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European Bank Efficiency and Performance: The Effects of Supranational Versus National Bank Supervision

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Introduction

In the 2000s the European banking market has been severely tested. In the run-up to the financial crisis of 2007–8 countries like Ireland and Spain experienced large bank-financed housing booms. The financial crisis of 2007–8 necessitated the bailing out of banks on a large scale, and the dust of these policies had not settled when Europe was confronted with the sovereign debt crisis. This crisis made painfully clear how intertwined Europe's banks and sovereigns actually are. In response, a Banking Union was proposed to help decouple the sovereign debt–bank risk nexus and to generally strengthen the resilience of the financial system in Europe.

The period leading up to the financial crisis witnessed increasing integration of European banking markets. In 2004, the new EU Takeover Directive provided a common framework for cross-border takeover bids. Basel II was also

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proposed in 2004 and subsequently implemented in the European Union via the Capital Requirements Directive in 2006. A notable part of Basel II is that it features risk sensitivity of regulatory capital. The crisis of 2007–8quickly revealed the weakness of this feature, as especially European banks that were subject to Basel II held many highly rated subprime assets that, ex post, turned out to be much riskier than anticipated, leaving European banks severely under-capitalized when losses on these assets materialized.

The many publicly funded bank bailouts that followed quickly led to a deterioration of public debt ratios in many European countries. The rescue package for the Greek government in May 2010 marked an important turning point in the sovereign debt crisis in the European (Monetary) Union (E(M)U) because it set a fundamental change to the financial architecture into motion. It constituted the third phase of global financial turmoil following the subprime mortgage meltdown in the USA and the subsequent banking crisis sparked by the failure of Lehman Brothers. Already at the inception of the EMU, numerous scholars warned about the potentially vicious nexus between the surrendering of exchange rate policy in a monetary union to bolster financial and macroeconomic shocks without establishing and strengthening alternative mechanisms (see, for example, Lane 2012). The most important of such missing alternative mechanisms, besides a fiscal union called for by many economists, was presumably the absence of a Banking Union (O'Rourke and Taylor 2013; Chap. 17 of this Handbook). Supranational monetary policy conducted by the European Central Bank (ECB) for economies with at times vastly different credit cycles paired with national responsibility for the prudential supervision of banks by national competent authorities (NCAs) gave rise to a series of undesirable side effects. Recent literature demonstrates, for example, how excess central bank liquidity sparked lending by risky banks to risky customers (Jiménez et al. 2012, 2014) and liquidity hoarding (Benmelech and Bergman 2012; Acharya and Merrouche 2013). Similarly, the preferential treatment of EMU sovereign debt regarding risk weights and resulting capital requirements has induced carry trade behaviour (Acharya and Steffen 2015) and additional risk-taking (Buch et al. 2013a, b).

In response to the sovereign debt–bank risk nexus and to generally strengthen the resilience of the financial system in Europe, proposals for a Banking Union were put forward at the EU summit in June 2012 with the aim to complete the legislative process by December of the same year. The proposal featured a three-pillar approach that consisted of the Single Supervisory Mechanism (SSM), the Single Resolution Mechanism (SRM) and the Single Deposit Guarantee Scheme, of which only the first two

eventually passed legislation. As aptly noted by policy observers such as Véron (2015), the reallocation of supervisory responsibility and power to the SSM at the supranational level constitutes a major change to the architecture of the European financial system. The SSM is part of the ECB and responsible for the supervision of approximately 6,000 banks in the EMU. The objective of the SSM is to ensure a harmonized development and application of supervisory rules and procedures in the EMU, thereby restoring trust in the banking system and ensuring efficient yet stable operations. Prior to assuming this responsibility, these banks were subject to a comprehensive assessment of their business conducted by the ECB in close cooperation with NCAs. As of November 2014 the SSM is operational and focuses on the direct supervision of 122 systemically relevant financial institutions, which together account for around 82 % of total assets. Whereas the SSM is the organization responsible for supervision, most banks thus continue to be supervised by NCA.

Table 11.1 provides some general trends for selected average performance indicators of a 2004–13 sample of European banks that is further discussed below. In this period, average return on equity (ROE) declined continuously, while return on assets (ROA) remained roughly constant. This is consistent with banks having to deleverage as a result of recent crises and regulatory efforts to recapitalize banks. Average banks' cost–income ratios do not show a clear trend over time, having decreased a bit during the 2007–8 crisis and rebounding to their pre-crisis levels in recent years. European bank revenues still depend to a large extent on interest income, albeit with a declining trend. This pattern reflects in part policy rates that declined dramatically, mimicked by interest expenses on deposits and other interest expenses that show a declining trend. Finally, consistent with more stringent regulation, banks' z-score measured as the number of standard deviations from default shows an upward trend, although credit risk in terms of loan impairment charges over gross loans has remained fairly constant over time.

Table 11.2 takes a more detailed look and shows average return on equity, capitalization and credit risk for a set of European countries in three subperiods: 2004–6, 2007–9 and 2010–13 (all variables winsorized at 1 % and further described below). It shows quite some heterogeneity across countries. For instance, Ireland's average return on equity declined from 19.3 % to 6.8 % from 2004–6 to 2010–13 as its capitalization also increased with a factor three across this period. Greece's average ROE halved, even though capitalization only dropped by 2.5 percentage points. Credit risk in most countries increased when comparing 2004–6 with either 2007–9 or 2010–13. The only exception is Germany which shows a decline in credit risk.

Table 11.1 Performance of European banks—selected indicators

Year	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Efficiency and performance										
Return on equity (%)	18.4	16.3	18.1	15.2	13.9	14.9	14.8	13.6	13.1	13.4
Return on assets (%)	1.1	1.1	1.3	1.1	1.0	1.1	1.1	1.0	1.1	1.1
Cost–income ratio (%)	45.8	48.5	44.2	41.0	37.8	43.1	46.3	44.8	44.1	44.0
Income structure (% of total revenues)										
Interest income on loans	65.8	64.4	62.3	65.3	66.8	63.6	62.3	62.9	60.7	59.3
Other interest income	24.4	26.7	25.8	23.5	23.2	21.5	20.9	20.9	20.7	19.3
Non-interest operating income	17.6	19.3	21.2	17.5	14.6	18.7	20.2	19.4	21.0	23.1
Expense structure (% of total expenses)										
Interest expenses—customer deposits	33.0	25.4	27.4	27.0	27.3	19.6	16.5	17.9	19.6	20.4
Other interest expenses	43.3	38.4	40.1	43.9	46.6	40.5	36.2	36.7	35.7	31.8
Personnel expenses	30.4	32.2	30.8	27.5	25.2	30.4	33.1	32.5	32.6	33.8
Other operating expenses	22.4	24.1	22.7	20.7	18.4	22.0	24.7	24.2	24.6	25.8
Risk and capitalization										
Capitalization	6.7	7.8	7.9	8.0	7.9	8.0	8.2	8.4	8.6	8.8
Credit risk	4.6	4.5	4.6	4.4	4.6	4.7	4.6	4.1	4.4	4.5
Z-score	32.4	34.7	35.3	34.2	32.7	33.9	35.3	37.6	39.2	39.1

This table reports selected indicators per country and period for the cost frontier estimation sample, column 4 of Table 11.3. Efficiency and performance and risk and capitalization indicators are defined in Table 11.3. Total revenues are defined as the sum of interest income on loans, other interest income, dividend income and non-interest operating income. Total expenses equal operating costs (TOC): the sum of interest expenses, loan impairment charges, other operating expenses and personnel expenses. All ratios are winsorized at 99 %

These descriptive statistics underpin the challenging environment with low interest rates and increasing non-performing loans in selected countries faced by European banks. Technological advancements pose both opportunities in terms of increased bank productivity and threats in terms of disruptive start-ups threatening banks' existing business models. Simultaneously, increased regulation through Basel III and the SSM place increasingly large burdens on banks. Questions related to many of these developments are related to bank productivity and efficiency, for which there exists an extensive literature.

In the remainder of this chapter we set out to do two things. First, we provide an overview of the key estimation methods for efficiency and discuss selected applications to the European banking sector. Second, we apply stochastic frontier analysis to investigate the extent to which the reallocation of supervisory powers is associated with efficiency differences between European banks. In doing so, we are particularly interested in whether direct supervision by the SSM as opposed to NCA is related to cost and profit efficiency.

