DBA 5101: Group Project 2: Estimating the Effect of a Banking Regulation

A reproduction of the research paper titled "Risk Targeting and Policy Illusions – Evidence from the Announcement of the Volcker Rule" (by Jussi Keppo & Josef Korte)

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Contents

1. Introduction

The Volcker Rule (formally Section 619 of the Dodd-Frank Wall Street Reform and Consumer Protection Act (DFA)) was first proposed in 2009 to restrict banks in the United States from making certain speculative investments and protect consumers by preventing a recurrence of risk factors central to the 2008 financial crisis. It specifically prohibits banks from using their own accounts to trade securities, derivatives, and other instruments (known as 'proprietary trading'), as well as high-risk investments in hedge funds or private equity.

In this report, we have used the banking data from 2004 to 2015 to evaluate the impact of the announcement of the Volcker Rule on banks' trading activities. This is measured through changes in banks' *trading asset ratio,* which is the proportion of banks' trading books relative to total assets. Results show that banks on average materially reduced their trading book size after the announcement of the rule, with banks that are the most affected showing larger overall reductions.

1.1 Hypothesis

While full compliance with the Volcker Rule was only required by mid-2015[1], we hypothesized that the announcement of the rule in Q3-2009 as part of the Dodd-Frank Act would have already spurred banks to take pre-emptive actions to comply. Indeed, it was reported as early as 2011[2] that major banks (e.g. Goldman Sachs, JP Morgan Chase, Bank of America) had already closed their proprietary trading desks.

This leads to the overall hypothesis for this paper:

"H1: Affected banks reduced their trading asset ratios post announcement of the Volcker Rule."

Relatedly, we expected that certain banks would be less affected and would reduce their trading asset ratios less. This includes banks that have low or no trading activity to begin with or fall within certain exemptions afforded in the Volcker Rule. Hence, as a robustness check, we tested whether the banks that are more affected have a stronger reaction overall. This affectedness threshold is defined as having a *trading asset ratio* of more than 3% as captured in the indicator variable *affected BHC*.

1.2 Data Summary

To test the above hypothesis, original and engineered features were used to model the impact of the Volcker Rule announcement to an institution's *trading asset ratio*.

1.2.1 Data Features

ORIGINAL DATA FEATURES	
• bankcode	• ln_assets
• trading_ratio	• cir
• affected_bhc	• deposit_ratio
• after_dfa	• loans_re_ratio
• roa	• liquidity
• leverage	• cpp
• credit_risk(npl)	

ENGINEERED FEATURES	
• qtr	• after_dfa * affectbhc
• affect	• after_dfa * affect
• affect_2007	• after_dfa * affectpfc
• non_trading BHC	
• roa_vol	
• z_score	
• post_fin_crisis	

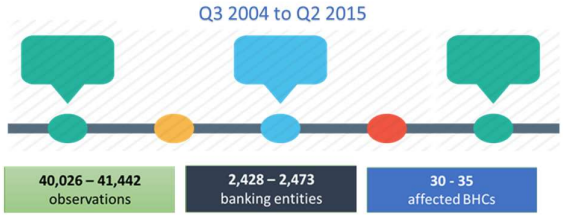
From the list of engineered features, notable items and their respective descriptions are highlighted as follows:

- **affect:** average trading asset ratio during the pre-DFA period (Q3 2004 - Q2 2009)
- **affect_2007**: takes the value of 1, if mean trading asset ratio over 15 quarters before announcement is greater than 3%
- **non_trading_bhc:** used to exclude entities with trading asset ratio = 0
- **interaction terms**: product terms v/s affect dfa for the robustness tests tackled in section 2.2

[1] See "Volcker Rule Implementation", Office of the Comptroller of the Currency, accessed 23.10.2021.
[2] See Liberto, Jennifer, "Prime time for Volcker rule", CNN, 10.10.2011.

1.2.2 Data Summary & Evaluation Approach

To maximize the available data, missing data points were neither imputed nor dropped immediately. An alternative approach was taken such that the missing records were dropped only for variables used in a model iteration. This approach yielded datasets of the following characteristics:



To gain an initial sense of how *trading asset ratio* changed pre- & post-announcement, this metric was tracked across time for both affected BHC and the control group (non-affected BHC). A slight decreasing trend was noted for the affected BHC group in the after DFA period and this is tested further in the following sections.

2. Evaluating Compliance with Volcker Rule

2.1 Baseline Tests Rationale & Roadmap

To validate the above hypothesis, four models were evaluated:

- **Model 1**: Naïve regression of trading ratio VS. timing of announcement ("after_dfa")
- **Model 2** : Model 1 + control variables
- **Model 3**: Model 1 + control variables + affect + interaction term ("after_dfa * affect)
- **Model 4**: Model 1 + control variables + affect + interaction term ("after_dfa * affect)+ fixed effect

The exercise starts from considering a simple model using a pre and post-announcement time split as base, then adds a control set, which includes:

Model 3 then builds in the check to see if BHCs that used to have higher trading asset ratio before the announcement of the rule would show the strongest reaction in terms of trading ratio. This is quite relevant especially given that majority of the BHCs had low or 0 trading ratios.

Model 4 seeks to control influences that are constant either over time or BHCs by adding entity and time fixed effects. This leads to the below formulation where for each BHC i in quarter t, we hypothesize the change in trading ratio to be modelled as :

$$\begin{aligned} Y_{i,t} = & \alpha + \beta_1 * afterDFA_t + \beta_2 * AFFECT_i \\ & + \beta_3 * (afterDFA_t * AFFECT_i) \\ & + \gamma_i + \delta_t + X_{i,t} + \epsilon_{i,t} \end{aligned}$$

- *affect* = average trading asset ratio during the pre-DFA period (Q3 2004 - Q2 2009)
- *after DFA* = 1 for quarters between Q3 2010 and Q2 2015
- *after DFA* = 0 for Q3 2004 to Q2 2009
- γ and δ are fixed effects that are time invariant or BHC invariant respectively
- X are control variables indicated in the infograph

2.2 Baseline Tests Outcomes and Commentary

The above model iterations were processed in Python. High level outcomes of each model are provided in Appendix B, Panel A. Detailed results, on the other hand, are shown in the code outputs (Appendix E – Snapshot of Coding). The formulation and a brief commentary for each model is provided as follows:

Model 1: Naïve regression of trading ratio VS. timing of announcement ("after_dfa")

$$trading\_ratio = \alpha + \beta_1 * after\_dfa$$

- The coefficient of *after_dfa* is positive and significant. In particular, coefficient is close to zero (0.00051)
- This implies there is no strong shift towards the lower trading asset ratios post announcement of Volcker Rule, when controlling the other effects.

Model 2 : Model 1 + control variables

$$trading\_ratio = \alpha + (\beta_1 * after\_dfa) + (\beta_2 * ln\_assets) + (\beta_3 * roa) + (\beta_4 * leverage) + (\beta_5 * liquidity) + (\beta_6 * deposit\_ratio) + (\beta_7 * credit\_ + (\beta_8 * loans\_re\_ratio) + (\beta_9 * cir) + (\beta_10 * cpp)$$

- Coefficient of the time indicator variable *after_dfa* was negative (-0.0010) and highly significant.
- There is a slight indication that affected BHCs started reducing their trading asset ratios post announcement of the Volcker Rule but still no strong shift.

Model 3: Model 1 + control variables + affect + interaction term ("after_dfa * affect)

$$trading\_ratio = \alpha + (\beta_1 * after\_dfa) + (\beta_2 * affect) + (\beta_3 * (after\_dfa * affect)) + (\beta_4 * ln\_assets) + (\beta_5 * roa) + (\beta_6 * leverage) + (\beta_7 * + (\beta_8 * deposit\_ratio) + (\beta_9 * credit\_risk) + (\beta_{10} * loans\_re\_ratio) + (\beta_{11} * cir) + (\beta_{12} * cpp)$$

- Included the *affect* variable and the interaction term "*affect*affect_dfa"*
- Purpose is to test whether the BHCs having high trading asset ratios pre-DFA responded stronger to the introduction of the Volcker Rule.
- Resulting coefficient of interaction term is negative (-0.161) and highly significant.
- This strongly indicates that the affected BHCs responded aggressively to the introduction of the Volcker Rule given magnitude of raw trading ratio values.

