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Determinants of soft budget constraints: How public debt affects hospital performance in Austria

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ABSTRACT

Soft budget constraints (SBCs) undermine reforms to increase hospital service efficiency when hospital management can count on being bailed out by (subnational) governments in case of deficits. Using cost accounting data on publicly financed, non-profit hospitals in Austria from 2002 to 2015, we analyse the association between SBCs and hospital efficiency change in a setting with negligible risk of hospital closure in a two-stage study design based on bias-corrected non-radial input-oriented data envelopment analysis and ordinary least squares regression. We find that the European debt crisis altered the pattern of hospital efficiency development: after the economic crisis, hospitals in low-debt states had a 1.1 percentage point lower annual efficiency change compared to hospitals in high-debt states. No such systematic difference is found before the economic crisis. The results suggest that sudden exogenous shocks to public finances can increase the budgetary pressure on publicly financed institutions, thereby counteracting a pre-existing SBC.

1. Introduction

In their quest to safeguard the financial sustainability of health-care systems, policymakers in several countries have implemented reforms targeting the efficiency of health-care service provision in public hospitals. A prime example is the introduction of payments based on prospective diagnosis-related groups (DRGs) (see Dan (2013), Kittelsen et al. (2007), but also Wagstaff and Moreno-Serra (2009) for surveys). Yet the effectiveness of these reforms is undermined as long as public hospitals can expect to be bailed out in times of financial distress, typically by subnational governments. Indeed, public hospitals are often subject to a soft budget constraint (SBC), i.e. ‘an *ex ante* behavioural regularity, which exerts an influence on the firm's decision’ (Kornai, 1979, 1986). Hospital bailouts are often the only politically viable option at hand when policymakers want to avoid snubbing their constituency.

Brekke et al. (2015) and Shen and Eggleston (2009) use the inverse of the probability of a hospital closure as a measure of budgetary softness. In many cases, however, the probability of hospital closure converges towards zero, if the probability of bailout is virtually 100% in practice. Alternatively, the problem can be expressed via the federal

governments' commitment not to bail out additional expenditure at the local level (see Bordignon and Turati (2009)). The central issue, however, remains unchanged: Why should hospital management care about efficiency and not simply act as a budget-maximizing bureaucrat, as outlined in Niskanen's model of bureaucracy (Niskanen (1968))? Most likely, there will be an implicit upper limit on the maximum deficit that is tolerated without the owners/financiers replacing the management. Hospital management hence faces the dilemma of maximizing hospital budget and avoiding being laid off. Using the probability of a bailout as a measure of the softness of budgetary constraints neglects this dimension.

When hospital closures are unlikely, there is an additional caveat to the approach used by Brekke et al. (2015) and Shen and Eggleston (2009). If the probability of hospital closure converges towards zero for all hospitals, the budgetary constraint is equally soft for all hospitals and there should be no systematic differences in the efficiency changes between hospital groups. However, we propose that systematic differences in efficiency change can indeed be observed in countries with subnational autonomy like Austria. While the likelihood of hospital closure approaches zero, the debt burden of the states, which ultimately have to absorb any hospital deficits within the state, significantly in-

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fluences the degree of budgetary softness, leading to systematic differences in state-level hospital efficiency changes. The financial crisis in 2009 and the subsequent European debt crisis constituted a strong exogenous shock to Austria's public finances. EU legislation, adopted as a consequence of the debt crisis, further exposed so-called 'hidden debts' in Austria, including the debt of publicly owned hospitals. It is likely that revealing the 'hidden debt' of public hospitals further aggravated the problem of public debt, i.e. the compliance with the Maastricht criteria, in the political domain. A key hypothesis for the present analysis is that states with relatively high public debt were hit hardest by this development, which considerably limited the financial leeway of these state governments. The financial crisis, therefore, caused a rift in the budgetary constraints of hospitals in high-debt states, tilting the dilemma of hospital management towards higher budgetary discipline by making running deficits in the aftermath of the financial crisis more problematic.

The empirical evidence from Austria is of interest for the following reasons: the Austrian DRG system does not cover the entire costs of publicly and privately owned non-profit hospitals providing publicly funded acute care (for simplicity referred to as 'public hospitals' henceforth). It only stipulates that at least 51% of hospital costs have to be financed out of market-like revenues (*Bundesgesetzblatt*, 2017b), thereby implementing a rather soft budget constraint. The 51%-rule was supposed to ensure that public hospitals could still be assigned to the private sector according to the European System of Accounts 1995 (ESA) (*Bundesgesetzblatt*, 2005). Any extra cost must be borne by regional authorities (state governments and municipalities) and the hospital owners (*Bundesgesetzblatt*, 2017a). In the past, publicly owned hospitals or hospital companies could count on the recovery of any extra cost, not least because of the high political pressure to ensure public hospital care. Since 2010, however, the ESA has deemed that any debt the state is held liable for must be assigned to the public sector. As a consequence, any deficits of public hospitals cause an increase in the ratio of government debt to gross domestic product (GDP) and thus endanger compliance with the Structural Pact 2012 (StP 2012) (*Bundesgesetzblatt*, 2013), which ratified the Treaty on Stability, Coordination and Governance in the Economic and Monetary Union (2012). Federal, state and local governments agreed to sustainably comply with a system of multiple fiscal rules introduced in 2017 to increase budgetary discipline. Non-compliance triggers financial sanction mechanisms, representing a major innovation compared to the Maastricht criteria.

The purpose of this paper is threefold: firstly, we investigate whether different degrees of SBC can arise even when hospital closure is not a politically viable option. As this is a scenario that may occur quite frequently for public hospitals, we adapt the approach for modelling SBC used in *Brekke et al. (2015)* and *Shen and Eggleston (2009)* to better account for such situations by using public debt as an indicator of budgetary softness. Secondly, we use the financial crisis in 2009 and the ensuing European debt crisis as an exogenous shock to the states' financial situations in our study framework, which affects hospital efficiency changes via the SBC, even though the probability of hospital closure remains negligible. Due to some methodical challenges related to the data in this study, our study design does not allow a causal interpretation of the results. Our results should, therefore, be considered as explorative rather than as definitive empirical evidence. The literature further suggests that there is also an association between hospital ownership and efficiency (see, e.g. *Chen et al. (2019)* for a short overview of the relevant literature) or ownership and budget constraints (see, e.g. *Eggleston (2008)*). Against this background, we thirdly assess whether private owners respond differently to changes in

the budgetary constraints compared to public owners. To serve our purposes we use a two-stage study design combining data envelopment analysis (DEA) with subsequent regression analysis.