Table 11.2 Performance European banks – selected indicators per country and period

	Return on equity			Capitalization			Credit risk		
Country / period	2004–2006	2007–2009	2010–2013	2004–2006	2007–2009	2010–2013	2004–2006	2007–2009	2010–2013
Austria	16.4	15.0	11.8	7.6	7.5	7.4	4.5	4.7	4.7
Belgium	11.1	11.9	11.6	6.5	7.0	6.8	3.9	4.2	4.2
Cyprus	22.1	18.8	22.2	7.9	8.8	8.0	4.6	4.9	5.7
Denmark	16.2	10.0	11.7	14.1	12.6	11.8	4.0	5.2	5.9
Estonia	15.9	17.3	13.2	16.5	12.3	15.6	3.9	5.6	6.0
Finland	13.7	14.8	12.7	8.4	10.6	8.9	4.0	4.5	4.3
France	17.5	15.3	14.6	9.1	9.3	9.8	4.2	4.4	4.4
Germany	18.8	14.8	14.5	6.1	6.3	7.6	4.8	4.6	3.9
Greece	18.1	17.6	9.1	12.5	10.6	9.9	4.6	4.9	6.3
Ireland	19.3	17.1	6.8	4.2	6.9	11.4	3.9	5.6	6.8
Italy	13.2	13.1	12.6	11.3	11.0	10.0	4.3	4.5	5.0
Latvia	24.1	20.1	13.3	9.2	9.5	9.8	4.2	6.0	6.2
Lithuania	14.6	14.4	11.4	9.2	9.3	10.3	4.4	5.8	5.5
Luxembourg	19.9	18.7	15.2	6.4	6.1	8.2	3.9	4.2	4.1
Malta	19.1	14.6	13.1	9.7	14.8	11.0	4.2	4.0	4.2
Netherlands	16.1	13.5	13.2	9.5	9.1	10.0	4.2	4.5	4.8
Portugal	19.6	18.1	12.4	8.8	9.6	10.2	4.4	4.6	4.8
Slovakia	15.0	15.0	14.5	10.7	12.0	12.7	4.4	5.3	4.9
Slovenia	18.1	17.9	15.3	9.1	8.2	7.8	4.4	4.8	6.4
Spain	16.1	17.4	12.6	7.8	8.3	8.0	4.2	4.5	5.0

This table reports selected indicators per country and period for the cost frontier estimation sample, column 4 of Table 11.3. Variable definitions of return on equity, capitalization and credit risk are provided in Table 11.3

Using Bankscope data for approximately 27,000 bank-year observations of European banks between 2004 and 2013, our main results suggest that SSM-supervised banks are both less cost and less profit efficient compared with non-SSM-supervised financial institutions. The cost efficiency difference is insignificant as of 2010. Specifying an indicator variable equal to one when a bank is supervised by the SSM as a covariate confirms the positive effect of SSM membership on the distribution of inefficiency also after controlling for observable bank traits. The analysis of banks that switched their SSM status indicates no significant effects for profit efficiency. However, for those banks that were already on the SSM list in 2013 and continued to be on the one published in 2015 we find a negative interaction term, indicating that these banks experienced lower cost inefficiency. Overall, we thus find evidence that supranational supervision by the SSM coincides with larger inefficiencies. This result may indicate an additional administrative burden, at least during the run-up towards a more homogeneous approach to banking supervision in the EMU.

Methodological Trends and Applications to Banking

Do economic agents employ and allocate scarce resources optimally to accomplish their objectives? This is the capstone question underlying a rich and continuously growing literature on the measurement of efficiency. The contributions by Koopmans (1951), Debreu (1951), Farrell (1957) and Leibenstein (1966) were pivotal in sparking the development of a more formal measurement of (in)efficiency.

Two main approaches emerged for gauging deviations of agents, such as banks, non-financial firms or households, from an optimal benchmark, such as output, profit or cost, conditional on their input choices, say capital and labour used in order to produce output. The first approach is deterministic and solves optimization problems with non-linear programming methods, such as Data Envelopment Analyses. A comprehensive review is Simar and Wilson (2013). The second approach is stochastic and imposes structure on the observable data to fit a benchmark function econometrically, the so-called stochastic frontier. Deviations from this benchmark are decomposed into a systematic inefficiency component and random deviations. An introduction to the foundations of stochastic frontier analysis (SFA) is available in Kumbhakar and Lovell (2000), and a comprehensive discussion of more recent methodological developments can be found in Parmeter and Kumbhakar (2014).

Given the scope of the extant efficiency literature, we will focus in this chapter on selected recent methodological trends in SFA and their applications to European bank efficiency.

Methodological Developments

Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977) developed independently the following "workhorse" stochastic production frontier model:

$$y_i = T\left(x_i;\beta\right) - u_i + v_i, \tag{11.1}$$

where y denotes the output of firm i generated by employing production factors x with a common production technology T( ). The difference to a canonical production function are the two error components $-u_i + v_i = \varepsilon_i$, which denote non-random deviations from the estimated log-linear function and random noise, respectively. The random error is assumed to be normally distributed with mean zero, whereas the most simple parametric assumption regarding the inefficiency component is a half-normal distribution with a mean μ, often equal to zero, and a standard deviation σ. Systematic deviations gauge inefficiency that may arise because of over-employing factors (technical efficiency, TE) and/or an inefficient allocation of resources at given factor prices (allocative efficiency, AE).

The modern SFA literature developed numerous advances in how to specify such models in terms of functional forms assumed for the kernel of Eq. (11.1), functional form and distributional assumptions regarding the error term components, methods to account for confounding factors in the environment or selection bias and many more. We limit ourselves here to a selection of these mostly methodological advances.

Firstly, the assumptions concerning the error term can influence firm-specific measures of inefficiency substantially. Beyond the most commonly employed (truncated) half-normal model, alternatives include a wide range, such as the gamma distribution suggested by Greene (1990) or more recently the treatment of inefficiency as a double-truncated normal (Almanidis et al. 2014). Horrace and Parmeter (2014) assume v to be Laplace-distributed and u to be distributed as truncated Laplace, which is particularly well suited for data featuring many firms close to full efficiency. Hafner et al. (2013) suggest a generalized SFA model, which generates well-defined efficiency measures even if the skew of errors is theoretically wrong, for example positive in a production model where inefficiencies should be strictly negative.

Secondly, the modelling of technical efficiency requires a careful definition of the outputs of the firm. Especially a multi-output setting is challenging because it requires a system approach of both the objective as well as factor demand functions to estimate TE and AE separately. Tsionas et al. (2015b) develop such a system approach in terms of a cost minimization instead of output maximization problem. They account for endogenous factor demand in the input distance functions by means of a flexible system employing first order conditions as restrictions. Their estimator generates both TE as well as AE and detects inefficiencies that remain unobserved in a conventional single-frontier model. Imprecise efficiency estimates might also arise from including "bad outputs", such as pollution. Kumbhakar and Tsionas (2015) develop a so-called by-product model, which combines directional distance functions and single efficient frontier approaches and allows for bad outputs. They use Baysian estimation methods to separate TE from environmental reasons to deviate from optimal output of "good" outputs taking into account endogenous factor demand and the presence of undesirable co-production of bad outputs. Related developments are the use of Baysian Generalized Methods of Moments techniques to allow for endogenous inputs and outputs (Agee et al. 2014), endogeneity corrections of quadratic directional distance functions (Atkinson and Tsionas 2015) or the specification of separate production functions for desirable und undesirable outputs (Murty et al. 2012).

Thirdly, when firm-specific efficiency scores inform policy making, for example in banking applications, it is crucial to ensure that they do not confound inefficient behaviour with environmental differences and unobservable differences across studied subjects. Bos et al. (2009) showed that already fairly simple single-technology SFA models that account for such heterogeneity controls z in the kernel, the error term components, or both lead to significantly different levels of inefficiency and, at times, rank orders of firms. To relax the assumption in the basic SFA that all firms are inefficient to some degree, Kumbhakar et al. (2013) develop a zero-inefficiency with single technology frontier, which can also accommodate fully efficient firms. A related model by Rho and Schmidt (2013) allows one to test for the assumption of zero inefficiency. Another alternative to the specification of controls z in exiting single-frontier models is to allow for parameter heterogeneity in the kernel. Greene (2005) suggests to this end a latent-class SFA, where subjects are sorted into different technology regimes. Bos et al. (2010) show that this approach can reconcile the absence of economic convergence in many growth studies due to the existence of different convergence clusters in cross-country such that countries converge only with respect to their relevant production frontier. Another reason for confounding inefficiency

with unobservable alternative factors is systematic sample selection. Greene (2010) proposes a simple and straightforward extension of the normal half-normal SFA model and demonstrates that accounting for selection bias leads to qualitatively different inference in a cross-country study on the efficiency of national health systems.

Fourthly, to the extent that inefficiency measures gauge properly the ability and/or willingness of a firm's management skill in optimal decision making, any static measurement falls short in investigating the effects, for example how policy changes affect TE and AE. Therefore, panel data models that help to identify time-varying inefficiency have been developed. The composite nature of the error term, however, poses a challenge to the proper specification of a true panel data estimator due to an incidental parameter problem. Greene (2005) develops a fixed-effect panel estimator that relies on maximum likelihood estimation (MLE). This model is extended by Chen et al. (2014). They utilize the joint density of the deviations from means to remedy the incidental parameter problem. Similarly, Colombi et al. (2011, 2014) apply closed-skew distributional assumptions for the error term components to develop random effects panel estimators that allow the generation of time-variant measures of, for example, short-run and firm-specific efficiency scores.