Model 4: Model 1 + control variables + affect + interaction term ("after_dfa * affect)+ fixed effects

$$trading\_ratio = \alpha + (\beta_1 * (after\_dfa * affect)) + (\beta_2 * ln\_assets) + (\beta_3 * roa) + (\beta_4 * leverage) + (\beta_5 * liquidity) + (\beta_6 * deposit\_ratio) + (\beta_7 + (\beta_8 * loans\_re\_ratio) + (\beta_9 * cir) + (\beta_{10} * cpp)$$

- Coefficient of interaction term is strongly negative i.e. -0.202 relative to model 3 and highly significant.
- This re-emphasizes that affected BHCs reacted aggressively to the introduction of the Volcker Rule.
- This aligns with the hypotheses that affected banks reduced their trading asset ratios post the announcement of the Volcker Rule.

2.2 Robustness Tests

To ensure these results are robust, 4 variations of the fixed effects model were run to ensure the overall model continues to be significant under various changes. The results are reported in Appendix B, Panel B.

2.2.1 Treatment Dummy

First, a difference-in-difference (DiD) approach is applied using a treatment dummy (*Affected BHC*) where affected BHC is defined as having an average trading asset ratio larger than 3% in the pre-DFA period. Treated banks had an average trading ratio of 11.4% before treatment.

Similar to model 4, the coefficient of the DiD term was negative and significant, showing that overall reduction in trading ratio for treated banks was 2.34% post-DFA . See Appendix B, Panel B, Column 1 for full results.

2.2.2 Propensity Score Matching

Secondly, propensity score matching was conducted in addition to the treatment dummy used, where treatment group observations (*affected BHC = 1*) were matched one-to-one with control group observations without replacement. Propensity scores are based on logistic regression over control variables excluding the CPP recipient indicator which was not relevant in the time period where matching was done (Q3-2005).

The regression results again produce a negative and significant DiD coefficient, showing overall reduction in trading ratio for treated banks was 2.91% post-DFA even with a drastic reduction in sample size. See Appendix B, Panel B, Column 2 for full results.

2.2.3 Pre-2007 Affectedness

Thirdly, we would like to address possible endogeneity from reverse causation in that trading ratio may cause changes in *Affect* (defined as average trading ratio pre-DFA). This is because post-financial crisis, banks may have taken steps to reduce trading ratio and hence including the 2007 to 2009 trading ratio in computing *Affect* may be endogenous. Thus, *affect (pre-2007)* was recomputed using only trading ratio data before 2007 up to the earliest available date (Q3-2004, i.e. approximately 10 quarters).

Even with *after DFA * affect (pre-2007)* substituted for *after DFA * affect*, the coefficient obtained is still negative, significant and similar to the original Model 4 (-0.205 with pre-2007 data vs -0.202 with full pre-DFA data), suggesting that changes post-financial crisis may not be a cause for concern in model robustness. See Appendix B, Panel B, Column 3 for full results.

2.2.4 Excluding non-trading BHCs

Finally, the current dataset has a significant number of BHCs with zero trading book (trading ratio = 0). As such, there may be additional unobserved factors that introduce more sources of (potentially non-constant) baseline bias from this group of BHCs. Thus, these records were excluded from the dataset and the regression with *after DFA * affect (Pre-2007)* was re-checked. Overall, the coefficient of *after DFA * affect (Pre-2007)* was still negative and significant (-0.186 with pre-2007 data vs -0.202 with full pre-DFA data), despite removal of these BHCs.

3. Conclusion

3.1 Results Interpretation

Overall, it can be concluded that affected banks did reduce trading ratio on average after the announcement of the Volcker Rule. This is evidenced by a persistent negative β_3 coefficient on the interaction term (*after DFA x affect)* that is robust under various changes in specifications. Furthermore, banks that are the most affected (*affected BHC = 1*, >3% mean trading ratio pre-DFA) showed the largest reductions overall. These affected banks had an average pre-DFA trading ratio of 11.4% and registered an average reduction of 2.34% compared to less-affected banks.

3.2 Usage of Results

While trading ratios have no doubt decreased, regulators should not interpret this as solid proof that the Volcker Rule has achieved its objectives of reducing the overall risk profile of banks in order to protect consumers. At best, this can be taken to show that from a balance sheet perspective (i.e. on paper), affected banks have indeed reduced the amount of trading assets on their balance sheet in order to comply with the rule.

However, the spirit of the rule is to ensure banks reduce risk overall, which has not been measured in this report. Further study would need to be done on whether banks' actual riskiness has changed, via studying changes in metrics that factor in some measure of returns volatility (e.g. z-score) following the announcement. Relatedly, numerous exceptions exist to the Volcker Rule which may dampen its effect overall in reigning in risk. These include exemptions from underwriting, market-making, hedging amongst other. As banks have overarching incentives to continue to grow shareholder returns, we remain skeptical of whether risk levels would meaningfully reduce as banks may continue to find permitted exceptions to maintain profitability whilst reducing prohibited trading activity.

Appendices

Appendix A - Variable Definitions & Summary Statistics

This displays the variable names, units, means, standard deviations, minimum / maximum values, number of observations and aliases in the accompanying code. Summary is taken from the full dataset (dataframe: df) before any rows with missing values are removed for regression to be performed.

Variable	Alias in Code	Unit	Mean	(Std. Dev.)	Min.	Max	N
Dependent variables							
Trading asset ratio	trading_ratio	Percent	0.27	2.00	0.00	42.97	41442
Explanatory variables and controls							
After DFA	after_dfa	Dummy	0.45	0.50	0	1	81560
Affect	affect	Percent	0.19	1.70	0	42.94	81560
Affect (pre-2007)	affectpfc	Percent	0.16	1.38	0	38.95	80200
Affected BHC	affected_bhc	Dummy	0.01	0.11	0	1	81560
Total assets (natural log)	ln_assets	ln(USD mn)	13.52	1.35	5.89	21.67	61771
Leverage ratio	leverage	Percent	9.35	4.25	-76.23	115.80	57017
Profitability	roa	Percent	0.18	0.61	-38.71	93.43	56938
Liquidity ratio	liquidity	Percent	5.36	5.18	0	84.35	55159
Deposit ratio	deposit_ratio	Percent	68.19	11.20	0	99.81	79172
Cost-income ratio	cir	Percent	53.15	35.60	-1247.83	4593.33	42382
Non-performing loan ratio	credit_risk	Percent	2.78	3.40	0	73.42	44432
Real estate loan ratio	loans_re_ratio	Percent	73.59	16.05	0	101.01	44432
CPP recipient indicator	cpp	Dummy	0.04	0.20	0	1	81560

Appendix B - Baseline Tests

Panel A reports the results of multivariate linear regression of the enactment effect of the Volcker Rule (part of the Dodd-Frank Act, hence modelled with After DFA) on the trading asset ratio of bank holding companies.

Panel B reports the results of various robustness tests on the results of the full Model 4 from Panel A.

Control variables consist of total assets, profitability, leverage ratio, liquidity ratio, deposit ratio, NPL ratio, RE loan ratio, cost-income ratio and an indicator variable of whether the bank was a recipient of the TARP CPP program.

Fixed effects are included on a quarter and BHC level in Model 4.

Significance levels are indicated by ***p<0.001, ** p<0.05, *p<0.1.

Standard errors are clustered at the BHC level and reported in parentheses.

Panel A: Baseline Tests

	(1)	(2)	(3)	(4)
Dependent variable			**Trading asset ratio**	
After DFA	0.00051**	-0.0010***	-0.00002	
	(0.00020)	(0.00021)	(0.00008)	
Affect			0.993***	
			(0.002)	
After DFA x Affect			-0.161***	-0.202***
			(0.003)	(0.047)
Controls	NO	YES	YES	YES
Fixed Effects	NO	NO	NO	YES
Observations	41,422	40,026	40,026	40,026
R-squared	0.000	0.234	0.902	0.925

