitals in Germany[1] in 2005 – sample and population

	Ownership		# beds	
Ownership form	**Sample**	**Population**	**Sample**	**Population**
Public	135 (41.0%)[2]	647 (35.1%)	446 (295)	386 (320)
Private-nonprofit	134 (39.8%)	712 (38.6%)	335 (178)	247 (163)
For-profit	62 (19.3%)	487 (26.4%)	271 (241)	121 (175)
All	331 (100%)	1846 (100%)	369 (253)	263 (281)
	Hospitals		**Beds**	
Sample to population share	18.0%		24.4%	

Notes: [1] Excluding purely psychiatric hospitals; [2] Shares of hospitals in parentheses.

Building a model to predict the PD is difficult in any small sample comprising only few defaults. In our case its direct estimation is impossible because there have been only very few actual hospital defaults in the past. For political reasons, those hospitals at high risk of default typically obtained public help and were artificially kept alive. But even if that were not the case, sample size would preclude a precise estimation: if we assumed an average default rate of 1.5% per year, we would only find on average 5 defaults per year in our sample. Given this restriction, instead of using statistical methods to construct a hospital rating from our balance sheet data, we rely on an existing quantitative rating tool. Its details are explained in the Appendix.

Explanatory variables

To prepare our analysis, we merge each hospital's PD with several individual and regional hospital characteristics based on different data sources. For our purposes, the most important characteristic is the ownership type, where we distinguish public (hospitals owned by public authorities), private nonprofit (secular and religious) and private for-profit hospitals. Further variables included are a measure of market power, hospital size in terms of the number of beds and its square and a hospital's relative cost level. To account for observable heterogeneity on regional level of the German Federal States we control for the regional level of public subsidies, ownership type-specific hospital capacity utilization on the level of the German Federal States, a dummy for the location of a hospital in East versus West Germany[5] and the yearly per capita level of income. Detailed definitions and descrip-

[5] Due to the specific situation in East Germany after re-unification, namely the lack of modern medical care in the early 1990ies, the level of public support differs remarkably between East and West in favor of East Germany.

tive statistics of all variables are available in the Appendix in Table A1.[6] Other potentially informative variables concerning average patient characteristics, which may impact upon the financial performance of hospitals, are not available in this study. However, former studies have not confirmed such characteristics to be important for the financial performance of hospitals (McCue et al. 1990, 1996).

2.2 Descriptive results

By construction the PD varies continuously between zero and one. Over all waves and hospitals the average (predicted) PD amounts to 1.29% (Table 2). For comparison: some 142 of 10,000 firms in the German health sector (NACE code 80) actually filed for bankruptcy in 2004 (Destatis 2006). On average, public hospitals exhibit an average PD of 1.54%, private nonprofits 0.95% and for-profits 1.39%. Around 16% of the hospitals face a PD above 2.6% (not in the table). The PD is changing over the years, with steady improvements observed among for-profit hospitals. Private nonprofit and, in an even more pronounced fashion, public hospitals experienced a decline of their financial performance up to 2003, and a recovery thereafter. This patterns is largely independent by new hospitals entering the sample as well as drop-outs from the sample. As shown in Table 2, the pattern hold in the balanced sample which based on the three most recent PDs. Thus, it seems that the downward trend displayed by private for-profit hospitals merely disguised the general economic problem arising in 2003.

One part of changes in the average PD over time may be due to hospital drop-outs from and entries into the sample. If they are not random with respect to the PD, then the PD cannot be compared over time. We therefore check whether the probability of an entry or a drop-out is systematically associated with a hospital's PD or its other characteristics. Table A2 in the Appendix presents the results of the corresponding multivariate probit models. We find no statistically significant relation association the PD and the probability of a drop-out. However, the results reveal a quantitatively modest, negative and statistically significant association between the PD and the probability of entering the sample in the year 2004. Overall, there is very little evidence of sample selection with respect to financial performance.

[6] We have also information on the number of hospitals in a hospital chain, the hospital's age, the population change between 1996 and 2005 and the share of people aged 60 or above, per income growth between 1996 and 2005 and the distinction between urban and non-urban regions. However, in all estimations these variables were statistically insignificant. We have therefore dropped them from the regressions.

