Cost Efficiency Analysis of Swedish Financial Enterprises: An Empirical Investigation

In this paper, ours research question that could analyze how efficiency in Swedish financial enterprises has changed since the banking crisis in 1993. We estimate the time-invariant and time-variant efficiencies of Swedish financial enterprises during from 1996 to 2011 with four different estimators. These estimators are the Pooled Model (Aigner et al. (1977)), the fixed effects model (Schmidt and Sickles (1984)), the random effects model (Battese and Coelli (1995)) and the true fixed effects model (Green (2005)) efficiency estimators. We predict cost function by employing panel stochastic frontier approach. These allow us to construct cost efficiency. In this research, cost efficiency measure estimated for the panel data consisting of six different financial enterprises from 1996 to 2011.

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1. Introduction

Before 1980, financial markets were highly regulated in Sweden. As government budget deficits and the public had been grown the obligation on banks (through liquidity ratios) to buy government and housing bonds become increasingly. A distortion in effect a growing share of deposits was transferred to the Government in exchange for low-interest-bearing long-term bonds. As a result, shared of regular bank loans to businesses and households declined. The much credit flows outside the regulated market challenged the traditional role of banks. In response, banks tried to bypass the interest rate regulations by showing their own finance companies-which formed an important part of the gray credit market. The term gray economy, however, refers to workers being paid under-the-table, without paying income taxes or contributing to such public services as Social Security and Medicare. It is sometimes referred to as the underground economy or "hidden economy" in Sweden (Biljer; 1991).

As the regulations were increasingly considered to be largely ineffective the authorities started a financial liberalization process in the late 1970s and proceeded gradually during the 1980s. Credit and bond markets were deregulated first followed by the removal of regulation on international transactions. The system of liquidity ratios for banks was abandoned in 1983 and the ceilings on commercial bank lending were removed in 1985. At the same time, restrictions on lending rates were lifted and by 1989 all remaining foreign exchange restrictions had been removed (Dress and Pazarbasioglu; 1998).

Summing-up, the 1983–1985 deregulation contributed to rapid credit expansion. The *immediate impact* on consumption and investment appears to have been limited. Expressed differently, the rationing effects of the abolished regulations do not seem to have been quantitatively important for the real decisions of households and corporations. On the other hand, no doubt financial flows were affected in an important way. Credits were increasingly channelled by financial institutions, such as banks and mortgage institutions, rather than direct between firms (for example trade credits) and between households (for example seller financed housing loans). Loans were also increasingly used for high-leverage financial investments. These effects on financial flows may, by their impact on asset prices, have had important effects on the banking crisis (figure.1) (Englund; (1999)).

In this paper, ours research question is that could analyze how efficiency in Swedish financial enterprises has changed since the banking crisis in 1993. We estimate the time-invariant and time-variant efficiencies of Swedish financial enterprises during from 1996 to 2011 with four different estimators. These estimators are the Pooled Model (Aigner et al. (1977)), the fixed effects model (Schmidt and Sickles (1984)), the random effects model (Battese and Coelli (1995)) and the true fixed effects model (Green (2005)) efficiency estimators. We predict cost function by employing panel stochastic frontier approach. These allow us to build cost efficiency.

In this research, cost measure was estimated for the panel data consisting of six different financial enterprises from 1996 to 2011. These financial enterprises have banks (including commercial banks, branches of foreign banks in Sweden, saving banks), credit market companies, housing credit institutions, other mortgage institutions, other credit market companies, securities brokerage companies. Database of each enterprises have been aggregated by the Statistics Sweden. In the next section, we conducted a literature review of stochastic frontier approach and related banking. Section 3 descriptive the methodology. Section 4 provides data and empirical results of Swedish banking case and finally Section 5 includes conclusions.

2. Literature Review

The literature that did direct influence to develop Stochastic Frontier Approach (SFA) was the theoretical literature on productive efficiency which began in the 1950s with the work of Koopmans (1951), Debreu (1951), and Shephard (1953). Koopmans provided a definition of technical efficiency: A producer is technically efficient if and only if it is impossible to produce more of any output without producing less of some other output or using more of some input. Debreu and Shephard introduced distance functions as a way of modelling multiple-output technology but more importantly from our perspective as a way of measuring the radial distance of a producer from a frontier in either an output-expanding direction (Debreu) or an input-conserving direction (Shephard). The association of distance functions with technical efficiency measures was pivotal in to develop the efficiency measurement literature.

Farell (1957) was the first to measure productive efficiency empirically (Drawing inspiration from Koopmans and Debreu but clearly not from Shephard). Farell (1957) showed how to define cost efficiency is defined as a measure of how far a bank's cost is from the best practice bank's cost if both were to produce the same output under the same environmental conditions and how to decompose cost efficiency into its technical and allocative components. He also provided an empirical application for U.S. agriculture although he did not use econometric methods.