The remainder of the paper is organized as follows. Section 2 provides a review of the relevant literature on SBC and Section 3 describes the methods, sample and data. Results are presented in Section 4 and Section 5 discusses potential shortcomings and future research.

2. Literature review

Research into the SBC started with two seminal papers by *Kornai (1979, 1986)*, who interpreted an SBC as a fiscal response of the government to avoid unemployment and secure public services in times of recession. *Kornai, Maskin, and Roland (2003)* broadened the range of SBC instruments, including tax concessions to foster certain producers, and administrative restrictions and import tariffs to hamper competitors. Theoretical models that attempt to predict the occurrence of an SBC are reviewed by *Maskin (1996)* who concludes that the centralization of credit allocation and production as well as public ownership of capital promote SBC.

More recent contributions recognize that a budget constraint may be not only softened but also tightened. *Bertero and Rondi (2000)* show that public enterprises respond positively in terms of productivity to a shift from soft to hard budget constraints while *Besfamille and Lockwood (2008)* predict that in a federal country, hard budget constraints may cause regional governments to underprovide public goods in their attempt to maintain budget balance.

Recently, several studies have linked SBC theory specifically to the behaviour and performance of hospitals. *Brekke et al. (2015)* note that an SBC not only covers a deficit but may also entail confiscation of profit. They predict a negative association between the probabilities of bailout and profit confiscation on the one hand and cost-containment efforts on the other. As regards cost efficiency, *Wright (2016)*, considering the responses of both public hospital and government to an SBC, applies game theory to identify conditions that promote the bailout of public hospitals. He concludes that an SBC hurts welfare while competition by a private hospital may enhance it. *Duggan (2000)* examines the responses of three hospital types (for-profit, private non-profit, and public) to financial incentives created by the US government in favour of indigent patients. The author shows that private for-profit and non-profit hospitals fail to use the additional revenue to improve quality of treatment for the poor; public ones do not seem to act more altruistically, even though they benefit from an SBC. *Shen and Eggleston (2009)* find that hospitals facing an SBC show less aggressive cost control behaviour, are less likely to shut down safety nets, and have better mortality outcomes. Investigating five hospital closures, *Capps et al. (2010)* find that the cost savings offset losses in terms of patient welfare in the US aggregate, but not locally. *Eggleston et al. (2009)* employ panel data on Chinese hospitals to estimate their probability of being bailed out in response to low or negative operating margins in the previous year. The authors relate this indicator of an SBC to hospital performance, with inconclusive results. In a similar vein, *Audibert et al. (2011)* use the extent of subsidies as an indicator of SBC to analyse the effects of health insurance reform on the technical efficiency of Chinese rural hospitals. They conclude that a higher revenue share of subsidies is negatively related to technical efficiency. In an interesting theoretical development, *Levaggi and Montefiori (2013)* see the regulator's inability to observe the patient type and to assert hard budget constraints as a reason for patient selection.

3. Methods, sample and data

3.1. Theoretical background

For analysing the effects of a shift from soft to hard budget constraints, we lean on the approach by Shen and Eggleston (2009), who measure the probability σ of the budget constraint being soft through the inverse of the probability of hospital closure. The probability of hospital closures in Austria is close to zero (although several hospital mergers took place, the individual locations very often continued to exist). We, therefore, link the probability σ of the budget constraint being soft with the budgetary situation of the state, measured as the ratio of financial debt to the state budget. Hospitals in states with a comfortable (critical) budgetary situation are considered to face a high (low) probability σ of the budget constraint being soft. The budgetary situation is critical and points to an impending tightening of budgetary constraints when the government debt ratio is above the average of all nine states. Conversely, the budgetary situation is comfortable if it is below the corresponding mean. This way, the SBC is endogenously determined. We use a time-invariant classification in two groups because we consider the debt ratio of one state relative to the debt ratios of other states to be more important than the (change in the) absolute debt ratio and to be a more conservative choice of estimating the effect of SBCs. For one thing, it is not clear how a unit change in the absolute debt ratio should be defined such that we can reasonably expect it to cause a change in the behaviour of states and hospitals. Additionally, it is unlikely that a change in the absolute debt ratio would have a uniform effect across the entire spectrum of debt ratios. The time-invariant classification circumvents this problem. The states' debt ratios further cluster the states into two groups (high-debt states and low-debt states). Keeping the number of groups that are compared to each other low allows keeping the number of observations per group as high as possible, which is beneficial in situations with small samples. Lastly, the time-invariant classification is a safer choice, because the timing of any effects is unclear, particularly as some efficiency-enhancing measures may take time to unfold (e.g. when older employees are not laid off, but their position is rather left unfilled once they retire).

The rationale behind linking the budgetary situation with the SBC and the hospital efficiency is as follows: the first relevant factor is the financial dependence of the state governments. State governments cannot levy taxes. They depend on the funds allocated based on negotiations with the federal government, creating a situation of vertical fiscal imbalance. A high debt ratio hence increases the dependence of the state government on the federal government, effectively reducing the space for political manoeuvring and the ability to handle costly bailouts. Accordingly, a high debt ratio also increases the credibility of the state government to commit to stricter budgetary rules and not to bail out hospital management.

The second relevant factor is the behaviour of hospital management. A priori, we assume hospital managers want to keep their jobs, which could be jeopardized if a bailout is required. However, the blame could be passed to the state government (similar to the blame game in Norway in the 1990s (Tjerbo and Hagen, 2009)), claiming that deficits are due to insufficient funding rather than poor management decisions. This reasoning is easier when the state's resources are abundant. The budgetary situation of the states thus increases the stakes associated with a bailout and requires both state governments and hospital management to adapt their behaviour.

We implicitly assume in our framework that a reduction in inputs does not affect the quality of hospital care. This is a strong assumption,

which is required by the missing availability of quality indicators for Austrian hospitals. Strict budgetary discipline may come at the expense of care quality and patients' well-being. But high expenditure levels in most European health-care systems and professional ethos could offset this effect and prevent a substantial decline in quality of care when budgets tighten. Of course, hospitals could also reduce the quality of amenities, e.g. meals, which could affect patient satisfaction but not their well-being.