Table 2
Mean probability of default by wave and ownership type – unbalanced and balanced samples

	2001-2005	2001	2002	2003	2004	2005
Unbalanced sample						
All	1.29	1.33	1.36	1.48	1.21	1.11
Public	1.54	1.36	1.73	1.83	1.40	1.37
Private nonprofit	0.95	0.95	0.81	1.07	0.98	0.87
For-profit	1.39	1.91	1.65	1.59	1.22	0.68
Balanced sample[1] - Based on three most recent PDs						
All	1.29	1.08	1.67	1.35	1.15	1.25
Public	1.71	1.09	2.69	1.73	1.49	1.67
Private nonprofit	0.94	1.19	0.85	0.98	0.96	0.89
For-profit	1.08	1.02	1.59	1.05	0.68	0.63

Notes: [1] Similar evidence is also available for balanced samples, spanning 2, 4 and 5 periods, respectively.

A rough check of the possible importance of path dependence in the PD is the inspection of changes of the location of hospitals in the PD distribution. Table 3 reports transitions over time between three broad categories of financial performance. We categorize all hospitals with PDs up to 1.0 percent as "green", those in the range of 1.0 percent to 2.6 percent as "yellow" and those above 2.6 percent as "red". "Green" hospitals are regarded as creditworthy and obtain loans at relatively low costs. For "yellow" hospitals, the raising of credit becomes more difficult and costly, but is usually still possible. "Red" hospitals face great difficulties in borrowing.

The table documents a high degree of persistence in the PD. In all cases hospitals are most likely to remain in the same category from one year to the next. Moreover, the likelihood of a transition to a category that is further away is always lower than the likelihood of a transition to a closer category.[7] Across ownership types, persistence as well as the rates of improvements are similar, when considering the "green" and "yellow" categories. However, there seems to be a significant difference across ownership types in the "red" category. The probability for for-profits to remain in this category is half the probability of public hospitals. Thus, improvements in financial performance for hospitals with a high PD seem more probable for private than public hospitals.

[7] This is also the case for two-year and three-year transitions. Results are available from the authors upon request.

Table 3
One-year transition matrices in the probability of default by ownership

	All				For-profits			
	Green$_t$	**Yellow$_t$**	**Red$_t$**	**Obs.**	**Green$_t$**	**Yellow$_t$**	**Red$_t$**	**Obs.**
Green$_{t-1}$	88%	10%	2%	421	88%	9%	3%	78
Yellow$_{t-1}$	36%	45%	19%	111	36%	50%	14%	22
Red$_{t-1}$	5%	28%	67%	99	13%	50%	38%	16
Obs.	416	118	97	631	79	26	11	116
	Private nonprofits				**Public**			
	Green$_t$	**Yellow$_t$**	**Red$_t$**	**Obs.**	**Green$_t$**	**Yellow$_t$**	**Red$_t$**	**Obs.**
Green$_{t-1}$	93%	5%	2%	170	83%	14%	3%	173
Yellow$_{t-1}$	31%	45%	24%	29	38%	43%	18%	60
Red$_{t-1}$	3%	31%	66%	29	4%	20%	76%	54
Obs.	168	31	29	228	169	61	57	287

Notes: Own calculations; "green" captures PDs ranging from 0.0 to 1.0 percent, "yellow" from 1.0 to 2.6 percent and "red" those above 2.6 percent.

3. Econometric models and estimation methods

The main goal of our analysis is to explain the PD of hospital i at time t, pd_{it}. The basic model is static. As the PD is bounded between 0 and 1, it is convenient to specify the model as a logistic function:

$$\log(pd_{it}) = \alpha_i + \beta' x_{it} + \varepsilon_{it}, \quad i = 1,...N, \tag{1}$$

where the coefficient α_i is a hospital-specific component capturing unobserved time-constant heterogeneity across hospitals, x_{it} is a set of observed variables associated with the hospitals' PDs, ε_{it} is a time- and individual-specific error term. Taking logarithms eliminates the lower bound of the PD. The upper bound of the PD should not pose a problem in estimation, because the highest PD in the sample is 0.3 and there are very few hospitals reaching these high values of the PD.

Equation (1) can be estimated using a "pooled" regression with correction of standard errors for clustering of hospitals and with random- or fixed-effects panel regressions. The "pooled" regression ignores hospital-specific unobserved heterogeneity and, similarly to the random-effects panel regression focuses on variations in the levels of the PD, while the fixed-effect estimator sheds light on the contribution of changes of explanatory variables on changes in the PD over time. That is, in the fixed-effects specification, the vector x_{it} can only comprise time-varying entries.

