UNIVERSITY OF BATH

Department of Economics

FEEDBACK SHEET

Candidate number	04598, 04586, 04527	
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Effects of Geographical Deregulation on the Returns To Scale of Commercial Banks in the U.S.

Candidate Numbers: 04598, 04586, 04527

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1 Descriptive Statistics

In the table below, descriptive statistics have been generated for the seven variables in the given data set:

- CT: Total Costs
- w_1: wage rate for labour
- w_2: interest rate for borrowed funds
- w_3: price of physical capital
- y_1: consumer loans
- y_2: nonconsumer loans
- y_3: securities, including nonloan financial assets

Within the table, the following statistics are reported for the variables mentioned above: number (n), mean, standard deviation (s.d), median, maximum (max), minimum (min), skewness and kurtosis and first quantile (1st Qu).

Variable	mean	std. dev.	median	max	min	skewness	kurtosis
CT	60337.13	449671.91	5186.70	12129396.01	183	18.25	405.63
w1	14.52	7.39	13.90	61.02	3.70	0.72	0.97
w2	0.01	0.01	0.007	0.29	4.47E-05	7.60	110.35
w3	0.04	0.02	0.04	0.33	0.007	3.86	35.49
y1	95652.14	366692.66	13761.61	6048775.91	80	9.39	112.16
y2	653931.05	4506701.65	55638.19	87124479.8	3020	14.30	238.08
y3	516858.67	3267159.26	57675.5	62132000	2900.62	14.42	239.72

Table 1: Descriptive Statistics

According to Table 1, CT, w_2, w_3, y_1, y_2 and y_3 are highly positively skewed to the right suggesting that the data is not normally distributed as the value is greater than (+) 1. However, the skewness for w_1 is 0.72 implying that it is moderately positively skewed to the right as it lies between 0 and (+) 1. Furthermore, the value of kurtosis for normally distributed data usually lies around a figure of 3 [1]. There is high kurtosis for CT, w_2, w_3, y_1, y_2 and y_3 as the value lies above 3, implying that the data may have fat tails and thus there maybe outliers in the data. However, for w_1, kurtosis is considered to be low as it is 0.97, and thus lies below 3. Low kurtosis implies that tails are thinner than in a normal distribution, and data may have to be re-evaluated and must be considered with caution.

2 Percentage of banks under each policy regime

The percentage of banks running under each policy regime at each quarter in 1986 is reported in Table 2. It is important to note that the percentage for policy four in each quarter is 0 as this policy was not implemented until the 1990s.

	Quarter 1 (%)	Quarter 2 (%)	Quarter 3 (%)	Quarter 4 (%)
Policy 1	21.67	21.67	21.67	21.67
Policy 2	60.09	59.66	59.66	59.66
Policy 3	18.24	18.67	18.67	18.67
Policy 4	0.00	0.00	0.00	0.00

Table 2: Banks under different policies across financial quarters

3 Regression Results of Policies

Variables here are defined as the following:

- $Y = ln(\frac{CT}{y3})$
- $X_1 = ln(\frac{w_1}{w_3})$
- $X_2 = ln(\frac{w_2}{w_3})$
- $X_3 = ln(y_1)$
- $X_4 = ln(y_2)$
- $X_5 = ln(y_3)$

Log returns are used in the model as multiplicative relationships are converted to additive relationships, thereby converting exponential trends to linear ones, making it more suitable to model [3]. In this section, three separate regressions using three different policies are run, with several statistical values being reported for each below.

In Table 3, from Policy 1, it can be said that all the variables apart from X_2 , are statistically significant due to the p-value which is approaching 0. However, for X2, the p-value is not statistically significant as it is 0.605 as it is greater than 0.05. Additionally, from the regressions carried out for both Policy 2 and Policy 3 in Table 3, it is observed that all variables are statistically significant as suggested by the p-value lying close to zero.

Furthermore, the adjusted R-squared statistic for all 3 policies lie above 0.99, implying that most of the variation occurring due to the different policies implemented can be explained by the variables. Also, as it can be seen from some of the plots (Appendices, B) of variables versus dependent variable, a considerable portion of those exhibit linear relationships. Lastly, the F-statistic, which tests for joint significance, suggests that all the variables are jointly significant and thus should remain in the model.

