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Analyzing Cost Structures in the Banking Industry – An Unconventional Approach

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Analyzing Cost Structures in the Banking Industry – An Unconventional Approach

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Our paper deals with empirical and technical problems to derive (conventional) cost functions in banks and other financial institutions. One main reason is based on the still ongoing discussion on inputs and outputs of financial intermediaries. A second obstacle is due to the fact that most of the banks are multi-product firms. The existing literature provides an impressive variety of methods but rather focuses on productivity or efficiency, respectively. We suggest a completely different approach instead which might be suitable to identify the relevant cost drivers in banking. Our "model" uses FDIC Call Report data to outline the procedure exemplarily for North Dakota. Of course, additional improvements are necessary, hence our contribution is work in progress on new ground.

Keywords: banking industry, cost structure, cost driver

JEL codes: G21, L21, L23

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1. Motivation

A fundamental part of traditional academic training in microeconomic theory consists of decoding the production processes of private enterprises. In a most common routine, we define a standard Cobb-Douglas-type production function whose partial derivatives with respect to each of the production factors capital and labor meet all the requirements of the well-known Inada conditions. Combined with perfect competition in all factor markets and an exogenously given budget constraint the optimal production technique can be derived, formally for example by solving a simple Lagrangian equation.

The result of the optimization process can either be the maximum production attainable from a given budget or the minimum costs of producing a given output. Applying the second version for a varying output leads to an optimized relationship between the total sum of expenses C and changing numbers of output entities x, commonly known as the cost function:

(1) $C = C(x) \;\; with \;\; \frac{dC}{dx} > 0 \;\; and \;\; C(0) \geq 0 \,.$

The assumption of rising costs with increasing output seems straightforward, positive expenses with zero output are due to fixed costs, e.g. caused by providing (temporarily) unused production capacity. Graphically, the typical cost function is a continuous monotonously increasing line in a framework with output x depicted on the abscissa and (total) costs C on the vertical axis. Note that x represents quantities (units, entities, weights …) while C stands for (monetary) values, hence, the two axes of the diagram have different dimensions.

The situation sketched so far is quite obviously true for enterprises operating in real goods markets or selling (physically) countable services. Problems regularly arise in the finance industry, in particular for monetary financial intermediaries (MFI). Not only does the discrimination between input and output turn out to be tricky, but also the ascertainment of the relevant number of services or goods produced proves to be rather difficult for banks and financial institutions.

The respective literature (Colwell/Davies 1992; Mlima/Hjalmarsson 2002; VanHoose 2017) distinguishes between the production approach (Benston 1965; Dewatripoint/ Tirole 1993; Berger/Humphrey 1997) on the one hand and the intermediation approach

(Sealey/Lindley 1977) on the other hand. The first concept particularly looks at the periodical number of all financial service transactions regardless of size or affiliation to one specific side of the balance sheet. The latter perspective defines deposits and additional items on the balance sheet's liability side as input while the asset side, including loans and securities, represents the bank's output.

Although different methods to distinctly identify input and output have been discussed (Alhadeff 1957; Berger/Humphrey 1991; Hancock 1985, 1991; Royster 2012), neither a broad consensus has been reached so far nor the remaining "technical" problem has even been addressed properly: the output's dimension. As we pointed out before, a typical cost function relates (physical) quantities and (monetary) values, whereas in the financial industry both output as well as expenses have identical dimensions.

Therefore, the contribution at hand develops a rather different procedure. We suggest a more deterministic approach to identify prime factors or structural features in the interaction between total cost of a bank and its balance sheet items. Since we are moving off the beaten tracks this is, quite naturally, work in progress. To focus on the core of our analysis it is useful to point out which topics we will not address:

1. Neither do we investigate efficiency nor do we pay particular attention to productivity in the banking industry.

2. Additionally, we do not apply a well-defined production function and we do not expect or even assume factor markets to be perfectly competitive.

Our paper is organized as follows: By reviewing the existing literature, the subsequent chapter discusses conventional methods of examining cost functions in the banking industry in more detail. In Section 3, we outline our own empirical examination method. Furthermore, we present the main numerical findings as well as possible economic interpretations. The closing chapter summarizes the paper's results and sketches ideas for further investigations.