To capture any persistence in the PD we include the lagged value of the PD ($pd_{i,t-1}$) as an explanatory variable in a dynamic model:

$$\log(pd_{it}) = \lambda \log(pd_{i,t-1}) + \widetilde{\alpha}_i + \widetilde{\beta}' x_{it} + \widetilde{\varepsilon}_{it}, \quad i = 1, \ldots N, \qquad (2)$$

where $0 \leq \lambda \leq 1$ measures the degree of persistence in the PD (Tamm et al. 2007). If $\lambda=1$, the PD is non-stationary and the model follows a random walk. In this case only changes in the PDs can be explained through x_{it} and not their levels. Transitory changes in x_{it} then have permanent effects on the PD. In contrast, if $\lambda=0$ the model is static as in (1), and the PD is not path-dependent. In this case, only hospital specific level-effects determine permanent differences in the PDs across hospitals. Temporary changes in the x_{it} then have only short-term effects. In the general case, where λ lies between zero and one, transitory changes in x_{it} have persistent effects on the PDs which are decreasing over time.

In an additional modeling step, we include in equation (2) interaction terms between ownership types and the lagged PD to analyze ownership-specific adjustments in the PDs. Further, to allow for more heterogeneity in behavior across ownership types we split the sample by ownership types and re-estimate equation (2). Additionally, we test for differences in the persistence of the PD due to different starting levels of the PD. The starting levels are defined by the categories "green", "yellow" and "red" as presented above. Thus, for each subsample we rerun the regressions by introducing interaction terms between each category of the PD and the lagged PD.

Based on the availability of up to five observations for each hospital, we are able to accommodate for the occurrence of unobserved individual heterogeneity and dynamics in the PD at the same time as in equation (2). Yet, by construction the lagged dependent variable is correlated with the current value of the composite error term $\widetilde{\alpha}_i + \widetilde{\varepsilon}_{it}$, and therefore OLS, random- and fixed-effects estimators yield inconsistent results (Baltagi 2001). Consistent estimates can be achieved by applying difference GMM, system GMM or bias-corrected Least Squares Dummy Variables (LSDVC) estimators. GMM estimators are introduced in more detail in Bond (2002), whereas the LSDVC is discussed in Bruno (2005).

In difference GMM, the regression equation is differenced first and twice lagged dependent variables ($pd_{i,t-2}$) are used as instruments for the first-order differenced lagged dependent variable (Anderson, Hsiao 1982). The efficiency of this estimator increases with the use of higher-order lagged endogenous variables as instruments, e.g. pd_{it-3}, and the use of additional variables with explanatory power. In the case of high persistence of the endogenous variable the first-differenced GMM may suffer from small sample bias and imprecision. In that case, system GMM as suggested by Arellano and Bover (1995) is a viable alternative estimation technique. System GMM estimates simultaneously level and first-difference equations to exploit additional moment conditions. The estimator needs to fulfil the assumption that the error term in the first period $\tilde{\varepsilon}_{it}$ and the first-differenced exogenous variables Δx_{it} be uncorrelated with the individual specific effect $\tilde{\alpha}_i$ (Blundell and Bond 1998).

In GMM the number of instruments varies with the extent to which the explanatory variables are exogenous, predetermined or endogenous with respect to the error term $\tilde{\varepsilon}_{it}$. When over-identified, the validity of the instruments can be tested on the basis of Sargan and difference Sargan tests, which can help to choose the appropriate model specification. Bond (2002) proposes a Sargan Test to test the assumption of strict exogeneity and, thus, to test the validity of the whole set of instruments. The difference Sargan test allows evaluating the validity of additional instruments. It is obtained by comparison of the Sargan statistics of a restricted and unrestricted model, where the restricted version includes the additional instruments and moment conditions.[8]

In this paper we present results for system as opposed to the difference GMM estimator, as the Sargan tests gave support to it. Moreover, we use the more efficient two-step procedure, where the second-step estimation is based on weighted results from a consistent first-step estimator. As there is a potential problem of underestimating the standard errors obtained from GMM in small samples, the corrected variance estimator proposed by Windmeijer (2005) is applied in all GMM estimations. Estimation is based on the STATA routine *xtabond2* (Roodman 2003).

