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The More the Merrier? Detecting Impacts of Bank Regulation After the Global Financial Crisis

Christian Kalhoefer and Guenter Lang*

Abstract

Governments worldwide reacted swiftly to the global financial crisis by tougher regulations. This paper investigates the impacts of the regulatory environment on operating costs using panel data of 2,200 German banks over the timeframe from 1999 to 2014. We estimate cost functions with and without proxies for regulation and analyze the results with respect to period, bank size, and group affiliation. Our results show that regulatory costs were peaking in 2001, 2008, and lately since 2012. Most interesting, however, is the asymmetry of regulation: Whereas the cost effects were symmetric for all banks until 2003, the last ten years were different. Larger institutions and savings banks could neutralize the impacts of increasing regulation on operating costs. In contrast, smaller banks, especially if they are cooperative banks, were facing significant cost increases. We therefore expect unintended structural shifts like a reduction in the diversity of banks, which are negative for competition, service quality, and for the stability of the financial system.

Immer mehr, immer besser? Eine Abschätzung der Regulierungsfolgen im Bankensektor nach der Globalen Finanzkrise

Zusammenfassung

Weltweit wurde als Folge der globalen Finanzkrise die Regulierung des Finanzsektors verschärft. Dieser Beitrag geht der Frage nach, welche Konsequenzen diese Regulierungsmaßnahmen für die operativen Kosten im Bankengeschäft haben. Auf der Basis von Paneldaten von 2,200 in Deutschland aktiven Banken über den Zeitraum von 1999 bis 2014 schätzen wir Kostenfunktionen mit und ohne Proxies für Regulierung und werten die Ergebnisse nach Beobachtungsjahr, Bankengröße, und Gruppenzugehörigkeit aus. Unsere Ergebnisse zeigen Kostenspitzen in den Jahren 2001, 2008, und zuletzt seit 2012. Am interessantesten sind jedoch die asymmetrischen Effekte der Bankenregulie-

* Prof. Dr. Christian Kalhoefer, ADG Business School/Steinbeis University, 56410 Montabaur, Germany; Corresponding author: Prof. Dr. Guenter Lang, Kuehne Logistics University, 20457 Hamburg, Germany. Email address: guenter.lang@the-klu.org

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rung: Während unsere Modelle bis einschließlich 2003 nahezu gleichmäßige Kostenbelastungen anzeigen, änderte sich dies deutlich mit dem Jahr 2004. Im Gegensatz zu großen Institute und Sparkassen, die die Regulierungskosten nahezu neutralisieren konnten, sahen sich kleine Institute und Genossenschaftsbanken mit deutlichen Kostensteigerungen konfrontiert. Als Folge dieser asymmetrischen Kostenwirkungen staatlicher Bankenregulierung erwarten wir unbeabsichtigte Strukturveränderungen wie z. B. Konzentrationsprozesse, die sich negativ auf Wettbewerb, Dienstleistungsqualität, und letztendlich auch negativ auf die Stabilität des gesamten Finanzsystems auswirken werden.

Keywords: Banks, Regulation, Operating Costs, Germany, Cost Function, Global Financial Crisis

JEL classifications: G21, G38

I. Introduction

Historically there are few pieces of the economy as tightly supervised and regulated as the financial sector. Traces of this regulation can be detected back to the Babylonian code of Hammurapi about 3,800 years ago, maybe even earlier. Well into the 20th century, financial regulation was designed to prevent "usury" by curbing interest rates (*Blitz/Long* 1965*; Starzec* 2013). Beginning in the 1970s, the character of financial regulation changed however: Interest rate ceilings disappeared, instead substituted by the macro-goal of stabilizing the financial system. Protecting depositors against losses and curbing the risk appetite of banks are the most important tools. This dramatic shift in the design of public regulation was triggered by the high inflation rates of the 1970s (*Sherman* 2009).

Though less dramatic, the global financial crisis 2008 changed the orientation of banking supervision again. The unprecedented scope of the crisis created massive amounts of bad loans, wiping out the capital reserves of many institutions, and was the trigger of a sovereign debt crisis (for an overview see *Lane* 2012 or *Mishkin* 2011). Especially for the EURO area, where the banking sector assets account for about 250 % of the GDP, the stabilization of this prime source of company finance was of utter importance. With the exception of Italy, all important member countries have a banking system with total assets larger than two times the GDP. Also, Europe is the home of most of the too-big-too-fail banks with assets larger than the GDP of their home countries. In contrast, the assets-GDP ratio of the U.S. banking system is only slightly higher than 50 %, making a prudent regulation of capital markets rather than of traditional banks more important. The largest U.S. bank, JP Morgan, has total assets of less than 20 % of the GDP, confirming substantial differences between the American and European financial systems (data from *Otker-Robe* 2011, WSBI & ESBG 2015).

Policy and bank supervisors delivered. As unprecedented as the global financial crisis was the speed of tightening regulatory rules as agreed in the G20 meeting in 2009 (G20 Research Group 2011). Equity requirements sharply increased, documentation and reporting standards were significantly extended, regulatory patterns were internationally harmonized, and the role of the supervisors was generally strengthened. As *Cecchetti* argues, the stability of financial sector clearly gained from these measures, and even more should be done to avoid large crises in the future (*Cecchetti* 2015).