Panel B: Robustness Tests

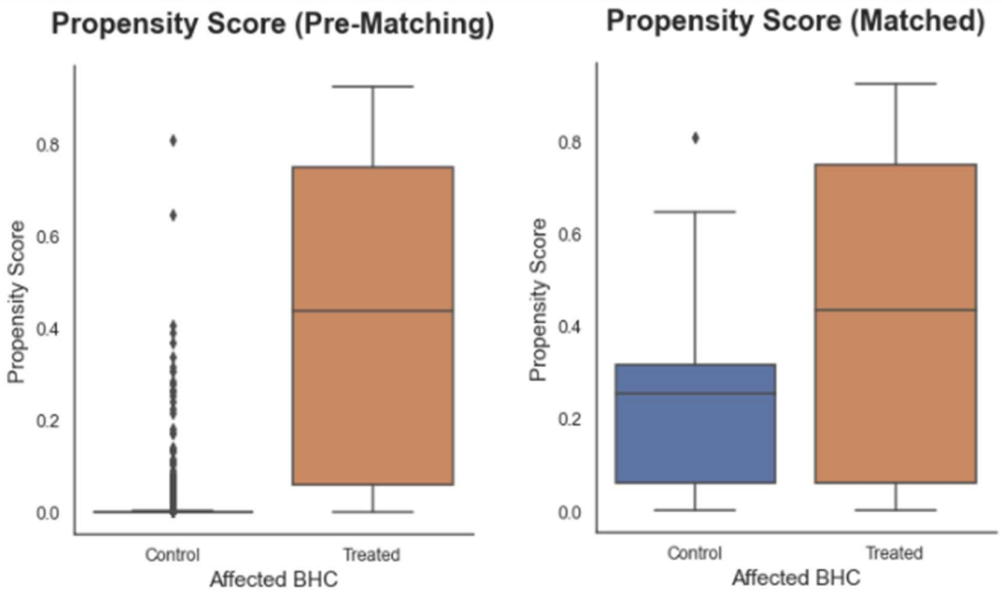
	(1)	(2)	(3)	(4)
Robustness test	**Treatment dummy**	**Propensity score matching**	**Pre-2007 affectedness**	**Excluding non-trading BHCs**
Dependent variable			**Trading asset ratio**	
After DFA x Affected BHC	-0.0234***	-0.0291***		
	(0.009)	(0.010)		
After DFA x Affect (pre-2007)			-0.205***	-0.186***
			(0.058)	(0.060)
Controls & Fixed Effects	YES	YES	YES	YES
Observations	40,026	1,228	38,783	4,493
R-squared	0.923	0.937	0.894	0.911

Appendix C - Propensity Score Matched Sample Summary Statistics

Propensity score matching was conducted as a robustness test of Model 4 and results were presented in Appendix B, Panel B, column (2). The matched sample was statistically more similar to the treatment group in the propensity for receiving treatment compared to the initial sample. **Significance levels** are indicated by ***p<0.001, ** p<0.05, *p<0.1.

The matched sample was derived from Q2-2005 which had the most number of treated instances observed in the same period (25 observations).

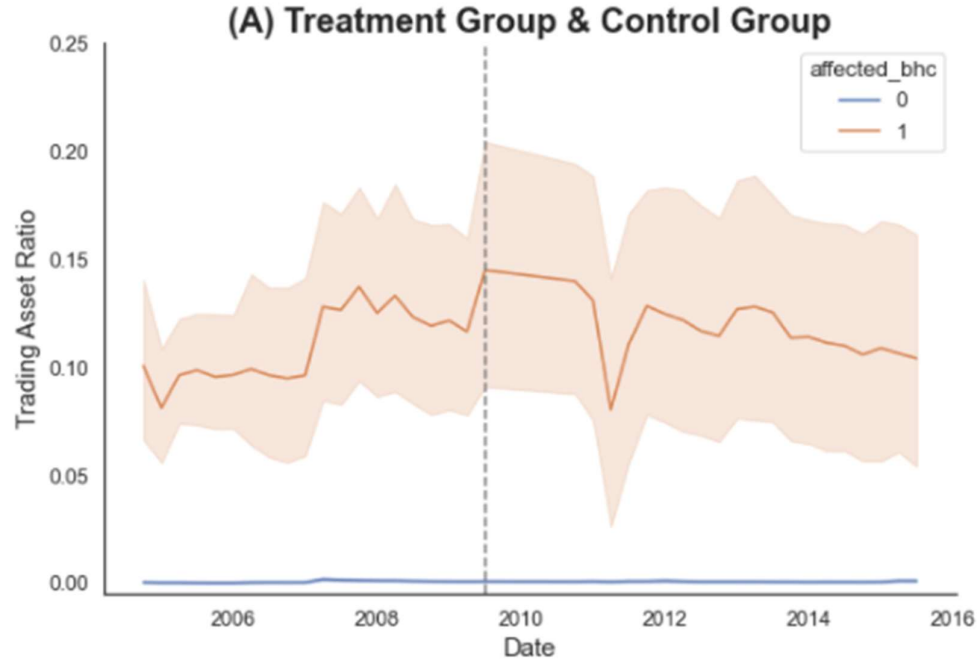
	Before Matching					After Matching				
	Control Group		Treated Group			Control Group		Treated Group		
	Mean	SD	Mean	SD	Difference	Mean	SD	Mean	SD	Difference
Dep. Variable	Affected BHC					Affected BHC				
Total assets	13.063	1.116	17.824	2.774	-4.761***	17.052	2.111	17.824	2.774	-0.771
					(0.231)					(0.697)
Leverage ratio	0.090	0.034	0.083	0.043	0.008	0.094	0.035	0.083	0.043	0.011
					(0.007)					(0.011)
Profitability	0.003	0.002	0.003	0.002	0.000	0.004	0.002	0.003	0.002	0.001**
					(0.000)					(0.001)
Liquidity ratio	0.037	0.028	0.052	0.047	-0.015***	0.058	0.075	0.052	0.047	0.006
					(0.006)					(0.018)
Deposit ratio	0.672	0.106	0.317	0.214	0.355***	0.388	0.199	0.317	0.214	0.071
					(0.022)					(0.058)
RE Loan ratio	0.727	0.148	0.495	0.256	0.233***	0.509	0.273	0.495	0.256	0.014
					(0.030)					(0.075)
Cost-income ratio	0.462	0.108	0.429	0.128	0.033	0.471	0.167	0.429	0.128	0.042
					(0.022)					(0.042)
NPL ratio	0.015	0.014	0.016	0.011	-0.001	0.014	0.011	0.016	0.011	-0.002
					(0.003)					(0.003)

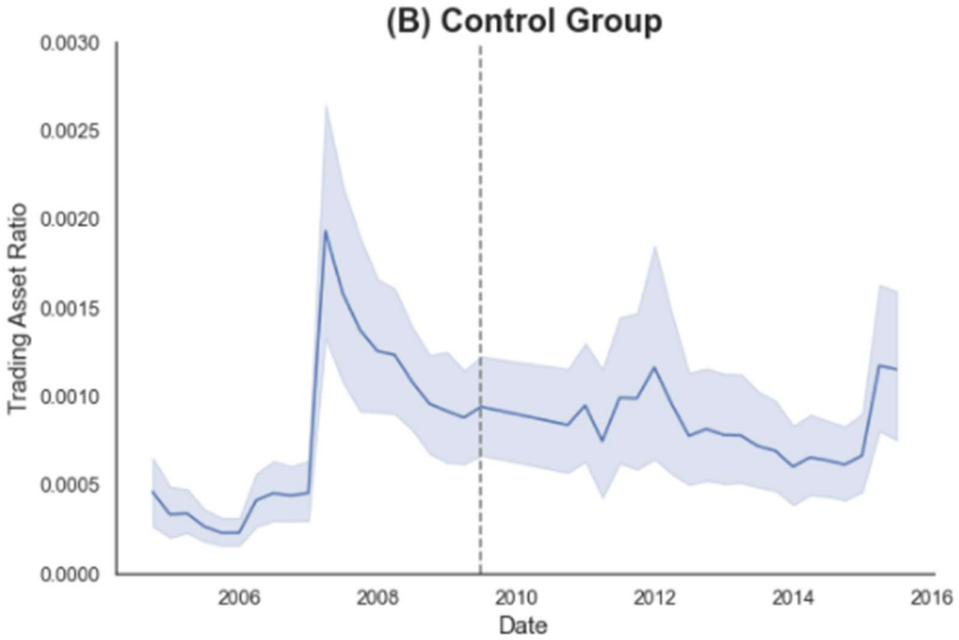


Appendix D - Figures

These figures show the quarterly trading ratio for banks in the treatment group (Panel A) and for the control group (Panel A & B) at a 95% confidence interval by quarter.

The vertical grey line represents the cut-off date (end of Q2-2009) right before the Volcker Rule was announced. Data continues from Q3-2010 onwards after the Dodd-Frank Act was signed into law. Hence, there is a gap in trend data from Q3-2009 to Q2-2010 which is not displayed here.