One potential problem with the GMM approach is that its properties hold asymptotically for a small number of periods, but a large number of individuals. In contrast, newer LSDVC estimators are available for panels with a small number of cross-sectional units. Bruno (2005) presents a LSDVC estimator for dynamic unbalanced panels. Monte Carlo evidence suggests the superiority of the LSDVC estimator according to bias and root mean square

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[8] By convention we speak of (difference) Sargan test, but actually present results of Hansen's J-statistic. Hansen's J-statistic is preferable to the Sargan test when there is heteroscedasticity.

error criteria as compared to GMM estimators, when the number of individuals is small. The estimator corrects for the inconsistency of LSDV estimation in dynamic panels by using a consistent dynamic first-step estimator, i.e. either Anderson and Hsiao (1982), Arellano and Bond (1991) or Blundell and Bond (1998). The estimator can implement three different approximation formulae for the inconsistency of the LSDV estimators which vary in the extent of approximation. Furthermore, within a small sample it is problematic to evaluate the variability of the coefficients. Bruno (2005) uses bootstrap methods which provide approximations to the sampling distributions of the estimated coefficients to test for their statistical significance.

We use the LSDVC estimator for two purposes. First, we compare, as a way of sensitivity analysis, whether the GMM results largely differ from LSDVC results, and thus if our results are sensitive to the estimator used. Second, we use the small sample property of LSDVC estimators to exploit the heterogeneity in behavior across hospitals, once we split the data into subsamples by ownership types. In all regressions we use the Blundell and Bond type of GMM estimation for bias-correction of the LSDV, 100 repetitions for the bootstrap variance-covariance matrix and bias approximation of order $N^{-1}T^{-2}$. Estimation is based on the STATA routine *xtlsdvc* (Bruno 2005).

4. Results

4.1 Static model

First, we present the results of the static model as in equation (1). The random effects specification was rejected by an augmented version of the Hausman test (Davidson and MacKinnon 1993).[9] We therefore present the results of the fixed-effects model (Table 4). To compare our results to previous research we add “pooled” regression results to highlight potential differences in the current level of the PD between hospitals of different ownership type (column 1). These cannot be analyzed in the fixed-effect specification because we do not have information about conversions of hospitals in ownership type in our sample. According to our estimates, private ownership is associated with a significantly lower PD than public ownership.

[9] In the traditional Hausman test the estimated difference between the covariance matrices of the coefficients of the random and fixed-effects model may not be positive definite. This has an effect on the statistical reliance of the test. We thus employ an augmented specification of the test as $\log(pd_{it}) = \overline{x_i}\lambda_1 + (x_{it} - \overline{x_i})\lambda_2 + \alpha_i + \varepsilon_{it}$. Under the null hypotheses $\lambda_1 = \lambda_2$ the model collapses to the random-effects estimator, whereas under the alternative we have a specification which conditions the estimates of time-varying variables on within-individual means, which is equivalent to fixed-effects.

Wilcox-Gök (2002) presents a qualitatively similar result for U.S. hospitals with average net revenue as the indicator of financial performance. Furthermore, the results suggest a nonlinear association between hospital size and PD, where small hospitals display a relatively high PD. Finally, there is a positive association between market power and the PD: a higher combination goes along with higher PDs.

Table 4
The probability of default –static model

	Pooled OLS		Fixed-effects	
	Coeff.	**SE**[1]	**Coeff.**	**SE**
Hospital characteristics				
Private for-profit	-0.840*	(0.469)	-	-
Private nonprofit	-0.775**	(0.318)	-	-
Beds	-0.003**	(0.001)	-0.003	(0.008)
Beds squared ($*10^{-3}$)	0.002**	(0.001)	0.002	(0.006)
Market concentration (HHI)	0.025***	(0.006)	-0.389**	(0.152)
Relative cost level	-0.479	(1.095)	-1.997	(1.556)
Regional characteristics				
Regional capacity utilization	-1.952	(4.778)	-3.054	(6.791)
Regional public subsidies	0.003***	(0.001)	-0.002	(0.004)
Regional income level	-0.001	(0.010)	-0.125**	(0.052)
East Germany	-1.060*	(0.591)	-	-
Constant	0.522	(4.181)	-	-
Observations	962		962	
Number of hospitals	331		331	
R-squared	0.10		0.04[2]	
F-Test (whole model)	6.87***		2.27**	
F-test for joint significance of bed variables	1.35		0.13	
Augmented Hausman test (χ^2)	-		26.35***	

Notes: [1] Huber-White robust standard errors, clustered at hospital level;[2] Within R-squared for fixed-effects estimation; ***Indicates significance at 1% level; **at 5% level; *at 10% level.