Rather than a macro-focused, this study has a micro-focused research question: What are the impacts of the regulatory changes on operating costs, and are there asymmetries in the cost impacts which could disadvantage certain categories of banks like smaller ones or savings banks? Actually, there may be many channels how regulation increases the costs of operating financial institutions. For example, increased requirements to record consultations with customers or rigorous reporting standards to supervisory authorities will increase operating costs, namely salaries, capital costs like expenses for software or information technology, and perhaps costs for legal issues. Organizational patterns will change and can increase operating costs. Increased capital requirements can have negative impacts on behavior and operating costs (*Almeida* 2014). There are also impacts for revenues, of course, for example due to a more careful credit behavior or because of macroeconomic consequences, but these impacts are not considered in this study.

Our approach is to estimate the operating cost function twice: Once with, once without proxies for regulation. Panel data covering 16 years and more than 2,200 banks operating in Germany – the largest providers of loans in the European Union – is used in our estimations. In a second step, the cost impact of regulation is broken down by year, bank size, and bank association, where we follow the classification of the German central bank (Deutsche Bundesbank) which disaggregates the universal banks into "cooperative banks", "savings banks" and "commercial banks".

We follow a stream of literature which is relatively small because most papers concentrate on technology characteristics of banks like scale economies and/or efficiency questions (for an overview see, e.g., *Berger/Mester 1997*; *Kolaric/Schiereck* 2014; *Kumar/Gulati* 2013 or *Amel* et al. 2004; for Germany see, e.g., *Fiorentino* et al. 2006). There are papers about the impact of regulation on costs and management efficiency, but most of them are of a cross-sectional nature and measure differences among countries (see, e.g., *Almeida* 2014; *Barth* et al. 2012; *Johnson* 2011; *Pasiouras* 2008; *Pasiouras* et al. 2009). Our contribution attempts to identify impact differentials over time, bank size, and group affiliation.

The structure of our paper is simple: In section II. we outline the methodological background which includes the identification of cost impacts from regulation. Section III. describes the data set and the variables used for estimation. In section IV. we present our empirical results; section V. sums up.

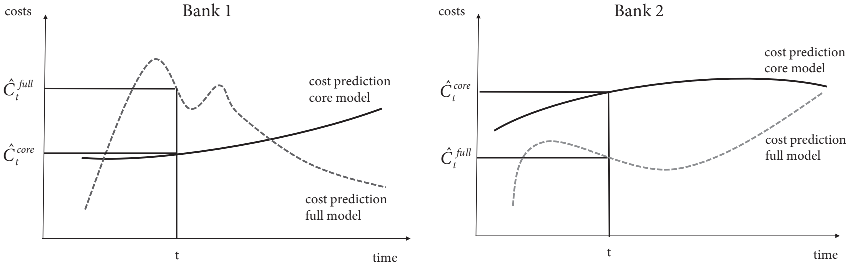
II. Methodological Procedure

It is a challenge to explain the cost effects of regulation for individual banks without direct knowledge of these costs from the accounting system of the banks. Actually, many cost impacts are hidden deeply in the processes of the banks, especially higher labor costs and perhaps higher fixed assets or other operating costs from software requirements. Because total operating costs are known, however, the traces of regulation can be unveiled by estimating a cost function complemented by proxies for the regulatory environment. A common choice for these proxies are the equity ratios of banks which are subject to regulation. In a typical research setup, the empirical strategy is to estimate a cost function with equity ratio as a control variable or a cost function which allows for firm-specific inefficiency. In the latter case, the inefficiency level is then explained by equity ratios and – maybe – other factors assumed to be relevant for the individual shortfalls in productivity (see, e. g., *Almeida,* 2014; *Lozano-Vivas/Pasiouras* 2010). Sometimes, country-specific variables like an index for the economic development or an index for economic freedom are added as proxy for regulation (*Becalli* et al. 2015; *Marezda* 2016).

Our empirical approach is slightly different because the focus of this study is on the banking industry of one country, where all institutes operate within the same regulatory environment. The procedure is as follows: In a first step, we estimate a core cost function with standard variables of a cost function only. In a second step, the function is made more flexible by adding regulatory proxies which allow for a non-uniform impact on the banks. Following the above mentioned papers, we also use the equity ratio as proxy, however in a more flexible form and in combination with other proxy variables. Our list of proxies includes equity ratios interacting with group association, and total bank size interacting with time dummies. This full model allows for a non-constant cost impact of regulation over time and for differences between the three groups "savings banks", "cooperative banks" and "commercial banks". That is, although the mean of the cost predictions $\hat{C}$ of both the core and the full model are the same, the individual predictions $\hat{C}^{core}_{n,t}$ and $\hat{C}^{full}_{n,t}$ may be different (n represents the bank, t represents the observation period). Following a similar idea in the literature about inefficiency (*Coelli* et al. 2005; *Kopp* 1981), the ratio $\hat{C}^{full}_{n,t}\ /\ \hat{C}^{core}_{n,t}$ allows for the identification of a non-uniform impact of regulation on the single banks over time:

$$(1)\quad if\ regimpact_{n,t} = \frac{\hat{C}^{full}_{n,t}}{\hat{C}^{core}_{n,t}} \begin{cases} > 1 & \text{bank } n \text{ in period } t \text{ relatively disadvantaged from regulation} \\ = 1 & \text{average impact of regulation on bank } n \text{ in period } t \\ < 1 & \text{bank } n \text{ in period } t \text{ relatively advantaged from regulation} \end{cases}$$

As a result of this definition, the mean of *regimpact* over all banks and all periods equals one. *Figure 1* visualizes that idea, with bank 1 sometimes benefitting, sometimes suffering from regulation (period *t*), and bank 2 continuously benefitting from regulation. “Benefitting” and “suffering” are relative terms, because the core cost function without time-, size- or type-specific proxies for regulation assumes that regulation would have been constant over the whole observation period. It is integrated in the parameters of the core function. In absolute terms, all firms will perhaps face extra costs from regulation, because regulation was – to a lower extent – also present before 1999, the first observation year of our data.