References

- *Jussi Keppo, Josef Korte (2016) Risk Targeting and Policy Illusions—Evidence from the Announcement of the Volcker Rule. Management Science 64(1):215-234*

Effect of Volker's Rule on BHC Trading Ratios and Risk Taking

Table of Contents

1. Import and Clean Dataset

In [1]:
```
# Import all required packages

import numpy as np
import pandas as pd
import datetime as dt

from linearmodels.panel import PooledOLS
from linearmodels.panel import PanelOLS
from linearmodels.panel.results import PanelEffectsResults
from linearmodels.panel import compare

import statsmodels.api as sm
from statsmodels.stats.weightstats import ttest_ind
from sklearn.linear_model import LogisticRegression
import seaborn as sns
import matplotlib.pyplot as plt

sns.set_style('ticks')
```

In [2]:
```
# Import data and do data integrity checks

df=pd.read_csv('DiD_data.csv')

# Clean headers, date format

df.columns=['bankcode','date','trading_ratio','affected_bhc','after_dfa','roa','leverage','ln_assets','credit_risk','cir','deposit_ratio','loans_re_ratio','liquidity','cpp']
df['date']=pd.to_datetime(df['date'], format='%Y%m%d')

# Initial sense check

results=df.describe().transpose()
results.reset_index(inplace=True)
results=results.merge(pd.DataFrame(df.isnull().sum()).reset_index(),how='left',on='index')
results=results.rename(columns={0:'missing'})
print('Columns with Missing Values')
```

```
print(results[results.missing!=0]['index'].values)
results
```

```
Columns with Missing Values
['trading_ratio' 'roa' 'leverage' 'ln_assets' 'credit_risk' 'cir'
 'deposit_ratio' 'loans_re_ratio' 'liquidity']
```

Out[2]:

	index	count	mean	std	min	25%	50%	75%	max	missing
0	bankcode	81560.0	1.803535e+06	803001.252533	1.020180e+06	1.118434e+06	1.248304e+06	2.537957e+06	3.836442e+06	0
1	trading_ratio	41442.0	2.650423e-03	0.020015	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	4.297271e-01	40118
2	affected_bhc	81560.0	1.248161e-02	0.111022	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	1.000000e+00	0
3	after_dfa	81560.0	4.511280e-01	0.497609	0.000000e+00	0.000000e+00	0.000000e+00	1.000000e+00	1.000000e+00	0
4	roa	56938.0	1.843923e-03	0.006116	-3.871374e-01	1.245900e-03	2.208552e-03	3.119110e-03	9.342769e-01	24622
5	leverage	57017.0	9.351764e-02	0.042513	-7.622810e-01	7.392833e-02	9.015964e-02	1.081844e-01	1.157965e+00	24543
6	ln_assets	61771.0	1.351636e+01	1.354361	5.888878e+00	1.262157e+01	1.323332e+01	1.394826e+01	2.166995e+01	19789
7	credit_risk	44432.0	2.775769e-02	0.033980	0.000000e+00	9.763676e-03	1.804622e-02	3.260448e-02	7.342224e-01	37128
8	cir	42382.0	5.314545e-01	0.355984	-1.247826e+01	4.133833e-01	5.023356e-01	6.152530e-01	4.593333e+01	39178
9	deposit_ratio	79172.0	6.818830e-01	0.112038	0.000000e+00	6.354172e-01	6.966798e-01	7.509852e-01	9.980935e-01	2388
10	loans_re_ratio	44432.0	7.359315e-01	0.160457	0.000000e+00	6.559185e-01	7.641267e-01	8.488745e-01	1.010109e+00	37128
11	liquidity	55159.0	5.355935e-02	0.051830	2.295185e-04	2.456928e-02	3.607538e-02	6.209538e-02	8.435430e-01	26401
12	cpp	81560.0	4.239823e-02	0.201497	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	1.000000e+00	0

1.1 Add Engineered Features and Create DataFrames

In [3]:
```
# Add qtr column for easier checks

time=pd.DataFrame(sorted(list(df.date.value_counts().index)))
time.columns=['date']
time['qtr']=time.index+1
time['qtr']= ['Q' + str(x) for x in time['qtr']]
df=pd.merge(df,time,on='date',how='left')
df=df.sort_values(by=['bankcode','date'])
```

In [4]:
```
# Compute rolling roa_std, affect_2007

roa_std=pd.DataFrame(df.groupby('bankcode', as_index=False)['roa'].rolling(7,min_periods=3).std().values)
alt_affect=pd.DataFrame(df.groupby('bankcode', as_index=False)['trading_ratio'].rolling(15).mean().replace(np.nan,0))
alt_affect['affect_pre2007']=[1 if x>=0.03 else 0 for x in alt_affect['trading_ratio'] ]
alt_affect.columns=['traderatio_roll15','affect_2007']
alt_affect=alt_affect.reset_index()[['affect_2007']]

df= pd.concat([df,roa_std,alt_affect],axis=1)
df.columns=['bankcode', 'date', 'trading_ratio', 'affected_bhc', 'after_dfa', 'roa',
       'leverage', 'ln_assets', 'credit_risk', 'cir', 'deposit_ratio',
       'loans_re_ratio', 'liquidity', 'cpp', 'qtr','roa_vol','affect_2007']

# non_trading_bhc, post_fin_crisis

df['nontrading_bhc']=[1 if x==0 else 0 for x in df['trading_ratio']]
df['post_fin_crisis']=[1 if x>2007 else 0 for x in df['date'].dt.year]
df.head()
```

Out[4]:

	bankcode	date	trading_ratio	affected_bhc	after_dfa	roa	leverage	ln_assets	credit_risk	cir	deposit_ratio	loans_re_ratio	liquidity	cpp	qtr	roa_vol	affect_2007	nontrading_bhc	post_fir

	bankcode	date	trading_ratio	affected_bhc	after_dfa	roa	leverage	ln_assets	credit_risk	cir	deposit_ratio	loans_re_ratio	liquidity	cpp	qtr	roa_vol	affect_2007	nontrading_bhc	post_fir
0	1020180	2004-09-30	0.0	0	0	0.002772	0.081957	15.601202	0.013304	0.463811	0.561805	0.593738	0.024337	0	Q1	NaN	0	1	
1	1020180	2004-12-31	0.0	0	0	0.003045	0.082480	15.630583	0.009732	0.456392	0.557617	0.601763	0.025446	0	Q2	NaN	0	1	
2	1020180	2005-03-31	0.0	0	0	0.002616	0.082074	15.644925	0.011830	0.444011	0.556980	0.600700	0.025153	0	Q3	0.000217	0	1	
3	1020180	2005-06-30	0.0	0	0	0.002647	0.081712	15.679702	0.013654	0.433771	0.571642	0.601042	0.023670	0	Q4	0.000196	0	1	
4	1020180	2005-09-30	0.0	0	0	0.002867	0.082944	15.661868	0.012456	0.400985	0.577408	0.581438	0.029793	0	Q5	0.000175	0	1	

In [5]:
```
# Add in affect (average trading ratio for pre dfa), interaction term
filt_predfa=(df['date']>='2004-07-01') & (df['date']<='2009-06-30')
affect_df=df[['bankcode','date','trading_ratio']][filt_predfa]

affect_df=affect_df.groupby('bankcode',as_index=False)['trading_ratio'].mean()
affect_df.columns=['bankcode','affect']
df=df.merge(affect_df,how='left',on='bankcode')

# Add in affect-2007 (average trading ratio for pre financial crisis), interaction terms
filt_predfa=(df['date']>='2004-07-01') & (df['date']<='2007-01-01')
affect_df=df[['bankcode','date','trading_ratio']][filt_predfa]

affect_df=affect_df.groupby('bankcode',as_index=False)['trading_ratio'].mean()
affect_df.columns=['bankcode','affectpfc']
df=df.merge(affect_df,how='left',on='bankcode')

# Interactions terms
df['afterdfa*affect']=df['after_dfa']*df['affect']
df['afterdfa*affectpfc']=df['after_dfa']*df['affectpfc']
df['afterdfa*affectbhc']=df['after_dfa']*df['affected_bhc']

df.head()
print(len(df))
```

```
81560
```