Regarding regional indicators, we do not find a significant impact of regional capacity utilization on the PD. High levels of regional public subsidies correlate positively and significantly with the PD, though. This could be interpreted as a negative effect of subsidies: Since so far there have not been clear economic criteria with respect to the distribution of subsidies to hospitals, subsidies need not increase efficiency. Possibly some subsidies were targeted at hospitals whose management had good political relations. Furthermore, we do not find regional income levels to be significantly related to the PD. Finally, East German hospitals have lower PDs than those in West Germany. The modernization of East German hospitals after German unification seems to have put them into a good financial shape.

Once variation within hospitals is captured by the fixed-effects estimator, few coefficients remain significant (column 2). The coefficient estimate on market power changes its sign, the coefficient estimate on the regional income level becomes significantly negative. Overall, differences in the current level of the PD within hospitals can hardly be accounted for by our observable attributes and by attributes of the market. This may be due to the fact that changes in the explanatory variables are of little magnitude during the short time frame of observation. For instance, 47% of all hospitals experienced no change in the number of beds and a further 33% of hospitals displayed changes that were lower than 10%.

Not only does variation between hospitals explain more of the variation in the PDs than variation within hospitals. Unobservable fixed-effects significantly contribute to the level of the PD as well, and therefore “explain” permanent differences in the PD across ownership-types. The fixed-effects from our regression results reveal that the mean fixed-effect is -0.017 for private for-profits, -1.625 for private nonprofits and 1.401 for public hospitals. The hypothesis that the mean fixed-effect from each of the private hospital types is not lower than the mean fixed-effect from public hospitals is rejected with a one-sided t-test on the 1 percent significance level. Thus, unobservable fixed-differences between ownership-types seem to drive permanent differences in the PD across ownership-types.

4.2 Dynamic model

Our analysis of state dependency in the PD is based on equation (2). Before reporting the results of the dynamic specification we report a simple OLS and fixed-effects estimation including the lagged PD as a covariate. The OLS estimates for the coefficient on the lagged PD are known to be biased upwards, whereas the results of the panel fixed-effects model are known to be biased downwards. The point estimates of the upper and lower bounds of the true coefficient are 0.765 (t-value: 31.65) and 0.134 (t-value: 2.11). The estimated coefficients serve as bounds, irrespective of specification (Bond 2002).

Table 5
The probability of default – dynamic model

	System GMM		LSDVC[1]	
	(1)[2]	(2)[3]	(1)	(2)
Probability of default$_{t-1}$	0.566***	0.580***	0.564***	0.581***
	(0.091)	(0.134)	(0.067)	(0.063)
Probability of default$_{t-1}$* Private for-profit	-	-0.088	-	-0.081
	-	(0.286)	-	(0.073)
Probability of default$_{t-1}$* Private nonprofit	-	-0.086	-	-0.172
	-	(0.217)	-	(0.116)
Private for-profit	-0.259	-0.197	-	-
	(0.509)	(0.676)	-	-
Private nonprofit	-0.194	-0.418	-	-
	(0.514)	(0.556)	-	-
Other hospital and regional variables[4]	Yes	Yes	Yes	Yes
Observations	614	614	614	614
Number of hospitals	283	283	283	283
AR(1)[5]	-3.52***	-3.40***	-	-
AR(2)	-0.40	-0.39	-	-
Sargan Statistic	0.570	0.490	-	-
Diff.-Sargan test (System vs. first-diff. GMM)	0.501(29)	0.141(32)	-	-
F-test (whole model)	6.77***	5.80***	-	-

Notes: [1] Bias-corrected least squares dummy variables estimator; [2] Without interactions between the PD and ownership types;[3] With interactions between the PD and ownership types; In columns 1-2 two-step GMM estimates with corrected standard errors are used (Windmeijer 2005); Variables treated as predetermined are: beds, beds squared, relative cost level, public subsidies; [4] Variables omitted from presentation are beds, beds squared, market concentration, relative cost level, regional level capacity, public subsidy, East Germany, regional income level; [5]AR(1) and AR(2) are tests for first- and second- order serial correlation in the first-differenced residuals (Arellano, Bond 1991); Sargan statistics are χ^2 distributed and not available in robust estimation as in column (1); Standard errors in parentheses; ***Indicates significance at 1% level; **at 5% level; *at 10% level. For easy reading, p-values for Sargan-test are reported only.