Bank 1 is alternately disadvantaged and advantaged from regulation. In period t, there is a relative disadvantage ($regimpact_{1,t} > 1$).

Bank 2 is relatively advantaged from regulation in all periods ($regimpact_{2,t} < 1$).

Figure 1: Estimating the Cost Impact of Regulation

Equation (2) shows how this idea is implemented for the available panel data set. The basic setup relies on a multi-output translog cost function, first introduced by *Christensen/Jorgenson/Lau* in 1973. It is the most widely used functional form in the empirical literature estimating cost or production functions. The translog form is attractive because the interactions among input prices, between input prices and outputs, and among outputs places no priori restrictions regarding factor substitution or size effects, but allows for non-homothetic technologies and scale economies. The Cobb-Douglas function, for example, is a specific case of the translog function. On top of that, it is relatively easy to analyze multi-output firms where neither economies of scope nor diseconomies of scope are predetermined. Finally, linear and squared terms of the time trend and equity shares allow for non-linear effects of these variables. In short, the flexibility of multi-output cost functions is enormous. Support for the translog function specifically in the banking industry with its multi-output characteristic is provided by *Zhu* et al. (2006), who demonstrate its empirical strength relative to other functional forms.

$$
\begin{aligned}
\ln C_{nt} &= a_n + \sum_i a_i \cdot \ln w_{nit} + \sum_k b_k \cdot \ln q_{nkt} \\
&+ \frac{1}{2}\sum_i \sum_j a_{ij} \cdot \ln w_{nit} \cdot \ln w_{njt} + \frac{1}{2}\sum_k \sum_l b_{kl} \cdot \ln q_{nkt} \cdot \ln q_{nlt} \qquad \text{core model} \\
&+ \sum_i \sum_k g_{ik} \cdot \ln w_{nit} \cdot \ln q_{nkt} + p_1 \cdot t + p_2 \cdot \frac{1}{2} t^2 + r \cdot D_{nt}^{merger} \qquad (2) \\
&+ \sum_{type} e_{type} \cdot D_n^{type} \cdot eq_{nt} + \frac{1}{2}\sum_{type} f_{type} \cdot D_n^{type} \cdot eq_{nt}^2 \qquad \text{+ regulatory proxies} \\
&+ \sum_t m_t \cdot D_t^{period} \cdot \ln TA_{nt} + \frac{1}{2}\sum_t n_t \cdot D_t^{period} \cdot \left(\ln TA_{nt}\right)^2 \qquad \text{= full model} \\
&+ e_{nt} \qquad \text{error term}
\end{aligned}
$$

Equation (2) disentangles the full cost function into three elements: The core (= restricted) model, an extension by regulatory proxies, and the error term. The core model explains total operating costs C of each bank n in period t by a bank-specific intercept a_n, input prices w, output quantities q, the observation period t, and the dummy D^{merger}. The latter two are control variables, where t allows for technological change over time. The dummy variable D^{merger} is defined to be equal to one if the bank n was involved in a merger in the observation period t and catches short-run cost disturbances, which are common during merger phases. We expect extra-costs from the about 600 mergers within the observation period.

The second part of the cost function (2) are proxies for the regulatory environment. First, we follow the main route of the literature and take the equity share eq as important proxy for regulation. To allow for a different impact on the different types of universal banks operating in Germany, i.e. cooperative banks/savings banks/commercial banks, equity is multiplied by a dummy indicating the three group affiliation D^{type}. A second proxy is the absolute size of the firm as measured by the total assets variable TA, which is multiplied by dummies for the single observation periods. This allows the identification of possible trends in the role of regulation as a cost burden for banks. From equations (1) and (2), the impact of regulation is measured as

$$
\begin{aligned}
regimpact_{n,t} = \quad & e^{a_n - \tilde{a}_n} \cdot \prod_i w_{nit}^{a_i - \tilde{a}_i} \cdot \prod_k q_{nkt}^{b_k - \tilde{b}_k} \cdot \prod_i \prod_j \left(w_{nit} \cdot w_{njt}\right)^{\frac{1}{2}\left(a_{ij} - \tilde{a}_{ij}\right)} \\
& \cdot \prod_k \prod_l \left(q_{nkt} \cdot q_{nlt}\right)^{\frac{1}{2}\left(b_{kl} - \tilde{b}_i \tilde{b}_{kl}\right)} \\
& \cdot \prod_i \prod_k \left(w_{nit} \cdot q_{nkt}\right)^{g_{ik} - \tilde{g}_{ik}} \cdot e^{\left(p_1 - \tilde{p}_1\right) \cdot t} \cdot e^{\left(p_2 - \tilde{p}_2\right) \cdot \frac{1}{2} t^2} \cdot e^{(r - \tilde{r}) \cdot D_{nt}^{merger}} \qquad (3) \\
& \cdot \prod_{type} e^{\left(e_{type} \cdot D_n^{type} \cdot eq_{nt}\right)} \cdot \prod_{type} e^{\left(f_{type} \cdot D_n^{type} \cdot eq_{nt}^2\right)} \\
& \cdot \prod_t TA_{nt}^{\left(m_t \cdot D_t^{period}\right)} \cdot \prod_t TA_{nt}^{\left(\frac{1}{2} n_t \cdot D_t^{period} \cdot \ln TA_{nt}\right)}.
\end{aligned}
$$

Parameters in (3) marked with tildes ("~") are estimated from the core model, parameters without a tilde are from the full model. Equation (3) shows that the relative impact of the regulation is dependent on the values of all regressors as well as on the difference in the parameter estimates between the core and the full model.