2. Characteristics of banks' cost functions – what do we know so far?

Before taking an inventory, an additional feature of financial intermediaries, not yet mentioned above, should be addressed: At least the so-called universal banks are multi-product enterprises. Hence, supplementary difficulties to derive typical cost functions arise. Taking all the specific features into consideration, Hughes/Mester (1993), for example, summarize bank firms' technology with a general transformation function consisting of all relevant inputs and outputs. In a next step, they formulate a stylized cost of production relationship as an objective of a credit institution's optimization strategy. Using a standard Lagrangian approach, the necessary conditions for producing a given level of output with minimal costs can be determined.

Similar procedures are applied in a number of papers (e.g. Bell/Murphy 1968; Benston 1965, 1972; Benston et al. 1982; Berger et al. 1987; Cerasi/Daltung 2000; Gilligan et al. 1984; Hughes et al. 2001), most of them dealing with questions regarding the optimal size of banking firms and the existence of economies of scale or economies of scope, respectively. The primary interest of research in this field is rather productivity-oriented than investigating the driving forces of total cost in finance firms.

A second strand of literature dwells with particular problems of efficiency in the banking industry. The most popular starting point is a translog cost function (Clark/Speaker 1994; Weill 2013) which reflects the already mentioned features of a Cobb-Douglas production technique. To use this model empirically once again requires differentiating between inputs and outputs. The identification of physical input factors is, naturally, straightforward, but even implementing equity as a part of the production function is disputable (e.g. Gischer/Stiele 2009).

Furthermore, to identify efficient structures in banking firms one does not necessarily need precise knowledge on the cost function but information on its shape is enough. As long as it is twice continuously differentiable with respect to all variables, the sufficient conditions for efficiency may be fulfilled. Anyhow, the large majority of empirical investigations did not concern more or less highly differentiated financial industries in reality (see Reichling/Schulz 2018 as an exemption), so even nationwide small and large banks with divergent business models or differing regional focus were mixed up and technically treated identically.

3. An alternative empirical design

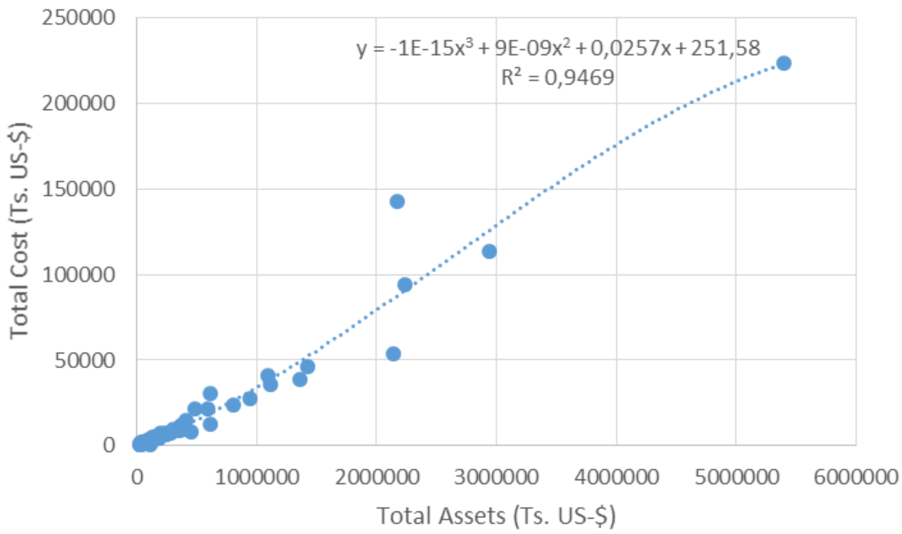
3.1. Introductory remarks

Our starting point is a remarkably simple assumption: All cost originators are finally included in the balance sheet, hence, total costs (tc) are positively connected with the balance sheet total (bst) or

(2) $tc = f(bst) \quad with \quad \frac{df}{dbst} > 0$.

Although this is an ad hoc relationship at first glance, a completely descriptive analysis reveals most surprising results. Conventional cost functions according to eq. (1) above can be illustrated by ordinary cubic polynomials. In our empirical investigations, we plotted the respective figures for all banks in North Dakota for each year in the observation period between 2001 and 2018.[2] In a single case only (2014), the R^2-value for a trend approximation based on a cubic polynomial was less than 0.9; see Figure 1 for the outcome in 2018 as an example.

