DSC5101 ANALYTICS IN MANAGERIAL ECONOMICS

Group Project 2

Effect Estimation On A Banking Regulation

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1. Executive Summary

The 2008 financial crisis was the largest and most dangerous crisis since the Great Depression of the 1930s. Hundreds of financial institutes worldwide have gone bankrupt and thousands of others were forced to receive extensive bailout from governments to survive. The profound impact of the crisis lasts even until today.

The objective of this project is to evaluate the real effect of Volcker Rule, which is the core part of Dodd-Frank Act that was legislated after the crisis, in the aim of reinforcing the regulation and reducing the bank's overall risk-taking in USA. The hypothesis that will be verified is that the affected banks started to reduce their trading asset ratios after the announcement of the Volcker Rule. Banks with larger trading asset ratios are affected more.

We used a panel data which consists of financial information of 8,128 bank holding companies (BHCs) in the U.S. We split the bank data into control group and treatment group and used Difference-in-Difference (DiD) model to evaluate. Result shows that Volcker Rule is indeed effective in terms of reducing banks' trading asset ratio, especially for those banks which had higher trading asset ratio prior to the financial crisis. We performed a few robustness test to validate our result, including using propensity score matching to reduce baseline bias, changing dummy variables to numeric variables and placebo test. The result of tests prove the validity of our findings.

In this report, section 2 will illustrate the baseline model and result comparison; section 3 explains the various robustness tests performed to validate the outcome of model and causal effect; further exploration was made on the model including placebo test and changing dummy covariates to continuous in section 4; section 5 briefly wrap up conclusion and discuss about the implication of the study.

2. Baseline Model

2.1 Data Cleaning

Before proceeding to model regression, we performed list-wise deletion on data entries with missing value. For some models in baseline test where control variables are not required, only entries with missing bhc_avgtradingratio were removed.

After we plotted the average trading asset ratio of control group and treatment group against time (*Refer to Appendix 1*), it was observed that both groups had a substantial surge in average trading asset ratio in 2007 Q1, and maintained at a higher level of trading asset ratio for the subsequent two years. Considering that the pre-2007 data might be already outdated that could no longer represent banks' trading asset ratio level, and it will affect the accuracy of our estimation, we decided to discard data prior to 2007 Q2. Nevertheless, a robustness test of pre-2007 affectedness was performed to ensure this manipulation of data does not change the result.

2.2 Baseline Model Identification and Result

Difference in Difference (DiD) was applied in the baseline model to test the impact of the Volcker Rule on banks' trading asset ratio.

$$Y_{i,t} = \alpha + \beta 1 * After\ DFA + \beta 2 * Affected\ BHC + \beta 3 * (After\ DFA_t * Affected\ BHC_i) + \gamma_i + \delta_t + X_{i,t} + \varepsilon_{i,t}$$

As our data is available on a BHC-quarter level, i indicates a particular BHC and t indicates a quarter. The dependent variable is the trading asset ratio, and the core explanatory variables are After DFAt, the indicator of whether a data point is after DFA, and Affected BHCi, which is the treatment dummy that is 0 for control group where the average trading asset ratio below 3% (as Volcker Rule has threshold of 3%) and 1 for treatment group. Bank holding company (*γi*) and time (*δt*) fixed effects were also used, along with a set of control variables (*Xi*,*t*).

A few baseline test were performed with different combination of variables included, and the results are shown below.

Baseline Tests				
	1	2	3	4
	OLS	**OLS**	**OLS**	**PLM**
Dependent Variable		Average Trading asset ratio		
After DFA	-4.619E-04	-0.0009262***	-1.444e-04	
Affected BHC			1.174e-01***	
After DFA x Affected BHC			-5.067e-02 ***	-0.030845***
Controls	NO	YES	YES	YES
Fixed Effect	NO	NO	NO	YES
Observations	41,442	23,607	23,607	23,607
Adjusted R-squared	5.83E-05	0.2347	0.5839	0.0698

Table 1: Baseline Tests

In the test (1) only After_DFA dummy variable was used. The β was not significant, and R-square was nearly 0, as a lot of the variables that has potential impact on the trading asset ratios were omitted in this model. In the test (2) after various control variables were added in, we have got significant β with much improved R-square, showing the fact that after the Volcker rule, all banks trading asset ratio started to shrink, though the magnitude is not much. In the test (3), we added the interaction of After_DFA and treatment dummy variables (Affected BHC). The result shows that the interaction has much stronger effect than after_DFA alone, implying that the treatment effect is highly likely to exist.