To ensure linear homogeneity in input prices and symmetry with respect to prices and quantities, we impose the usual restrictions:

$$
\begin{aligned}
& \sum_{i=L,K} a_i = 1 \qquad \sum_{j=L,K} a_{ij} = 0, \quad i = L,K \quad \sum_{i=L,K} g_{ik} = 0, \quad \forall k \qquad (4) \\
& a_{ij} = a_{ji}, \quad i,j = 1,2 \quad b_{kl} = b_{lk}, \quad \forall l,k.
\end{aligned}
$$

With this modest set of constraints, most of the theoretical requirements of a cost function are not enforced, but we hope that the data confirms our economic expectations. Consequently, we test for these theoretical requirements – concavity, monotony with respect to quantities and prices – in the empirical part. Especially the curvature behavior of empirically estimated cost functions is a common problem, because the condition of concavity with respect to input prices is violated in many empirical studies (see *Diewert/Wales* 1987 for imposing restrictions to ensure concavity).

Estimating a cost function rather than a production function should also help to reduce the endogeneity problem because the assumption of exogenous input prices is more reasonable than one of exogenous input quantities (*Kutlu/Liu/Sickles* 2019, p. 20). Potential endogeneity is further reduced by making use of panel data allowing for time-invariant unobserved heterogeneity. This unobserved heterogeneity is captured by the firm-specific constants a_n in equation (2).

III. Data

We use an unbalanced panel of German banks, obtained from the database BANKSCOPE, for the estimation process. Banks with incomplete information were deleted, as well as banks with zero inputs or outputs, specialized banks (e.g. real estate banks), umbrella groups of the savings and cooperative banks (e.g. "Landesbanken"), and very big players with global business models and strong investment banking activities (e.g. "Deutsche Bank"). As for the last group, we used a cut-off size of €100bn in terms of total assets to avoid biased results from the inclusion of outliers in the German banking market. The confinement to small and medium-sized universal bank makes us optimistic that our results provide a representative picture of the cost drivers in the German banking industry.

After these corrections, the final sample consists of more than 2,200 individual banks, representing about 75 % of the banking industry in Germany, and covers the 16-year period from 1999 to 2014. All three groups of the German banking industry – cooperative banks, savings banks, commercial banks – and all size classes are well represented in our dataset. International banks with a banking license for Germany are included in the group "commercial banks". The total number of observations is about 21,000 for the whole observation period, i.e. about 10 years per bank. Table 1 shows the distribution of the by size, categorized by total assets, and bank type.

Table 1

Number of Observations by Size Class and Bank Type

	1st size quintile	2nd size quintile	3rd size quintile	4th size quintile	5th size quintile	all size classes
commercial banks	108	77	110	198	442	935
savings banks	350	528	1144	2223	2933	7178
cooperative banks	3793	3624	2975	1808	845	13054

Size is measured in terms of total assets. Class limits determined for each year separately.

Due to our research focus on the impact of regulation on operating costs, inputs and outputs are defined in line with the "production approach" rather than the "intermediation approach" (see, e.g., *Berger/Humphrey* 1992, for a discussion of outputs in the banking sector). That is, deposits are considered an output, and costs are consequently defined as the sum over labor costs and other operating costs, but not funding costs. The related input quantities are the number of employees and the amount of fixed assets, respectively, As for the output quantities, two different models are estimated: Model I with a mix of level and flow variables, and model II which uses flow variables only (Table 2),

Table 2

Output Definitions of the Estimated Model Versions

	output components	Inputs
Model I	I. customer loans II. customer deposits III. fees and commissions	I. employees II. physical capital
Model II	I. fees and commissions II. net interest revenues	

All variables are expressed in real terms of the year 2010 using the CPI deflator.[1] Table A-1 in the appendix provides a statistical description of the data used for our estimations.

IV. Empirical Results

We have estimated eight versions of our empirical model as provided in equation 2: Core and full model of both output definitions (see table 2), applying both the fixed and alternatively the random effects estimator for our panel data. All estimations and the analysis of the results have been carried out in GAUSS. Table 3 shows the statistical properties of the estimations. It turned out that the fixed effects estimator is the best choice for all model versions. Heteroscedasticity-robust standard errors (*Baltagi* 1995, p. 13) have been used for inference. The results from the fixed effects estimator confirm the significance of most of the slope parameters, with only minor differences between the two output specifications. Also, around 90 % of the more than 2,200 firm specific intercepts are significant. Table 2A in the appendix provides the detailed results of the fixed-effects estimations.

[1] When alternatively using the GDP deflator instead of the CPI index, we did not find significant changes of the estimation results and their statistical properties.

Table 3

Statistical Properties of the Estimated Cost Functions

	Model I	Model II
conclusion of Hausman test	fixed effects (α=1 %)	fixed effects (α=1 %)
F-test for equality of firm dummies	H_0 rejected for α=1 %	H_0 rejected for α=1 %
F-test of model irrelevance	H_0 rejected for α=1 %	H_0 rejected for α=1 %
R^2 full model	0.993	0.992
R^2 core model	0.963	0.966
share of significant slope parameters (α=10 %)	80.0 %	61.8 %
share of significant slope parameters (α=1 %)	44.0 %	47.2 %
share of significant intercepts (α=10 %)	89.4 %	89.2 %
share of significant intercepts (α=1 %)	79.9 %	78.3 %

Significance based on heteroscedasticity-robust standard errors.