The Returns To Scale are calculated as:

$$RTS = \left[\sum_{j=1}^{3} \frac{\partial}{\partial \ln y_j} C\left(\frac{w_1}{w_3}, \frac{w_2}{w_3}, y_1, y_2, y_3\right)\right]^{-1} \tag{1}$$

- **Policy 1:** 0.9949
- **Policy 2:** 1.0238
- **Policy 3:** 1.0509

Table 3: Regression Results of various policies

	Dependent variable:		
	Y		
	Policy 1	Policy 2	Policy 3
	(1)	(2)	(3)
X1	0.216***	0.230***	0.391***
	(0.018)	(0.012)	(0.020)
X2	0.002	0.014***	0.039***
	(0.605)	(0.003)	(0.007)
X3	0.140***	0.138***	0.243***
	(0.006)	(0.004)	(0.009)
X4	0.422***	0.362***	0.329***
	(0.009)	(0.006)	(0.013)
X5	0.443***	0.476***	0.379***
	(0.009)	(0.006)	(0.011)
Constant	−0.134	0.104	−0.363***
	(0.111)	(0.072)	(0.134)
Observations	404	1,114	346
R^2	0.993	0.995	0.995
Adjusted R^2	0.993	0.995	0.995
Residual Std. Error	0.082 (df = 398)	0.101 (df = 1108)	0.116 (df = 340)
F Statistic	11,363.600*** (df = 5; 398)	40,462.570*** (df = 5; 1108)	14,389.880*** (df = 5; 340)
Note:			*p<0.1; **p<0.05; ***p<0.01

4 Conclusion

Having calculated the returns to scale (hereafter RTS) for all three policies discussed above, this section evaluates which policy would be the best to implement. It is important to note that RTS can be classified into three different types: increasing (>1), decreasing (<1) and constant (=1).

The RTS under policy one is 0.993 which is less than 1. Thereby, under this policy regime, banks are experiencing decreasing RTS. This could be explained by the unit banking approach taken under this policy, whereby banks are geographically restricted to one area as they are only allowed to have one branch and thus are only able to access a limited clientele base.

However, under policy two, the RTS of banks is 1.023821 which is greater than 1, meaning that banks here are experiencing increasing returns to scale. The limited branching policy implemented here, can account for the increased returns to scale seen relative to policy one, as banks are allowed to operate a few branches opposed to one. Thus, banks can now make more efficient use of their resources relative to those in policy one.

Under policy three, an RTS of 1.050985 is observed, suggesting that there are increasing returns to scale, which is higher relative to banks returns under policy two. A large proportion of this could be attributed to the geographical deregulation banks are able to experience under policy three as banks are allowed to open more branches state-wide. Thus, economies of scale are able to occur, leading to a more efficient and productive use of resources.

After testing the three policies implemented in 1986, it can be said that policy three is considered to be the best in this context as it produces the highest RTS for commercial banks. Moreover, when analysing the policies above, it can be seen that the role of geographical deregulation has played a part in the productivity and thus returns to scale of the commercial banks in the USA, whereby greater geographical deregulation leads to higher returns to scale for commercial banks.

This rationale is reinforced by Jayaratne and Strahan (1997) , who state that through geographical deregulation, the banking industry has seen an increase in its efficiency and performance over the years.[4] According to Jayaratne and Strahan (1997), geographical deregulation has led to the expansion of better performing, in turn enabling it to make a more productive use of its resources and achieving economies of scale.[4] Prior to this, the lack geographical mobility prevented these banks from being able to expand and efficient. Thus, in the subsequent periods of deregulation which removed restrictions on interstate and intrastate banking that have followed, the market share of profitable banks has sharply risen, as deregulation has forced selection where poor-performing banks to lose ground to the more profitable banks as they are forced to compete within the same industry, that have lower cost structures due to the scale of their operations. Radecki (as cited in [2]), supports this with empirical data, as it is noted that in 1963 13,291 U.S. banks operated 13,581 branches whilst in 1997, the number of banks fell to 9,143 but the number of branches increased exponentially to 60,320. This implies that whilst the number of banks opened has fallen, the more profitable banks have seen an increase in its scale of operations.

References

[1] C. Brooks. *Introductory econometrics for finance.* Cambridge university press, 2019.

[2] M. Z. Clarke. Geographic deregulation of banking and economic growth. *Journal of Money, Credit, and Banking*, 36(5):929–942, 2004.

[3] C. Ford. University of virginia library research data services sciences, Aug 2018.

[4] J. Jayaratne and P. E. Strahan. The benefits of branching deregulation. *Economic Policy Review*, 3(4), 1997.