After the fixed effect factors are added in test (4), which is our final baseline model, the interaction of After_DFA and Affected_BHC is still significant. So we can draw our preliminary conclusion that banks with trading asset ratio above Volcker rule's threshold (≧ 3%) would reduce more in trading asset ratio than other banks. However, this conclusion yet to be tested for robustness.

3. Robustness Tests

In order to test the robustness of our baseline model, the following tests were performed.

3.1 Pre-2007 Effect

As explained earlier, we removed data prior to 2007 Q2 to eliminate the effect of outdated data. In order to examine the possible bias of this process, we performed a pre-2007 effect test. The Affected_BHC was redefined as 15-quarter average trading asset ratio prior to 2007. This will eliminate the transient effect before and during financial crisis, which might cause bias and endogeneity to our conclusion. The result of test is more or less similar as baseline, which proves validity of our model and data cleaning method.

Robustness Tests			
	1 **Pre-2007 Effect**	2 **Propensity Score Matching**	3 **Excluding Non-trading BHCs**
Dependent Variable	Average Trading asset ratio		
After DFA x Affected BHC	-0.20485***	-0.03255022***	-0.03339305***
Controls	YES	YES	YES
Fixed Effect	YES	YES	YES
Observations	39,311	939	939
Adjusted R-squared	0.0044772	0.17758	0.16482

Table 2: Robustness Test

3.2 Propensity Score Matching

To reduce the imbalance of data within control group and treatment group, we utilized the propensity score matching technique to create a smaller control groups with banks that are more similar to those under treatment group in terms of control variables. Observations are selected based on similar propensity score matching with the treatment group. The ratio of observations between new control group and treatment group is 3:1 (*Refer to Appendix 3 for the propensity score matching result*). After replacing original dataset by propensity matched dataset, the result was still significant and coefficient is also similar compared to the baseline model, with significant improvement in R-squared. All the robustness test performed hereafter used propensity matched dataset instead of original dataset.

3.3 Excluding Non-trading BHCs

There are many banks with 0 trading asset ratio in the data set. As these banks are considered as conventional banks which do not participate in trading business, Volcker Rule is not applicable to them at all. Therefore, we carried out another robustness test which excluded these banks from data. The result shows that even non-trading banks were excluded, the β was still significant and of same magnitude level, which proved the robustness of our model.

3.4 Placebo Test

It can be derived from the baseline model that the treated group responds strongly to the introduction of the Volcker Rule. However, we cannot firmly conclude yet that the decline in trading asset ratio is due to the Volcker Rule. Thus, we conducted a placebo test to shuffle the treatment point, as well as control and treatment groups.

We iteratively assigned quarters in between 2008 Q1 to 2012 Q4 as the treatment quarter, and with each assigned quarter, we further shuffled the treatment dummy by randomly assigning banks into control and treatment groups. By plotting a histogram (*Refer to Appendix 2*) on all the coefficients we get from the iteration of placebo tests, it can be observed that the mean is close to 0, and we assume that the slight decline in trading asset ratio during placebo period is due to 2008 financial crisis. Compare with our actual model, there were no overlapping between the true coefficient and coefficients from the placebo tests. Therefore, this approach validates that the strong decline in average trading asset ratio for the affected banks is due to the introduction of the Volcker Rule.

4. Further Exploration of the Model

In order to further explore how banks with different level of trading asset ratio would be affected by the Volcker Rule, as well as how the treatment effect would last in quarters following the introduction of Volcker Rule, we now change treatment dummy Affected BHC and After DFA indicator into continuous variables.

Continuous variable for Affected BHC is Affect, which equals 0 for control group, and banks' average trading asset ratio before the introduction of the rule (2007 Q2 to 2009 Q2) for treatment group. The continuous time variable equals to 0 for pre-DFA period, and 1 for the first quarter after DFA (2010 Q3) with increment of 1 for every following quarters. Three 3 models were run based on different combination of dummy or continuous variable for the two factors.