Aigner et al. (ALS hereafter) (1977) proposed a model in which errors were allowed to be both positive and negative but in which positive and negative errors could be assigned different weights. Ordinary least squares emerge as a special case of equal weights and a deterministic frontier model emerges as another special case. They considered estimation for the case in which the weights are known and for the more difficult case in which the weights are unknown and are to be estimated with the other parameters in the model. They did not estimate the model and to our knowledge no one else has estimated the model. Nonetheless, there is a short step from Aigner, Amemiya and Poirier model with larger weights attached to negative errors to a comprised error stochastic production frontier model. The step took a year. SFA originated with two papers published nearly simultaneously by two teams on two continents. Meeusen and van den Broeck (MB hereafter) (1977) appeared in June and Aigner et al. (1977) appeared a month later. The ALS paper was in fact a merged version of a pair of remarkably similar papers one by Aigner and the other by Lovell and Schmidt. The ALS and

MB papers are themselves very similar. Both papers were three years in the making and both appeared shortly before a third SFA paper by Battese and Corra (1977) the senior author of which had been a referee of the ALS paper. These three original SFA models shared the comprised error structure mentioned previously and each was developed in a production frontier context.

Schmidt and Sickles (1984) were applying fixed effects and random effects models to estimate the efficiencies of the firms. In this study, the efficiencies of the firms were assumed to be time-invariant which might not be a proper assumption for long panel data. So, they had considered estimation of a stochastic frontier production model, given panel data. They had provided various estimators, depending on whether one was willing to assume that technical inefficiency (the individual effect, in panel-data jargon) was uncorrelated with the regressions and on whether one was willing make specific distributional assumptions for the errors. They had showed how to test these assumptions.

Battese and Coelli (1995) proposed a model for technical inefficiency effects in a stochastic frontier production function for panel data. Provided the inefficiency effects are stochastic the model lets to estimate both technical change in the stochastic frontier and time-varying technical inefficiencies.

Green (2005) proposed extensions that circumvent two shortcomings of fixed and random effects estimator approaches. The conventional panel data estimators assume that technical or cost inefficiency is time invariant. Second, the fixed and random effects estimators force any time invariant cross unit heterogeneity into the same term that is being used to capture the inefficiency. Inefficiency measures in these models may be picking up heterogeneity in addition to or even instead of inefficiency.

Berger and Humphrey (1997) surveys 130 studies that apply frontier efficiency analysis to financial institutions in 21 countries. The aims of paper were to summarize and critically review empirical estimates of financial institution efficiency and to try to arrive at a consensus view. They find the various efficiency methods do not necessarily yield consistent results and suggest some ways that these methods might be improved to bring about findings that are more consistent, accurate, and useful. Then, the implications of efficiency results for financial institutions in the areas of government policy, research and managerial performance. Almost all the studies which estimate efficiency and then regress it on sets of explanatory variables have been unable to explain more than just a small portion of its total variation. While some differences have been found little published information exists about those influences that are under direct management control such as the choice of funding sources wholesale versus retail orientation, etc. Theirs paper report that cost and productive efficiency average 84 percent when parametric estimation techniques are used and 72 percent when nonparametric techniques are used.

In Swedish case, the purpose of Battese et al. (2000)'s paper was to analyze the impact of the deregulation of Swedish banking industry in the mid-1980's and the consequent banking crisis on productive efficiency and productivity growth in the industry. An unbalanced panel of Swedish banks was studied over the period from 1984 to 1995. A total of 1275 observations were analyzed for 156 banks that were observed for two and twelve years. The inefficiency effects in the labour-use frontier were modelled in terms of the number of branches, total inventories and the type of bank and year of observation. The technical inefficiencies of labour use of Swedish banks were found to be significant with mean inefficiencies a year estimated to be between about 8 and 15 percent over the years of study.

The Heshmati (2001)'s paper is concerned with to estimate labour demand. Focus is on to estimate productivity and efficiency of labour in Swedish savings banks. The labour productivity and efficiency is defined in terms of a shift in the labour demand over time and the bank's distance from the labour demand frontier respectively. Empirical results showed that the average labour efficiency is about 96%.

This paper of Gjirja (2004) analyses the impact of deregulation and the subsequent banking crisis on the efficiency of labour in Swedish banking sector. A translog stochastic frontier model is adopted in order to estimate the labour input requirement function and to assess bank technical efficiency. Furthermore, the parameters of the stochastic frontier function are simultaneously estimated with the parameters of a model for the technical inefficiency effects. The analysis suggests that there is capacity for substantial labour efficiency improvements in Swedish banking industry. It is also shown that deregulation positively affected productivity growth. However, no such positive impact was found on labour use efficiency. In addition, the banking crisis affected the efficiency of labour utilization in Swedish banks in a negative way, considering the involved outputs and inputs ("effects of deregulation and banking crisis on the labour use efficiency in Swedish banking industry"). The fast pace of changes in the economic environment and the increasing globalization of financial services dictate an increase in the awareness of financial institutions about their economic performance.