Before economically analyzing the results, we checked ex-post whether the theoretical requirements of a cost function are fulfilled. Actually, the results are very encouraging: For between 98 % and 99.6 % of our more than 21,000 observations, the partial derivatives of the cost function with respect to output quantities and input prices have the correct (= positive) sign. Concavity with respect to input prices was examined by the sign of the price elasticities of demand for the inputs, which have the expected negative sign in close to 100 % of all observations. Table 4 presents the detailed results.

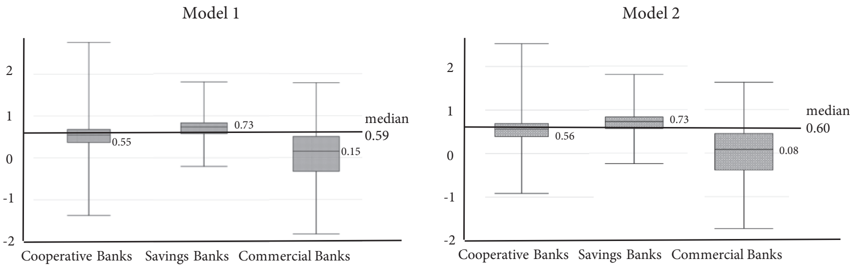
Table 4

Theoretical Properties of the Estimated Cost Functions

Criterion	Model I	Model II
increasing in output quantities	98.1 %	99.4 %
increasing in input prices	99.3 %	99.6 %
negative own-price elasticity (concavity in input prices)	99.8 %	99.9 %

Entries show the percentage of the sample size (=21,167 observations) where the requirement is fulfilled. Results for full model include proxies for regulation.

We start the economic analysis by examining the firm-specific intercepts of the roughly spoken 2,200 banks. Figure 2 shows the distribution of the fixed effects by banking group and for both models, with the boxes representing 50 % of the observations. Actually, the differences between model I and model II are small, but they are large between the three types of banks. Although the whiskers for the cooperative group are long, the relatively small boxes for cooperative and savings banks show that these banks are far more homogenous than commercial banks. Commercial banks are more disperse, but – at the average – have lower intercepts than their rivals. That implies a cost disadvantage for cooperative and savings banks relative to commercial banks for the same level of all explaining variables like outputs and input prices: Because of the log form of the cost function, intercepts have a multiplicative impact upon absolute costs. Reasons for these cost differences are omitted variables like output per branch, regional closeness of the branches, or management quality. Especially the extensive network of branches may play a critical role (for empirical evidence see, e.g., *Lang/Welzel* 1998).[2] Actually, ANOVA tests confirm that the group affiliations significantly explain the level of intercepts.



Figures show results for full models which include proxies for regulation.

Figure 2: Box Percentile Plots of the Fixed Effects

Turning to the impact of supervision on banks, we first conducted F-tests to examine the statistical significance of the regulatory proxies for the costs of the German banking system. As Table 5 shows, the null hypothesis of the joint irrelevance of the proxy variables can be clearly rejected at a significance level of 1 % or even less. The differences between both model versions appear minor, with model II – where outputs are defined as flow variables – being slightly more significant than model I. Also, most of the individual parameters are highly significant, with equity for savings banks being the exception. The public ownership of savings banks may be an explanation for this somewhat unexpected result. For cooperative banks as well as for commercial banks, the equity level is signi-

[2] We abstained from using the number of branches as a regressor in the cost function because there were too many missings in the *BANKSCOPE* dataset. Some authors using cross-sectional data over many countries use the country averages of the branches density (see, e.g., *Pasiouras* 2008), what is only appropriate for cross-country datasets.

Table 5

Significance of the Regulatory Proxies

	Model I	Model II
F statistics H_0: $e_{type} = f_{type} = m_t = n_t = 0$ ($\forall$ *type*, *t*)	55.3	105.1
degrees of freedom	$df_1 = 38$ $df_2 = 18{,}883$	$df_1 = 38$ $df_2 = 18{,}888$
p-value	0.0 %	0.0 %

ficant. All in all, however, our idea that regulation has time- and bank-type specific impact on the operating costs of banks has robust statistical support.

To evaluate the impact of regulation over time, we first calculated the variable "regimpact" for each individual bank. The result is plotted in Figure 3, which shows the annual mean values over the observation period 1999 to 2014 after normalizing "regimpact" to 1999=100. As this chart shows, the choice of the outputs does not really matter for the result – we observe a similar result for both output versions. The negative cost effects of regulation have a maximum in the periods 2002/2003, 2005/2006, and 2012/2013/2014, that is after implementing additional measures in the aftermath to the global financial crisis. From an economic perspective, however, the relatively high costs since 2012 don't seem very concerning – the earlier peaks easily reached the same level.

When disaggregating "regimpact" by the size of the banks, a much more interesting result emerges: Larger banks were able to neutralize the negative cost im-

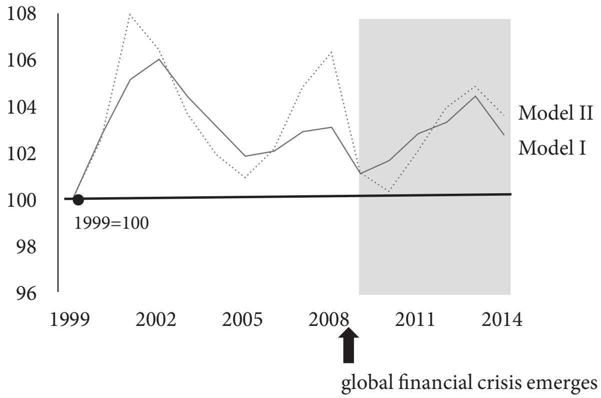


Figure 3: Estimated Cost Impact of Public Regulation

pacts of regulation, whereas smaller banks were more and more affected. The upper part of Figure 4 clearly shows that trend. Smaller banks got increasingly disadvantaged over the observation period, with operating costs lately about 6 % higher compared to a scenario without regulatory changes. In contrast, operating costs of larger banks were barely affected from these changes. For them, the variable "regimpact" remains more or less constant at the level of 1999, what implies that the relative competitive advantage against their smaller competitors has increased over time.