Conversely, lower hospital efficiency may also just reflect higher quality of care. Overall, it is unclear, whether the relationship between hospital efficiency, budgetary discipline and quality of care is that close. Empirical evidence suggests that higher efficiency can be realised without curbing quality of care (Piacenza and Turati, 2014; Street et al., 2014).

3.2. Sample and data

Austrian hospitals can be classified using various and partly overlapping structural features (Bundesgesetzblatt, 2017a), including, inter alia, the level of care (standard, extended, maximum, and specialized, the categorization depending on the number and combination of the minimum required medical specialties), type of financing (DRG-based, non-DRG-based), benefit status (non-profit, for-profit) and ownership (public or private). We confine our analysis to DRG-financed non-profit hospitals, because legal requirements, service level as well as cost accounting and performance data are unified for this group.

In 2015, 120 hospitals were eligible for DRG financing through state health funds, accounting for approximately 71% of the nationwide bed capacity. Of these 120 hospitals, 65 provided standard care, 23 offered extended care, 7 maximum, and 25 specialized care. Only 29 hospitals were privately owned, 25 thereof by religious orders. The 120 hospitals had costs of around € 12.7 billion in 2015.

The accounting data provided by the Ministry of Health cover the years 2002–2015. We only focus on the inpatient sector for three reasons: first, the documentation of outpatient services was reformed in 2014, making a structural break in outpatient coding likely. In addition, coding accuracy in outpatient departments before 2014 was not as high as in inpatient departments because the level of outpatient services provided had no impact on the level of funding. Lastly, distortions in outpatient data are likely following differences in the hospital structure and their mapping in terms of coding algorithms (Rous, 2015).

The observation period is split into two subperiods (2002–2008, and 2009 to 2015) following a major revision of the DRG system, which came into force in 2009, resulting in substantially increased DRG credits per case and changes in the relative cost weights between the different DRG groups. With inputs stable, this would be reflected by sudden and artificial surges and drops in hospital efficiency within a DEA framework. Since the break in the time series coincides with the onset of the financial crisis, we exploit this circumstance to test whether there was a break in the pattern of hospital efficiency change associated with the timing of the financial crisis. By performing the DEA analyses separately for the two subperiods, we do not consider any efficiency changes from 2008 to 2009 that are likely to be skewed by the DRG re-weighting. In contrast to the immediate re-weighting implications, the impact of a budgetary constraint on the catch-up should be more gradual as hospital management requires some time to take action. A gradual effect following a change in case-mix towards more lucrative DRGs is unlikely, as DRG-funded public hospitals are obliged by law to admit any person in need of care so that patient selection is almost impossible. In addition, hospital management cannot freely decide on

the beds per speciality, as these are subject to central planning by the state governments.

Although DRG weights are set at the national level, the monetary value of a DRG point may differ between the states, since the ex-ante allocated funds per state are ex-post divided by the total number of DRG points of all hospitals in the respective state. In this regard, a hospitals' ability to generate additional revenue by increasing output (DRG points) are limited. This implies that extra funds are needed in case of overshooting costs. The states have the possibility of allocating funds beyond DRG funds to the different hospitals, not only to address a hospital's specific role in the state's health-care system, but also to cover occurring deficits. How generous this additional funding can be, therefore, depends crucially on the state's financial situation.

Fig. 1 shows the development of the debt ratio in the nine states. Following the previously introduced definitions, the budgetary situation in 2002–2008 is critical in five states (Burgenland, Carinthia, Lower Austria, Salzburg and Vienna) and comfortable in four states (Upper Austria, Styria, Tyrol and Vorarlberg). Between 2009 and 2015, the budgetary situation changes for two states (Burgenland and Styria).

3.3. Methods: data envelopment analysis

In the first stage, we use DEA to assess hospital efficiency changes over time. Most of the analysed hospitals start from a state of inefficiency, i.e. they use more inputs than necessary to provide a specific output level. By reducing inputs while keeping output stable, these hospitals can improve their technical efficiency. Assuming there are no changes in the production technology (i.e. shifts in the production frontier), hospitals then move closer to the production frontier, i.e. they catch up. We compute the period t catch-up by:

$$catch-up^t = \frac{Efficiency^t}{Efficiency^{t-1}},$$

with a $catch-up^t < (>) 1$ indicating deterioration (improvement) in efficiency from period t-1 to period t.

Within the DEA framework, we fall back on technical efficiency. We cannot compute economic efficiency, which secures a particular output level at the lowest cost, as the required data are not available.

DEA is chosen over the alternative stochastic frontier analysis (SFA)

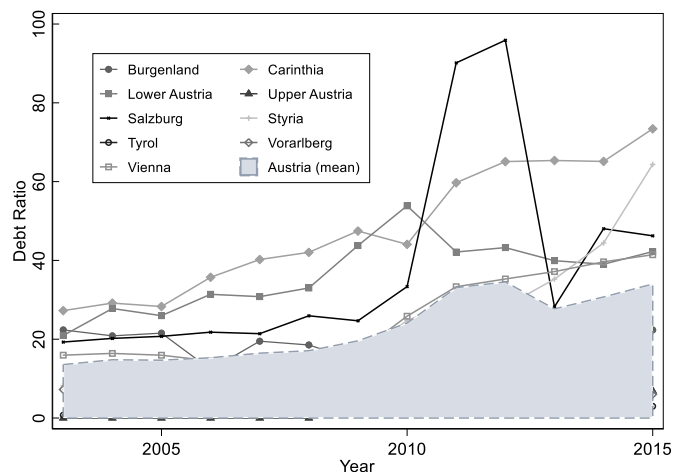


Fig. 1. Development of the debt ratio of the nine Austrian states from 2003 to 2015.

(Aigner et al., 1997) as SFA requires the specification of a functional relationship between inputs and outputs, usually boiling down to the Cobb–Douglas variant in spite of its severe restriction of unitary elasticity of substitution (see, e.g. Varian (1992), Ch. 1.9). In addition, DEA can deal with multiple outputs without requiring their transformation into costs as a scalar exploiting the duality of output maximization and cost minimization (which holds only at the efficient point). By contrast, estimating a cost function applying SFA requires data on factor prices, information that is unavailable for public Austrian hospitals.