Fifthly, an important challenge in SFA compared to alternative methods is the need for parametric assumptions in general, which are usually hard to motivate by economic theory. An important methodological development therefore pertains to approaches that leave increasingly many of these assumptions unnecessary. Martins-Filho and Yao (2015), for example, extend earlier studies by Kumbhakar et al. (2007) and suggest a non-parametric frontier, which hinges on an error density function characterized by a known, finite parameter vector. Kousmanen and Kortelainen (2012) suggest a two-step approach that combines deterministic data envelopment analysis (DEA) with parametric SFA. The first step gauges the shape of the benchmark frontier without having to impose any parametric form a priori. Inefficiency is then obtained in the second stage as conditional expectations relative to the residuals from this first stage. Along a related train of thought, Battese et al. (2004) suggest a so-called meta-frontier, which envelops separately estimated stochastic frontiers, say for firms in different countries, with a non-deterministic encompassing benchmark, the meta-frontier. Simar et al. (2014) use a local polynomial least-squares technique to obtain the frontier, which is computationally substantially less demanding compared to local MLE. Other developments focus on the specification of the error term instead of obtaining parameters of the production kernel as such. For example, Parmeter et al. (2014) estimate the determinants of inefficiency

non-parametrically and Horrace and Parmeter (2011) relax distributional assumptions on the inefficiency component u.

This highly selective review of some of the recent methodological advances highlights the continuous and fast-growing nature of the econometrics literature, which focuses on the determination of efficient frontiers and associated inefficiency scores. Important strides have been made towards increasingly less rigid assumptions, important concerns about possible endogeneity of frontier components, as well as adequately separating firm inefficiency from other observable and unobservable factors. Next, we review a similarly selective set of papers that apply SFA to the European banking industry.

SFA in European Banking

Much of the policy effort prior to the financial crisis of 2007–8 was dedicated to the establishment of a single banking market in the European Union. This approach reflects the notion that a level playing field should strengthen competition, thereby eliminating existing inefficiencies in the provision of financial services and products, and ultimately fostering the integration of European banking markets.

A number of studies test whether national banking markets indeed converged. Weill (2009) uses panel SFA methods for a sample of European banks from ten countries to test for β- and σ-convergence between 1994 and 2005. He reports that cost efficiency improved in all countries for different banking sectors, that is, commercial, savings and cooperative banks. Moreover, banking systems that started out from lower levels of cost efficiency improve faster and the dispersion of inefficiency declines over time. Thus, he provides important evidence for both β- and σ-convergence. Casu and Girardone (2010) ask the same research question, but expand the country coverage significantly to banks from 26 EU countries between 1997 and 2003. They use non-parametric DEA to obtain cost efficiency measures and model their convolution over time more explicitly using dynamic panel generalized method of moments (GMM) estimators. Whereas they confirm both β- and σ-convergence, in contrast to Weill (2009) they report declining efficiency levels, thereby corroborating possibly important changes in inference due to methodological choices.

Alternatively, excessive cross-country heterogeneity in terms of environmental factors may be the main driver of diverging results. Koutsomanoli-Filippaki et al. (2009), for example, focus on just a subsample of banking markets in ten Central and Eastern European (CEE) countries between 1998 and 2003.

Using directional distance functions, they generate a Luenberger productivity indicator, which is decomposed into efficiency changes and technological change. They report generally a low level of cost efficiency, which does not improve over time. Productivity gains are instead driven mainly by technological progress. Correspondingly, they also find that foreign banks consistently outperform domestic ones. This result for CEE banking markets indicates the existence of barriers to how foreign banking may aid market integration. Correspondingly, Fang et al. (2011) report for six South-Eastern European banking markets that such efficiency gaps also exist between domestic and foreign banks. But on the basis of cost and profit efficiency estimated with SFA, they report in contrast that efficiency differences converge over time and that efficiency generally improves, mostly due to the development of institutions and a concentration of market power among fewer banks.

These diverging results highlight the need to account adequately for heterogeneity in efficiency measurement by allowing for different transformation technologies, which constitute the benchmark against which inefficiency indicators are measured. Already for a sample of US banks only, for example, Kumbhakar et al. (2013) show that an estimator allowing for fully efficient banks yields significantly different efficiency levels and rankings for individual banks compared to more conventional single-frontier estimates. Likewise, Koetter and Poghosyan (2009) apply the latent-class model of Greene (2005) to show that already within German banking only three different technology regimes exist. These technology regimes cannot be identified solely with institutional differences, such as bank types like commercial, savings and cooperatives, and therefore have to be modelled econometrically. Since they show for each of the regimes significantly different profiles in terms of efficiency, market power and risk-taking, it seems reasonable to expect such differences to exist at the European, cross-country level as well. Bos and Schmiedel (2007) take these into account by applying the meta-frontier method of Battese et al. (2004) to a sample of banks from all major European countries to test for the existence of a single, that is, integrated market frontier in the EU between 1993 and 2004. They do confirm the existence of such a single meta-frontier.

The proper measurement of banking market integration and the associated effects on bank efficiency and competition are important beyond the implications for financial markets alone. Extending the extant literature on the nexus between finance and growth, a number of studies have shown for both national (Koetter and Wedow 2010) as well as regional markets in different European economies (Hasan et al. 2009) that a sheer expansion of credit alone did not spark significant additional economic growth. Using cost and profit efficiency measures obtained with a latent-class SFA model in the case

of Germany and a single-frontier SFA method accounting for heterogeneity in the inefficiency distribution for the explanation of regional growth at the European level, they show that the quality of intermediaries in terms of bank efficiency matters for growth, while the seminal measure of financial development, credit over gross domestic product (GDP), does not.

At the same time, additional competitive pressure arising from an increasingly integrated banking market might also induce banks to take excessive individual risks, ultimately contributing to an increase of systemic risk (see Chap. 7 of this Handbook).

Fiordelisi et al. (2011) estimate accordingly the cost, profit and revenue efficiency of commercial banks from EU-26 prior to the crisis. For a sample ranging from 1995 to 2007 they subsequently use Granger causality tests to show that higher cost and revenue efficiency Granger causes lower probabilities of bank defaults (PD). Although better bank capitalization precedes cost efficiency improvements, they find no evidence for Granger causality between capital ratios and bank risk. Thus, efficiency might be an important channel by which policies aiming to strengthen the resilience of the banking system by means of higher capital requirements help accomplish the ultimate objective of lower probabilities of bank default.

An open question from their work remains, however, whether results can be generalized to banks for which implied PDs based on rating information is not available. This is particularly important in studying European banking markets, where the vast majority of financial institutions are neither listed on capital markets nor do they issue rated debt. As an alternative, Assaf et al. (2013) resort to an accounting-based, well-established measure of bank risk, namely non-performing loans (NPL). For a sample of Turkish commercial banks, they use Baysian estimation techniques and specify NPL as a bad output in the vein of Kumbhakar and Tsionas (2015). Accounting for credit risk in the form of bad (NPL) outputs alters efficiency estimates significantly. They find evidence of productivity growth due to technical change but a decline in efficiency, and report as well that foreign banks are both more productive and efficient.

Against the backdrop of the more recent turmoil in European banking markets due to the financial crisis of 2007–8 and especially the sovereign debt crisis that started in 2010, further research on the relationship between bank efficiency and risk in more recent years is particularly important. Two studies in this regard are Tsionas et al. (2015a) and Matousek et al. (2015). The former employ Baysian dynamic frontier models to estimate both technical and allocative efficiency among banks from 15 European countries between 2005 and 2012. Impulse response functions show a difference in the short-

and long-term dynamics of efficiency. Their results suggest only a mild drop in efficiency in the short run after the crisis, which rebounds soon after. An important insight for policy makers is furthermore that allocative efficiency depends positively on the capitalization of banks. The latter study also treats NPL explicitly as an undesirable output using parametric distance functions when investigating possible convergence in terms of bank efficiency before and after the shock represented by the financial crisis. They provide evidence not only that efficiency declined in the aftermath of the crisis, but also that it halted integration and convergence. Instead, they show that their findings indicate the formation of separate convergence clubs.

In the light of these developments, it is startling that so far no research exists on the efficiency implications of the pervasive regulatory measures passed after 2007–8 in pursuit of establishing a common regulatory framework in the form of the European Banking Union. Therefore, we provide next a simple exercise to test for the implications of introducing supranational microprudential supervision in the form of the Single Supervisory Mechanism.

Specification and Data

Specification

We focus here on the efficiency effect of being a bank that is supervised by the SSM according to the latest list of the ECB (2015) while controlling for observable bank traits that gauge the profitability, risk and size of the banking firms. To this end we use the conditional mean model, suggested initially by Coelli (1995).