Does the legal form of the bank play a role for the impact of regulation? To answer this interesting question, "regimpact" was disaggregated by the three types "cooperative banks" (private), "savings banks" (municipal), and "commercial banks" (private). The result is plotted in the lower part of Figure 4. Both models find that the differences among the banks grew over time, with savings banks recently being the least affected ones. In contrast, cooperative banks clearly suffered the most in the recent years, where this trend is especially pronounced in model 1. Following model 1, the whole burden of the post-crisis regulation is on the cooperative sector, i.e. the sector with the largest number of banks. As for commercial banks, the results of both models differ: Model 1 sees commercial banks not affected in the last years, but model 2 sees commercials banks very similar to cooperative banks.

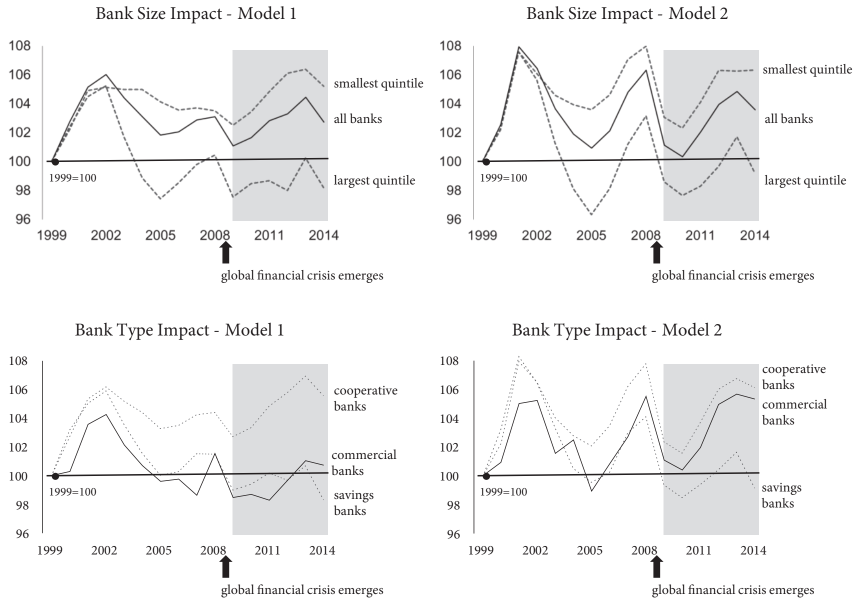


Figure 4: Impact of Public Regulation by Banks Size and by Bank Type

V. Conclusion

The paper analyzes the consequences of the tougher regulatory measures in the financial sector which have been introduced in the aftermath of the global financial crisis. We focus on relative rather than absolute cost impacts, because the direct impact of regulation on the operative costs like additional labor expenses are not explicitly shown in the available data. Two alternative models with different output specifications were used, where each model was estimated with and without proxies for regulation. Based on a 16-year panel covering more than 2,200 banks, the estimations are statistically significant and fulfill the theoretical requirements of a cost function. The differences between the two models are small, confirming the robustness of the results.

When comparing the cost estimations with and without proxies for regulations, the impact of regulation on costs turns out to be wave-like: Troughs in 1999/2000, 2004/05 and 2008/09 are followed by peaks in 2000/01, 2006/07, and lately since 2012. Most important, the results confirm that the regulatory measures are asymmetric, that is their impacts depend on bank size and group affiliation. This asymmetry emerged between 2003 and 2005 and strengthened ever since. Cooperative banks, no matter their size, suffered the most from the regulatory changes, whereas savings banks appeared relatively immune. Commercial banks are in between. With respect to bank size, the processes of larger banks turned out to be relatively robust against regulation, i.e. their operative costs with and without proxies for regulation are very similar. In contrast, smaller banks were heavily impacted by regulation. The relative costs of smaller banks in the last years of the observation period were at an all-time high.

The conclusions from our finding are not optimistic. Recent regulatory measures, intended to stabilize the financial sector by reducing the risk attitude of the market participants, actually triggered higher operating costs. Unfortunately, this productivity decrease was not parallel for all banks, but we could observe a strong bias of the impact in favor of larger banks and in favor of savings banks. Consequently, we conclude that there was a significant shift of relative competitive viability since 2009 in favor of medium-sized and large savings banks, which at the end will trigger the market exit of small cooperative and small commercial banks. The warning of *Ferri (2016)*, who sees the diversity of the European banking industry endangered by the post-crisis regulation, is therefore confirmed with respect to cooperative banks, but not with respect to savings banks.

That result is stunning. Following widespread belief, the challenge of regulation is the existence of big players and too-big-to-fail banks, which could destabilize the whole financial system in case of a failure. If our findings are correct, then the current regulation system will destroy stability by triggering more mergers and more acquisitions, that is an increase in the concentration and an increase in the number of big banks (for a discussion see *Restrepo-Tobon* et al. 2015 or *Quaglia/Spendzharova* 2017). As a side effect, higher concentration can also lead to less competition, what will mean higher prices for the customers and a lower service quality especially in rural areas. We conclude that banking supervisors would be well advised to clearly distinguish between small/medium sized banks and larger banks. Only larger institutions with, let's say, total assets of more than 1 bn of EUROs should be subject to the full scope of financial supervision. In contrast, smaller institutions are not system-relevant but important for the development of rural areas and for competition. We therefore advocate a deregulation for smaller banks to the very core of regulation: Deposit insurance, liquidity requirements, and equity requirements.