There are some known limitations to the DEA approach: first, the units need to belong to the same technological universe, using the same types of input to produce the same types of output. Second, the discriminatory power of DEA depends on the total number of inputs m and outputs s relative to the number of n units assessed. Our sample satisfies the rule of thumb (see, e.g. Cooper et al. (2007), chapters 1 and 4) requiring that

$$n > \max\{(m \cdot s), 3 \cdot (m + s)\} \tag{1}$$

Third, the selection of variables has to be particularly careful since there are no tests for judging statistical significance, or stability of the efficiency results. Fourth, DEA is not robust to measurement errors, especially at the extreme ends of the isoquant, which can affect all efficiency scores by shifting the entire isoquant.

We performed sensitivity analyses regarding homogeneity and the choice of variables to address these issues. To increase the robustness, the data-generating process (DGP) is simulated using the bootstrap algorithm proposed by Tone (2013), which assumes input and output data to follow a triangular distribution. Since this imparts a stochastic property to the efficiency scores, a second-stage analysis relating them to changes in the softness of the budget constraints using regression analysis can be justified. Mitropoulos et al. (2018) recently used a similar method to make use of a second-stage regression to estimate the effect of hospital reforms following the financial crisis on efficiency development in Greek hospitals.

For the DEA, we use the input-oriented non-radial efficiency and super-efficiency models developed by Tone (2001, 2002) (see appendix). The input orientation is justified by noting that public hospital management has more discretionary power over inputs than outputs. The use of the non-radial model has the advantage of capturing input savings beyond their proportionate reduction as in the radial alternative.

The bias-corrected catch-up is used as the dependent variable to form a panel data set to estimate the relationship between budget constraints and hospital efficiency change. As the catch-up is based on the bias-corrected estimator for the unobserved efficiency obtained in the first stage, we avoid the fallacy of ignoring the bias term owing to the inherent serial correlation in the estimated catch-up (Simar and Wilson, 2007).

The DEA input-output specification (Model I) is based on the relevant literature (Sommersguter-Reichmann, 2005; Hadji et al., 2014; Hollingsworth, 2008; Jakobs et al., 2006; O'Neill et al., 2008) and the peculiarities of the Austrian hospital system (Sommersguter-Reichmann, 2000; Czypionka et al., 2014; Hofmarcher et al., 2002) and avoids typical pitfalls of DEA applications as described in Dyson et al. (2001). Full-time equivalents (FTEs) of physicians (PHYS), nurses (NURSE) and other staff (OTHER) serve as proxies of labour inputs, imputed costs (including depreciation and interest) as a proxy for capital input. Operating (OPER_COST) and secondary costs (SEC_COST) cover the other resources to provide inpatient care. As output, we use

Table 1
Model specifications.

Variables	Labels	Units of measurement ^a	Model I	Model II	Model III
Inputs:					
Physicians	PHYS	FTE	x	x	x
Nurses	NURSE	FTE	x	x	x
Other staff	OTHER	FTE	x	x	x
Imputed costs	IMP_COST	€	x	x	x
Primary costs less labour and imputed costs	OPER_COST	€	x		x
Medical costs (Cost of medical commodities, consumables and third-party services)	MED_COST	€		x	
Operating costs less medical costs	NONMED_COST	€		x	
Secondary costs (Cost of auxiliary cost centres allocated to inpatient cost centres)	SEC_COST	€	x	x	x
Outputs					
Diagnosis-related groups (DRG) credits	CREDITS	Number	x	x	
MEL ^b credits	MEL_CREDITS	Number			x
HDG ^c + other credits	HDG_CREDITS	Number			x

^a Costs are deflated to 2000 prices.

^b Credits based on major medical procedures.

^c Credits based on main diagnostic groups.

DRG credits (CREDITS), which reflect case-mix and thus severity-adjusted services.

To judge the stability of efficiency results, we investigate two additional input-output specifications. In Model II, we decompose operating costs into medical (MED_COST) and non-medical operating costs (NONMED_COST) to see if differences in resource use for medical supplies and consumables affect catch-up (see, e.g. [Sommersguter-Reichmann and Stepan, 2015](#)). In Model III we decompose DRG credits into credits based on major medical procedures (MEL_CREDITS) and other credits (mostly credits that use the principal diagnosis to charge the services) (HDG_CREDITS), because we assume specialized hospitals to be efficient in the production of either MEL or HDG credits, but not necessarily in their aggregate.

Hospitals must be part of a homogeneous universe to be amenable to DEA. Therefore, we exclude the three university hospitals (Vienna, Graz and Innsbruck) because university hospitals have teaching and research responsibilities and are hence not comparable to other ‘regular’ general hospitals. Then we remove outliers using the super-efficiency approach ([Banker and Chang, 2006](#); [Hofmarcher et al., 2002](#)) for the input-output specifications in [Table 1](#). Outliers are hospitals with super efficiency higher than 1.5 times the inter-quantile range (25% and 75%). As Austrian public hospitals are subject to a unified cost accounting and reporting software, outliers are assumed to result from measurement error, DRG upcoding, or inhomogeneous technology. In any case, hospital efficiency is likely to be distorted.

In the case of hospital mergers, we compute efficiency scores for the respective subperiod using virtual mergers between the merged hospitals in the years prior to the merger. In the case of mergers of hospitals operating at different care levels, the care level specification of the actual merger is used retrospectively for the virtual merger. Finally, in the case of zero inputs, the hospital is dropped from the sample for the relevant subperiod, including hospitals that ceased their operations during the subperiod.

We eliminate a total of 19 hospitals in each subperiod, resulting in a final sample of 110 hospitals in the subperiod 2002 to 2008 and 109 hospitals in the subperiod 2009 to 2015 for Model I. As different input specifications yield different outliers, the outlier analysis resulted in different sample sizes for each model specification ([Table 2](#)). The descriptive statistics for the variables included in the main DEA Model I are provided in the appendix.

Table 2

Hospitals excluded from the sample per model specification and observation period.

	Model I		Model II		Model III	
	2002–08	2009–15	2002–08	2009–15	2002–08	2009–15
All hospitals	129	128	129	128	129	128
University hospitals	3	3	3	3	3	3
Outliers	10	6	10	8	14	12
Zero input	6	10	6	10	11	14
N	110	109	110	109	101	99

3.4. Methods: regression analysis

In the second stage of the analysis, we utilize the (semi-)time-invariant budgetary situation as a proxy for the softness of the budget constraint. Several factors hinder the implementation of an identification strategy that would allow a causal interpretation of the results: The (semi-)time-invariant variable, in combination with the volatility of the efficiency scores inhibits a difference-in-difference approach as the changing budgetary situation complicates the assignment to the treatment and control group, and the common-trend assumption between the two groups is violated. The small sample size and the lack of suitable data bars the use of an instrumental variable regression.