Continuous Covariates			
	1	2	3
	Continuous Affect	**Continuous Time**	**Continuous Time & Affect**
Dependent Variable	Average Trading asset ratio		
After DFA x Affect	-0.25783497***		
Time x Affected BHC		-0.00189529***	
Time x Affect			-0.01965436***
Adjusted R-squared	0.26138	0.10868	0.20979

Table 3: Continuous Covariates (All with Controls & Fes, with no. of observations being 939)

The interaction terms of Time and Effect, either being dummy or continuous, turned out to be negative and significant across all three models, which is consistent with the results in the previous models, implying a higher chance that treatment effect exists.

Model (1) uses continuous Affect, while keeping After DFA as dummy variable. Comparing the result with the original model, its better t-value and adjusted R-squared imply that continuous Affected BHC is a better fit. The more negative coefficient also indicates that after the Volcker Rule is introduced, the higher average trading asset ratio that a bank is holding, the more the ratio would drop. Model (2) uses continuous After DFA, while keeping Affected BHC as dummy variable. The coefficient is quite close to 0, implying that the trading asset ratio of the affected BHCs did saw some decrease quarter over quarter after the Volcker Rule was introduced, but in a very low rate, which is probably because the Volcker Rule is not fully enforced until 2017. Model (3) uses continuous variable for both After DFA and Affected BHC.

5. Conclusion

We have done the analysis of effect on the US bank holding companies in trading asset ratio as a result of introduction to the Volcker Rule. Result shows that the **affected banks decrease their trading assets significantly after the announcement of the new regulation.** From our testing with continuous time and affect, it is obvious that **the banks with highest trading asset ratio prior to the announcement of the Volcker Rule responded most**.

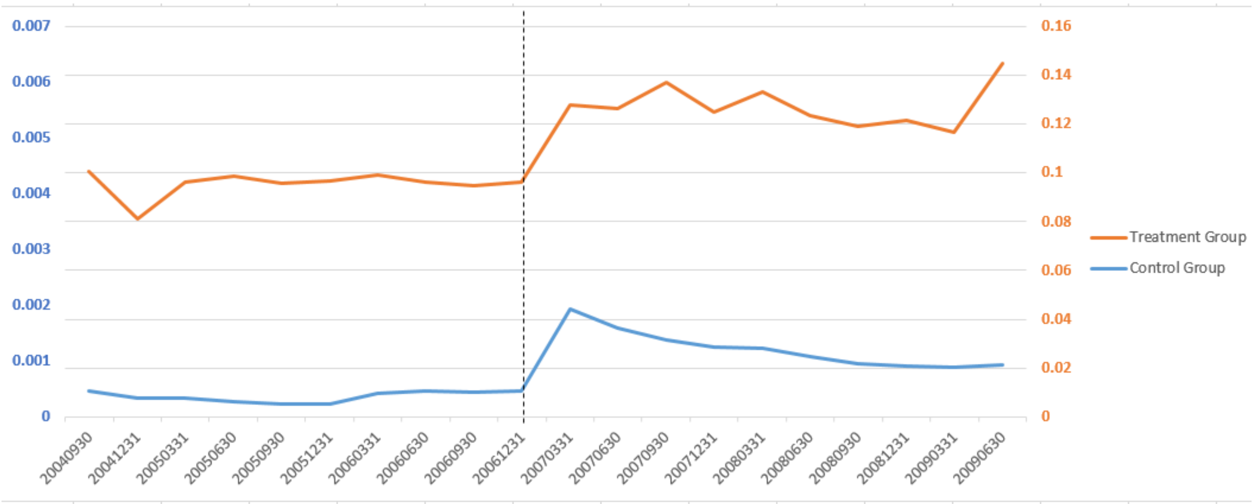
Even though the trading asset ratio decreases due to the Volcker Rule, the overall bank risk do not decrease according to Prof Jussi Keppo's paper *Risk Targeting and Policy Illusions – Evidence from the Announcement of the Volcker Rule* (2016). It is mainly on account of banks optimizing their risk levels by increasing the asset return risk or raising the leverage. **From this, regulators can learn that they have to enforce another law in parallel with the Volcker Rule if they want to reduce the overall risk of banks.**