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Appendix

Table A-1

Statistical Description of the Dataset

variable	description	mean	standard deviation	min	max	CAGR of mean 1999–2014
C	total cost (mio EURO)	27.3	66.4	0.5	2,485.9	+0.2 %
w_1	input price of labor (wage cost/employee in TEUR)	54.0	11.9	21.3	198.4	0.0 %
w_2	input price of capital (operating costs/fixed assets)	1.06	2.84	2	17,511	+2.2 %
x_1	input quantity of labor (number of employees)	285	496	280	279	0.0 %
x_2	input quantity of capital (fixed assets; mio. EUR)	15.2	24.0	0.2	614.4	–1.6 %
q_1	output: loans to customers (mio. EUR)	724	2,182	0.1	54,458	+0.3 %
q_2	output: deposits from customers (mio. EUR)	917	2,202	0.1	82,223	+1.6 %
q_3	output: fees and commissions (mio. EUR)	8.0	27.5	0.1	1,258	+1.5 %
q_4	output: net interest revenues (mio. EUR)	29.8	66.4	0.1	2,096	–0.3 %
eq	equity ratio (equity share of total assets)	0.066	0.032	0.002	0.874	+4.2 %
TA	total assets (mio. EUR)	1,461	4,286	2.2	96,714	+0.5 %

Observed time period:	1999–2014
Number of observed banks:	2,229
Average number of observation years per bank:	9.5
Number of observed mergers:	591
Number of observations:	21,167

All EURO-values in constant prices of the year 2010 (CPI deflated).

Source: BANKSCOPE; own calculations.

Table A-2

Slope Parameters of the Cost Function

Variable	*Full Model I* Parameter	Standard Error	*Full Model II* Parameter	Standard Error	*Core Model I* Parameter	Standard Error	*Core Model II* Parameter	Standard Error
$\ln w_1$	0.5530	0.0525 ***	0.6729	0.0293 ***	0.5587	0.0567 ***	0.3079	0.0326 ***
$\ln w_2$	0.4470	0.0525 ***	0.3271	0.0293 ***	0.4413	0.0567 ***	0.6921	0.0326 ***
$0.5 \ln w_1 \ln w_1$	–0.0511	0.0117 ***	–0.0483	0.0123 ***	–0.0544	0,0129 ***	–0.0378	0.0120 ***
$0.5 \ln w_1 \ln w_2$	0.0511	0.0117 ***	0.0483	0.0123 ***	0.0544	0,0129 ***	0.0378	0.0120 ***
$0.5 \ln w_2 \ln w_2$	–0.0511	0.0117 ***	–0.0483	0.0123 ***	–0.0544	0,0129 ***	–0.0378	0.0120 ***
$\ln q_1$	–0.0722	0.0332 **			0.1098	0.0363 ***		
$\ln q_2$	–0.1272	0.0710 *			0.1792	0.0854 **		
$\ln q_3$	0.4466	0.0483 ***	0.0489	0.0620	0.5993	0.0622 ***	0.3224	0.0511 ***
$\ln q_4$			0.2820	0.0362 ***			0.4338	0.0392 ***
$0.5 \ln q_1 \ln q_1$	0.0168	0.0039 ***			0.0523	0.0056 ***		
$0.5 \ln q_1 \ln q_2$	0.0164	0.0059 ***			–0.0337	0.0069 ***		
$0.5 \ln q_1 \ln q_3$	–0.0278	0.0058 ***			–0.0202	0.0074 ***		
$0.5 \ln q_2 \ln q_2$	0.0441	0.0087 ***			0.1042	0.0102 ***		
$0.5 \ln q_2 \ln q_3$	–0.0350	0.0067 ***			–0.0678	0.0097 ***		
$0.5 \ln q_3 \ln q_3$	0.0743	0.0119 ***	0.0797	0.0219 ***	0.0877	0.0142 ***	0.1046	0.0208 ***
$0.5 \ln q_3 \ln q_4$			–0.0625	0.0109 ***			–0.0949	0.0143 ***
$0.5 \ln q_4 \ln q_4$			0.0772	0.0151 ***			0.1126	0.0154 ***
$\ln w_1 \ln q_1$	–0.0114	0.0068 *			–0.0119	0.0076		
$\ln w_1 \ln q_2$	–0.0150	0.0096			–0.0336	0.0103 ***		
$\ln w_1 \ln q_3$	0.0057	0.0075	0.0110	0.0104	0.0147	0.0083 *	0.0166	0.0120

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(Table A-2: Continued)