Although unobserved state- and hospital-specific factors are likely to affect hospital efficiency over time, the (semi-)time-invariant SBC variable does not allow using a fixed-effects model. While this comes at the expense of the time dimension not being fully exploited, the specification is more robust to the unclear timing of the SBC effect. To consider unobserved state- and hospital-specific factors, we, therefore, include a set of time-variant and time-invariant hospital characteristics ([Czypionka et al., 2014](#)).

We run the following time-invariant regression model separately for the pre-crisis and post-crisis periods:

$$\hat{Y}_{it} = \alpha + \beta YEAR_t + \gamma B_i + \delta X_{it} + \varepsilon_{it} \tag{2}$$

where the dependent variable \hat{Y}_{it} is the bias-corrected catch-up of hospital i at time t . $YEAR_t$ is a categorical variable capturing

Table 3
Summary statistics of variables used in the regression analysis based on DEA Model I.

Variable:	Sample: Model I 2003–2015				
	Obs/Freq	Mean/%	Std dev	Min	Max
Ownership	1314			0	1
Public	1014	77.17%			
Private	300	22.83%			
Hospital Type	1314			1	4
Maximum care	24	1.83%			
Extended care	318	24.20%			
Special care	264	20.09%			
Standard care	708	53.88%			
Population	1314			1	3
Density					
Low	246	18.72%			
Medium	612	46.58%			
High	456	34.70%			
Patient Structure					
0–19 years	1313	0.077537	0.1140641	0	0.9800371
20–39 years	1313	0.1553441	0.0697382	0	0.4777778
60–79 years	1313	0.3571567	0.0877378	0	0.6085526
80+ years	1313	0.1634871	0.0745245	0	0.6171053
Hospital Size					
Number of beds	1314	349.8813	279.1053	30	1581
Case-Mix^a					
HHI	1313	0.128748	0.1662139	0.0382349	1
Super-efficiency Level					
2002	103	0.8230939	0.2117899	0.455462	1.455367
2009	109	0.8496697	0.2170794	0.490956	1.474389
Performance Indicator					
Catch-up	1314	1.01025	0.1015358	0.5701498	1.824302

^a Case-mix is measured using the Herfindahl–Hirschman-Index (HHI), a statistical indicator that allows capturing the degree of concentration of single hospitals between the main groups of DRG-points in the Austrian DRG system: $HHI = \sum_{i=1}^n a_i^2$ with $a_i = \frac{x_i}{\sum_{j=1}^N x_j}$ where x_i = number of hospital stays with the i^{th} HDG (main diagnostic groups) or MEL (major medical procedures) group.

countrywide development at time t , B_i is a categorical variable indicating the budgetary situation for hospital i with γ capturing the effect of interest. X_{it} is a matrix capturing a variety of additional hospital characteristics (e.g. type, ownership, case-mix, patient structure) we control for. X_{it} also includes a variable that decomposes hospitals in efficiency quartiles based on the efficiency in (2002 and 2009, respectively) to account for the heterogeneity in efficiency change due to their starting position in the two subperiods (2002–2008 and 2009–2015). Table 3 summarizes the variables used in the regression analysis over both periods.

The model is estimated with pooled OLS using White's heteroscedastic-consistent standard errors, which provides consistent

Table 4
Bias-corrected catch-up with Model I in DRG-financed hospitals in Austria from 2002 to 2008, by states (N = 110).

Catch-Up	Critical				Comfortable					Ø
	Burgenland	Carinthia	Lower Austria	Salzburg	Vienna	Upper Austria	Styria	Tyrol	Vorarlberg	
2003	1.0435	1.0172	1.0071	1.0897	0.9974	1.0380	1.0084	1.0202	0.9713	1.0172
2004	0.9453	0.9730	1.0245	0.9532	0.9651	1.0157	1.0111	0.9899	0.9485	0.9883
2005	0.9915	1.0188	0.9960	0.9690	1.0281	0.9882	0.9552	1.0169	0.9917	0.9936
2006	0.9877	0.9786	0.9922	1.0464	1.0519	0.9815	1.0493	0.9852	0.9990	1.0170
2007	1.0887	1.0159	1.0135	1.0101	1.0240	1.0007	1.0177	1.0242	1.0193	1.0196
2008	1.0559	0.9820	1.0192	1.0030	0.9909	1.0176	1.0113	1.0322	1.0062	1.0097
Ø 2002 – 2008	1.0188	0.9976	1.0088	1.0119	1.0096	1.0069	1.0088	1.0114	0.9893	1.0076

estimates for DEA scores in a second-stage regression (Hoff, 2007; McDonald, 2009) and the catch-up as it has similar statistical properties. The estimation strategy does not suffice to establish a truly causal relationship between the SBC and the efficiency development. However, it can still highlight systematic differences between groups of hospitals (budgetary situation) following a common shock to public finances, hinting at a relationship.

4. Results

We report the bias-corrected catch-up based on 1500 replications at the state level separately for the two subperiods (Table 4 and 5) alongside with the average indices per year (last column) and per state (last row).

States in critical budgetary situations show higher average catch-ups, whereas hospital efficiency remains stable in states in comfortable budgetary situations. The rapid increase in the debt ratio from 2010 to 2011 in Salzburg reflects a second exogenous shock to the public finances following the initial shock in 2009, resulting in a catch-up of 1.05 and 1.06 in 2012 and 2013, respectively.

The catch-up results at the state level are fairly robust to disaggregating operating costs into medical and non-medical operating costs (Model II) and CREDITS into HDG_CREDITS and MEL_CREDITS (Model III).

The effect of the states' debt ratios on hospital efficiency changes via the channel of tightening or relaxing the SBC is more thoroughly isolated through the second-stage regression specified in Equation (2). Relevant results using Model I are reported in Table 6.

The hospital-level covariates ownership, hospital type, population density of the catchment area, patient structure, case-mix and size (using the actual number of beds/100 as a proxy to allow for meaningful effects of one-unit changes) do not influence efficiency changes.