More specifically, we specify a cost frontier where we explain the operating cost TOC of bank i in year t as a function of output quantities y_k, input factor prices w_l and further controls z, which includes our variable of interest, namely an indicator equal to one if the bank is supervised by the SSM. To control for technical change we also specify next to country fixed effects a time trend t, its squared term t^2 and interactions with the direct production terms y and w:[1]

$$\begin{aligned}\ln TOC = \alpha_{\text{country}} &+ \sum_k \beta_k \ln y_k + \sum_l \beta_l \ln w_l + \frac{1}{2}\sum_k \sum_m \beta_{k,m} \ln y_k \ln y_m \\ &+ \frac{1}{2}\sum_l \sum_m \beta_{l,m} \ln w_l \ln w_m + \sum_k \sum_l \beta_{k,l} \ln y_k \ln w_l + \eta t \\ &+ \lambda t^2 \sum_k \beta_{t,k} \ln y_k t + \sum_l \beta_{t,l} \ln w_l t + yz + \mathbf{v} + \mathbf{u}.\end{aligned} \tag{11.2}$$

For the profit frontier, we replace the log of total cost by the log of total operating profits before tax *PBT*.[2] As is common in many bank efficiency studies, we choose a translog functional form and define variables below. For our purposes, it is more relevant to note that contrary to ordinary least squares (OLS) estimation, the error term in Eq. (11.1) features two components. The first term v is random noise and normally distributed with an expected value of zero. The second term u captures inefficiency. In line with Coelli (1995), we assume that it is drawn from a truncated half-normal distribution with mean μ. We furthermore specify this mean of the inefficiency distribution to depend also on the control variables z:

$$\mu = \gamma z. \tag{11.3}$$

Parameters are estimated by maximizing the joint-likelihood function after imposing the necessary restrictions, such as homogeneity of degree one, by dividing all factor prices and the dependent variables by one of the factor prices. Given estimated parameters, we obtain bank-specific point estimates of cost and profit efficiency (CE and PE) using the method by Jondrow et al. (1982) as $E_i = E\{\exp(u_i)|\varepsilon_i\}$, where $\varepsilon = u \pm v$. Hence, inefficiency leads to higher than optimal cost and lower than optimal profits, respectively.

Bank Data

We obtain balance sheet and profit and loss account information for all universal banks that are active in 20 member states of the European Union from the Bankscope database for the time period 2004 until 2013.[3] We select all banks with specializations equal to those in the lists of SSM-supervised banks. All variables are defined in Table 11.3. Total operating cost equals the sum of interest expenses, loan impairment charges, other operating expenses and personnel expenses. Total profits before tax is the profit before impairment charges. To specify an according cost and profit frontier, we follow the intermediation approach of Sealey and Lindley (1977) and assume that banks hold

Table 11.3 Variable definition and sources

Name	Acronym	Description	Source
Total securities	y1	Total securities in € millions	Bankscope
Gross loans	y2	Gross loans in € millions	Bankscope
Off-balance sheet activities	y3	The sum of managed securitized assets, other off-balance sheet exposures, guarantees, acceptances and documentary committed credit lines in € millions	Bankscope
Cost of fixed assets	w1	Operating expenses divided by fixed assets	Bankscope
Cost of labour	w2	Personnel expenses divided by number of employees	Bankscope
Cost of borrowed funds	w3	The sum of interest expenses and other interest expenses divided by total deposits and money market funding	Bankscope
Significant supervised entity 16-03-2015	SSE	Dummy variable indicating a significant supervised entity, as indicated by the European Central Bank on their list of 16 March 2015	European Central Bank
Significant supervised entity 10-10-2013	SSE_oct2013	Dummy variable indicating a significant supervised entity, as indicated by the European Central Bank on their preliminary list of 10 October 2013	European Central Bank
Equity	Z	Total equity in € millions	Bankscope
Operating costs	TOC	The sum of interest expenses, loan impairment charges, other operating expenses and personnel expenses	Bankscope
Profits before tax	PBT	Pre-impairment operating profit in € millions	
Return on equity	ROE	Pre-impairment operating profit as a percentage of total equity	Bankscope
Capitalization	CAPITAL	Equity as a percentage of total assets	
Z-score	ZSCORE	Sum of CAPITAL and returns on assets, defined as PBT over Total Assets, divided by the standard deviation of ROA	Bankscope
Credit risk	CREDITRISK	Loan impairment charges as a percentage of gross loans	Bankscope
Cost–income ratio	CI_RATIO	The sum of personnel and other operating expenses divided by total revenues	Bankscope
Total assets	Total_assets	Total assets in € millions	Bankscope
Size indicator	SIZE	A quartile indicator indicating the quartile of total assets distribution a bank belongs to in each year	Bankscope

securities (y_1), originate loans (y_2) and engage in off-balance sheet activities (y_3) to generate income. As is common in the bank efficiency literature, we also specify the log level of equity capital because it can be used as a netput to fund bank assets. Banks employ fixed assets, labour and borrowed funds to generate output. We approximate the rental price of fixed assets (w_1) by dividing fixed assets by operating expenses. The price of labour (w_2) is obtained as the sum of personnel expenditure divided by the number of employees. The rental price of funds (w_3) results from dividing interest expenses by interest-bearing liabilities.

Table 11.4 depicts descriptive statistics for the cost frontier sample in panel A and for the profit frontier sample in panel B. We show the distributional properties for the entire sample, the group of banks supervised by the SSM according to the March 2015 list and those supervised by NCAs. Both cost and frontier data show clearly that SSM banks are significantly larger, directly reflecting the focus on size to define systemically relevant financial institutions. Whereas SSM banks exhibit higher mean factor cost for both labour and borrowed funds, these differences are not statistically significant.

Aside from the bank production technology data, we also specify further controls in logs to gauge systematic differences across banks other than the responsible supervisor. Empirical banking studies that measure the stability and soundness of banks by capturing risk and return traits, such as Wheelock and Wilson (2000), inspire our choice of controls. The capital ratio is measured as the ratio of equity to total assets to measure possible differences of banks' risk–return preferences. To measure risk more explicitly, we furthermore include the z-score as in Laeven and Levine (2009) as the sum of return on equity and capitalization divided by the (time-invariant) standard deviation of each bank's returns. This measure therefore grasps the bank's distance to default. In addition, we specify the ratio of loan impairment charges to gross total loans as an indicator of credit risk. As a metric of operational cost efficiency we also include the cost-to-income ratio in the profit frontier. In the cost frontier, we specify instead the return on equity to gauge the profitability of the bank explicitly. Finally, we account for size differences as another source of systemic deviations from both optimal cost and profits by means of an ordinal indicator per quartile of the annual asset distribution. All factor prices and control variables expressed in ratios are winsorized at the 1st and 99th percentile. Data expressed in monetary terms that are used to generate variables are deflated by country-specific consumer price indices to price levels in 2005.

Clearly, many of these covariates are correlated with another, adding to inherent multicollinearity issues that result from the specification of the many interaction terms in a translog functional form. Therefore, we present our