In Table 5 we first present estimates based on system GMM (columns 1 and 2). The Sargan tests are favorable to treating all hospital-specific variables as predetermined and the regional market variables as exogenous. We omit from the table the results of other explanatory variables than ownership form and lagged PD, as they were mostly insignificant, which could be expected from the results of the fixed-effects specification of the static model.[10]

[10] Results are available from authors upon request.

In all specifications we reject the null hypothesis of no first-order correlation and do not reject the hypothesis of second-order autocorrelation. This implies that estimates are consistent (Arellano and Bond 1991). In all specifications the statistic of the Sargan Test is insignificant on conventional significance levels (p-value of at least 0.25 as suggested by Roodman (2007)) indicating that our over-identifying restrictions are valid. In comparison to first-differenced GMM the Hansen statistic does not deteriorate strongly when using the system GMM estimator. As a matter of fact, the additional moment conditions in the system GMM are not rejected to be valid at the 10%-level (p-values of 0.501 and 0.141, respectively).

Within the system GMM models, the final sample size reduces to 614 observations. Due to the small sample size no further lags are included in the regression. The estimated coefficient on the lagged dependent variable is highly statistically significant. According to the estimate around 57 to 58 percent of a PD in $t-1$ is translated into the next period's PD. This value is far from zero, but also far from one, indicating a significant amount of transitions in the individual PDs over time. The negative coefficients of interactions between the lagged PD and ownership types are not significantly different from zero suggesting that ownership-specific path dependence in the PD is not relevant. There is hardly any difference in the described effects when using the LSDVC estimator (columns 3 and 4), thereby providing support for the validity of the estimation results.

It may well be, however, that hospitals are more heterogeneous than allowed for in the estimation strategy so far. To account for more heterogeneity in behavior, we split the sample by ownership types and estimate model 2 via LSDVC (Table 6). We now see that persistence in the PD differs across ownership types. Public hospitals have the highest persistence, closely followed by private for-profits and a relatively low persistence for private nonprofits (columns (1) in Table 6). The main contribution of Table 6 is to allow the persistence in the PD to differ by starting categories – "green", "yellow" and "red" – of the PD. The results reveal that public hospitals in the "green" category change their PD significantly faster than hospitals in the initial category "red". Thus, it seems that public hospitals with high PDs are – if at all – very slow to reduce their PDs. Contrary to that, we do not see any difference in performance due to starting levels of the PD for private hospitals.

Table 6
The probability of default – various starting levels

	Public hospitals		Private nonprofit hospitals		Private for-profit hospitals	
	(1) [1]	**(2)** [2]	**(1)**	**(2)**	**(1)**	**(2)**
Probability of default$_{t-1}$	0.669***	0.746***	0.231**	0.174	0.560***	0.616***
	(0.093)	(0.086)	(0.106)	(0.114)	(0.156)	(0.165)
Probability of default$_{t-1}$* "Green"-Probability of default in t=0	-	-0.431**	-	0.036	-	-0.548
	-	(0.169)	-	(0.240)	-	(0.823)
Probability of default$_{t-1}$* "Yellow"-Probability of default in t=0	-	-0.284	-	0.088	-	-0.260
	-	(0.307)	-	(0.216)	-	(0.205)
Other hospital and regional variables[3]	Yes	Yes	Yes	Yes	Yes	Yes
Observations		278		223		113
Hospitals		(119)		(111)		(53)

Notes: [1] Without interactions between the PD and starting category of the PD;[2] With interactions between the PD and starting category of the PD;[3] Variables omitted from presentation are beds, beds squared, market concentration, relative cost level, regional level capacity, public subsidy, East Germany, regional income level; Estimates based on LSDVC: In all regressions we use the Blundell and Bond type of GMM estimation for bias-correction of the LSDV, 100 repetitions for the bootstrap variance-covariance matrix and bias approximation of order $N^{-1}T^{-2}$; ***Indicates significance at 1% level; **at 5% level; *at 10% level.