Paper of Papadopoulos (2008) explores the issue of efficiency in Scandinavian banking by applying the Fourier functional form and the stochastic cost frontier approach in calculating inefficiencies for a large sample of Finnish, Swedish, Danish and Norwegian banks from 1997 to 2003. The findings suggest the largest sized banks are the least efficient banks and the smallest sized banks are the most efficient. The strongest economies of scale are displayed by Danish banks while the weakest economies of scale are reported by Finnish banks. The findings suggest that medium sized banks report the strongest economies of scale and the largest and smallest banks weaker economies of scale and therefore the notion that economies of scale increase with bank size cannot be confirmed. The impact of technical change in lessening bank costs (generally about 3% and 5, 4% an annual) be systematically increasing with bank size. The largest banks are reaping the greater benefits from technical change. Overall, the results show the largest banks in their sample enjoy greater benefits from technical progress, although they do not have scale economy and efficiency advantages over smaller banks.

3. Methodology

One can get the cost efficiency of a bank by employing either nonparametric or parametric approaches. Nonparametric (non-stochastic) cost efficiency is calculated by employing linear mathematical programming techniques. On the other hand, parametric (stochastic) cost efficiency is derived from a cost function in which variable costs depend on the input prices, quantities of variable outputs, random error and inefficiency.

$C_b = C(\mathrm{y}_i, p_k, \varepsilon_b), b = 1, \ldots, n$ (1.1)

where C_b stands for financial enterprises total operational costs, y_i represents the vector of quantities of financial enterprises variable outputs, p_k is the vector of prices of financial enterprises variable inputs and ε_b is a composite error term, through which the cost function varies stochastically. The cost function provides an indirect representation of the possible technology because it is mainly a specification for the minimum cost of producing the output vector, y, given the cost drivers, such as price vector, p, in the input market, managerial inefficiency, some exogenous economics factors or pure luck.

The term ε_b can be partitioned into two parts as follows:

$\varepsilon_b = u_b + e_b$ (1.2)

where u_b refers to endogenous factors and e_b refers to exogenous factors that impact the cost of the bank production. Thus the term u_b denotes a rise in the cost of bank production because of the inefficiency factor that may result from the mistakes of management, such as non-optimal employment of the quantity or mix of inputs given their prices. On the other hand, e_b represents a temporary rise or fall in the bank's costs because of the random factor that ma system from a data or measurement error or unexpected or uncontrollable factors (such as weather luck, labour strikes, war, etc.) that cannot be changed b the management.

Firstly, we defined to Aigner all. (1977) define a firm's cost function as follows:

$lnC_b = f(\mathrm{y}_i, p_k) + \varepsilon_b$ where $\varepsilon_b = u_b + e_b$ (1.3) [the Pooled Model](PM hereafter)

where f is a functional form and $\varepsilon_b = u_b + e_b$ is the composite error term. Parametric and non-parametric efficiency techniques differ in how the disentangle the comprised error term,ε_b. Non- parametric techniques assume that there is no error and attribute any deviation from the best practice bank's cost to inefficiency. On the other hand, parametric techniques assume that the inefficiencies follow an asymmetric distribution, mostly the half-normal and random errors follow a symmetric distribution, the standard normal. In other words, random factors are assumed to be identically distributed as normal variants and the value of the error term in the cost function is equal to zero on the average. Thus, inefficiency scores are derived from a normal distribution $N(0, \sigma_u^2)$ but truncated below zero.The underlying reason for the truncated normal distribution assumption is that inefficiencies cannot be negatively sign (Isik and Hasan; 2002).

Secondly, Schmidt and Sickles (1984) approach, fit be ordinary (within-groups) OLS, followed by translation of the constants:

$$\ln C_b = f(y_i, p_k) + \varepsilon_b (1.4)$$

[the Fixed Effects Model](FM hereafter)

$$u_b = a_b - \min(a_b) (1.5)$$

In (1.5) equation, definition of a_b amounts to counting the real efficiency firm in the sample. The definition of $\min(a_b)$ amounts to counting the most efficient firm in the sample as average efficient scores.

Finally, the Battese and Coelli (1995) model specification may be expresses as:

$$lnC_b = f(y_i, p_k) + u_b + e_b \text{ (1.6) [the Random Effects Model](RM hereafter)}$$

the e_b are random variables which are assumed to be iid. $N(0, \sigma_e^2)$, and independent of the u_b which are non-negative random variables wich are assumed to account for technical inefficiency in cost function and are assumed to be independently distributed as truncations at zero of the $N(\mu_{it}, \sigma_u^2)$ distribution: where:

$$u_b = z_{bt}\delta \quad (1.7)$$

where z_{bt} is which may influence the efficiency of a firm and δ is parameters to be estimated.

Battese and Coelli (1995) once again use the parameterisation from Battese and Corra (1977), replacing σ_e^2 and σ_u^2 with $\sigma^2 = \sigma_e^2 + \sigma_u^2$ and $\gamma = \sigma_u^2/(\sigma_e^2 + \sigma_u^2)$. The log-likelihood function of this model is presented in the appendix in the Battese and Coelli (1995).