Figure 1: *Total Cost and Total Assets of Banks in North Dakota in 2018*



Source: FDIC; own calculations

Actually, these somehow perplexing results awakened our particular attention. Before we present our specific findings, the data sample needs to be described and motivated.

[2] More detailed information on the data sample will be provided in the following paragraphs.

When investigating national or regional banking industries we inevitably are reliant on panel data which includes indications of institutions of different size and, furthermore, divergent business models. Additionally, varying competitive conditions should be taken into consideration. Since we were aware that we break new ground, a limited and less complex sample was useful. We made a random choice out of US states with especially rural structures and quite homogenous financial industries, e.g. served by community banks following rather similar business strategies. Therefore, North Dakota looked like an obvious choice. To control for a structural break caused by the financial crisis, induced by the Lehman Brothers' insolvency in September 2008, we process annual data for the observation period from 2001 to 2018.

3.2. Data and descriptive statistics

Annual Data on all balance sheet items were derived from the respective *Consolidated Report of Condition and Income* (generally referred to as the "call report") collected by the Federal Deposit Insurance Corporation (FDIC). The period under observation is 2001 to 2018, covering 104 financial institutions in 2001 and 75 in 2008, respectively.

Table 1: *Descriptive statistics*

Variable	Obs	Dimension	Mean	Std. Dev.	Min	Max
total costs	1,625	tsd. US$	11316.53	34923.42	70	432037
liquidity	1,625	tsd. US$	14046.42	41329.2	64	767320
securities	1,625	tsd. US$	38287.37	90847.33	0	1646308
customer loans	1,625	tsd. US$	180559.6	502551	20	5977342
non-liquid assets	1,625	tsd. US$	12786.71	39561.18	54	665650
total assets	1,625	tsd. US$	251597	610148.6	4716	6217663
deposits	1,625	tsd. US$	167857.1	373389.5	1342	4603122
fulltime equivalent employees	1,625	1 employee	6.39	1527.50	3	1950

Derived variables were: total costs (interest and noninterest expenses), liquidity, securities, customer loans (including consumer loans, loans secured by real estate, loans to finance agricultural production and commercial loans), non-liquid assets (including intangible assets, trading assets, investments in companies and other owned real estate), total assets, deposits (transaction and non-transaction accounts), number of full-time equivalent employees, interest rate adjusted customer loans as well as interest rate adjusted deposits.[3] Overall, we have 1615 observations. Descriptive statistics are stated in Table 1. The smallest financial institution under observation – in terms of total assets – is the Turtle Mountain State Bank with 47,2 million US$ in 2007, the largest institution is the U.S. Bank National Association ND with 6217,7 million US$ in 2012, respectively.

3.3. Empirical Estimation Method

Based on the specified model and the data described above, the following analysis aims to present the empirical estimates. To identify the relationship between the selected balance sheet items and total costs, a multiple linear regression model is applied using Stata. This model can be written as follows:

$$(3) \qquad tc_{it} = \beta_0 + \beta_1 lq_{it} + \beta_2 s_{it} + \beta_3 clradj_{it} + \beta_4 nla_{it} + \beta_5 dradj_{it} + \beta_6 ftee_{it} + \epsilon_{it}$$

where tc_{it} represents total cost for bank i in period t and so forth*,* while ε is an error term.

When estimating the parameters in an OLS regression model we potentially have to deal with the problem of (perfect) multicollinearity between (some of) the explanatory variables. Although the existence of multicollinearity would not result in our OLS estimation outcome being biased, standard errors may be inefficient. If this is the case, estimated coefficients would be less precise such that the validity of the results with regard to each individual independent variable would be strongly impaired. The high R^2 in our initial model suggested to check on the possibility of multicollinear predictors. Therefore, we computed a simple correlation matrix for the explanatory variables, displayed in table 2. Looking at the results, several correlation coefficients appear to be fairly high; some of them are not far from approaching the value of one.

[3] Interest rates were adjusted by using conversion factors derived from the (effective) Federal Funds Rate.