Reference

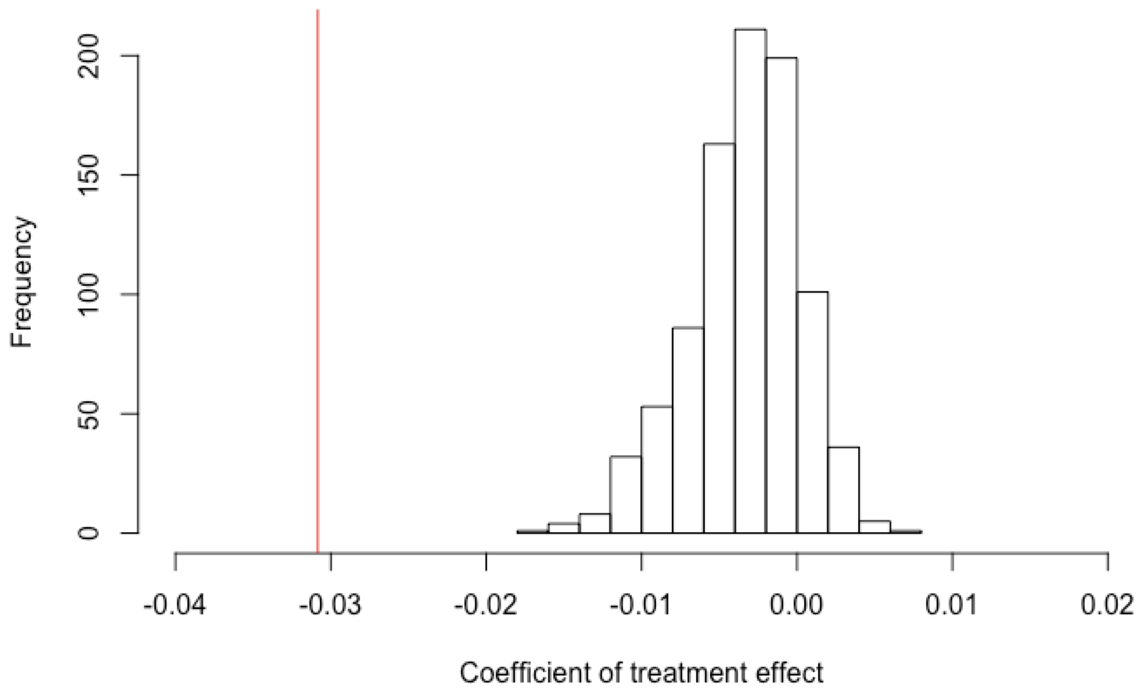
Keppo, J., Korte, J., 2016. Risk Targeting and Policy Illusions – Evidence from the Announcement of the Volcker Rule.

APPENDIX

Appendix 1 : Banks' Average Trading Asset Ratio Before 2009



Appendix 2 : Placebo Test Result



Appendix 3 : Placebo Test Result

Statistics in 2007 Q4 before Matching

	Treated Group		Control Group		
	Mean	SD	Mean	SD	Diff
dep_roa1	0.0027	0.003356173	0.0024	0.0033	0.0003
					(-0.003243)
dep_lnassets	18.1655	1.327543	14.0654	1.1755	4.1 **
					(-0.00057671)
dep_leverage	0.0849	0.03146514	0.0906	0.031	-0.0057
					(0.0018078)
dep_liquidity	0.0355	0.02325643	0.0287	0.0233	0.0069 ***
					(-0.0056253)
dep_depositratio	0.3414	0.1233709	0.6786	0.1128	-0.3373
					(0.00039165)
dep_creditrisk_total3	0.0218	0.02042081	0.0204	0.0205	0.0015 *
					(0.0028518)
dep_loans_REratio	0.4955	0.1468477	0.7525	0.1407	-0.257
					(-0.0012078)
dep_cir	0.359	0.1827555	0.3827	0.1835	-0.0236
					(-0.00000055642)
dep_cpp_bankquarter	0	0	0	0	0
					(-0.0002059)

Statistics in 2007 Q4 after Matching

	Treated Group		Control Group		
	Mean	SD	Mean	SD	Diff
dep_roa1	0.0027	0.008138532	0.004	0.0071	-0.0013
					(0.04913562)
dep_lnassets	18.1655	2.508014	17.9531	2.2388	0.2123
					(-0.00210636)
dep_leverage	0.0849	0.05603645	0.0883	0.0458	-0.0034 *
					(0.0661203)
dep_liquidity	0.0355	0.0195669	0.0276	0.0171	0.008 *
					(-0.02724133)
dep_depositratio	0.3414	0.2172213	0.3857	0.2113	-0.0443 .
					(0.01863968)
dep_creditrisk_total3	0.0218	0.01411336	0.0163	0.0126	0.0055 **
					(0.11201019)
dep_loans_REratio	0.4955	0.223594	0.5807	0.1745	-0.0852 *
					(-0.02533014)
dep_cir	0.359	0.7280614	0.3392	0.7137	0.0198
					(0.00030505)
dep_cpp_bankquarter	0	0	0	0	0
					(-0.00276922)