This model specification also encompasses a number of other model specifications as special cases. If we set T=1 and z_{bt} contains the value one and no other variables (i.e. only constant term), then the model reduces to the truncated normal specification in Stevenson (1980), where δ_0 (the only element in) will have the same interpretation as the μ parameter in Stevenson (1980). It should be noted, however, that the model defined by (1.6) and (1.7).

Green (2005) reformulated the stochastic frontier specifically to explore these aspects. It was called the stochastic frontier model in a 'true' fixed effects formulation. The estimated parameters ρ_i, b_j, c_m that are given the true values for the structural parameters in the model. A set of 'true' values for u_{bt} is generated for each firm and reused in every replication. These `inefficiencies` are maintained as part of the data for each firm for the replications. The firm specific values are produced using $u_{bt}^* = |U_{bt}^*|$ where U_{bt}^* a random draw from the normal distribution with mean zero is and standard deviation[1]. Thus, for each firm, the fixed data

[1]Doing the replications with a fresh set of values of u_{bt}^* generated in each iteration produced virtually the same results. Retaining the fixed set as done here facilitates the analysis of the results in terms of estimation of a set of invariant quantities (Green (2005)).

constant term a_i, the inefficiencies u^*_{bt} and the financial enterprises total operational costs data lnC^*_{bt} produced using

$LnC^*_{bt} = \rho_b + f(y_b, p_k) + u^*_{bt}$ [the TRUE Fix Effects Model](TRUE FM hereafter) (1.9)

By this device, the underlying data to which we will fit the fixed effects model actually are generated by an underlying mechanism that exactly satisfies the assumptions of the true fixed effects stochastic frontier model and in addition, is based on a realistic configuration of the right-hand side variables. Each replication, r, is then produced by generating a set of disturbances $e_{bt}(r), t = 1, \ldots, 16, b = 1, \ldots, 6,$ from the normal distribution with mean 0 and standard deviation. The data that enter each replication of the simulation are then $lnC_{bt}(r) = lnC^*_{bt} + e^*_{bt}$ (r). The estimation was replicated 100 times to produce the sampling distributions. We computed the sampling error in the computation of the inefficiency for each of the 96 observations in each replication, $du_{bt}(r) = estimated\ u_{bt}(r) - u^*_{bt}$. The value was not scaled, as these are already measured as percentages (changes in log cost); we have analyzed the raw deviations, $du_{bt}(r)$. The mean of these 96 deviations is computed for each of the 100 replications (Green (2005)).

We first need to specify a relationship (function) between bank production and bank cost in order to estimate the inefficiency u_b and random e_b factors of the composite error term ε_b. To that end, we specify banks as multi-product and multi-input firms and estimate the following translog cost function:

$$\ln C_b = \alpha_0 + \sum_i^5 \beta_i \ln y_i + \frac{1}{2}\sum_i^5 \beta_{ij} \ln y_i \ln y_j + \sum_k^4 \gamma_k \ln p_k + \frac{1}{2}\sum_l^4 \sum_m^4 \gamma_{lm} \ln p_l \ln p_m + \sum_i^5 \sum_k^4 \rho_{ik} \ln y_i \ln p_k + \varepsilon_b$$
$$(i \neq j, l \neq m, i \neq k)(1.8)$$

where, ln is natural logarithm, C_b is the b th bank's total (interest and non interest) costs; y_i is the i th output; p_k is k th input price and ε_b is the composite error term.

Technical Inefficiency Score (TIES hereafter) is measured by Table.1.

Table.1 Econometric specifications of the stochastic cost frontier

	State Specific Inefficiency u_b, u_{bt} and z_{bt}	Random statistical noise	TIES
PM model (Half-normal)	$u_{bt} \sim N^+(0, \sigma_u^2)$	$e_{bt} \sim N^+(0, \sigma_e^2)$	$E(u_{bt}/(u_{bt} + e_{bt})$
FM model (Half-normal)	$u_b \sim N^+(0, \sigma_u^2)$	$e_{bt} \sim N^+(0, \sigma_e^2)$	$E(u_b/(u_b + e_{bt})$
TRUE FM (Half-normal)	$u_{bt} \sim N^+(0, \sigma_u^2)$	$e_{bt} \sim N^+(0, \sigma_e^2)$	$E(u_{bt}/(u_{bt} + e_{bt})$
RM model (Truncated- normal)	$u_b = N^+(\mu_{bt}, \sigma_u^2)$, $u_b = \delta z_{bt}$, $z_{bt} \sim N^+(0, \sigma_z^2)$	$e_{bt} \sim N^+(0, \sigma_e^2)$	$E(z_{bt}/(z_{bt} + e_{bt})$

4. Data and Definition of Variables

4.1. Data and Description of Variables

In this context, this core chapter uses the distribution free approach to estimate levels of cost efficiency of individual financial enterprises in Sweden. We use the annually panel data of the all financial enterprise of Sweden for the period from 1996 to 2011. These financial enterprises have banks (including commercial banks, branches of foreign banks in Sweden, saving banks), credit market companies, housing credit institutions, other mortgage institutions, other credit market companies, securities brokerage companies. Database of each enterprises have been aggregated by the Statistics Sweden. We used two distinct dependent and nine independent variables consisting of five outputs and four inputs. The maximum-likelihood estimates of the parameters of the model are obtained using a modification of the econometric software. Descriptive statistics of the key variables are presented in Table.2.