Table 2: *Correlation matrix I*

Correlations
(obs=1,625)

	tc	*lq*	*s*	*clradj*	*nla*	*dradj*	*ftee*
tc	1						
lq	0.7523*	1					
s	0.4358*	0.3622*	1				
clradj	0.7437*	0.6229*	0.3299*	1			
nla	0.9325*	0.7721*	0.5141*	0.6392*	1		
dradj	0.4620*	0.2858*	0.5223*	0.6261*	0.4264*	1	
ftee	0.9112*	0.7173*	0.6173*	0.6342*	0.8805*	0.5846*	1

* indicates significance at the 10% level of significance.

One potential cause of multicollinearity is that the movements of the independent variables' levels over time are related. In order to see whether also the variables' differences are highly correlated we transformed the predictors in first differences form. As the corresponding correlation coefficients, depicted in table 3, are clearly smaller it can be concluded that using the first differences of the independent variables provides remedy to the multicollinearity problem to some extent without impairing the validity of our regression.

Table 3: *Correlation matrix II*

Correlations in first differences
(obs=1,490)

	dtc	*dlq*	*ds*	*dclradj*	*dnla*	*ddradj*	*dftee*
dtc	1						
dlq	0.2994*	1					
ds	0.1813*	-0.0997*	1				
dclradj	0.6576*	0.2615*	-0.0255	1			
dnla	0.4064*	0.2642*	0.2029*	0.0138	1		
ddradj	0.4012*	-0.0275	-0.1534*	0.5983*	0.0670*	1	
dftee	0.2801*	0.0269	0.0629*	0.1040*	0.1672*	0.1756*	1

* indicates significance at 10% level.

Estimating the model by using first differences also addresses the problem of omitted, time-invariant variables that usually occur with panel data. In particular, applying OLS by employing first differences will eliminate any omitted explanatory time-constant error terms and thus controls for the unobserved (potential) heterogeneity of the banks in our sample. Taking into account these considerations, the following regression will be run:

(4.1) $tc_{it} - tc_{it-1} = \beta_0 + \beta_1(lq_{it} - lq_{it-1}) + \beta_2(s_{it} - s_{it-1}) + \beta_3(clradj_{it} - clradj_{it-1}) + \beta_4(nla_{it} - nla_{it-1}) + \beta_5(dradj_{it} - dradj_{it-1}) + \beta_6(ftee_{it} - ftee_{it-1}) + u_{it} - u_{it-1}$

alternatively

(4.2) $dtc_{it} = \beta_0 + \beta_1 dlq_{it} + \beta_2 ds_{it} + \beta_3 dclradj_{it} + \beta_4 dnla_{it} + \beta_5 ddradj_{it} + \beta_6 dftee_{it} + du_{it}$

where the idiosyncratic error term $u_{it} = \varepsilon_{it} - c_i$, with c_i representing the omitted, time-invariant variable for bank i.

3.4. Main findings

Table 4 reports the OLS regression results based on the use of a first differences model (4.2) for the entire period of 2000 to 2018. The overall regression performs quite well. The R^2-adjusted value of 0.63 implies that the independent variables included have a high explanatory power, i.e. that they explain more than 60% of the variation in total cost. The F-Test value of 417.86 and the p-value of less than 1% for the data variables indicate the well fit of the regression model.

The estimation results suggest that five out of the six independent variables can significantly explain the variation in total cost across the banks. In particular, there is a statistically significant positive relationship of changes in total costs with the amendment of the volume of liquidity, securities, interest rate adjusted customer loans and non-loan assets as well as with the alteration of the number of full-time equivalent employees. Whereas the interpretation of the coefficients for the exogenous variables denominated in thousand US$ is straight forward, the explication for *dftee* needs at least a short hint. Since employment is labelled in numbers, the coefficient has to be multiplied with the respective annual change of employees of a single bank in a particular period. Hence, the numerical outcome is most probably smaller than for every other exogenous variable and so is the relative impact of adjustments in employment on changes in total cost. This indicates that on average the variation of number of employees is of lower relative importance for total costs than changes in liquidity. Coefficients for the other three variables are smaller even than for liquidity, assuming values between 0.01 and 0.04 such that these variables' relative importance for total costs seems to be comparatively weak. For interest rate adjusted deposits and the constant term there is no statistically significant correlation with total costs.

