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Allocative and technical efficiency of social banks vis a vis conventional banks

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Abstract

This paper investigates the technical and allocative efficiency of social banks vis-a-vis conventional banks. We propose a simple modeling approach of stochastic frontier analysis that identifies both allocative and technical efficiency. The estimation is rather cumbersome, and we opt for a simple likelihood function and Maximum Likelihood estimator. We, then, employ a bank-level data set for social banks that provide credit to social firms and conventional banks. Stochastic frontier analysis results are of interest as they show that social banks are underperforming in terms of both technical and allocative inefficiency.

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1.Introduction

The main, common banking business model is oriented toward individualistic preferences rather than collectivism. Individualistic preferences focus on the self, while collectivist orientations emphasise social objectives. To this date, there is limited research on social banks vs conventional, individualistic banks (see Barigozzi and Tedeschi 2015; and Cornee et al. 2020). Barigozzi and Tedeschi (2015) show that ethical, social banks would finance ethical projects. The Authors also show that ethical investors also enjoy a 'social responsibility premium' when borrowing money from social, ethical banks and report that the market for ethical projects in the credit market is fully segmented if the premium for loans of social banks is close to the premium of conventional banks. Cornee et al. (2020) demonstrate that social banks that provide banking services to social causes and credit to other social-minded firms would be less profitable than conventional banks.

The business model of social banks has been a topic of debate among scholars for some years (see for a review Cornee et al. 2020). There is skepticism because social banks do not meet conventional banking standards. Conventional banks are required to make a profit, have capital reserves, and provide good customer service. However, social banks do not always meet these standards. For example, some social banks have been known to make little or no profit and their capital reserves are usually quite low. Furthermore, social banks tend to provide poor customer service. For example, they often take too long to answer customer queries and they charge high fees. They have found that these banks do not have a sustainable business model. For example, some social banks rely on government subsidies to remain afloat. This means that the banks can run into financial problems if the government cuts back on its assistance. Furthermore, social banks are often not transparent about their operations. This means that customers do not know how the banks make money and how they plan to finance their operations in the long term.

Following the above literature, this paper defines social banking as Cornee et al. (2020) arguing that social banks provide credit to other social firms. Our focus is to study whether there are differences between conventional and social banks in terms of their underlying technical and allocative inefficiency using a cost function. It is important to measure technical inefficiency as it would reveal inefficient use of bank inputs that would result in higher bank costs and lower bank profitability and output. In addition, a bank, given bank inputs, could opt for a sub-optimal allocation of bank inputs that also results in bank output losses. We measure this sub-optimal allocation of bank inputs with the bank allocative inefficiency. To this date, we are not aware of any study that offers such evidence though the conventional and social banks follow different bank models, with social banks being predominantly non-profitable financial organisations.

In what follows, Section 2 provides our modelling while Section 3 discusses the sample and reports the main findings. The last Section offers some conclusions.

2. A model of technical and allocative inefficiency

The starting point of our model is Kumbhakar (1997) who follows from Farrell, (1957), Schmidt and Lovell (1979). In some detail, we define a bank cost function as:

$$\ln C_i^a = \ln C^*(w_i^*, q_i) + \ln G(w_i, q_i, \xi_i) + u_i \quad (1)$$

where $G(w_i, q_i, \xi_i)$ follows from $G(.) = \sum_j S_{j,i}^* e^{-\xi_{j,i}}$ with $S_{j,i}^* = \partial \ln C^*(.)/\partial \ln w_{j,i}^*$.

The u_i in Equation (1) represents the technical inefficiency and $u_i \geq 0$, while the allocative inefficiency is noted by ξ_j. Moreover, the bank production function could be represented as $q_i = f(x_i e^{-u_i})$ where q_i is the bank output and x_i is a vector of J bank inputs for bank i (i = 1, …, n), and $u_i \geq 0$ measures bank input-oriented technical inefficiency (see Farrell, 1957). Technical inefficiency measures the percentage that a bank over-uses bank inputs to produce a given level of bank output. Therefore, the higher the u_i the higher the bank technical inefficiency, implying that technical inefficient banks have higher costs and produce less bank outputs due to inefficient use of bank inputs. In addition, a bank could opt for a sub-optimal allocation of the various bank inputs. We measure this with the allocative inefficiency ξ_j in Equation (1). Allocative inefficiency is of some importance for social banks as they could lean towards sub-optimal proportions of bank inputs to comply with their social objectives.