In [6]:
```
df.describe().transpose()
```

Out[6]:

	count	mean	std	min	25%	50%	75%	max
bankcode	81560.0	1.803535e+06	803001.252533	1.020180e+06	1.118434e+06	1.248304e+06	2.537957e+06	3.836442e+06
trading_ratio	41442.0	2.650423e-03	0.020015	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	4.297271e-01
affected_bhc	81560.0	1.248161e-02	0.111022	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	1.000000e+00
after_dfa	81560.0	4.511280e-01	0.497609	0.000000e+00	0.000000e+00	0.000000e+00	1.000000e+00	1.000000e+00
roa	56938.0	1.843923e-03	0.006116	-3.871374e-01	1.245900e-03	2.208552e-03	3.119110e-03	9.342769e-01
leverage	57017.0	9.351764e-02	0.042513	-7.622810e-01	7.392833e-02	9.015964e-02	1.081844e-01	1.157965e+00
ln_assets	61771.0	1.351636e+01	1.354361	5.888878e+00	1.262157e+01	1.323332e+01	1.394826e+01	2.166995e+01
credit_risk	44432.0	2.775769e-02	0.033980	0.000000e+00	9.763676e-03	1.804622e-02	3.260448e-02	7.342224e-01
cir	42382.0	5.314545e-01	0.355984	-1.247826e+01	4.133833e-01	5.023356e-01	6.152530e-01	4.593333e+01
deposit_ratio	79172.0	6.818830e-01	0.112038	0.000000e+00	6.354172e-01	6.966798e-01	7.509852e-01	9.980935e-01

	count	mean	std	min	25%	50%	75%	max
loans_re_ratio	44432.0	7.359315e-01	0.160457	0.000000e+00	6.559185e-01	7.641267e-01	8.488745e-01	1.010109e+00
liquidity	55159.0	5.355935e-02	0.051830	2.295185e-04	2.456928e-02	3.607538e-02	6.209538e-02	8.435430e-01
cpp	81560.0	4.239823e-02	0.201497	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	1.000000e+00
roa_vol	70846.0	1.369174e-03	0.004522	0.000000e+00	2.921768e-04	5.474640e-04	1.201051e-03	4.932900e-01
affect_2007	81560.0	3.273664e-03	0.057123	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	1.000000e+00
nontrading_bhc	81560.0	4.442374e-01	0.496884	0.000000e+00	0.000000e+00	0.000000e+00	1.000000e+00	1.000000e+00
post_fin_crisis	81560.0	6.081658e-01	0.488163	0.000000e+00	0.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00
affect	81560.0	1.926730e-03	0.016979	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	4.294264e-01
affectpfc	79701.0	1.365020e-03	0.012976	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	3.894519e-01
afterdfa*affect	81560.0	9.402853e-04	0.012727	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	4.294264e-01
afterdfa*affectpfc	79701.0	5.873688e-04	0.008270	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	2.941263e-01
afterdfa*affectbhc	81560.0	5.811672e-03	0.076013	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	1.000000e+00

In [7]:
```
# DataFrame to use for model 1, drop 40,118 rows with nil trading_ratio values

df_b1= df.dropna(subset=['trading_ratio'])
df_b1.describe().transpose()
```

Out[7]:

	count	mean	std	min	25%	50%	75%	max
bankcode	41442.0	1.759544e+06	805589.140458	1.020180e+06	1.108097e+06	1.209828e+06	2.467474e+06	3.836442e+06
trading_ratio	41442.0	2.650423e-03	0.020015	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	4.297271e-01
affected_bhc	41442.0	1.703586e-02	0.129406	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	1.000000e+00
after_dfa	41442.0	4.037933e-01	0.490663	0.000000e+00	0.000000e+00	0.000000e+00	1.000000e+00	1.000000e+00
roa	41328.0	1.851036e-03	0.006871	-3.871374e-01	1.298545e-03	2.245943e-03	3.119124e-03	9.342769e-01
leverage	41407.0	9.250672e-02	0.037183	-1.398172e-01	7.392285e-02	8.960092e-02	1.068090e-01	1.157965e+00
ln_assets	41442.0	1.393009e+01	1.426113	5.888878e+00	1.315108e+01	1.361323e+01	1.437415e+01	2.166995e+01
credit_risk	41426.0	2.798249e-02	0.034134	0.000000e+00	9.898671e-03	1.821179e-02	3.288328e-02	7.342224e-01
cir	41362.0	5.326924e-01	0.359555	-1.247826e+01	4.137489e-01	5.034823e-01	6.170951e-01	4.593333e+01
deposit_ratio	41440.0	6.705997e-01	0.129683	0.000000e+00	6.190178e-01	6.892053e-01	7.531588e-01	9.980935e-01
loans_re_ratio	41426.0	7.354156e-01	0.160466	0.000000e+00	6.554661e-01	7.636554e-01	8.487003e-01	1.010109e+00
liquidity	40140.0	5.012775e-02	0.048916	2.295185e-04	2.377774e-02	3.421294e-02	5.664693e-02	8.435430e-01
cpp	41442.0	6.906037e-02	0.253560	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	1.000000e+00
roa_vol	37111.0	1.172189e-03	0.002333	0.000000e+00	2.917573e-04	5.334151e-04	1.060385e-03	7.257425e-02
affect_2007	41442.0	4.536461e-03	0.067201	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	1.000000e+00
nontrading_bhc	41442.0	8.742821e-01	0.331535	0.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00
post_fin_crisis	41442.0	5.444477e-01	0.498026	0.000000e+00	0.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00
affect	41442.0	2.790370e-03	0.020825	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	4.294264e-01
affectpfc	40121.0	1.846871e-03	0.015608	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	3.894519e-01
afterdfa*affect	41442.0	1.332381e-03	0.015912	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	4.294264e-01

	count	mean	std	min	25%	50%	75%	max
afterdfa*affectpfc	40121.0	7.031473e-04	0.009370	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	2.941263e-01
afterdfa*affectbhc	41442.0	7.359683e-03	0.085473	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	1.000000e+00

In [8]:
```
# Replace any infinity values with NaN

pd.options.mode.chained_assignment = None
df_b1.replace([np.inf, -np.inf], np.nan, inplace=True)
print(df_b1.isnull().sum())
```

```
bankcode                0
date                    0
trading_ratio           0
affected_bhc            0
after_dfa               0
roa                   114
leverage               35
ln_assets               0
credit_risk            16
cir                    80
deposit_ratio           2
loans_re_ratio         16
liquidity            1302
cpp                     0
qtr                     0
roa_vol              4331
affect_2007             0
nontrading_bhc          0
post_fin_crisis         0
affect                  0
affectpfc            1321
afterdfa*affect         0
afterdfa*affectpfc   1321
afterdfa*affectbhc      0
dtype: int64
```

In [9]:
```
# DataFrame to use for model 2-4, dropped additional 1416 rows based on nil control values

drop_b2_nancols=['roa',
 'leverage',
 'credit_risk',
 'cir',
 'deposit_ratio',
 'loans_re_ratio',
 'liquidity']

df_b2=df_b1.dropna(subset=drop_b2_nancols)
df_b2.describe().transpose()
```

Out[9]:

	count	mean	std	min	25%	50%	75%	max
bankcode	40026.0	1.758412e+06	805063.671465	1.020180e+06	1.107997e+06	1.209716e+06	2.467474e+06	3.836442e+06
trading_ratio	40026.0	2.503848e-03	0.019591	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	4.297271e-01
affected_bhc	40026.0	1.566482e-02	0.124177	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	1.000000e+00
after_dfa	40026.0	3.896967e-01	0.487688	0.000000e+00	0.000000e+00	0.000000e+00	1.000000e+00	1.000000e+00
roa	40026.0	1.814628e-03	0.004791	-1.241662e-01	1.280377e-03	2.239816e-03	3.120696e-03	1.660869e-01
leverage	40026.0	9.190957e-02	0.035191	-1.367974e-01	7.360926e-02	8.920620e-02	1.063232e-01	6.933124e-01
ln_assets	40026.0	1.388976e+01	1.393736	1.049759e+01	1.313461e+01	1.358267e+01	1.431727e+01	2.166825e+01

	count	mean	std	min	25%	50%	75%	max
credit_risk	40026.0	2.832874e-02	0.034504	0.000000e+00	9.988749e-03	1.846549e-02	3.335707e-02	7.342224e-01
cir	40026.0	5.290953e-01	0.281027	-1.247826e+01	4.120157e-01	5.000958e-01	6.124870e-01	1.782285e+01
deposit_ratio	40026.0	6.732617e-01	0.125551	0.000000e+00	6.215510e-01	6.905751e-01	7.536152e-01	9.980935e-01
loans_re_ratio	40026.0	7.380457e-01	0.157675	0.000000e+00	6.584495e-01	7.654379e-01	8.496745e-01	1.010109e+00
liquidity	40026.0	4.987668e-02	0.047876	2.295185e-04	2.376944e-02	3.416439e-02	5.651428e-02	5.649345e-01
cpp	40026.0	6.925498e-02	0.253890	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	1.000000e+00
roa_vol	35925.0	1.161220e-03	0.002302	6.006708e-06	2.913425e-04	5.334151e-04	1.051269e-03	7.257425e-02
affect_2007	40026.0	4.696947e-03	0.068374	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	1.000000e+00
nontrading_bhc	40026.0	8.806776e-01	0.324172	0.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00
post_fin_crisis	40026.0	5.351771e-01	0.498767	0.000000e+00	0.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00
affect	40026.0	2.655032e-03	0.020361	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	4.294264e-01
affectpfc	38783.0	1.749196e-03	0.015373	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	3.894519e-01
afterdfa*affect	40026.0	1.214218e-03	0.015233	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	4.294264e-01
afterdfa*affectpfc	38783.0	6.325902e-04	0.008925	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	2.941263e-01
afterdfa*affectbhc	40026.0	6.470794e-03	0.080182	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	1.000000e+00