Table 4: *Estimation results period 2001 to 2018*

Source	SS	df	MS
Model	4.3213e+10	6	7.2021e+09
Residual	2.5560e+10	1483	17235496.5
Total	6.8773e+10	1489	46187258.1

Number of obs	=	1490
F(6, 1483)	=	417.86
Prob > F	=	0.0000
R-squared	=	0.6283
Adj R-squared	=	0.6268
Root MSE	=	4151.6

dtc	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
dlq	.0116449	.0037709	3.09	0.002	.004248	.0190418
ds	.0360955	.0048659	7.42	0.000	.0265508	.0456402
dclradj	.0259429	.0008934	29.04	0.000	.0241903	.0276954
dnla	.1433439	.0075278	19.04	0.000	.1285777	.1581101
ddradj	–.000108	.0012857	–0.08	0.933	–.00263	.002414
dftee	27.32849	2.968531	9.21	0.000	21.50552	33.15145
_cons	103.4509	108.3008	0.96	0.340	–108.9881	315.8899

Tables 5 and 6 contain the estimation results separated for the period before and after the financial crisis, i.e. the periods from 2001 to 2008 and 2009 to 2018, respectively. From table 5 one can see that for the sub-period 2001 to 2008 the adjusted R^2 assumes a value of 0.9, which implies an extremely high explanatory power of the predictor variables included. In contrast, the R^2-adjusted value of 0.45 for the sub-period after the financial crisis is much lower, suggesting that the independent variables cannot explain as much of the variation in total cost as they can for the first sub-period.

The results for the 2001 to 2008 sub-period are statistically significant from zero for all variables apart from *ddradj* and the constant term, as was the case also for the entire period sample. Except for the liquidity variable whose correlation coefficient is slightly below zero, the significant coefficients all show a positive sign. The adjustment of full-time equivalent employees seems to be of greater relative importance for total costs compared to the complete interval of investigation. Other than *ddradj* all other coefficients are rather in the same range as for the total period 2001 to 2018.

Table 5: *Estimation results period 2001 to 2008*

Source	SS	df	MS
Model	4.6422e+10	6	7.7370e+09
Residual	4.8602e+09	658	7386316.37
Total	5.1282e+10	664	77232461.6

Number of obs	=	665
F(6, 1483)	=	1047.48
Prob > F	=	0.0000
R-squared	=	0.9052
Adj R-squared	=	0.9044
Root MSE	=	2717.8

dtc	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
dlq	–.0123578	.0032076	–3.85	0.000	–.0186561	–.0060594
ds	.0305145	.0041413	7.37	0.000	.0223828	.0386462
dclradj	.0375729	.000675	55.66	0.000	.0362475	.0388983
dnla	.1860592 .	.0061366	30.32	0.000	.1740096	1981088
ddradj	–.0102441	.0010163	–10.08	0.000	–.0122398	–.0082484
dftee	106.713	10.78721	9.89	0.000	85.53152	127.8945
_cons	20.00886	106.9299	0.19	0.852	–189.9561	229.9739

For the period after the financial crisis (see table 6), all independent variables included show a positive coefficient that is significantly different from zero, except for the interest rate adjusted customer loans. Particularly, the *dclradj* coefficient is also significant but assumes a value slightly below zero. The coefficient of the constant term is, again, not significantly different from zero. It is further noticeable that the *dftee* coefficient of the second sub-period corresponds almost exactly to the same coefficient estimated for the entire period. As regards the two sub-periods, it appears that the security coefficients are remarkably similar while the coefficients *dlq* and *ddradj* are relatively higher – though still close to zero – in the period after the financial crisis. By contrast, with a coefficient of roughly 0.09, the non-loan assets variable decreased by approximately 0.1 from the first sub-period to the second one.

Table 6: *Estimation results period 2009 to 2018*

Source	SS	df	MS
Model	7.8320e+09	6	1.3053e+09
Residual	9.6004e+09	818	11736387.4
Total	1.7432e+10	824	21155759

Number of obs	=	825
F(6, 1483)	=	111.22
Prob > F	=	0.0000
R-squared	=	0.4493
Adj R-squared	=	0. 4452
Root MSE	=	3425.8

dtc	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
dlq	.0617202	.0062421	9.89	0.000	.0494677	.0739727
ds	.0250752	.0069522	3.61	0.000	.011429	.0387214
dclradj	–.015905	.0017593	–9.04	0.000	–.0193582	–.0124518

dnla	.0869558	.0131675	6.60	0.000	.0611097	.1128019
ddradj	.0374431	.0025331	14.78	0.000	.032471	.0424152
dftee	27.86718	2.600624	10.72	0.000	22.7625	32.97186
_cons	21.44144	122.1034	0.18	0.861	–218.2314	261.1143