To simplify, we model of the cost function in (1) we formulate

$$\ln C_i^a = \ln C^0(w_i, q_i) + \ln C^{AL}(w_i, q_i, \xi_i) + u_i \quad (2)$$

where $C^0(w_i, q_i)$ is the cost frontier, that can be estimated from (1) as

$\ln C^0(.) = \ln C^a(. \mid \xi_{j,i} = 0 \, \forall \, j, u_i = 0) = \ln C^*(.) \mid \xi_{j,i=0}$ (since $\ln G(.) \mid \xi_{j,i=0} = 0$)

while the allocative inefficiency is estimated as

$\ln C^{AL}(w_i, q_i, \xi_i) = \ln C^a \mid_{u_i=0} - \ln C^0(.) = \ln C^*(w_i^*, q_i) + \ln G(w_i, q_i, \xi_i) - \ln C^0(.)$.

In the empirical application, we fit a translog functional form as:

$$\ln C^*(w_i^*, q_i) = \alpha_0 + \sum_j \alpha_j \ln w_{j,i}^* + \gamma_q \ln q_i + \tfrac{1}{2}\gamma_{qq}\left(\ln q_i\right)^2 + \tfrac{1}{2}\sum_j \sum_k \beta_{jk} \ln w_{j,i}^* \ln w_{k,i}^* + \sum_j \gamma_{jq} \ln w_{j,i}^* \ln q_i \quad (3)$$

with the cost shares of inputs:

$$\ln(C_i^a / w_{1,i}) = \ln C_i^0(\tilde{w}_i, q_i) + \ln C_i^{AL}(\tilde{w}_i, q_i, \xi_i) + u_i, \quad (4)$$

$$S_{j,i}^a = S_{j,i}^0(\tilde{w}_i, q_i) + \eta_{j,i}(\tilde{w}_i, q_i, \xi_i), \; i = 1, \dots, n; j = 2, \dots, J \quad (5)$$

where $\tilde{w}_i = (w_{2,i}/w_{1,i}, \dots, w_{J,i}/w_{1,i})$, $S_{j,i}^a = w_{j,i} x_{j,i} / C_i^a$ the cost share of input j.

$C_i^0(\tilde{w}_i, q_i)$ is normalized by $w_{1,i}$ and $S_{j,i}^0 = \partial \ln C_i^0(.)/\partial \ln w_{j,i}$.

Note also that the $\ln C_i^0(\tilde{w}_i, q_i)$ is

$$\ln C_i^0(.) = \alpha_0 + \sum_{j=2}^{J} \alpha_j \ln \tilde{w}_{j,i} + \gamma_q \ln q_i + \tfrac{1}{2}\gamma_{qq}\left(\ln q_i\right)^2 + \tfrac{1}{2}\sum_{j=2}^{J}\sum_{k=2}^{J} \beta_{jk} \ln \tilde{w}_{j,i} \ln \tilde{w}_{k,i} + \sum_{j=2}^{J} \gamma_{jq} \ln \tilde{w}_{j,i} \ln q_i, \quad (6)$$

$$S_{j,i}^0 = \alpha_j + \sum_{k=2}^{J} \beta_{jk} \ln \tilde{w}_{k,i} + \gamma_{jq} \ln q_i, \quad j = 2,...,J, \quad (7)$$

and

$$\ln C_i^{AL} = \ln G_i + \sum_{j=2}^{J} \alpha_j \xi_{j,i} + \sum_{j=2}^{J}\sum_{k=2}^{J} \beta_{jk} \xi_{j,i} \ln \tilde{w}_{k,i} + \tfrac{1}{2}\sum_{j=2}^{J}\sum_{k=2}^{J} \beta_{jk} \xi_{j,i} \xi_{k,i} + \sum_{j=2}^{J} \gamma_{jq} \xi_{j,i} \ln q_i, \quad (8)$$