In [10]:
```
# Check if all BHCs are still represented

bhc_all=len(list(df.bankcode.value_counts().index))
bhc_df_b1=len(list(df_b1.bankcode.value_counts().index))
bhc_df_b2=len(list(df_b2.bankcode.value_counts().index))

dfs=['All','Drop Nil Trading Ratios','Drop Nil Control Values']
bhcs=[bhc_all,bhc_df_b1,bhc_df_b2]
pd.DataFrame({'DataFrame': dfs, 'BHC Scope':bhcs}).set_index('DataFrame')
```

Out[10]:

DataFrame	BHC Scope
All	2473
Drop Nil Trading Ratios	2473
Drop Nil Control Values	2428

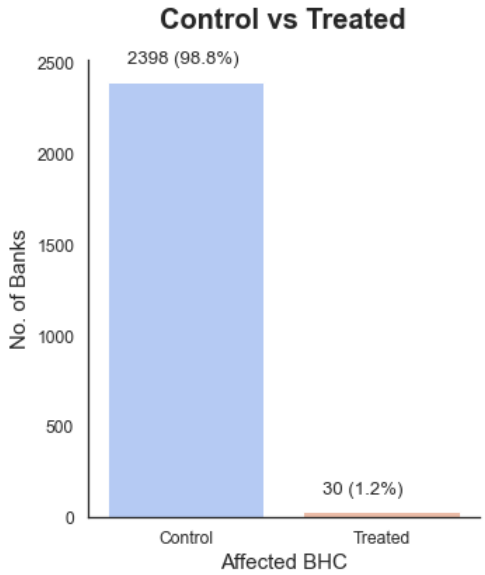
In [11]:
```
# Visualize number of treatment and control group members

for i in [df_b2]:

  df_group = i[['bankcode', 'affected_bhc']].drop_duplicates()

  sns.set(style='white',font_scale=1.1)
  fig = plt.figure(figsize=[5,6])
  ax = sns.countplot(data=df_group,x='affected_bhc',palette='coolwarm')
  ax.set_xticklabels(['Control','Treated'])
  for p in ax.patches:
          ax.annotate(str(p.get_height())+' ('+str((p.get_height()/len(df_group)*100).round(1))+'%)', (p.get_x()+0.1, p.get_height()+100))
  plt.title('Control vs Treated', weight='bold', fontsize = 20, y=1.05)
  plt.xlabel('Affected BHC', fontsize = 15)
```

```
plt.ylabel('No. of Banks', fontsize = 15)
sns.despine()
```

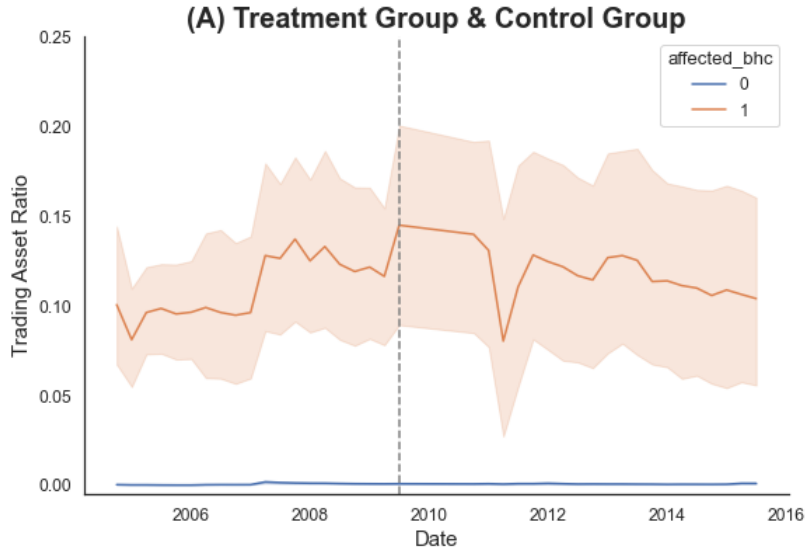


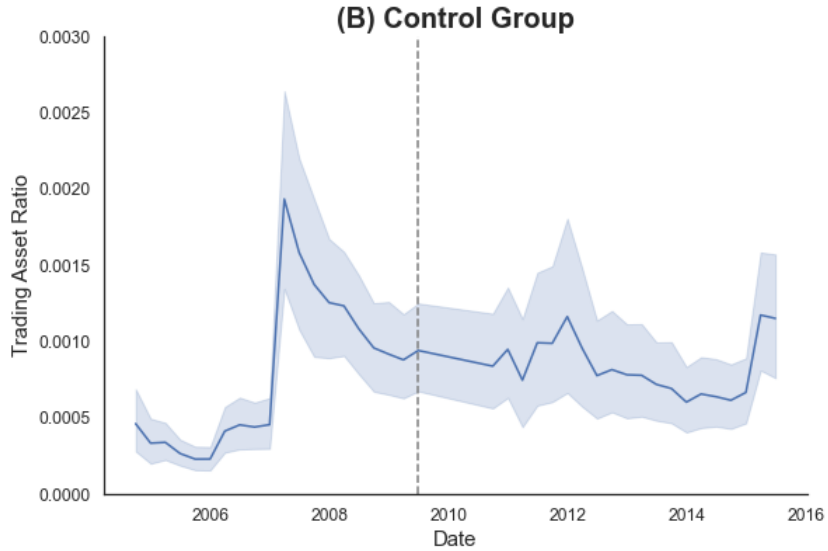
In [12]:
```
# Check the average trading ratio by affected_bhc and control_bhc over time

for i in [df_b1]:

    # Plot Treatment vs Control
    fig = plt.figure(figsize=[9,6])
    sns.lineplot(x="date", y="trading_ratio",
              hue="affected_bhc", data=i, ci = 95).axvline('2009-06-30 00:00:00', color='grey', linestyle = '--')
    plt.ylim(-0.005,0.25)
    plt.title('(A) Treatment Group & Control Group', fontweight="bold", fontsize = 20)
    plt.xlabel('Date', fontsize = 15)
    plt.ylabel('Trading Asset Ratio', fontsize = 15)
    sns.despine()

    # Plot Control Only
    control = i[i['affected_bhc']==0]
    fig = plt.figure(figsize=[9,6])
    sns.lineplot(x="date", y="trading_ratio",
                 data=control, ci = 95).axvline('2009-06-30 00:00:00', color='grey', linestyle = '--')
    plt.ylim(0,0.003)
    plt.title('(B) Control Group', fontweight="bold", fontsize = 20)
    plt.xlabel('Date', fontsize = 15)
    plt.ylabel('Trading Asset Ratio', fontsize = 15)
    sns.despine()
```





2. Evaluating Changes in Trading Book: Initial Compliance with Volcker Rule

2.1 Baseline Tests

We proceed to test our overall model as formulated for BHC i in quarter t:

$$\begin{aligned} Y_{i,t} =& \alpha + \beta_1 * afterDFA_t + \beta_2 * AFFECT_i \\ &+ \beta_3 * (afterDFA_t * AFFECT_i) \\ &+ \gamma_i + \delta_t + X_{i,t} + \epsilon_{i,t} \end{aligned} \tag{1}$$

Model 1: After_DFA without controls or fixed effects

In [13]:
```
df_test=df_b1.copy()
df_test = df_test.set_index(['bankcode', 'date'])

y = df_test['trading_ratio']
X = df_test['after_dfa']
X = sm.add_constant(X)
base_1 = sm.OLS(y,X).fit()
base_1.summary()
```

Out[13]:

OLS Regression Results

Dep. Variable:	trading_ratio	**R-squared:**	0.000
Model:	OLS	**Adj. R-squared:**	0.000
Method:	Least Squares	**F-statistic:**	6.419
Date:	Sun, 24 Oct 2021	**Prob (F-statistic):**	0.0113
Time:	23:22:48	**Log-Likelihood:**	1.0329e+05
No. Observations:	41442	**AIC:**	-2.066e+05
Df Residuals:	41440	**BIC:**	-2.066e+05
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.0024	0.000	19.207	0.000	0.002	0.003
after_dfa	0.0005	0.000	2.534	0.011	0.000	0.001

Omnibus:	71532.559	**Durbin-Watson:**	0.198
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	57471366.578
Skew:	12.333	**Prob(JB):**	0.00
Kurtosis:	183.761	**Cond. No.**	2.45

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [14]:
```
# Expand on decimal places for standard errors from Model 1
print(base_1.bse[1:2])
```

```
after_dfa    0.0002
dtype: float64
```

Model 2: After_DFA with controls, without fixed effects.