Table 11.4 Summary statistics, cost and profit frontier

	Full sample					SSEs					All others				
	mean	sd	p5	p95	N	mean	sd	p5	p95	N	mean	sd	p5	p95	N
Panel A: Cost frontier															
SSE	0.03	0.17	0.00	0.00	27,301										
y1	3,629.74	37,543.68	9.80	5,616.64	27,301	76,045.56	193,596.33	294.29	316,996.78	784	1,488.70	13,594.93	9.60	3,102.79	26,517
y2	5,556.08	31,537.30	44.76	17,309.81	27,301	88,311.31	132,249.44	1,902.00	396,465.56	784	3,109.34	17,293.59	44.15	10,805.40	26,517
y3	3,368.01	30,500.01	6.00	6,537.03	27,301	59,263.51	147,841.79	421.99	322,174.03	784	1,715.41	14,738.35	5.84	4,003.57	26,517
w1	184.68	419.67	31.11	700.00	27,301	182.59	332.92	33.08	512.53	784	184.74	421.97	31.04	708.48	26,517
w2	68.13	32.27	39.34	134.46	27,301	71.92	41.62	25.05	153.01	784	68.01	31.95	39.86	134.01	26,517
w3	2.77	2.06	1.04	5.80	27,301	4.39	3.44	1.04	13.27	784	2.73	1.99	1.04	5.60	26,517
Z	542.43	3,061.09	7.29	1,727.25	27,301	8,384.45	13,776.11	289.60	43,436.00	784	310.58	1,473.49	7.10	1,178.76	26,517
TOC	468.60	2,864.86	4.09	1,294.62	27,301	7,621.70	12,627.19	140.13	37,591.75	784	257.12	1,477.91	4.07	798.88	26,517
PBT	81.88	579.61	0.94	238.36	27,301	1,357.30	2,809.62	13.31	7,022.30	784	44.17	251.51	0.94	167.64	26,517
ROE	30.79	8.84	18.56	45.62	27,301	32.34	10.56	17.03	49.51	784	30.75	8.78	18.63	45.31	26,517
CAPITAL	8.06	4.26	3.46	15.70	27,301	6.01	3.69	1.79	11.78	784	8.12	4.26	3.63	15.76	26,517
ZSCORE	35.40	26.09	8.22	81.18	27,301	31.50	29.64	6.62	87.06	784	35.51	25.97	8.32	81.00	26,517
CREDITRISK	4.50	1.10	3.37	6.30	27,301	4.61	1.17	3.80	6.74	784	4.50	1.10	3.36	6.29	26,517
CI_RATIO	43.85	15.24	17.66	68.24	27,301	30.12	14.95	3.93	53.17	784	44.25	15.05	18.80	68.58	26,517
Total_assets	11,493.71	78,214.20	90.52	29,920.57	27,301	199,473.75	359,724.94	4,312.68	967,359.43	784	5,935.91	37,436.52	89.74	17,782.23	26,517
Panel B: Profit frontier															
SSE	0.03	0.17	0.00	0.00	26,228										
y1	3,481.72	36,187.58	11.12	5,375.00	26,228	74,660.64	187,693.70	272.03	320,695.03	754	1,374.91	12,349.33	10.78	2,990.23	25,474
y2	5,526.80	31,557.16	49.46	17,178.48	26,228	88,800.36	134,076.92	1,902.00	397,777.00	754	3,062.00	16,810.52	48.98	10,805.40	25,474
y3	3,309.71	30,587.95	6.35	6,453.79	26,228	60,277.80	150,374.46	410.34	332,614.59	754	1,623.52	13,998.93	6.25	3,983.65	25,474
w1	175.14	399.62	31.28	615.44	26,228	174.63	305.38	32.16	486.93	754	175.15	402.07	31.28	620.00	25,474
w2	67.28	31.40	39.53	131.09	26,228	71.84	41.94	25.02	158.30	754	67.15	31.02	39.99	130.47	25,474
w3	2.75	2.00	1.05	5.70	26,228	4.31	3.34	1.00	11.56	754	2.70	1.93	1.05	5.48	25,474
Z	543.85	3,087.15	7.84	1,720.08	26,228	8,542.51	13,974.73	280.12	44,521.27	754	307.10	1,445.61	7.69	1,176.38	25,474
TOC	454.29	2,812.30	4.40	1,246.01	26,228	7,484.50	12,572.55	137.78	37,788.00	754	246.20	1,401.51	4.35	779.93	25,474

(*continued*)

Table 11.4 (continued)

	Full sample					SSEs					All others				
	mean	sd	p5	p95	N	mean	sd	p5	p95	N	mean	sd	p5	p95	N
PBT	88.30	579.80	1.01	248.77	26,228	1,450.27	2,812.33	41.25	7,270.06	754	47.98	236.19	1.01	174.48	25,474
ROE	31.62	7.90	21.59	45.86	26,228	33.41	9.22	19.60	50.10	754	31.57	7.85	21.59	45.71	25,474
CAPITAL	8.01	4.10	3.55	15.32	26,228	6.09	3.71	1.93	11.80	754	8.06	4.10	3.72	15.38	25,474
ZSCORE	36.31	26.03	10.07	82.40	26,228	32.07	28.91	7.29	87.06	754	36.43	25.93	10.28	82.27	25,474
CREDITRISK	4.50	1.07	3.39	6.21	26,228	4.56	1.08	3.80	6.47	754	4.50	1.07	3.37	6.21	25,474
CI_RATIO	42.90	13.63	17.88	64.29	26,228	29.90	13.84	4.12	51.74	754	43.28	13.43	19.03	64.53	25,474
Total_assets	11,243.19	77,003.21	97.84	29,045.16	26,228	198,582.11	358,050.81	4,052.93	1,005,473.39	754	5,698.18	35,294.87	96.36	17,554.85	25,474

This table reports summary statistics for the cost and profit frontier estimation samples, respectively columns 4 of Tables 11.5 and 11.6

results below in four steps, gradually adding these control variables to both the kernel of the frontiers shown in Eq. (11.1) as well as determinant of the mean of the inefficiency distribution shown in Eq. (11.2).

Single Supervisory Mechanism Data

The four criteria to select which banks are directly supervised emphasize the size of financial institutions, either in absolute terms or relative to the size of the host economy.[4] Recent studies indeed find that larger European banks tend to be more efficient in terms of scale economies (Beccalli et al. 2015), but also caution that part of these efficiencies may be due to implicit too-big-to-fail subsidies (Davies and Tracey 2013), which might even be increased when officially considered systemically important by the SSM. Therefore, we estimate the effect of being a bank supervised by the SSM on both cost and profit efficiency using a simple stochastic frontier analysis model by Coelli (1995), thereby essentially comparing banks with NCA supervision to those supervised by the ECB.

We also analyse the fact that the list of systemically relevant banks changed over time. Specifically, the ECB published together with the procedure of the comprehensive assessment in preparation of the SSM a list of included banks in October 2013. The final list of SSM-supervised banks that was published, in turn, in March 2015 contained some additional banks, but also omitted a few from this initial list. While these changes might merely reflect changes to the fulfilment of the defined criteria to be considered systemically relevant, such as Lithuania joining the SSM, these changes might also partly reflect a political bargaining process (De Rynck 2014). Although we are not aiming to explain this political bargaining process, we want to test whether exposure to different supervisory styles, and possibly alternative objectives of NCA compared to those of the SSM, influence bank efficiency.[5] A more rigid approach to regulation might reduce the efficiency of bank operations if it imposes excessive administrative burdens on banks, as representatives of the financial industry frequently claim. Therefore we are particularly interested to test if efficiency differentials exist for banks that switched from SSM supervision status into NCA status or vice versa.

Our main variable of interest is an indicator equal to one whether a bank was supervised by the SSM according to the latest list of systemically relevant financial institutions (ECB 2015). All banks that are chartered in member countries of the EMU are automatically subject to micro-prudential supervision by the SSM. Most of these are, however, in practice supervised by

NCA. The SSM report indicates that 122 entities are directly supervised, covering 82 % of total assets in the EMU banking industry (ECB 2015). From this report, we are able to match for up to 108 banks the identity and the required cost frontier data. For the profit frontier sample, we are able to match up to 107 banks listed by the SSM with Bankscope data.

In addition, we compare the contemporary list of SSM-supervised banks to the preliminary one published in March 2013 during the preparations for the comprehensive assessment conducted by the ECB.[6] Thereby, we can account for possible efficiency differences if banks either entered the list or were reallocated to the supervisory authority at the national level. For both the cost and the profit frontier samples we find that seven banks disappeared from the list and six new ones were added.[7] To test whether these changes from supranational to national responsibility, or vice versa, for supervision can also explain efficiency differences, we specify in Eq. (11.2) an interaction term of the indicator variables whether a bank was part of the SSM list in 2013 and 2015, respectively. We realize that whether a bank is supervised by the SSM is clearly not exogenous to a bank's costs and profits. In particular, it is likely that there are omitted variables driving both. We leave it to future work to solve these issues as it would benefit from having both a period before and after the implementation of the SSM.

Results

Frontier Estimation Results

Consider first the parameter estimates of the cost frontier depicted in Table 11.5. To conserve on space, we only show in each pair of columns (1) through (4) the effect of the vector of control variables z on the kernel of the cost frontier in the left subcolumn (CF) and the mean of the inefficiency distribution in the right subcolumn (μ), respectively. Results for all direct and interaction terms of cost frontier arguments shown in Eq. (11.1) are available upon request.

When we control only for the size and profitability of banks, column pair (1) shows neither an effect of SSM supervision on the cost kernel nor one on the inefficiency distribution. Larger banks that are more profitable exhibit larger cost *ceteris paribus*, but the effect on the location of the first moment of the inefficiency distribution has opposing effects. Whereas size correlates with a higher average inefficiency, more profitable banks are found to yield a lower mean inefficiency.