$$\eta_{j,i} = \frac{S_{j,i}^0 \left\{1 - G_i \exp(\xi_{j,i})\right\} + a_{j,i}}{G_i \exp(\xi_{j,i})}, \quad j = 2,...,J \quad (9)$$

where $G_i = \sum_{j=2}^{J} (S_{j,i}^0 + a_{j,i}) \exp(-\xi_{j,i})$, $a_{j,i} = \sum_{k=2}^{J} \beta_{jk} \xi_{k,i}$.

The above cost function is helpful for our analysis because it provides a decomposition of technical inefficiency, u_i, and allocative inefficiency, $\ln C_i^{AL}$.

To facilitate the estimation which is rather difficult we employ the likelihood function as in Mamatzakis et al. (2015) that takes the form:

$$L(\beta, \sigma_v, \sigma_u, \Omega; y, X) \propto$$

$$\sigma^{-n} \prod_{i=1}^{n} \Phi(-\tfrac{\lambda}{\sigma}[\zeta_i - \ln C^{AL}(\xi_i, \beta]) \cdot \prod_{i=1}^{n} |\det D\xi_i(\eta_i, \beta)| \times$$

$$\det(\Omega)^{-n/2} \exp\left\{-\tfrac{1}{2\sigma^2}\sum_{i=1}^{n}[\zeta_i - \ln C^{AL}(\xi_i, \beta)]^2 - \tfrac{1}{2}\sum_{i=1}^{n} e_i(\eta_i, \beta)' \Omega^{-1} e_i(\eta_i, \beta)\right\}, \quad (10)$$

where $e_i(\eta_i, \beta) = \xi_i(\eta_i, \beta) - \bar{\xi}(\eta_i, \beta)$, and $\bar{\xi}(\eta_i, \beta) = n^{-1}\sum_{i=1}^{n} \xi_i(\eta_i, \beta)$.

So that the Maximum Likelihood estimator becomes: $\hat{\Omega}(\beta) = n^{-1}\sum_{i=1}^{n} e_i(\eta_i, \beta) e_i(\eta_i, \beta)'$.

Note that the estimation is rather cumbersome, and full details are provided in Mamatzakis et al. (2015). To maximize the log-likelihood functions in (10) we opt for the Nelder-Mead simplex maximization technique that does not require numerical derivatives. We compute standard errors for the parameters using the Berndt–Hall–Hall–Hausman algorithm that follows on first-order derivatives of the log-density with respect to the parameters.

3. Data description and Empirical Findings

For the estimation of bank cost, we employ the intermediation approach for the definition of bank inputs and outputs, proposed by Sealey and Lindley (1977), which assumes that the bank collects funds, using labor and physical capital, to transform them into loans and other earning assets. We specify three inputs, labor, physical capital, and financial capital, and two outputs, loans, and other earning assets (government securities, bonds, equity investments, CDs, T-bills, equity investment etc.). For the estimation of cost and alternative revenue efficiency, input prices are required. The price of financial capital total interest expenses divided by total interest-bearing borrowed funds, while the price of labor is defined as the ratio of personnel expenses to total assets. The price of physical capital is the ratio of other administrative expenses to fixed assets. Following Färe et al. (2004) who argue that using bank equity as a quasi-fixed input in the analysis of bank profit efficiency is sufficient to account for both the risk-based capital requirements and the risk-return trade-off that bank owners face, we include equity as a fixed netput.

We employ data from the Bankscope database provided by Bureau van Dijk. The period covered by the sample extends from 2008 to 2018. We include banks located in the group of 20 countries classified as old EU as in Cornee et al. (2019) (i.e., EU-15 plus Cyprus, Iceland, Malta, Norway, and Switzerland). We exclude real-estate banks, public banks, and the central institutions of cooperative groups. We define SBs as Cornee et al. (2019) to include banks that are members of the European Federation of Ethical and Alternative Banks (FEBEA) and the Global Alliance for Banking on Values (GABV). This implies that we include 21 SBs. In addition, as in Cornee et al. (2019) we follow geographic and statutory filters so that we select 25 additional SBs (see Table A1 in Cornee et al. 2019 for more details on the sample of European SBs).