In [15]:
```
df_test=df_b2.copy()
df_test = df_test.set_index(['bankcode', 'date'])

y = df_test['trading_ratio']

keep=['after_dfa','ln_assets', 'roa', 'leverage', 'liquidity', 'deposit_ratio',
      'credit_risk','loans_re_ratio', 'cir', 'cpp']
```

```
X = df_test[keep]
X = sm.add_constant(X)

base_2 = sm.OLS(y,X).fit()
base_2.summary()
```

Out[15]:

OLS Regression Results

Dep. Variable:	trading_ratio	**R-squared:**	0.234
Model:	OLS	**Adj. R-squared:**	0.234
Method:	Least Squares	**F-statistic:**	1222.
Date:	Sun, 24 Oct 2021	**Prob (F-statistic):**	0.00
Time:	23:22:48	**Log-Likelihood:**	1.0595e+05
No. Observations:	40026	**AIC:**	-2.119e+05
Df Residuals:	40015	**BIC:**	-2.118e+05
Df Model:	10		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.0207	0.002	-13.677	0.000	-0.024	-0.018
after_dfa	-0.0010	0.000	-4.868	0.000	-0.001	-0.001
ln_assets	0.0043	7.27e-05	59.434	0.000	0.004	0.004
roa	0.0321	0.022	1.484	0.138	-0.010	0.075
leverage	-0.0495	0.003	-19.054	0.000	-0.055	-0.044
liquidity	-0.0006	0.002	-0.297	0.766	-0.005	0.003
deposit_ratio	-0.0337	0.001	-41.532	0.000	-0.035	-0.032
credit_risk	0.0203	0.003	7.224	0.000	0.015	0.026
loans_re_ratio	-0.0138	0.001	-23.362	0.000	-0.015	-0.013
cir	0.0010	0.000	2.921	0.003	0.000	0.002
cpp	-0.0016	0.000	-4.407	0.000	-0.002	-0.001

Omnibus:	63938.993	**Durbin-Watson:**	0.174
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	43593657.697
Skew:	10.478	**Prob(JB):**	0.00
Kurtosis:	163.312	**Cond. No.**	3.55e+03

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 3.55e+03. This might indicate that there are
strong multicollinearity or other numerical problems.

In [16]:
```
# Expand on decimal places for standard errors from Model 2
print(base_2.bse[1:2])
```

```
after_dfa    0.000213
```

```
dtype: float64
```

Model 3: After_DFA, Affect and After_DFA * Affect with controls, without fixed effects.

In [17]:
```
df_test=df_b2.copy()
df_test = df_test.set_index(['bankcode', 'date'])

y = df_test['trading_ratio']

keep=['after_dfa', 'affect', 'afterdfa*affect','ln_assets', 'roa', 'leverage', 'liquidity', 'deposit_ratio',
      'credit_risk','loans_re_ratio', 'cir', 'cpp']

X = df_test[keep]
X = sm.add_constant(X)

full_model = sm.OLS(y,X).fit()
full_model.summary()
```

Out[17]:

OLS Regression Results

Dep. Variable:	trading_ratio	**R-squared:**	0.902
Model:	OLS	**Adj. R-squared:**	0.902
Method:	Least Squares	**F-statistic:**	3.061e+04
Date:	Sun, 24 Oct 2021	**Prob (F-statistic):**	0.00
Time:	23:22:49	**Log-Likelihood:**	1.4705e+05
No. Observations:	40026	**AIC:**	-2.941e+05
Df Residuals:	40013	**BIC:**	-2.940e+05
Df Model:	12		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.0030	0.001	-5.469	0.000	-0.004	-0.002
after_dfa	-2.039e-05	7.68e-05	-0.266	0.791	-0.000	0.000
affect	0.9925	0.002	402.166	0.000	0.988	0.997
afterdfa*affect	-0.1611	0.003	-52.818	0.000	-0.167	-0.155
ln_assets	0.0002	2.72e-05	8.258	0.000	0.000	0.000
roa	-0.0051	0.008	-0.656	0.512	-0.020	0.010
leverage	0.0013	0.001	1.338	0.181	-0.001	0.003
liquidity	-0.0005	0.001	-0.709	0.479	-0.002	0.001
deposit_ratio	0.0004	0.000	1.298	0.194	-0.000	0.001
credit_risk	0.0017	0.001	1.724	0.085	-0.000	0.004
loans_re_ratio	-0.0007	0.000	-3.500	0.000	-0.001	-0.000
cir	0.0002	0.000	1.465	0.143	-6.33e-05	0.000
cpp	-0.0002	0.000	-1.936	0.053	-0.000	3.08e-06

Omnibus:	51911.637	**Durbin-Watson:**	0.524
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	103525182.575
Skew:	6.371	**Prob(JB):**	0.00

Kurtosis:	251.822	**Cond. No.**	3.55e+03

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 3.55e+03. This might indicate that there are
strong multicollinearity or other numerical problems.

In [18]:
```
# Expand on decimal places for standard errors from Model 3
print(full_model.bse[1:4])
```

```
after_dfa          0.000077
affect             0.002468
afterdfa*affect    0.003051
dtype: float64
```

Model 4: After_DFA * Affect with controls and fixed effects.

In [19]:
```
df_fe=df_b2.copy()
df_fe['bankcodecluster'] = df_fe['bankcode']

keep=['afterdfa*affect','ln_assets', 'roa', 'leverage', 'liquidity', 'deposit_ratio',
      'credit_risk','loans_re_ratio', 'cir', 'cpp', 'bankcode','date','bankcodecluster']

X_clean = df_fe[keep]
X_clean=pd.get_dummies(data=X_clean,columns=['bankcode','date'])

X = X_clean.drop(['bankcodecluster'], axis = 1)

y=df_fe['trading_ratio']

# Specify clustering to ensure standard errors are clustered by bankcode
full_model_fe = sm.OLS(y,X).fit(cov_type = 'cluster', cov_kwds={'groups': X_clean['bankcodecluster']})
```

In [20]:
```
# Define a function to print out statsmodel statistics excluding fixed effects dummies
def sm_summary(model):
    params = model.params[0:10]
    stderr = model.bse[0:10]
    pval = model.pvalues[0:10]
    tstat = model.tvalues[0:10]
    summary_statistics = {'beta':params, 'std_error': stderr, 'p-value': pval, 'tstat': tstat}
    summary = pd.DataFrame(summary_statistics).round(4)
    print('Results (fixed effects parameters not shown):')
    print('R-squared:'+str(round(model.rsquared,4)))
    print('Number of observations:'+str(model.nobs))
    print('Errors clustered at the entity level.')
    return summary
```

In [21]:
```
sm_summary(full_model_fe)
```

```
Results (fixed effects parameters not shown):
R-squared:0.9253
Number of observations:40026.0
Errors clustered at the entity level.
```

Out[21]:

	beta	std_error	p-value	tstat
afterdfa*affect	-0.2024	0.0470	0.0000	-4.3047
ln_assets	-0.0002	0.0005	0.7499	-0.3188

	beta	std_error	p-value	tstat
roa	0.0064	0.0080	0.4211	0.8045
leverage	0.0048	0.0038	0.2065	1.2633
liquidity	-0.0012	0.0028	0.6596	-0.4405
deposit_ratio	0.0007	0.0011	0.5409	0.6114
credit_risk	0.0010	0.0019	0.6133	0.5053
loans_re_ratio	-0.0103	0.0046	0.0242	-2.2539
cir	0.0003	0.0002	0.0569	1.9042
cpp	-0.0000	0.0004	0.9878	-0.0152

2.2 Robustness Tests

2.2.1 Treatment Dummy

Run Model 4 with treatment dummy (After_DFA *AffectedBHC) instead of interaction term (After_DFA* Affect).