Table 11.5 Cost frontier estimates

	(1)		(2)		(3)		(4)	
	CF	μ	CF	μ	CF	μ	CF	μ
SSE	−0.0008	0.2028	−0.0909***	1.6103***	−0.0713***	1.5655***	−0.0323*	1.9513***
	[0.969]	[0.350]	[0.000]	[0.000]	[0.001]	[0.000]	[0.061]	[0.000]
lnSIZE	0.3075***	0.6453***	0.0773***	1.3173***	0.0678***	1.3028***	0.0890***	2.6297***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
lnROE	0.3514***	−1.5067***	0.2364***	−1.4872***	0.1902***	−0.6081***	0.0133**	−0.0884
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.039]	[0.167]
lnCAPITAL			−0.8073***	1.4018***	−0.7979***	1.6520***	−0.7551***	2.1802***
			[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
lnZSCORE					−0.0042	−1.5946***	0.0235***	−2.6725***
					[0.311]	[0.000]	[0.000]	[0.000]
lnCREDITRISK							0.7927***	−2.9731***
							[0.000]	[0.000]
Observations	27,497	27,497	27,497	27,497	27,301	27,301	27,301	27,301
# Banks	3,789	3,789	3,789	3,789	3,648	3,648	3,648	3,648
# SSEs	108	108	108	108	106	106	106	106
# Countries	20	20	20	20	20	20	20	20
σ(v)	0.3159	0.3159	0.2871	0.2871	0.2781	0.2781	0.2191	0.2191
σ(u)	0.7547	0.7547	0.7404	0.7404	0.7665	0.7665	0.9913	0.9913

This table shows the cost frontier estimations of Eq. 11.1 for 2004–2013 using a truncated normal distribution for the inefficiency term. Columns labelled CF show the coefficients of the kernel of the cost frontier; those labelled μ show coefficients for the mean of the inefficiency distribution. For brevity we only show the results on the control variables *z* included in the kernel and the mean of the inefficiency distribution. All estimations include country fixed effects in the cost function. σ(v) and σ(u) indicate the standard deviation of the error term and technical efficiency, respectively. P-values are reported in square brackets: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The insignificance of the SSM indicator variable in both the kernel and the inefficiency distribution might reflect the fact that it was the primary criterion for the ECB to select banks that ought to be supervised at the supranational level. To differentiate between alternative bank traits in a more detailed fashion, we therefore gradually add in columns (2) through (4) as further controls. We specify the log of the equity capital ratio, the z-score and a measure of credit risk results in parameter estimates of the SSM indicator that consistently indicate two effects. Firstly, banks that are supervised by the SSM exhibit significantly lower cost levels compared to banks supervised at the national level. The magnitude of this effect varies between nine and three basis points and is therefore rather small. This effect may indicate that the exposure to homogenous supervisory practices exerts cost discipline on supervised banks. Secondly, the effect on the mean of the inefficiency distribution is in turn significantly positive throughout. The economic magnitude associated with these coefficients is not straightforward to interpret because the marginal effects depend on the distribution of the estimated total error ε given that inefficiency scores are obtained as conditional means according to the Jondrow et al. (1982) method. We therefore discuss below estimated efficiency scores that we average across all banks per year, separated by SSM versus non-SSM-supervised institutions.

All the additional controls are also statistically significant, underpinning the importance of controlling for environmental factors in both the cost frontier as well as the determination of the inefficiency distribution's location and shape. Our results indicate lower costs for banks that are better capitalized and are exposed to lower credit risk while simultaneously yielding lower z-scores, that is, those that are less distant from default in terms of capital and earnings buffers relative to earnings volatility. The results also show that the mean of the cost inefficiency distribution depends positively on higher capitalization ratios, but negatively on more credit risk and more stable banks in terms of the z-score. The first finding is in line with the notion that capital is an expensive source of funding for banking activities. The second result underscores the danger of mistakenly identifying more risky loan portfolios as efficient banking operations. Overall, the results corroborate the importance of accounting explicitly for risk factors, which are likely to capture very different aspects of banking risk such as the z-score and credit risk, to avoid confounding effects on estimated inefficiency.

Table 11.6 shows parameter estimates for the profit frontier. Across all specifications in column pairs (1) through (4) we estimate a positive effect of the SSM indicator variable on both the level of profits before tax, but also the mean of the profit inefficiency distribution.

Table 11.6 Profit frontier estimates

	(1)		(2)		(3)		(4)	
	PF	μ	PF	μ	PF	μ	PF	μ
SSE	0.2342***	0.5512***	0.2119***	0.4176***	0.1808***	0.3449***	0.1949***	0.3903***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.000]	[0.000]
lnSIZE	0.3575***	2.5278***	0.2807***	2.2662***	0.2736***	1.7108***	0.2817***	1.7178***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
lnCI	−0.5947***	−2.1500***	−0.6077***	−1.8324***	−0.5634***	−1.6327***	−0.5195***	−1.5552***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
lnCAPITAL			−0.3290***	−0.6704***	−0.2703***	−0.3039***	−0.2447***	−0.2137***
			[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
lnZSCORE					−0.1349***	−0.8542***	−0.1300***	−0.9453***
					[0.000]	[0.000]	[0.000]	[0.000]
lnCREDITRISK							0.1875***	−0.8982***
							[0.000]	[0.000]
Observations	26,328	26,328	26,328	26,328	26,228	26,228	26,228	26,228
# Banks	3,704	3,704	3,704	3,704	3,606	3,606	3,606	3,606
# SSEs	107	107	107	107	105	105	105	105
# Countries	20	20	20	20	20	20	20	20
σ(v)	0.3258	0.3258	0.3166	0.3166	0.2877	0.2877	0.2831	0.2831
σ(u)	1.2249	1.2249	1.1456	1.1456	1.1292	1.1292	1.1396	1.1396

This table shows the profit frontier estimations of Eq. 11.1 for 2004–2013 using a truncated normal distribution for the inefficiency term. Columns labelled PF show the coefficients of the kernel of the profit frontier; those labelled μ show coefficients for the mean of the inefficiency distribution. For brevity we only show the results on the control variables *z* included in the kernel and the mean of the inefficiency distribution. All estimations include country fixed effects in the kernel. σ(v) and σ(u) indicate the standard deviation of the error term and technical efficiency, respectively. P-values are reported in square brackets: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Regarding the former result, banks that are supervised by the SSM tend to exhibit, according to our estimation results, 18 and 23 basis points higher profit levels. Supranational supervision might in fact aid banks to boost profits, potentially due to imposing risk management discipline and requiring banks to report in a more granular fashion details of their operations, even after we control explicitly for size, profitability and risk.

The latter estimation result also indicates, however, that banks under the supervision of the SSM exhibit significantly higher means of the profit inefficiency distribution. This finding might indeed confirm practitioners' claims of an increased regulatory burden of systemically relevant financial institutions compared to smaller and less relevant competitors that are supervised at the national level. But given that the interpretation of these coefficients is a bit cumbersome, we turn next to a discussion of estimated mean cost and profit efficiency levels.

Mean Efficiency of SSM Versus Non-SSM Banks Over Time

Figure 11.1 depicts the dynamics of average cost inefficiency developments of banks that are supervised by the SSM compared to those that are not, where higher cost inefficiency scores indicate less efficient banks, that is, a score of one indicates no inefficiencies.

At the beginning of the sample period, those banks that eventually were supervised by the SSM exhibit significantly higher levels of cost inefficiency on the order of almost 50 % above optimal cost compared to the smaller banks eventually supervised by national authorities. The latter group of banks exhibits around 20 % higher costs in excess of estimated optimal cost levels and also a much more narrow dispersion of cost inefficiency. Starting in 2010, the year of the European sovereign debt crisis and the beginning of Banking Union initiatives, these differences continued to exist but were no longer statistically significant. This development might indicate that the inception and the progress of the Banking Union also marked the start of converging cost efficiency, possibly due to efforts to homogenize banking supervision rules and in particular their application in practice in member states of the EMU. The development of cost inefficiency also indicates, however, that banks tended to become increasingly cost inefficient irrespective of where supervisory authority rests. One interpretation of this result is that increased supervisory burden is one of the reasons for these cost efficiency losses. Put differently, regulators might face a trade-off between incurring some slack in terms of operational efficiency of banks when tightening regulation with the aim to enhance the resilience and financial stability of the banking industry. Further research

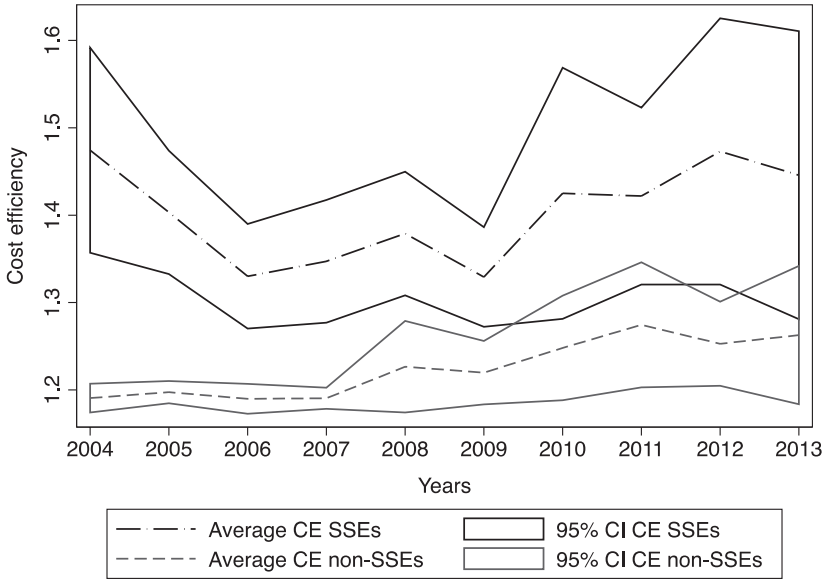

Fig. 11.1 Cost inefficiency of SSEs vs non-SSEs. This figure shows average cost inefficiency (CE) and its 95 % confidence interval (CI) for significant supervised entities (SSEs) and non-SSEs. Cost inefficiency is calculated as average technical inefficiency in each year. Technical inefficiency is derived from the cost function estimates in column (4) of Table 11.5

in such an efficiency–financial stability trade-off is warranted. An alternative explanation is that banking supervision in an increasingly materializing Banking Union forced banks to reveal inefficient operations independently of whether supervision is actually conducted centrally or decentralized. Future research seeking to identify the causal relationship between the organization of supervision and bank efficiency, which is beyond the scope of this chapter, is therefore warranted.