5. Conclusion

This paper has considered the dynamics of the financial performance of acute care hospitals focusing on the role of ownership. It has used the yearly probability of default (PD) to measure financial performance. Previous analyses of financial performance have used more simple econometric techniques and have not investigated the dynamics of financial performance over time. Our models allow for state dependence in financial performance as well as unobserved individual heterogeneity.

Our results demonstrate that public hospitals tend to exhibit a PD that is significantly above average. This association indicates that public ownership may be conflicting with financial soundness, but it does not prove this relationship to be causal. When we analyze the longitudinal characteristics of our sample, we find that unobservable fixed-differences account for much of the permanent differences in the PD across ownership-types. More specifically, these persistent differences increase the PD of public versus private hospitals. In contrast, private ownership, both of nonprofit and for-profit orientation, score equally well in terms of financial robustness.

The panel analyses further point out that PD is characterized by a significantly positive state dependence. On average around 60% of the pre-period PD is carried over to the next period. This value, however, is also far from 100% indicating a large amount of transitions, i.e. improvements and deteriorations, in financial performance over time. In particular, hospitals displaying a low financial performance in one period might be able to recover over time.

Yet, our findings suggest that hospitals are quite heterogeneous with respect to path dependence in the PD. First, public hospitals display the highest persistence, closely followed by private for-profits. By contrast, we find a relatively low persistence for private nonprofits. Second, public hospitals which start with a poor financial standing remain in that state or even deteriorate over time relative to public hospitals with a favorable starting position. Thus, it seems that public hospitals with high PDs are – if at all – very slow to reduce their PDs. Contrary to that, we do not see any difference in performance due to starting levels of the PD for private hospitals. In a market which is characterized by over-capacities, these results provide a clear recommendation for economic policy: Closing down the worst low-performers appears to be a more promising strategy than the decision to restructure all low-performers.

In this study, only a short panel of data was available. Future research that is based on more observations per unit may give further insights in the long-term ability of hospitals to change their financial soundness. With a longer panel it would also be possible to see more clearly whether hospitals are able to improve their financial standing by changes in the hospitals' characteristics. Furthermore, it would be interesting to examine how conversions in ownership-type affect the PD.

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Appendix

Modelling the probability of default

Its limited sample size precludes the direct estimation of PDs from our hospital data base. Instead, we apply the logit score of Engelmann et al. (2003) to predict the PD associated with each hospital. The formula is as follows:

Logit score =

5.65 – 0.98 × liabilities/assets – 1.37 × bank debt/assets +

2.42 × cash/current liabilities + 2.08 × cashflow/(liabilities-advances) –

0.81 × current assets/net sales – 1.49 × current liabilities/assets –

5.26 × accounts payable/net assets + 0.19 × net sales/assets +

0.28 × (net sales – material cost)/personnel costs +

8.21 × ordinary business income/assets – 0.17 × net sales one year ago.

This rating tool has been developed for German medium-sized companies on the basis of 325,000 balance sheets spanning the years 1987 to 1999.

About 3,000 of the units were identified as legal insolvencies. The quality of a rating system mainly depends on the fit to predict default accurately. Engelmann et al. (2003) show that their logit score outperforms the Altman's Z-score (Altman 1968), the conventional benchmark model in the financial literature to predict a default.

We further checked the efficiency of the model against *Moody's KMV RiskCalc*™, a leading credit rating model for corporations. In the first step, we create a broad sample of medium-sized firms with full information in those accounting data which are needed to produce both rating scores. About 15,972 balance sheet data, mainly from the years 2002 and 2003 are considered to test for the accuracy, with 81 firms identified as legal insolvencies. In the second step, we apply the concept of a receiver operating characteristic (ROC) curve to prepare the test on differences between two rating models. The ROC-curve is a binary classification model that is frequently used to compare the efficiency of rating models (Engelmann et al. 2003). The chi(2) test on differences of the areas below the ROC curves shows a p-value of 0.1232 and thus, the null hypothesis of similar areas below the ROC curves is not be rejected at the significance level of 1%.