Table.2 Descriptive statistics

Variable					
Description	**Name**	**Mean**	**Std. Dev.**	**Maximum**	**Minimum**
The total value of cost (in SEG) for financial enterprises involved	**C**	9.00284	1.756784	11.38893	5.826
value of lending to credit institutions (in SEG) for financial enterprises	**LC**	10.80651	1.788699	14.46671	8.059276
Value of lending to the general public (in SEG) for financial enterprises	**LG**	12.41369	2.210613	14.90403	6.841615
Value of bonds and other interest bearing securities (in SEG) for financial enterprises	**BS**	9.121946	3.678666	13.61924	0
Variable which has value of intangible fixed assets (in SEG) for financial enterprises	**IFA**	5.192042	2.63881	9.604745	0
Value of other assets (in SEG) for financial enterprises	**OA**	10.22882	1.40276	13.77414	7.524021
Value of deposits and funding from the general public (in SEG) for financial enterprises	**DF**	9.429938	2.931397	14.83895	0
Variable which has value of securities issued (in SEG) for financial enterprises	**SI**	11.06731	3.902551	14.60159	0
Value of other liabilities (in SEG) for financial enterprises	**OL**	10.40868	1.390364	13.88323	8.437717
Value of equity (in SEG) for financial enterprises	**EQ**	10.36678	1.314107	12.9904	7.849714

Red : Output Blue: İnput

4.2. Empirical Results

In this section, we presented and discussed the efficiency results obtained indirectly from a functional form on cost of financial enterprises.

Table.3 Estimated coefficients of cost function (t-values in parentheses)

Variable	Pooled Model Translog Coefficient	Time-Invariant Fixed Model Coefficient	Time-Invariant TRUE Fixed Model Coefficient	Time-Variant Random Model Coefficient
Constant	-33.12928***	Varies	Varies	-32.7411094***
	(-22.88557)			(-33.4756)
ln (LC)	4.241569***	0.250294	0.201364	4.7642288***
	(6.046996)	(0.158966)	(0.112564)	(6.2500)
ln (LG)	2.60297***	8.364753***	7.952142***	1.0622897
	(2.858027)	(9.648387)	(3.297862)	(1.2603)
ln (BS)	0.286457	-1.476749*	-1.624532*	0.2075516**
	(1.1205)	(-1.75137)	(-1.792365)	(2.5871)
ln (IFA)	0.408624***	-0.087644	-0.0561473	0.2452078
	(3.338358)	(-0.245951)	(-0.201547)	(1.2705)
ln (OA)	-0.876248*	-1.092939	-1.145638	-0.1814513
	(-1.65388)	(-0.817192)	(-0.943651)	(-0.2229)
ln (DF)	-0.865292***	-2.245854***	-2.156987***	-0.6518904
	(-3.215903)	(-2.851529)	(-3.146219)	(-1.2054)
ln (SI)	-5.107554***	-3.331713***	-3.689437***	-4.9145871***
	(-11.28488)	(-6.580564)	(-6.896417)	(-9.9300)
ln (OL)	-2.19455***	0.864651	0.649872	-2.7805700***
	(-3.186602)	(0.408246)	(0.348364)	(-3.4005)
ln (EQ)	8.679645***	5.188403*	4.136452	8.6082594***
	(10.1941303)	(1.983075)	(5.843616)	(10.1853)
Log-likehood	-106.42147	-106.42147	-107.29020	79.18072
Sigma(σ)	1.749129	1.756784		1.758790
R^2	0.995246	0.998076		0.991467

***, ** and *: coefficients are significantly different from zero at the 99%, 95% and 90% confidence levels respectively.(by Statistical Sweden)

The estimation results of the frontier cost inefficient models using the PM, the FM and the RM are given in Table.3[2].Given that most of the variables are in logarithmic form, the coefficients can be interpreted as estimated elasticises. The results suggest that the lending to general public is quantity - elastic, with estimated elasticises of 2.20, 8.40 and 1.05 for the PM, the FM and the RM. The results also suggest that the security issued is price - elastic, with an estimated elasticity of -6.60 for the PM but only about -3.10 for the FM and -2.95 for the RM.

In the cost translog function, homogeneity condition is, the signs of the coefficients of the stochastic frontier are as expected, with the exception of the negative estimate of input variables (without the value of equity for three models.) and the positive estimate of output variables. Results of the sum of all coefficients are equal to negative for cost function. In this connection, each model is provided the homogeneity condition in ours estimations.