3.1. Results of the Translog Cost Function

In this section we report the translog cost function estimations for both SBs and conventional banks. Tables 1 and 2 reports the estimated results of the parameters obtained by panel estimation, based on the stochastic frontier analysis. Empirical results indicate that the estimated translog cost function is well behaved, as the signs on the coefficients are consistent with curvature conditions, while the magnitudes of the estimated elasticities are plausible and statistically significant for the most variables. The positive values of the cost inputs variables indicate that an increase in these cost inputs will lead to an increase in cost inefficiency.

Table 1: Parameter Estimates of the Tranlsog Cost Function: Social Banks

Variable	Parameter Estimates	Variable	Parameter Estimates
$\ln y_1$	0.56***	$\ln y_1 * \ln w_2$	0.077***
	(0.21)		(0.015)
$\ln w_1$	0.58*	$\ln y_1 * \ln w_3$	0.016
	(0.27)		(0.60)
$\ln w_2$	0.78***	$\ln w_1 * \ln w_2$	0.06*
	(0.28)		(0.03)
$\ln w_3$	0.92***	$\ln w_1 * \ln w_3$	0.30***
	(0.42)		(0.11)
$\ln y_1^2$	0.2	$\ln w_2 * \ln w_3$	0.01
	(0.47)		(0.02)
$\ln w_1^2$	0.25*	C	4.25**
	(0.13)		(1.83)
$\ln w_2^2$	0.10***	$F(14,282)$	148.74
	(0.03)	Prob>F	0.000
$L n w_3^2$	0.39***		
	(0.11)	Ad. R^2	0.58
$\ln y_1 * \ln w_1$	0.071		
	(0.53)	Observations	296

Notes: ***, ** and * represent significance at the 1%, 5% and 10% levels, respectively. Standard errors are in parentheses. All are Authors' calculations.

Table 2: Parameter Estimates of the Tranlsog Cost Function: Conventional Banks

Variable	Parameter Estimates	Variable	Parameter Estimates
lny_1	0.461***	lny_1*lnw_2	0.236***
	(0.011)		(0.078)
lnw_1	0.250*	lny_1*lnw_3	0.161***
	(0.019)		(0.059)
lnw_2	0.472***	lnw_1*lnw_2	0.05
	(0.118)		(0.23)
lnw_3	0.154***	lnw_1*lnw_3	0.28***
	(0.172)		(0.09)
lny_1^2	0.15	lnw_2*lnw_3	0.001
	(0.044)		(0.322)
lnw_1^2	0.01*	C	1.98***
	(0.43)		(0.673)
lnw_2^2	0.231	F(14,1130)	129.33
	(0.203)	Prob>F	0.000
Lnw_3^2	0.39***		
	(0.11)	Ad. R^2	0.338
lny_1*lnw_1	0.071		
	(0.53)	Observations	1144

Notes: ***, ** and * represent significance at the 1%, 5% and 10% levels, respectively. Standard errors are in parentheses. All are Authors' calculations.

Having derived the translog cost function parameter estimates Table 3 presents the average technical and allocative efficiency scores for SBs over the period 2008-2018. Our results reveal that estimates the average cost inefficiency of SBs is in the range of 0.23 to 0.60, which in comparison with conventional banks is rather higher (see Mamatzakis et al. 2015). The average allocative efficiency is estimated at 0.177, ranging from 0.047 to 0.53. On the other hand, conventional banks have lower allocative and technical inefficiency and are in line with most of the literature that estimates the average cost efficiency in the range of 0.16 to 0.32 that is comparable with previous results in the literature (see Mamatzakis, et al. 2015). Average allocative efficiency is estimated at 0.141, ranging from 0.038 to 0.42. We also report in Table 3 (see last column) p-values that statistically test whether technical and allocative inefficiency between social and conventional banks are equal. All the reported p-values reject the null hypothesis and thereby inefficiency scores between social and conventional banks differ at 1% statistical significance level.