Figure 11.2 depicts the corresponding dynamics for estimated profit efficiency across SSM and non-SSM banks over time, where higher profit efficiency indicates more efficient banks, that is, a score of one indicates no inefficiencies. As before, non-SSM-supervised banks exhibit significantly higher levels of profit efficiency. They realize around 70 % of estimated optimal, potential profits compared to a mere 50 % realized by the larger, SSM-supervised competition. Lower profit efficiency scores among larger banks are to some extent in line with earlier bank efficiency studies. This result is also consistent with more recent evidence on the role of organizational complexity in large banks that prevents the efficient (internal) allocation of capital and optimal realization of profitable project opportunities, as discussed, for example, in Cetorelli and Goldberg (2014).

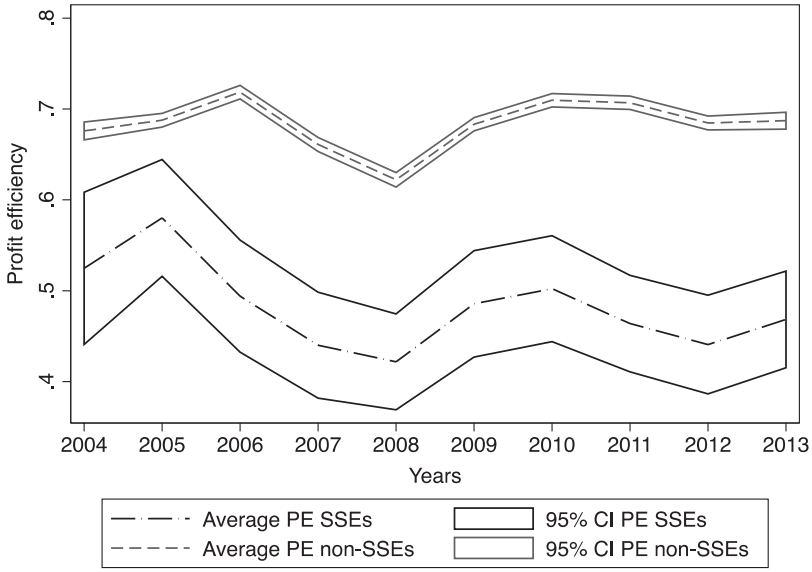

Fig. 11.2 Profit efficiency of SSEs vs non-SSEs. This figure shows average profit efficiency (PE) and its 95 % confidence interval (CI) for significant supervised entities (SSEs) and non-SSEs. Profit efficiency is calculated as average technical efficiency in each year. Technical efficiency is derived from the profit function estimates in column (4) of Table 11.6

Contrary to cost inefficiency, the differences between SSM and non-SSM-supervised banks are persistent. This development may indeed indicate a sustained higher regulatory burden for systemically relevant banks facing more detailed reporting requirements. Alternatively, this persistent difference may also indicate an excessively favourable treatment of banks by NCA, akin to the extreme forms of regulatory capture experienced during the S&L crisis in the USA during the late 1980s and early 1990s (see Kane 1990).

Switching Supervisory Regimes

We therefore investigate next the effects of inclusion and exclusion from the list of systemically relevant financial institutions published in ECB (2015) relative to the one published by the ECB (2013) in preparation for the Comprehensive Assessment preceding the handover of supervisory authority from national authorities to the ECB. Specifically, in Table 11.7 we show results from cost frontier (panel A) and profit frontier (panel B) estimations where we include next to the indicator of systemically relevant banks

Table 11.7 Frontier estimates, SSEs vs SSEs 2013

	(1)		(2)		(3)		(4)	
	CF/PF	μ	CF/PF	μ	CF/PF	μ	CF/PF	μ
Panel A: Cost frontiers								
SSE	−0.6719***	2.8036***	−0.4894***	2.0122***	−0.4995***	2.3120***	−0.2870***	1.3753*
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.059]
SSE_2013	0.2957***	−2.3613	0.1860*	−5.2160	0.0881	0.4755	−0.0983	2.3543***
	[0.010]	[0.679]	[0.064]	[0.676]	[0.285]	[0.706]	[0.131]	[0.000]
SSE × SSE_2013	0.4231**	−0.4752	0.2504*	4.7711	0.3834***	−1.3015	0.3799***	−1.7820*
	[0.010]	[0.934]	[0.057]	[0.702]	[0.001]	[0.336]	[0.000]	[0.065]
Observations	27,497	27,497	27,497	27,497	27,301	27,301	27,301	27,301
# Banks	3,789	3,789	3,789	3,789	3,648	3,648	3,648	3,648
# SSEs	108	108	108	108	106	106	106	106
# SSEs 2013	109	109	109	109	107	107	107	107
Panel B: Profit frontiers								
SSE	−0.3060***	−1.2547	−0.3252***	−0.9719	−0.2889***	−0.7135	−0.2621**	−0.7131
	[0.003]	[0.168]	[0.002]	[0.225]	[0.005]	[0.276]	[0.011]	[0.297]
SSE_2013	0.2754**	0.5821	0.1917	0.5504	0.1844*	0.3011	0.1944*	0.4537
	[0.022]	[0.297]	[0.116]	[0.257]	[0.090]	[0.481]	[0.071]	[0.291]
SSE × SSE_2013	0.3104*	1.2838	0.3938**	0.8902	0.3257**	0.7953	0.2997**	0.6860
	[0.055]	[0.232]	[0.016]	[0.345]	[0.034]	[0.313]	[0.049]	[0.399]
Observations	26,328	26,328	26,328	26,328	26,228	26,228	26,228	26,228
# Banks	3,704	3,704	3,704	3,704	3,606	3,606	3,606	3,606
# SSEs	107	107	107	107	105	105	105	105
# SSEs 2013	108	108	108	108	106	106	106	106

This table shows cost and profit frontier estimations that correspond to those in Tables 11.5 and 11.6, respectively. In this table we add an indicator variable, SSE_2013, equal to one when a bank is on the preliminary list of significant supervised entities as published by the ECB in 2013, and zero otherwise. We also add an interaction between SSE and SSE_2013. All estimations include country fixed effects in the kernel of the cost and profit functions. P-values are reported in square brackets: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

according to the 2015 list also an indicator of when the bank was included on the preliminary list published in 2013, as well as the according interaction term.

The four pairs of columns correspond to the gradual inclusion of additional control variables in the tables above, which we, however, no longer report to conserve on space.

The results for the cost frontier in panel A confirm across columns, first of all, the importance of controlling for observable bank traits gauging their size, risk and return profile. In the most saturated specification in the pair of columns (4), the indicators for both SSM supervision according to the 2013 and the 2015 list, respectively, confirm the baseline results of a higher mean cost inefficiency. The interaction term is significantly negative, indicating that the large group of banks that remained throughout the process of setting up the SSM as part of the Banking Union exhibited a lower mean cost inefficiency relative to those banks that either entered the contemporary list of systemically relevant institutions or were excluded from it since the announcement of the comprehensive assessment in 2013. We tabulate below mean cost inefficiency levels across all four categories of banks.

Consider first the effects for the level of cost reflected by the estimated coefficients specified in the kernel of the cost frontier. We find that banks eventually supervised by the SSM exhibited lower levels of cost relative to the time when they were not part of the SSM list. The effect for those banks on the 2013 list is in turn not significant. The significantly positive interaction term in subcolumn CF/PF in (4), the kernel, indicates that banks switching between national and supranational supervision had operating costs, *ceteris paribus*, 28 basis points lower compared to those banks that stayed in their supervisory regime. Together, these results suggest that clarity about which authority supervises a bank reduces cost inefficiencies, that is, the ability to attain optimal cost, but is associated with banks generally exhibiting slightly higher levels of operating cost.

With regards to the effects of SSM versus non-SSM supervision on profit efficiency, the bottom panel B of Table 11.7 shows that the statistical significance is much weaker once we include an interaction term. In the most saturated specification in column (4), only the effects on the kernel of the optimal profit frontier are significantly different from zero. Contrary to the baseline effects reported above, banks that are eventually supervised according to the regime communicated in 2015 incur lower levels of profit, whereas banks that were already on the 2013 list exhibit a slightly positive effect on their level of profits before tax. Relative to the group of switching banks, profit levels of non-switchers are also significantly higher. Therefore, in particular, banks that entered the supranational supervisory regime only in the course of events after 2013 appear to generate lower levels of profits.