Table.4 Cost Inefficiency Scores

	Pool Model	**Fix Model**	**TRUE Fix Model**	**Random Model**
μ	0.222375	0.197960	0.233028	0.055706
Std. Dev.	0.119003	0.088867	0.233028	0.011719
Maximum	0.048774	0.0	0.016417	0.033087
Minimum	0.771586	0.329265	0.528317	0.077064

Table.4 provides descriptive statistics for the overall Swedish estimated 'cost inefficiency scores' for the 6 different financial enterprises for the period from 1996 to 2011. This shows that the estimated u_b is about 12% to 38%. Then, the technical efficiency[3] of financial enterprises is 94%, 77%, 81% and 78% for the RM, the TRUE FM, the FM and the PM.

[2] We want to find fit model in these estimators. We use some hypothesis tests for our estimators. Firstly, we could compared pool model and fix model. The likelihood ratio test provides to find which model is more fit in our database. In this test, the null hypothesis is the pool model ($H_0 = The\ Pool\ Model$). The likelihood ratio test formulates $\left(Likelihoodratio_{estimate} = -2\left[loglike_{pool\ model} - loglike_{fix\ model}\right]\right)$. We calculated $Likelihoodratio_{estima\ te}$ =582.43. $Chi - square(8, 0.05)_{table}$ is 15.507 for our example. Result of $Likelihoodratio_{estimate}$ >. $Chi - square(8, 0.05)_{table}$, we reject to the null hypothesis.

Secondly, we could compare the fix model and the random model. The Hausman test provides to find which model is more fit in our database. In this test, the null hypothesis is the random model ($H_0 = The\ Random\ Model$). The Hausman test formulate:$\{H_{estimate}$ = $\beta FM - \beta RM'\ cov\beta FM - \beta RM - 1\beta FM - \beta RM$. We calculated $Hestimate$=50.715. $Chi - square(8,\ 0.05)table$ is 15.507 for our example. Result of $H_{estimate}$ >. $Chi - square(8, 0.05)_{table}$, we reject to the null hypothesis. Thirdly, we could compare the fix model and the TRUEfix model. The Hausman test provides to find which model is more fit in our database. In this test, the null hypothesis is the fix model ($H_0 = The\ Fix\ Model$). The Hausman test formulate:$\left\{H_{estimate} = \left(\widehat{\beta_{TRUEFM}} - \widehat{\beta_{FM}}\right)' cov\left(\widehat{\beta_{TRUEFM}} - \widehat{\beta_{FM}}\right)^{-1}\left(\widehat{\beta_{TRUEFM}} - \widehat{\beta_{FM}}\right)\right\}$. We calculated $H_{estimate}$ =42.469. $Chi - square(8, 0.05)_{table}$ is 15.507 for our example. Result of $H_{estimate}$ >. $Chi - square(8, 0.05)_{table}$, we reject to the null hypothesis.

[3] Technical Efficiency Score = 1-Technical Inefficiency Scores

Table.5 Correlation among Inefficiency Estimates

	Pool model	Fixed model	TRUE Fix model	Random model
Pool model	1			
Fixed model	0.41568	1		
TRUE Fixed model	0.81814	0.71587	1	
Random model	0.41923	0.98467	0.72694	1

Table.5 provides correlation among efficiency estimates of our models. Among the notable features of the results is the high correlation between the random model and the fixed model estimates, but the pool model is lower correlations across the two modelling platforms, time-varying and time-invariant effects. Then, the TRUEfix model has a very high correlation between the pool, the random and the fix models.

We want to find fit model in these estimators. We use some hypothesis test for our estimators. These tests show that the TRUEfix model is fit model in our database. The Hausman test result is support it. The following explanations are based on the TRUE fix model.

Table.6 Average Technical Inefficiency Scores (TIES) from 1996 to 2011 (by the TRUE FM)

	Average TIES	Efficiency in order
Banks	0.1462125	2
Credit market companies	0.21165	6
Housing credit institutions	0.14839375	4
Other mortgage institutions	0.13868125	1
Other credit market companies	0.14834375	3
Securities brokerage companies	0.16249375	5

Figure.2 provides a summary of individual inefficiency scores of financial enterprises. We compared with each individual inefficiency of financial enterprises the other mortgage institutions are the most efficient than another financial enterprises. Other credit market companies are the lowest inefficient than other financial enterprises. This result show that the other mortgage institutions are more successfully for the cost-management than others. Next, Banks (saving, commercial and investment) are successfully in these financial enterprises. So, the credit market companies are had the worst efficient score in all of financial system. Housing credit intuitions and Credit market institutions are higher inefficiency than another four financial enterprises (Table.6). Especially, Housing credit intuitions and Credit market institutions have been affected by some enterprise scandals. This reason affects efficiency for the housing credit intuitions. In 2011 and 2010, inefficiency score of the housing credit intuitions are highest than all of years. So, inefficiency score of credit market institutions changed to 2010 and 2011. These years (2010 and 2011) inefficiency score of credit market institutions are lowest than all of years. These events will be depending on the subprime mortgage crises of 2008(Figure.2).