Overall, these findings suggest that the changes of the number of employees and variations of non-loan assets seem to have had a greater relative influence on adjustments of total costs in the first sub-period compared to the second one, as was the case for interest rate adjusted customer loans, though less markedly. By contrast, the coefficient figures imply that liquidity and interest rate adjusted deposits played a greater role for total cost in the second sub-period. Based on these results, it may be inferred that the importance of the predictors for the amount of total costs changed over time, with the financial crisis potentially having been a major contributor to this.

To determine if there indeed was a structural change in the parameters following the outburst of the financial crisis, we use a Chow test for structural breaks. The Chow test is an application of the F-test, proposed by Chow (1960), which tests whether the coefficients in two linear regressions computed for two different data sets are equal. More specifically, proceeding from the starting point of partitioning the data, the Chow test calculates the sum of error squares for the entire period and for both sub-periods separately. If the sum of the square of errors for the total period is significantly higher than the sum of error squares for both sub-periods separately, a structural break is assumed to exist.

Table 7 presents the results of the Chow test of possible differences between the parameters measuring the correlations between the explanatory variables and total cost for the two sub-periods separately. In our case, the Chow test is highly significant for the breakpoint of 2008, even at the 1% level, such that we reject the null hypothesis of equality of the estimated coefficients. This corresponds to our expectation, supporting the hypothesis that during the financial crisis the importance of the independent variables for the amount of total costs has changed fundamentally.

Table 7: *Chow test results*

Test	F	df	P>|F|
Chow	37.92	7	0.000

4. Conclusions

The primary aim of our analysis is to answer the question: How do total cost in a banking firm react to changes in the structure of its portfolio? We applied a novel and purely deterministic technique to investigate the outcome for the banking industry in North Dakota for the period 2001 to 2018.

With very few exemptions, all of the estimated coefficients for the exogenous variables are highly significant; the explanatory power of the model applied looks fairly promising. The coefficients can be interpreted as additional cost of an isolated change of the respective item. For example, holding additional liquidity of 1,000 US$ induces a 0.116 bp/US$ increase in total cost in the entire period 2001 to 2018. These expenses may occur, for instance, due to managing the portfolio, reporting and monitoring. The respective coefficients illustrate all impacts of additional assets or liabilities on total cost that have not been passed onto usual market terms.[4] At last, the coefficient for *dftee* captures the residual overhead of changes in employment.

Not really surprisingly, we find that the particular figures differ significantly for the sub-periods before and after the financial crisis. Additional liquidity has become significantly more expensive while dealing with increased commercial loans has even been able to reduce additional expenses. This result, at least partly, reflects the historically unique development of the overall level of interest rates. Since the postulate of a "Lower Zero Bound" does no longer hold, the business strategies for "traditional" (community) banks had to be adopted. Our findings fit to the assumption that (regional) banks' relative market power for commercial loans increased while the opposite is true for the deposit sector.[5]

Additionally, the effectivity of labour input in the banking landscape improved impressively. However, very careful explanation is necessary: We do not address efficiency; efficiency might as well be unaffected or even deteriorated. Effectivity reflects the positive development of passing relevant amounts of employments' overhead onto usual

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[4] Actually, VanHoose (2017, 36 ff.) introduces a quite similar idea („implicit cost function"), however without any closer characterization.

[5] Indeed, the majority of banks either did not try or has not been able to charge negative interest rates for deposits, which would have been necessary to cover full cost.

market terms. Furthermore, our analysis focuses on the cost structure only; for presenting a complete picture, both income and revenues would have to be taken into account, too.

Of course, so far, we offer a novel idea to study the behaviour of banks and banking industries empirically by using accessible and reliable data. In following steps, we plan to check for "technical" improvements of the estimation model, e.g. by controlling for size effects. Furthermore, we want to use the presented approach to examine additional US states[6], and try to detect structural differences between particular (regional) industries.

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[6] Although our model can be applied to almost any (national) banking market, the variety of accessible data is unique for the US.

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