Variable	Full Model I		Full Model II		Core Model I		Core Model II	
	Parameter	Standard Error	Parameter	Standard Error	Parameter	Standard Error	Parameter	Standard Error
$\ln w_1 \ln q_4$			0.0040	0.0073			0.0024	0.0096
$\ln w_2 \ln q_1$	0.0114	0.0068 *			0.0119	0.0076		
$\ln w_2 \ln q_2$	0.0150	0.0096			0.0336	0.0103 ***		
$\ln w_2 \ln q_3$	–0.0057	0.0075	–0.0110	0.0104	–0.0147	0.0083 *	–0.0166	0.0120
$\ln w_2 \ln q_4$			–0.0040	0.0073			–0.0024	0.0096
t	–0.0116	0.0330	–0.0111	0.0315	–0.0124	0.0007 ***	–0.0136	0.0013 ***
0.5 t t	0.0008	0.0038	0.0014	0.0037	0.0001	0.0001	0.0011	0.0001 ***
D^{merger}	0.0242	0.0054 ***	0.0265	0.0055 ***	0.029	0.0051 ***	0.0453	0.0062 ***
$D^{comm} \cdot eq$	1.6071	1.0485	1.9109	1.0571 *				
$D^{comm} \cdot eq^2$	–2.7592	2.1849	–3.6343	2.1806 *				
$D^{sav} \cdot eq$	0.4928	0.8188	0.4913	0.8159				
$D^{sav} \cdot eq^2$	–6.0468	9.3995	–7.5528	9.2195				
$D^{coop} \cdot eq$	–0.1230	0.5809	–0.3933	0.5900				
$D^{coop} \cdot eq^2$	14.3212	5.8556 **	14.5859	5.8702 **				
$D_{99} \cdot \ln TA$	0.7045	0.1254 ***	0.6617	0.1212 ***				
$D_{00} \cdot \ln TA$	0.7225	0.1222 ***	0.6798	0.1178 ***				
$D_{01} \cdot \ln TA$	0.7263	0.1197 ***	0.6837	0.1151 ***				
$D_{02} \cdot \ln TA$	0.7283	0.1183 ***	0.6841	0.1143 ***				
$D_{03} \cdot \ln TA$	0.7351	0.1174 ***	0.6887	0.1135 ***				

	Full Model I		*Full Model II*		*Core Model I*		*Core Model II*	
Variable	Parameter	Standard Error	Parameter	Standard Error	Parameter	Standard Error	Parameter	Standard Error
$D_{04} \cdot \ln TA$	0.7374	0.1173 ***	0.6905	0.1136 ***				
$D_{05} \cdot \ln TA$	0.7324	0.1178 ***	0.6864	0.1132 ***				
$D_{06} \cdot \ln TA$	0.7257	0.1177 ***	0.6805	0.1131 ***				
$D_{07} \cdot \ln TA$	0.7225	0.1174 ***	0.6785	0.1122 ***				
$D_{08} \cdot \ln TA$	0.7141	0.1177 ***	0.6687	0.1125 ***				
$D_{09} \cdot \ln TA$	0.7059	0.1172 ***	0.6520	0.1135 ***				
$D_{10} \cdot \ln TA$	0.7047	0.1183 ***	0.6485	0.1145 ***				
$D_{11} \cdot \ln TA$	0.7052	0.1176 ***	0.6483	0.1147 ***				
$D_{12} \cdot \ln TA$	0.7071	0.1186 ***	0.6489	0.1183 ***				
$D_{13} \cdot \ln TA$	0.7007	0.1203 ***	0.6415	0.1160 ***				
$D_{14} \cdot \ln TA$	0.6934	0.1218 ***	0.6344	0.1203 ***				
$0.5 \cdot D_{99} \cdot (\ln TA)^2$	–0.0353	0.0188 *	–0.0224	0.0180				
$0.5 \cdot D_{00} \cdot (\ln TA)^2$	–0.0393	0.0183 **	–0.0265	0.0186				
$0.5 \cdot D_{01} \cdot (\ln TA)^2$	–0.0397	0.0179 **	–0.0266	0.0180				
$0.5 \cdot D_{02} \cdot (\ln TA)^2$	–0.0401	0.0177 **	–0.0270	0.0175				
$0.5 \cdot D_{03} \cdot (\ln TA)^2$	–0.0428	0.0175 **	–0.0293	0.0175				

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(Table A-2: Continued)

Variable	*Full Model I* Parameter	*Full Model I* Standard Error	*Full Model II* Parameter	*Full Model II* Standard Error	*Core Model I* Parameter	*Core Model I* Standard Error	*Core Model II* Parameter	*Core Model II* Standard Error
$0.5 \cdot D_{04} \cdot (\ln TA)^2$	–0.0444	0.0176**	–0.0308	0.0173*				
$0.5 \cdot D_{05} \cdot (\ln TA)^2$	–0.0438	0.0178**	–0.0304	0.0174*				
$0.5 \cdot D_{06} \cdot (\ln TA)^2$	–0.0422	0.0178**	–0.0290	0.0173*				
$0.5 \cdot D_{07} \cdot (\ln TA)^2$	–0.0413	0.0177**	–0.0284	0.0172*				
$0.5 \cdot D_{08} \cdot (\ln TA)^2$	–0.0395	0.0178**	–0.0262	0.0170*				
$0.5 \cdot D_{09} \cdot (\ln TA)$	–0.0382	0.0175**	–0.0230	0.0170				
$0.5 \cdot D_{10} \cdot (\ln TA)^2$	–0.0378	0.0178**	–0.0222	0.0171				
$0.5 \cdot D_{11} \cdot (\ln TA)^2$	–0.0381	0.0175**	–0.0223	0.0173				
$0.5 \cdot D_{12} \cdot (\ln TA)^2$	–0.0389	0.0176**	–0.0226	0.0173				
$0.5 \cdot D_{13} \cdot (\ln TA)^2$	–0.0369	0.0178**	–0.0205	0.0175				
$0.5 \cdot D_{14} \cdot (\ln TA)^2$	–0.0362	0.0179**	–0.0199	0.0179				

Table shows results of fixed-effects estimation (slope parameters only).
Number of observations: = 21,167. Number of banks: 2,229.
*, ** or *** denotes estimates significantly different from zero at the 10 %, 5 % or 1 % level (robust standard errors).
GAUSS has been used for all calculations.