5. Summary and conclusion

In this paper, ours main motivation is that could analyze how efficiency in Swedish financial enterprises has changed since the banking crisis in 1993. We estimate the time-invariant and time-varying inefficiencies of Swedish financial enterprises during from 1996 to 2011 with three different estimators. These estimators are the Pooled Model (Aigner et al. (1977)), the fixed effects model (Schmidt and Sickles (1984)) and the random effects model (Battese and Coelli (1995)) efficiency estimators. We predict cost function by employing panel stochastic frontier approach. This allows us to construct cost efficiency.

In this research, this is an indication of cost efficiency measure are estimated for the panel data consisting of six different financial enterprises from 1996 to 2011. These financial enterprises have banks (including commercial banks, foreign bank´s branches in Sweden, saving banks), credit market companies, housing credit institutions, other mortgage institutions, other credit market companies, securities brokerage companies. Each of enterprise's database is aggregated by the Statistics Sweden.

In briefly, the estimates for the stochastic cost inefficiency using these approach show the overall Swedish Financial System estimated 'cost efficiency scores'. These shows the other mortgage institutions are the most efficient than another financial enterprise. Other credit market companies are the lowest inefficient than other financial enterprises. Banks (saving, commercial and investment) are successfully in these financial enterprises. So, the credit market companies are had the worst efficient score in all of financial system. Housing credit intuitions and credit market institutions are higher inefficiency than another four financial enterprises. These results support the period from 1990 to 1993. Accordingly, mortgage intuitions are structurally stronger than banks and financial companies.

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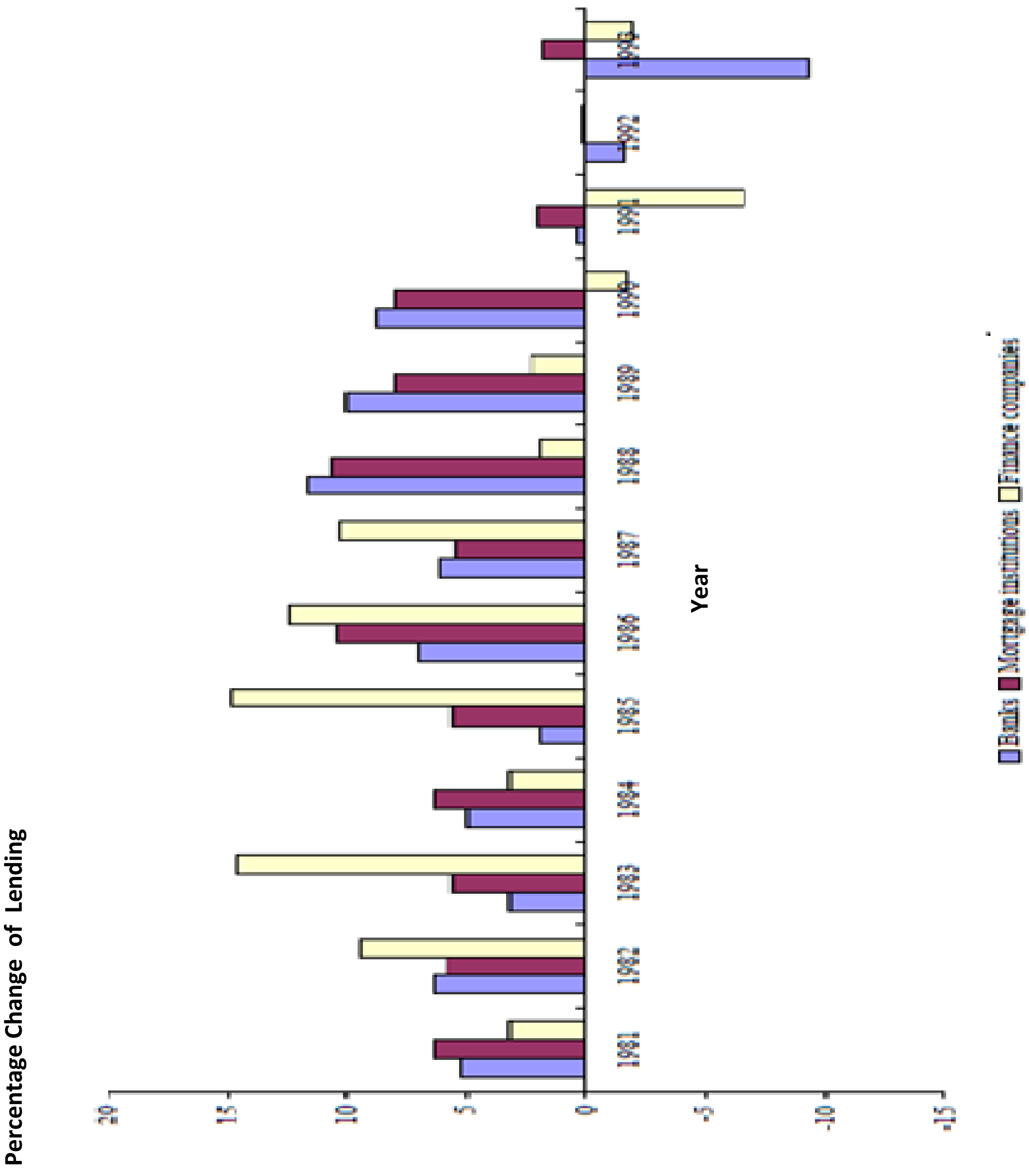
8.Appendix