Over time, average technical inefficiency remains broadly stable up to 2013 for both banks and decreases thereafter for two years. Technical inefficiency despite the improvement in 2014 and 2015 it increases thereafter. Allocative efficiency exhibits a similar trend, showing a clear downward trend after 2009 and the financial crisis. This trend continues up to 2013, but then increases in 2015 and 2016.

Clearly, SBs have a higher threshold of inefficiencies for both technical and allocative inefficiency. This implies that SBs by promoting social causes and providing credit to ethical, social firms are on average around 50% more technically inefficient than their competing conventional banks. From a frontier point of view, this underperformance of SBs would increase their operational costs both in terms of additional bank inputs but also in terms of the allocation of existing bank inputs. For example, for each loan they provide, SBs need more bank inputs than conventional banks.

Table 3: Average Technical and Allocative Cost Inefficiency Scores by Year

	Conventional Banks	Social Banks	p-value
Average Technical Cost Inefficiency			
2008	0.2525	0.3535	0.000
2009	0.235	0.329	0.000
2010	0.1875	0.2625	0.000
2011	0.215	0.301	0.000
2012	0.2375	0.3325	0.000
2013	0.265	0.371	0.000
2014	0.165	0.231	0.000
2015	0.1925	0.2695	0.000
2016	0.3225	0.4515	0.000
2017	0.2775	0.3885	0.000
2018	0.3114	0.6055	0.000
Average Technical Inef.	0.2419	0.3541	0.000
Average Allocative Cost Inefficiency Scores			
	Conventional Banks	**Social Banks**	**p-value**
2008	0.156	0.195	0.000
2009	0.136	0.17	0.000
2010	0.076	0.095	0.000
2011	0.066	0.0825	0.000
2012	0.048	0.06	0.000
2013	0.102	0.1275	0.000
2014	0.198	0.2475	0.000
2015	0.204	0.255	0.000
2016	0.428	0.535	0.000
2017	0.108	0.135	0.000
2018	0.038	0.0475	0.000
Average Allocative Inef.	0.141	0.177	0.000

Note: Authors' estimations.

Previous research by Mykhayliv and Zauner (2018) (see also Cornée, et al. 2020) on efficiency measures based on accounting ratios, like Cost to Income Ratio and Overheads to Total Assets, show that social banks are less efficient compared to conventional banks. The present findings confirm previous research as we show that social banks prioritise social objectives rather than optimising in terms of lower cost and higher profit. Therefore, social banks use more bank inputs and opt for a sub-optimal allocation of bank inputs and thereby are less technical and allocative efficient vis a vis conventional bank.

Social banks are particularly technical inefficient compared to conventional banks because they would use more bank inputs to enhance loans' screening, primarily targeting social, ethical, and sustainable investments. Cornée, et al. (2020) discusses that persuading social objectives comes at a higher cost and thereby lower bank output. Our findings confirm that social banks are technical inefficient compared to conventional banks. We also find that social banks have higher allocative inefficiency compared to conventional banks as they allocate bank inputs suboptimally. However, the difference of allocative inefficiency between social and conventional banks are lower than their corresponding technical inefficiency. This is not surprising given that both types of banks require certain proportions of bank inputs (i.e., both banks are labour intensive) in their underlying production process. Thus, social banks have little leeway to diverge from conventional banks in their allocation of bank inputs.

6. Conclusion

This paper employs a flexible translog cost function bank model to estimate bank technical and allocative inefficiency for social and conventional banks. Results are of interest as they show that social banks are underperforming in terms of both technical and allocative inefficiency. The results appear to provide support to the theoretical model of Barigozzi and Tedeschi (2015) that predict that social banks would be less efficient and less profitable than conventional banks.

The above findings should be interpreted with some caution given that social banks are aiming to finance social projects and future research should consider the social return of social bank outputs that could provide positive common externalities to the society above any market-based return or premiums.

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