With regard to the debt ratio, we find no systematic differences across hospitals in the pre-crisis period 2002–2008 as opposed to the post-crisis period 2009–2015, where a 1.56 percentage point lower catch-up in states in a comfortable budgetary situation is observed. This effect is significant at the 5% level (p-value = 0.019). Controlling for the heterogeneity in the initial efficiency levels using efficiency quartiles (see columns (3) and (4)) reduces both size and statistical significance of the SBC effect in the post-crisis period, with a 1.12 percentage point lower annual catch-up significant at the 10% level (p-value = 0.099). The effect of the efficiency quartiles is strong and highly significant in both subperiods, revealing considerable differences in the catch-up between hospitals in the bottom and top quartiles. This effect is robust to different specifications of the underlying DEA model, and also to using tertiles or quintiles for the initial efficiency levels.

With an R^2 ranging from roughly 0.01 to 0.03, the overall fit of the

Table 5
Bias-corrected catch-up with Model I in DRG-financed hospitals in Austria from 2009 to 2015, by states (N = 109).

Catch-Up	Critical					Comfortable				Ø
	Carinthia	Lower Austria	Salzburg	Styria	Vienna	Burgenland	Upper Austria	Tyrol	Vorarlberg	
2010	1.0055	1.0349	0.9735	1.0658	1.0101	0.9650	0.9839	0.9941	0.9872	1.0115
2011	1.0406	1.0536	1.0142	1.0458	1.1154	1.0458	1.0097	0.9974	1.0152	1.0457
2012	1.0513	1.0090	1.0485	0.9931	1.0109	0.9960	0.9833	1.0017	0.9780	1.0078
2013	0.9639	0.9959	1.0618	1.0297	1.0034	1.0706	0.9994	1.0009	1.0129	1.0112
2014	1.0046	0.9938	1.0038	0.9842	1.0124	0.9734	1.0207	1.0164	0.9877	1.0012
2015	1.0116	0.9942	0.9782	0.9708	1.0394	0.9796	1.0114	1.0012	0.9939	1.0004
Ø 2009–2015	1.0129	1.0136	1.0133	1.0149	1.0319	1.0051	1.0014	1.0019	0.9958	1.0130

Table 6
OLS regression results with catch-up based on DEA Model I: regressions run separately for the two pre- and post-crisis subperiods and controlling for different starting levels of efficiency.

Dependent Variable:	(1)	(2)	(3)	(4)
	Catch-Up	Catch-Up	Catch-Up	Catch-Up
Regression Period:	2003–2008	2010–2015	2003–2008	2010–2015
	Coeff (Std error)	Coeff (Std error)	Coeff (Std error)	Coeff (Std error)
Ownership				
Private	−0.0104 (0.0114)	0.0137 (0.00994)	−0.00532 (0.0119)	0.0139 (0.00995)
Hospital Type				
Maximum care	0 (.)	0 (.)	0 (.)	0 (.)
Extended care	0.0180 (0.0221)	0.0243 (0.0177)	0.0142 (0.0236)	0.0206 (0.0180)
Special care	0.0237 (0.0272)	0.0380* (0.0214)	0.0115 (0.0285)	0.0222 (0.0217)
Standard care	0.00503 (0.0246)	0.0315 (0.0217)	−0.00297 (0.0267)	0.0258 (0.0225)
Population Density				
Low	0 (.)	0 (.)	0 (.)	0 (.)
Medium	−0.000731 (0.0132)	−0.00415 (0.0108)	−0.00218 (0.0130)	−0.00540 (0.0108)
High	−0.00142 (0.0146)	0.00499 (0.0122)	−0.00548 (0.0153)	−0.000929 (0.0128)
Patient Structure				
0–19	−0.122 (0.110)	0.0155 (0.0724)	−0.132 (0.108)	−0.0163 (0.0720)
20–39	−0.240 (0.198)	0.104 (0.158)	−0.244 (0.194)	0.0138 (0.156)
60–79	−0.188 (0.194)	0.0885 (0.130)	−0.197 (0.191)	0.0223 (0.130)
80+	−0.0125 (0.121)	0.0336 (0.0605)	−0.0334 (0.121)	0.00924 (0.0583)
Hospital size				
Number of beds	−0.00124 (0.00229)	0.00228 (0.00226)	−0.00108 (0.00232)	0.00235 (0.00221)
Case-Mix				
HHI	−0.0246 (0.0272)	−0.0182 (0.0210)	−0.00642 (0.0272)	0.00852 (0.0203)
Budgetary Situation				
Critical	0 (.)	0 (.)	0 (.)	0 (.)
Comfortable	0.00165 (0.00915)	−0.0156** (0.00661)	−0.000673 (0.00977)	−0.0112* (0.00679)
Initial Efficiency – Quartiles				
1st - Bottom			0 (.)	0 (.)
2nd			−0.0135 (0.0146)	−0.00421 (0.0135)
3rd			−0.0176 (0.0141)	−0.0240** (0.0111)
4th - Top			−0.0322** (0.0134)	−0.0303*** (0.00998)
Constant	1.125*** (0.126)	0.925*** (0.0833)	1.155*** (0.123)	0.987*** (0.0852)
N	617	648	617	648
R ²	0.0124	0.0173	0.0215	0.0320
F-Statistic	0.62	1.10	0.94	1.89

Heteroscedasticity robust standard errors in parentheses.

*p < 0.10.

**p < 0.05.

***p < 0.01.

regression models is low. This could indicate that the catch-up is not well described by the chosen covariates and differences are likely to be caused by unobserved confounders, such as managerial ability, informal structures of leadership, etc. These variables are, however, not available. But considering the high volatility of efficiency scores obtained from DEA and that hospital-level data is used – which results in a low number of not only observations but also groups for comparison – the low model fit is not surprising.

The effect of the debt ratio is not robust to alternative DEA model specifications. In Model II, the effect of the comfortable budgetary situation loses size and significance in the post-crisis period. In Model III, the budgetary effect misses significance at the 10% level in the post-crisis period, albeit not by very much. The size of the effect remains roughly the same.