Appendix 4 : R Code

```
library(readr)

dat <- read_csv("C:/Users/SONG/Desktop/DiD_data2.csv")

data_clean$w == data_clean$affect

#clean data without na for all fields

data_clean <- dat[complete.cases(dat),]

data_clean_full <- data_clean

data_clean <- subset(data_clean,rssd9999>20070331)

summary(data_clean)


#clean data without na for avgtradingratio column

data_clean_avgtradingratio <- dat[!is.na(dat$bhc_avgtradingratio),]

data_clean_avgtradingratio <- subset(data_clean_avgtradingratio,rssd9999>20070331)


#for later placebo test benchmarking

model_0 <-plm(bhc_avgtradingratio~after_DFA_1:treat_3_b_avg +
dep_lnassets+dep_leverage+dep_liquidity+dep_depositratio+dep_creditrisk_total3+dep_loans_REratio+dep_cir+
dep_cpp_bankquarter, data = data_clean,index=c("rssd9001","rssd9999"),model="within")

summary(model_0)


##############################################################

################### Baseline tests #######################

##############################################################


# model 1: OLS, no control, no fixed effect

model_DFA <- lm(bhc_avgtradingratio~after_DFA_1,data=data_clean_avgtradingratio)

summary(model_DFA)


# model 2: OLS, with control,  no fixed effect

model_controls_noFE <- lm(bhc_avgtradingratio~after_DFA_1+
dep_roa1+dep_lnassets+dep_leverage+dep_liquidity+dep_depositratio+dep_creditrisk_total3+dep_loans_REratio+dep_cir+dep_cpp_bankquarter, data = data_clean)

summary(model_controls_noFE)
```

```
# model 3: OLS, interaction of after DFA * trading ratio, with control, no fixed effect

model_Affect_DFA <-
lm(bhc_avgtradingratio~after_DFA_1*treat_3_b_avg+dep_roa1+dep_lnassets+dep_leverage+dep_liquidity+dep_depositratio+dep_creditrisk_total3+dep_loans_REratio+dep_cir+dep_cpp_bankquarter, data = data_clean)

summary(model_Affect_DFA)


#model 4: PLM, after DFA:trading ratio, with control & fixed effect

library(plm)

model_Affect_DFA_plm <- plm(bhc_avgtradingratio~ after_DFA_1:treat_3_b_avg +dep_roa1 +
dep_lnassets+dep_leverage+dep_liquidity+dep_depositratio+dep_creditrisk_total3+dep_loans_REratio+dep_cir+
dep_cpp_bankquarter, data = data_clean,index=c("rssd9001","rssd9999"),model="within")

summary(model_Affect_DFA_plm)



###########################################################################

#################   Robustness tests  ###################################

###########################################################################


#Robustness test model 1 : Pre-2007 effect

model_pre_2007 <- plm(bhc_avgtradingratio~ after_DFA_1:Pre_2007_Affect+ dep_roa1 +
dep_lnassets+dep_leverage+dep_liquidity+dep_depositratio+dep_creditrisk_total3+dep_loans_REratio+dep_cir+
dep_cpp_bankquarter, data = data_clean_full,index=c("rssd9001","rssd9999"),model="within")

summary(model_pre_2007)


#Robustness test model 2 : Propensity score matching

library("MatchIt")

data_20070331<-subset(data_clean,rssd9999==20070930)

summary(data_20070331)


model_match<-matchit(treat_3_b_avg~
dep_roa1+dep_lnassets+dep_leverage+dep_liquidity+dep_depositratio+dep_creditrisk_total3+dep_loans_REratio+dep_cir+dep_cpp_bankquarter,data=data_20070331, method ="nearest", ratio=3,replace=TRUE)

summary(model_match)

data_match<-match.data(model_match)
```

```
## matched data model

selectedRows <- (data_clean$rssd9001 %in% data_match$rssd9001)

data_withMatchBanks <- data_clean[selectedRows,]

model_w2.2 <- plm(bhc_avgtradingratio~after_DFA_1:treat_3_b_avg + dep_roa1+