Source: Wallander (1994) table A1.

Figure.1 Lending from Banks, Mortgage Institutions and Financial Companies (percentage changes)

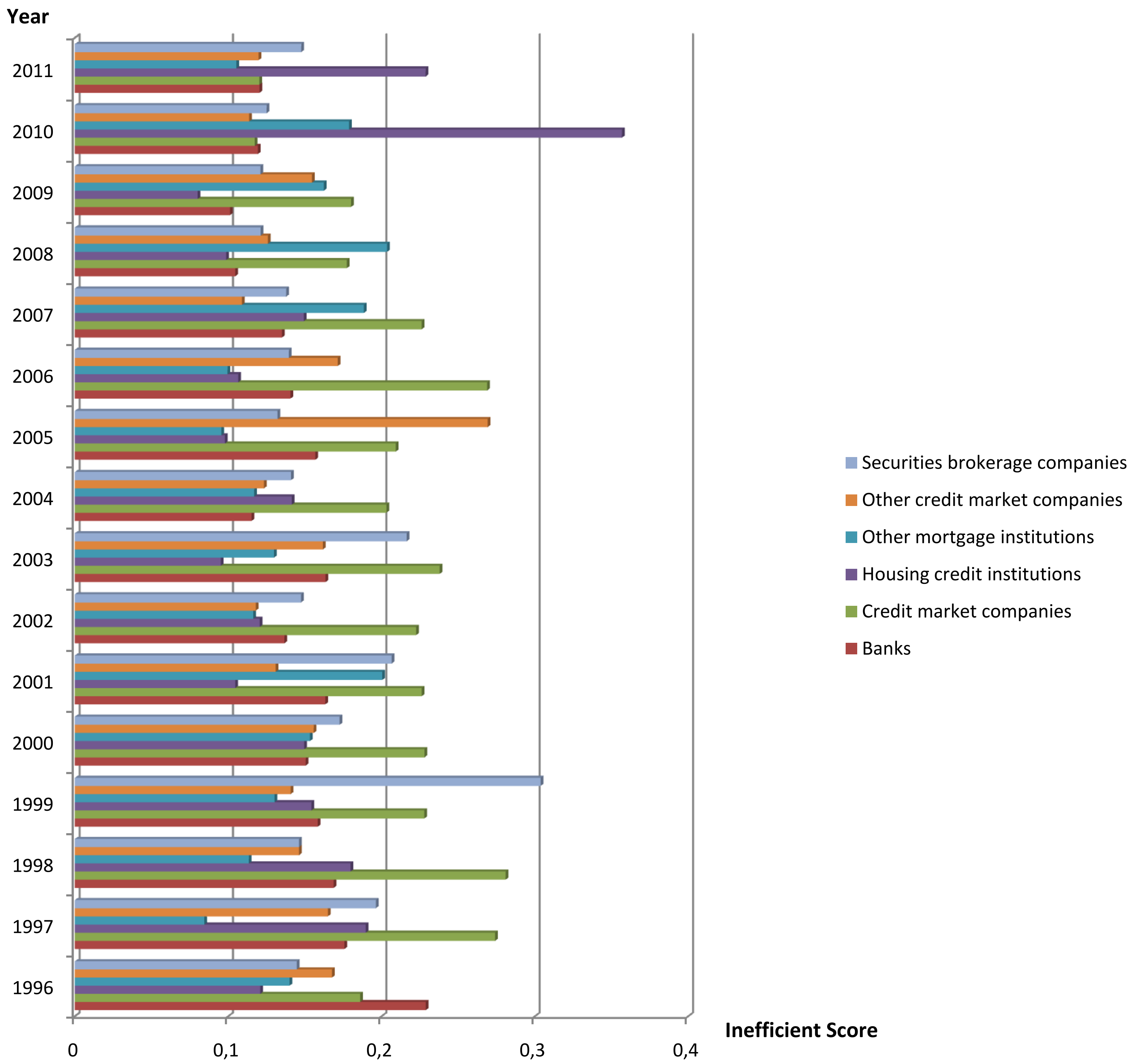


Figure.2 Estimated 'Individual Inefficiency of Financial Enterprises'

(the TRUE FM, from 1996 to 2011)