5. Conclusions

In this paper, we analyse the effect of a tightening of budget constraints on hospital efficiency change of Austrian DRG-financed hospitals resulting from an exogenous shock to public finances. We use an input-oriented slacks-based DEA efficiency model to compute the annual catch-up over a period of 13 years. In the second stage, we analyse the impact of the budgetary situation of the states on hospital efficiency change using a pooled OLS regression. The main motivation to investigate the association of the budgetary situation of the financing body and the hospital efficiency is that any policy measures to increase the efficiency of hospital service provision are undermined whenever hospitals are subject to a SBC.

We consider the peculiarities of the Austrian health-care system as we neither abstract from the problem that, in practice, hospital closure might be virtually impossible, nor do we assume the existence of SBCs to be exogenously given. We rather argue that a tightening or further softening of an SBC is closely related to the financial situation of the financing government body, i.e. the state government. We thereby explore the possibility of using the state government's public debt ratio as a proxy for the changes in the SBC.

Using cost-accounting data from Austrian DRG-financed hospitals from 2002 to 2015, we find that hospitals with low initial levels of efficiency have successfully improved efficiency. Hospitals with high initial levels of efficiency seem to face less pressure to further improve efficiency so that their catch-up is considerably lower. The results could reflect that it is probably simpler to reap higher efficiency gains from low initial levels compared to higher efficiency levels. It could also be argued that the results only show that reforms aimed at improving efficiency – mostly targeted at low-performance hospitals – were successful. But this is not the entire story. We find a change in the pattern of nationwide hospital efficiency change coinciding with (but presumably caused by) the financial crisis in 2009. In the aftermath of the financial crisis, a systematic difference between hospitals in states with a high debt burden and hospitals in states with a low debt burden emerges, even though the possibility of hospital closures is still negligible. If budgetary constraints were the same in all states regardless of the debt burden – as a consequence of the unchanged probability of hospital closures – and if the initial level of efficiency were the only

decisive factor for the differences in efficiency change, there should be no systematic differences. Yet controlling for this effect, we find that efficiency change is still 1.1 percentage points lower in states in a comfortable budgetary situation. This suggests that exogenous shocks to the public finances increase the budgetary pressure on public financing bodies, thereby counteracting the effect of potentially pre-existing SBCs. Concerning ownership, we do not find empirical evidence that privately owned hospitals respond differently to changing budgetary restrictions than publicly owned hospitals.

There are some limitations to the study design, which may impact the result. First, there are only nine Austrian states. As the debt ratio is defined at the state level, only nine groups are available for comparison, which makes it more difficult to obtain significant results, particularly when the effect is not very strong. This is also a possible explanation for why the results somewhat depend on the DEA model specifications (in addition to the generally low number of observations, and the varying sample sizes due to different outliers). We further stress that the high volatility of the efficiency scores impedes a causal interpretation of our regression results. As our estimates could be subject to omitted variable bias, they should be interpreted as explorative. A second limitation is that there is still no quality indicator available for hospital services. A good opportunity for future research would be to use a broader definition of efficiency that also includes a quality dimension, allowing for the possibility that decreases in cost can come at the expense of the quality of the health-care services provided to patients. And lastly, a possible shortcoming of measuring the state debt ratio as financial debt to overall budget is that the debt ratio does not include information about the assets of states vis-à-vis their financial liabilities, as the relevant information was not available for a sufficiently long period. Including this information in future research could help to more accurately capture the effect of the public debt ratio on the budgetary constraints of hospitals.

CRedit authorship contribution statement

Michael Berger: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing - original draft, Visualization. **Margit Sommersguter-Reichmann:** Conceptualization, Methodology, Software, Validation, Investigation, Data curation, Writing - original draft, Supervision. **Thomas Czypionka:** Conceptualization, Methodology, Validation, Investigation, Writing - original draft, Supervision, Funding acquisition, Project administration.

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Appendix

Data envelopment analysis: descriptive statistics

Table 7
Descriptive statistics for Austrian non-profit hospitals in the period 2002–2008 included in Model I (N = 116^a).

Variables	2002		2003		2004		2005		2006		2007		2008	
	Mean	Std dev	Mean	Std dev	Mean	Std dev	Mean	Std dev	Mean	Std dev	Mean	Std dev	Mean	Std dev
Inputs:														
Physicians	52	51	53	51	54	51	55	50	56	50	51	51	59	53
Nurses	229	219	231	216	234	216	238	219	241	219	219	243	245	223
Other staff	40	60	40	60	41	60	42	62	42	63	40	62	40	51
Imputed costs in €1000	764.75	1295.65	737.80	1204.36	849.65	1692.27	847.80	1386.43	834.40	1397.03	882.98	1459.65	902.76	1391.83
Primary costs less labour and imputed costs in €1000	4505.78	4805.03	4727.61	4989.31	4847.37	5064.68	5082.77	5184.64	5252.54	5352.16	5364.75	5414.58	5548.81	5567.02
Medical costs (cost of medical commodities, consumables and third-party services) in €1000	3586.71	3680.36	3727.58	3764.879	3828.01	3937.54	3967.78	4124.65	4109.08	4306.49	4168.671	4360.42	4304.08	4508.51
Operating costs less medical costs in €1000	919.07	1275.07	1000.03	1373.17	1019.36	1289.56	1114.99	1230.03	1143.47	1312.80	1196.08	1340.79	1244.73	1347.67
Secondary costs (cost of auxiliary cost centres allocated to in-patient cost centres) in €1000	18560.89	20650.86	19691.34	22181.57	19902.83	21358.05	20244.24	21505.40	20670.97	21837.52	21458.62	22488.24	22670.57	23536.56
Outputs														
DRG credits (in 1000)	36088.65	33096.47	36970.38	33417.16	38191.20	34416.24	38749.20	35078.81	39647.84	35742.81	40373.91	36499.80	41322.16	37307.81
MEL credits (in 1000)	19401.64	21100.22	20208.09	21761.57	21046.69	22653.12	21743.97	23453.61	22462.63	24452.63	23292.33	25385.91	23966.05	26058.39
HDG + other credits (in 1000)	16687.02	13510.20	16762.29	13177.99	17144.52	13326.68	17005.23	13040.80	17011.32	12693.77	17081.59	12581.60	17356.12	12756.81

^a Includes hospitals with zero inputs (i.e. when at least one, but not all, inputs were zero in a period).

Table 8
Descriptive statistics for Austrian non-profit hospitals in the period 2009–2015 included in Model I (N = 112^{a,b}).