dep_lnassets+dep_leverage+dep_liquidity+dep_depositratio+dep_creditrisk_total3+dep_loans_REratio+dep_cir+
dep_cpp_bankquarter, data = data_withMatchBanks,index=c("rssd9001","rssd9999"),model="within")

summary(model_w2.2)


#Robustness test model 3: Excluding non-trading BHCs

data_withMatchBanks_new = subset(data_withMatchBanks,bhc_avgtradingratio>0)


model_w2.3 <- plm(bhc_avgtradingratio~after_DFA_1:treat_3_b_avg+ dep_roa1 +
dep_lnassets+dep_leverage+dep_liquidity+dep_depositratio+dep_creditrisk_total3+dep_loans_REratio+dep_cir+
dep_cpp_bankquarter, data = data_withMatchBanks_new,index=c("rssd9001","rssd9999"),model="within")

summary(model_w2.3)



##########################################################################

###################### Placebo Test ######################################

##########################################################################



#placebo test 1

data_DFA <- data_clean

data_DFA <- data_DFA[data_DFA$bhc_avgtradingratio > 0,]

set.seed(0230036)

bank <- unique(data_DFA$rssd9001)

RUN <- 100

model_coeff <- vector()

model_p <- vector()


#assigning treatment quarters

for(j in c(15:30)){
```

```
  data_DFA$after_DFA_1 = ifelse(data_DFA$quarterID<j,0,1)
  for(i in 1:RUN){
    random <- sample(bank, 100)
    random1 <-split(random, sample(1:2, 100,replace = TRUE))
    selectedRows <- (data_DFA$rssd9001 %in% random1[[1]])
    summary(selectedRows)
    data_treated <- data_DFA[selectedRows,]
    data_treated$treat_3_b_avg <- 1
    #View(data_treated)

    selectedRows <- (data_DFA$rssd9001 %in% random1[[2]])
    data_control <- data_DFA[selectedRows,]
    data_control$treat_3_b_avg <- 0
    #View(data_control)

    data_placebo <- rbind(data_treated,data_control)
    #View(data_placebo)
    #model
    model_placebo <- plm(bhc_avgtradingratio~after_DFA_1:treat_3_b_avg +
dep_lnassets+dep_leverage+dep_liquidity+dep_depositratio+dep_creditrisk_total3+dep_loans_REratio+dep_cir,
data = data_placebo,index=c("rssd9001","rssd9999"),model="within")
    model_coeff <- append(model_coeff,model_placebo$coefficients["after_DFA_1:treat_3_b_avg"])
    #model_p <- append(model_p,summary(model_placebo)$coefficients["after_DFA_1:treat_3_b_avg",4])
  }
}
hist(model_coeff, xlim=c(-0.07,0.07))
abline(v=model_0$coefficients["after_DFA_1:treat_3_b_avg"],untf = FALSE,col=2)
```

```
#############################################################################
############## Continuous Covariates ######################################
#############################################################################


#Model 1: Continuous Effect (w)

model_1 <- plm(bhc_avgtradingratio~after_DFA_1:new_w  + dep_roa1+
dep_lnassets+dep_leverage+dep_liquidity+dep_depositratio+dep_creditrisk_total3+dep_loans_REratio+dep_cir+
dep_cpp_bankquarter, data = data_withMatchBanks,index=c("rssd9001","rssd9999"),model="within")

summary(model_1)


#Model 2: Continuous time (t)

model_t2 <- plm(bhc_avgtradingratio~t*treat_3_b_avg  + dep_roa1+
dep_lnassets+dep_leverage+dep_liquidity+dep_depositratio+dep_creditrisk_total3+dep_loans_REratio+dep_cir+
dep_cpp_bankquarter, data = data_withMatchBanks,index=c("rssd9001","rssd9999"),model="within")

summary(model_t2)


#Model 3: Continuous effect and time (w&t)

model_wt2 <- plm(bhc_avgtradingratio~t*new_w  + dep_roa1+
dep_lnassets+dep_leverage+dep_liquidity+dep_depositratio+dep_creditrisk_total3+dep_loans_REratio+dep_cir+
dep_cpp_bankquarter, data = data_withMatchBanks,index=c("rssd9001","rssd9999"),model="within")

summary(model_wt2)
```