Appendices

A R Code

```
# Based on guide by lecturer Bin Peng.
rm(list = ls()) # Clean the memory. Make sure we start from blank.
cat("\014")     # Send ctrl+L to the console and therefore will clear the screen

# getwd() # Give you the current working directory
# setwd() allows you to change the working directory
setwd("/Users/yashvirsurana/Desktop/University of Bath/Financial Economics/")
# NOTE: Place all R code we create and any data we need to call from within R in this R working directory.

df_bank <- read.table("large_bank.csv", header = TRUE, sep = ",")
print(head(df_bank)) # Take a quick look at the data set in R
cat("\n\n")

#Q1
#-------------------------------------------------------
# Below we use data of year 1986
year1986 <- c(1,2,3,4)
L_tot    <- dim(df_bank)[1] # Return the total number of rows in your data set
ind_tot  <- 1:L_tot
ind_1986 <- ind_tot[ is.element(df_bank$t, year1986) ] # Give the TRUE indices of the data of year 1987
df_bank  <- df_bank[ind_1986,]

# Descriptive Stats for 1986 - Generic Way
print( summary(df_bank) )
cat("\n\n")

# Descriptive Stats for 1986 - YS way
library(psych) #--Added by YS, psych gives sd, median, range, skew, kurtosis,etc
desc_stats <- describe(df_bank) #--Added by YS
write.csv(desc_stats, file = "desc_stats.csv")

#Q2
#-------------------------------------------------------
# We focus on all quarters in 1986 and all four policies.
Quarter_nos <- c(1,2,3,4) # For year 1986, quarter 3 means t = 3
Policy_nos  <- c(1,2,3,4)

for (q in Quarter_nos) { # loop over quarters
  for (p in Policy_nos) { # loop over policies
    # Get the indices of the rows with "Policy = p" and "Quarter = q",
    # i.e., identify the data needed for our application
    ind_U <- which(df_bank$POLICY == p & df_bank$t == q)
    cat("The proportion of policy", p, "at Quarter", q, "is",length(ind_U)/466, "\n")
  }
}

#Q3
#-------------------------------------------------------
Policy_nos  <- c(1,2,3)
models <- list()

for (p in Policy_nos) {

  ind_U <- which(df_bank$POLICY == p) # & df_bank$t == 1)
  # Constructe the variables for OLS regression
  temp <- df_bank[ind_U,]
  Y <- log( temp$COST/temp$P_DEPOSI_w3 )
  X <- matrix(0, nrow = length(Y), ncol = 5)
  X[,1] <- log( temp$P_LABOR_w1/temp$P_DEPOSI_w3 )
  X[,2] <- log( temp$P_FUNDS_w2/temp$P_DEPOSI_w3 )
  X[,3] <- log( temp$CON_LOAN_y1 )
  X[,4] <- log( temp$NONC_LOA_y2 )
  X[,5] <- log( temp$SECURITI_y3 )

  OLS_output <- lm(Y ~ X)
  models <- list(models, OLS_output)
  # summary(OLS_output)
  print(summary(OLS_output))#$coefficients[,1:2])
  RTS <- 1/sum( summary(OLS_output)$coefficients[4:6,1] )
  cat("\nRTS is", RTS, "\n")

  # Generate Plots for Variables V Y
  coeffs  <- c(1,2,3,4,5)
  for (i in coeffs) {
    jpeg(file = paste('Policy',p,'_Y_X',i,'.jpeg', sep = ''))
    plot(Y, X[,i])
    dev.off()
  }
```

```
}

# Print Latex Tables for the Report
library(stargazer)
stargazer(models[[1]][[1]][[2]], models[[1]][[2]], models[[2]],column.labels=c("Policy 1","Policy 2", "Policy 3"), align=TRUE)
models[1]
```

B Regression Plots

Figure 1: Policy 1

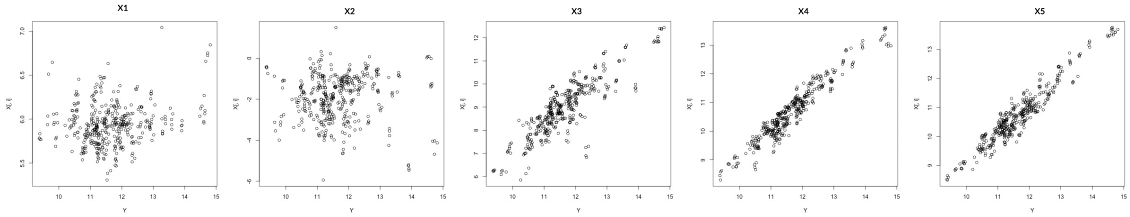

Figure 2: Policy 2

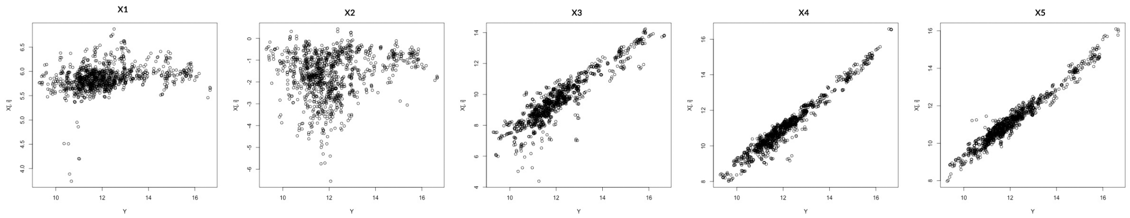

Figure 3: Policy 3