Variables	2009		2010		2011		2012		2013		2014		2015	
	Mean	Std dev	Mean	Std dev	Mean	Std dev	Mean	Std dev	Mean	Std dev	Mean	Std dev	Mean	Std dev
Inputs:														
Physicians	63	57	65	57	65	57	65	57	66	58	66	58	67	58
Nurses	257	240	258	233	258	233	259	234	261	238	261	237	263	236
Other staff	42	51	42	51	43	50	43	49	43	49	43	48	43	48
Imputed costs in €1000	811.36	1112.40	887.70	1509.98	886.55	1478.24	868.17	1384.97	587.07	1399.98	848.79	1336.07	821.15	1163.60
Primary costs less labour and imputed costs in €1000	5897.64	5963.68	5957.55	6071.48	5793.28	5875.53	5763.22	5924.26	5882.40	5985.09	5916.66	6063.89	6123.60	6260.754
Medical costs (cost of medical commodities, consumables and third-party services) in €1000	4486.60	4839.49	4479.91	4885.49	4264.43	4715.07	4245.41	4717.99	4334.05	4744.37	4353.81	4816.31	4539.66	5069.29
Operating costs less medical costs in €1000	1411.04	1468.88	1477.64	1561.11	1528.85	1536.55	1517.82	1596.61	1548.35	1665.19	1562.85	1659.07	1583.94	1631.46
Secondary costs (cost of auxiliary cost centres allocated to in-patient cost centres) in €1000	24400.85	25506.38	24901.14	26129.65	25123.51	26159.12	24937.63	25728.68	24834.48	25173.65	25121.99	25536.23	26127.47	26227.26
Outputs														
DRG credits (in 1000)	48017.73	44790.64	48723.01	45221.10	48926.99	45467.85	48894.23	45344.47	49458.32	46302.79	49639.06	46632.84	49784.93	46444.98
MEL credits (in 1000)	26226.52	29347.11	27078.46	30367.20	27543.14	30578.70	27669.33	30700. ^a	28063.92	31460.98	28420.45	32103.83	28675.80	32125.79
HDG + other credits (in 1000)	21791.21	17869.77	21644.56	17351.80	21383.86	17217.28	21224 ^b 90	17121.85	21394.24	17445.19	21218.61	17273.99	21109.13	16991.91

^a Includes hospitals with zero inputs (i.e. when at least one, but not all, inputs were zero in a period), but excludes hospitals that were closed entirely (i.e. when all inputs were zero in a period).

^b Difference in sample size due to hospital closures in 2009 (N = 115), 2010–2012 (N = 114) and 2013–2014 (N = 113).

Data envelopment analysis: method

Assume that $j = 1, \dots, n$ hospitals produce $r = 1, \dots, s$ outputs y_r using $i = 1, \dots, m$ inputs x_i . The production possibility set is assumed to satisfy the axioms stated in Charnes et al. (1978) and Banker et al. (1984). The input-oriented non-radial efficiency for hospital k , which belongs to the set t of units to be analysed ('reviewed') and uses $x_{i,k}^t$ input quantities to produce $y_{r,k}^t$ output quantities, is evaluated with respect to the reference set f as follows,

$$\min_{e_i^-, \lambda} \delta_k^t = 1 - \frac{1}{m} \cdot \sum_{i=1}^m \frac{e_i^-}{x_{i,k}^t} \tag{3}$$

subject to

$$x_{i,k}^t = \sum_{j=1}^n x_{i,j}^f \lambda_j + e_i^-, \quad i = 1, \dots, m \tag{4}$$

$$y_{r,k}^t \leq \sum_{j=1}^n y_{r,j}^f \lambda_j, \quad r = 1, \dots, s \tag{5}$$

$$\sum_{j=1}^n \lambda_j = 1 \tag{6}$$

$$\lambda_j \geq 0 (\forall j), e_i^- \geq 0 (\forall i) \tag{7}$$

If the set of reviewees t to be analysed is identical with the reference set f , i.e. if $t = f$, the linear programme defined in (3) to (7) is always feasible and corresponds to the model proposed in Tone (2001). The efficiency measure δ then satisfies $\delta \leq 1$, with $\delta = 1$, indicating efficient service provision if and only if there is no excess input e_i^- . The slack variables e_i^- then indicate the maximum savings potential in the respective input with respect to the reference technology. The convexity constraint $\sum \lambda_j = 1$ reflects variable returns-to-scale (VRS) and is omitted under constant returns-to-scale (CRS).

If reviewee k is removed from the reference set f , i.e. $t \neq f$, Tone (2002) proposed the following super-efficiency model:

$$\min_{e_i^-, \lambda} \delta_k^{t'} = 1 + \frac{1}{m} \cdot \sum_{i=1}^m \frac{e_i^-}{x_{i,k}^t} \tag{8}$$

subject to

$$x_{i,k}^t \geq \sum_{j=1}^n x_{i,j}^f \lambda_j - e_i^-, \quad i = 1, \dots, m \tag{9}$$

$$y_{r,k}^t \leq \sum_{j=1}^n y_{r,j}^f \lambda_j, \quad r = 1, \dots, s \tag{10}$$

$$\sum_{j=1}^n \lambda_j = 1 \tag{11}$$

$$\lambda_j \geq 0 (\forall j), e_i^- \geq 0 (\forall i) \tag{12}$$

The super-efficiency measure δ' satisfies $\delta' \geq 1$, with $\delta' > 1$, indicating the minimum average expansion rate of inputs, which still guarantees that the pertinent unit is located on the frontier of reference set f . As only non-oriented models ensure feasibility of super-efficiency models, infeasible solutions to (8) to (12) may also occur.

To increase the robustness of the efficiency scores, we use the bootstrapping technique proposed by Tone (2013) to simulate the data-generating process (DGP) as follows:

Step 1 Compute the input-oriented non-radial efficiency δ based on the actual input and output data.

Step 2 Repeat the following substeps $b = 1, \dots, B$ times:

- i. Simulate the input/output data assuming a triangular distribution for the input-output data with data variations being taken from historical data
- ii. Compute the input-oriented non-radial efficiency $\hat{\delta}_b$ based on the simulated input and output data

We then derive a bias-corrected efficiency $\tilde{\delta}$ by

$$\tilde{\delta} = 2 \cdot \delta - \frac{1}{B} \cdot \sum_{b=1}^B \hat{\delta}_b$$

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