Variable Definitions and descriptive statistics

Table A1
Variable Definitions and descriptive statistics

Variable	Definition	Mean	Standard deviation
Hospital level			
Probability of default (PD)	Predicted one-year probability of default, based on logit scores.	1.29	2.28
Private nonprofit	1, if private not-for profit hospital, 0 otherwise	0.38	0.48
Private for-profit	1, if private for profit hospital, 0 otherwise	0.19	0.39
Public	1, if publicly owned hospital, 0 otherwise	0.43	0.50
Market power[1]	Herfindahl-Hirschman-Index	2412.14	1653.16
Beds	Number of beds	369.34	253.86
Relative cost level[2]	Hospital base rate	-0.05	0.11
Regional level			
Regional capacity utilization[3]	Yearly hospital capacity utilization	0.78	0.04
Public subsidies[4]		1.01	0.24
East Germany	1, if hospital is situated in East Germany, 0 otherwise	0.26	0.44
Regional income level	County's yearly average real income level per capita relative to the German average	1.03	0.30

[1]This index is defined as the sum of the squared market shares of all hospitals in hospital's *i* market within each of the 16 available fields of medicine (ophthalmology, surgery etc.), respectively. For each hospital, the 16 specific HHIs are averaged to get a hospital-wide HHI. The hospital's local market is defined as the sum of beds in maximum distance of 50 kilometres. Higher values of HHI correspond to higher levels of market power. – [2]Under the old reimbursement scheme the hospital's reimbursement for direct services for patients was based on base rates, which are supposed to reflect the hospitals' individual average cost levels. Thus, hospitals providing the same care received different levels of reimbursement. We divide the hospital's individual base rates by the average base rate of a German Federal State to arrive at a measure of relative cost levels. – [3]Measured at the level of the German Federal States and differing by ownership type specific hospital. – [4]The sum of all public funds directed to basic reinvestment per bed in a Federal State related to the average value for East German as well as West German Federal States.

Analysis of the probability of an entry or a drop-out depending on the PD

In our estimations, we use the observations of all hospitals that are in the sample for more than just a single wave. To gauge the relevance of selective drop-outs, we relate the hospital characteristics in the previous period to the incidence of a drop out in an auxiliary analysis. The dependent variable is coded as 1 if the hospital dropped out from the sample and 0 otherwise. We also conduct a similar analysis for new entries into the sample, using the contemporaneous characteristics as explanatory factors. Thus, the dependent variable is coded as 1 if the hospital dropped into the sample and 0 for those who were already in wave *t*. The probability of entries is modeled separately for each wave starting in 2002. In all regressions we model interactions between the PD and the ownership-form to see if the association of the PD with the probability of an entry or a drop-out varies between ownership forms.

Table A2 shows the partial effects of the regressors on the probability of an entry or drop-out along with the significance levels. Concerning observable sample selection on the PD, there is no statistically significant relation between the probability of a drop-out and the PD. As a minor exception, the results indicate a statistically significant and negative association between the PD and the probability of an entry in the year 2004. Private nonprofit hospitals have a higher probability to drop-out or to enter in 2003 and 2005. There are no non-linearities between ownership status and the PD, as the interaction effects are statistically not significant. The year effects (not shown in the table) have a strong and decreasing negative effect on the probability of an entry. Other statistically significant effects have very low magnitudes.

Table A2
Partial effects of probit models on the probability of a drop-out or an entry

	Drop-out	**Entry**			
		2002	**2003**	**2004**	**2005**
Log(PD)	-0.008	-0.037	0.014	-0.040**	0.002
Log(PD) * private nonprofit	0.010	0.029	-0.027	0.020	-0.011
Log(PD) * private for-profit	0.001	0.031	-0.050	0.035	0.001
Private nonprofit	0.209***	0.057	0.181**	0.032	0.0021*
Private for-profit	0.040	-0.013	-0.135	0.001	-0.004
Beds	-0.001**	-0.001***	-0.001	-0.001	0.001***
Beds*beds	0.001	0.001***	0.001	0.001	0.001**
HHI	0.001***	0.001***	0.001***	0.003***	-0.004*
Relative cost level	0.104	-0.583	0.103	-0.239	-0.002**
Public subsidies	0.003**	-0.001	-0.014	-0.001***	0.004**
Regional income	0.001	-0.001	-0.002	0.007	-0.011
East Germany	-0.026	-0.068	0.022	0.019	0.019
Observations	631	169	232	269	157
Log likelihood	-315.3	-98.3	-121.9	-113.1	-75.9

Notes: Significance levels: *** p<0.01, ** p<0.05, * p<0.10; Huber-White robust standard errors given.