Table 11.8 Cross tabulation, SSEs vs SSEs 2013

Panel A: Cost frontier			
	SSE_2013 = 0	SSE_2013 = 1	Total
SSE = 0			
Average CE	1.225	1.454	1.225
SD CE	1.225	0.598	1.225
# Observations	26,477	40	26,517
# Banks	3,535	7	3,542
SSE = 1			
Average CE	1.284	1.413	1.404
SD CE	0.327	0.545	0.534
# Observations	53	731	784
# Banks	6	100	106
Total			
Average CE	1.225	1.415	1.230
SD CE	1.224	0.547	1.211
# Observations	26,530	771	27,301
# Banks	3,541	107	3,648
Panel B: Profit frontier			
	SSE_2013 = 0	SSE_2013 = 1	Total
SSE = 0			
Average PE	0.684	0.586	0.684
SD PE	0.204	0.267	0.204
# Observations	25,434	40	25,474
# Banks	3,494	7	3,501
SSE = 1			
Average PE	0.479	0.477	0.478
SD PE	0.189	0.266	0.261
# Observations	53	701	754
# Banks	6	99	105
Total			
Average PE	0.684	0.483	0.678
SD PE	0.204	0.267	0.208
# Observations	25,487	741	26,228
# Banks	3,500	106	3,606

This table reports tabulations of cost inefficiency (CE) and profit efficiency (PE) calculated from the cost frontier estimations and profit frontier estimations in, respectively, columns 4 of Tables 11.5 and 11.6. Cost inefficiency and profit efficiency are calculated as technical efficiency

To compare the levels of cost and profit efficiency more directly, we show in Table 11.8 the according mean levels of efficiency across groups of banks.

Consistent with Fig. 11.1, Panel A illustrates that the largest group of banks, which continued to be supervised by NCAs throughout, exhibit the lowest cost inefficiency on the order of 22 %. The 100 banks that were consistently allocated to the supervisory regime at the supranational level, in turn, exhibit mean cost inefficiency of around 41 %, although these differences are not

statistically significantly different from zero. Potentially more interesting are the seven banks that were not included in the communication of 2013, but listed in ECB (2015). These banks were on average also more cost inefficient (45 %) compared to nationally supervised banks. Likewise, those banks that used to be included in the ECB (2013) communication but were excluded from the contemporary list of systemically relevant institutions exhibit a lower mean cost inefficiency compared to currently SSM-supervised banks on the order of 28 %, which is in turn slightly larger than the continuously non-SSM-supervised banks.

Again, it is important to note that we cannot infer from our analysis whether larger foregone cost savings are the consequence of SSM supervision, for example due to a higher regulatory burden for these banks, or whether a potentially more objective supranational supervision that is facing fewer entrenchment challenges compared to NCAs causes these differences, corroborating once more the need for future research into the causal relationship between supervisory setups and bank efficiency.

The bottom panel B of Table 11.8 sketches a similar picture for the comparison of mean profit efficiency scores. Those 3,494 banks consistently considered to be supervised by NCAs are on average more profit efficient (68 %) compared to any other group. The 99 banks indicated in both ECB communications to be supervised by the SSM exhibit the lowest profit efficiency (48 %). The seven banks coming under SSM supervision are, contrary to the cost efficiency case, better able on average to realize optimal profits, exhibiting a mean profit efficiency on the order of 59 % compared to an average of 48 % for those banks that were excluded from the list since 2013. Importantly, these differences are once more not statistically significant and therefore provide only a qualitative indication.

Conclusion

The (regulatory) need to increase capital buffers in the aftermath of the financial crisis exerted considerable pressure on bank profitability in many European countries. Whereas the resilience of the average bank in the system might have increased due to increasing mean capitalization, simple descriptive statistics also show that credit risk was not subdued in all countries after the financial and/or the sovereign debt crisis similarly. One reason might be related to the trade-off faced by regulators between financial stability and bank efficiency. Imposing rules and regulation that enhance the resilience of the entire system, for instance higher capital requirements, might burden the

relative ability of European banks to efficiently transform savings into credit and other financial services.

This chapter provides a selective review of methodological advances in the parametric efficiency measurement literature to obtain firm-specific measures of efficiency, taking into account in particular environmental factors and unobserved heterogeneity that might be confounded with inefficient behaviour. The subsequent review of applications to European banking provides little evidence of convergence among European banking systems once heterogeneity across national banking systems is accounted for more explicitly. We also show that so far little empirical work exists on the effects of recent micro-prudential regulation at the European level, which might have fostered exactly such lacking integration.

Against the backdrop of the commencement of the European Banking Union in general and the inception of supranational banking supervision by the Single Supervisory Mechanism (SSM) in particular, we therefore estimate the cost and profit efficiency of European banks conditional on an indicator under which prudential regime they fall: SSM or national competent authority (NCA). Our results indicate that banks supervised by the SSM according to the list of systemically relevant financial institutions published in ECB (2015) exhibit both lower cost and profit efficiency compared to banks supervised by NCAs.

Besides the around 100 banks continuously indicated to fall under SSM supervision since the first announcement of banks included in the comprehensive assessment, we identify around six to seven banks that either were excluded from SSM supervision and relegated back to NCAs or came under SSM supervision according to ECB (2015) without having been listed in the notes preceding the comprehensive assessment, which prepared the grounds for the handover of supervisory responsibility starting in 2013. These switches of supervisory regime are informative because they might indicate the outcome of a political power struggle over where to locate the primary de facto authority to audit the financial soundness of financial institutions despite the *de jure* responsibility of the SSM. We find that banks that are supervised by the SSM according to the ECB (2013) list, but are excluded from the ECB (2015) list, exhibit higher cost inefficiency compared to both banks that switched to SSM supervision and those that have stayed on the SSM list. Banks switching into the SSM regime exhibit lower profit efficiency compared to those switching back into NCA supervision, whereas the levels of profit efficiency are generally lower for banks that were announced to fall under SSM supervision throughout.

The empirical outcomes might be due to two competing explanations. Banks under SSM supervision might face a significantly larger regulatory burden, which reduces their ability to attain minimal cost and hampers the realization of optimal profits. This explanation would be in line with frequent concerns voiced by the financial industry. Alternatively, a more homogeneous supervisory approach by supranational teams that are possibly less sensitive and therefore less able to transparently address any possible shortcomings at former national champions could be the reason why the larger, systemically relevant banks exhibit efficiency losses. The scope of this chapter does not yet permit any inference on the causal nature of the relationship between the regulatory architecture and efficiency, which warrants important future research.

Notes

1. We suppress bank and time subscripts throughout to conserve on space.
2. We excluded banks that incurred losses because the logarithm of negative numbers is not defined.
3. The sampled countries are: Austria, Belgium, Cyprus, Denmark, Estonia, Finland, France, Germany, Greece, Italy, Ireland, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Portugal, Slovakia, Slovenia, Spain.
4. According to article 39 and related articles of the SSM Framework Regulation ECB (2014), a supervised entity can be classified as SSE if the following hold: firstly, its total assets exceed more than €30 billion or 20 % of national GDP; secondly, the bank is one of the three most significant credit institutions in a member state; thirdly, the bank received funds from the European Stability Mechanism; and fourthly, total assets exceed €5 billion and cross-border assets relative to liabilities in more than one other participating member state relative to the ratio of total assets to liabilities is larger than 20 %.
5. Different supervisory cultures among European NCA are documented by Carretta et al. (2015), who analyse the speeches of the heads of supervisory authorities in 15 EU countries between 1999 and 2011 and relate these scores to observed risk-taking behaviour by banks. They report, for example, that a more directional approach to supervision with narrow interpretation and strict enforcement of rules induced additional risk-taking by banks.
6. Note that the criteria used to define SSEs in ECB (2013) are very similar to the final criteria in ECB (2014) on the basis of which the list of SSEs in 2015 was constructed (ECB 2015).
7. The banks initially included in the comprehensive assessment, but excluded from the list in 2015, are: Banco de Caja Espana de Inversiones Salamanca y Soria SA (ES), Wüstenrot & Württembergische (DE), KfW Ipex Bank (DE), Credito Valtellinese Soc Coop (IT), Clearstream Banking SA (LU), Credito Emiliano SpA-

CREDEM (IT), SID—Slovene Export and Development Bank (SV). The banks not inlcuded in the 2013 list, but supervised by the SSM according to ECB (2015), are: Sberbank Europe AG (AT), VTB Bank AG (AT), UniCredit Banka Slovenija (SV), AB DNB Bankas (LT), AB SEB Bankas (LT), and Swedbank AB (LT).

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