In [22]:
```
df_fe=df_b2.copy()
df_fe['bankcodecluster'] = df_fe['bankcode']

keep=['afterdfa*affectbhc','ln_assets', 'roa', 'leverage', 'liquidity', 'deposit_ratio',
      'credit_risk','loans_re_ratio', 'cir', 'cpp', 'bankcode','date', 'bankcodecluster']

X_clean = df_fe[keep]
X_clean=pd.get_dummies(data=X_clean,columns=['bankcode','date'])

X = X_clean.drop(['bankcodecluster'], axis = 1)

y=df_fe['trading_ratio']

# Specify clustering to ensure standard errors are clustered by bankcode
treatdum_fe = sm.OLS(y,X).fit(cov_type = 'cluster', cov_kwds={'groups': X_clean['bankcodecluster']})

sm_summary(treatdum_fe)
```

```
Results (fixed effects parameters not shown):
R-squared:0.9229
Number of observations:40026.0
Errors clustered at the entity level.
```

Out[22]:

	beta	std_error	p-value	tstat
afterdfa*affectbhc	-0.0234	0.0088	0.0079	-2.6571
ln_assets	-0.0001	0.0005	0.8293	-0.2155
roa	0.0062	0.0077	0.4196	0.8072
leverage	0.0022	0.0048	0.6488	0.4554
liquidity	-0.0004	0.0030	0.8922	-0.1355
deposit_ratio	0.0008	0.0012	0.5382	0.6155
credit_risk	-0.0000	0.0020	0.9928	-0.0090
loans_re_ratio	-0.0096	0.0046	0.0381	-2.0741
cir	0.0003	0.0002	0.0642	1.8508
cpp	-0.0002	0.0005	0.6781	-0.4150

In [23]:
```
# Finding mean of trading_ratio for affected BHCs only
tradingratio_afbhc = df_b2[df_b2['affected_bhc']==1][df_b2['after_dfa']==0]['trading_ratio'].mean()
print('Mean trading ratio of affected BHCs before DFA:{a:.2f}%'.format(a=tradingratio_afbhc*100.0))
```

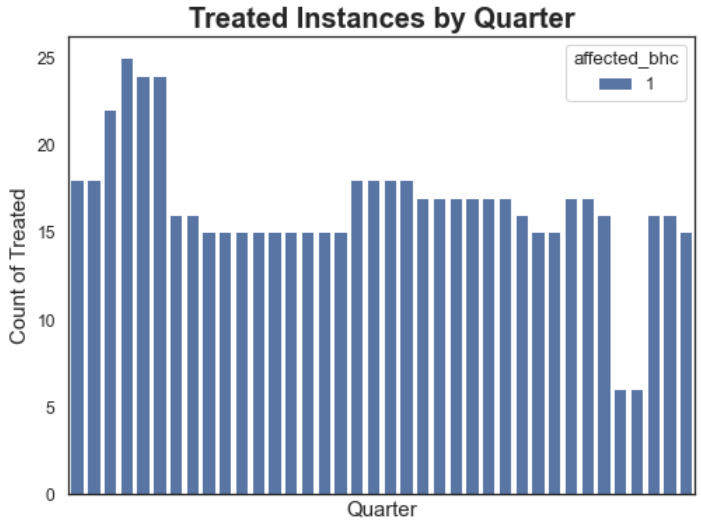
```
Mean trading ratio of affected BHCs before DFA:11.36%
<ipython-input-23-98230e34738c>:2: UserWarning: Boolean Series key will be reindexed to match DataFrame index.
  tradingratio_afbhc = df_b2[df_b2['affected_bhc']==1][df_b2['after_dfa']==0]['trading_ratio'].mean()
```

2.2.2 Propensity Score Matching

Select a control group using Propensity Score Matching

In [24]:
```
# The following shows that the 4th quarter of data is most appropriate to run propensity score
# matching with max number of control samples.

fig = plt.figure(figsize=[8,6])
sns.countplot(x='date', hue="affected_bhc", data=df_b2[df_b2['affected_bhc']==1])
plt.title('Treated Instances by Quarter', fontweight="bold", fontsize = 20)
plt.xlabel('Quarter', fontsize = 15)
plt.ylabel('Count of Treated', fontsize = 15)
plt.tick_params(axis='x', which='both', bottom=False, top=False, labelbottom=False)
plt.show()
```



Filter out 2005-06-30 quarter data to perform Propensity Scoring and Matching

In [25]:
```
# Use 2005-06-30 (Captures 25 affected_bha)
df_prop = df_b2[df_b2['date'] == '2005-06-30 00:00:00']

# Keep only the factors which contribute to similarity of banks in receiving treatment (>3% trading asset ratio)
df_prop = df_prop[['bankcode', 'affected_bhc', 'ln_assets', 'leverage', 'roa', 'liquidity',
                   'deposit_ratio', 'loans_re_ratio', 'cir', 'credit_risk']]

# Reset index, preserve bankcode to link back
df_prop.reset_index(inplace = True, drop=True)

# Dataframe of bank features
df_prop.head()
```

Out[25]:

	bankcode	affected_bhc	ln_assets	leverage	roa	liquidity	deposit_ratio	loans_re_ratio	cir	credit_risk
0	1020180	0	15.679702	0.081712	0.002647	0.023670	0.571642	0.601042	0.433771	0.013654
1	1020201	1	18.788057	0.078767	0.001485	0.046566	0.362995	0.642943	0.372252	0.015216
2	1020395	0	12.374304	0.071236	0.005520	0.045001	0.697034	0.692422	0.350210	0.009197
3	1020582	0	12.402913	0.124981	0.005700	0.032582	0.634618	0.779218	0.378423	0.004032
4	1020676	0	13.421321	0.046549	0.000888	0.028740	0.534096	0.638958	0.669077	0.036593

Perform Scoring using Logistic Regression

In [26]:

```
# Set a random seed
np.random.seed(1111)

# Split into X and y for Logistic Regression
X = df_prop[['ln_assets', 'leverage', 'roa', 'liquidity', 'deposit_ratio', 'loans_re_ratio', 'cir','credit_risk']]
y = df_prop['affected_bhc']

# Initialize a Logistic Regression classifier with a large C to turn off regularisation
propensity = LogisticRegression(C = 100)
propensity.fit(X, y)

# Get propensity score (probability that bank is in class 1)
pscore = propensity.predict_proba(X)
df_prop['propensity_score'] = pscore[:,1]

# Take only the columns with propensity scores to do matching
prop_cols = ['bankcode','propensity_score']
df_prop_control = df_prop[df_prop['affected_bhc']==0][prop_cols]
df_prop_treated = df_prop[df_prop['affected_bhc']==1][prop_cols]

# Shuffle the treated group and reset index for for-loop
df_prop_treated_reset = df_prop_treated.sample(frac=1).reset_index(drop=True)

# Match only the nearest neighbour
n = 1

# Set index of control as bankcodes to allow joining later
df_dist = df_prop_control.set_index('bankcode')

# Set up a list to collect the indices of matched pairs
matched = []

# For each point in treated, find the index locations in the control group with the closest score
for i in range(len(df_prop_treated_reset)):
    df_dist['diff'] = df_dist['propensity_score'] - df_prop_treated_reset.iloc[i,1]

    # Select point(s) with the closest absolute value difference from the treated point
    closest = df_dist[['diff']].abs().nsmallest(columns = 'diff', n=n)

    # Remove sampled point from the dataset (sampling without replacement)
    df_dist = df_dist.drop(closest.index)

    # Collect the n closest points for each treatment point and the treatment point
    matched.append(closest.index.to_list())
    matched.append([df_prop_treated_reset.iloc[i,0]])

# Unpack the selected control list
matched_unpack = []
for sublist in matched:
    for item in sublist:
```

```
        matched_unpack.append(item)

# Convert selected controls + treatment list to a DataFrame
matched_df = pd.DataFrame(matched_unpack, columns =['bankcode'])

# Use selected control list to innerjoin the propensity df and recover details
matched_df = pd.merge(df_prop, matched_df, on='bankcode')

# Final dataframe with 25 test instances matched with 25 control instances
# Sort by the order of matching
sorter = matched_unpack
matched_df['bankcode'] = matched_df['bankcode'].astype("category")
matched_df['bankcode'].cat.set_categories(sorter, inplace=True)
matched_df.sort_values(['bankcode'],inplace=True)

print('Rows: '+str(len(matched_df)))
matched_df
```

```
Rows: 50
```

Out[26]:

	bankcode	affected_bhc	ln_assets	leverage	roa	liquidity	deposit_ratio	loans_re_ratio	cir	credit_risk	propensity_score
38	2307280	0	17.653505	0.024267	0.000724	0.051802	0.020084	0.096453	0.169943	0.005400	0.808690
41	2816906	1	19.718945	0.012703	0.000816	0.095237	0.014958	0.281824	0.210076	0.012355	0.916653
44	2945824	0	19.759441	0.068822	0.006034	0.000520	0.008836	0.753158	0.825331	0.002539	0.645551
33	1951350	1	21.160093	0.073600	0.003340	0.037994	0.109765	0.383825	0.395564	0.028513	0.923534
11	1071191	0	13.632062	0.094215	0.002407	0.033870	0.696862	0.644261	0.446683	0.014095	0.002644
30	1417360	1	12.464819	0.066302	0.001457	0.020476	0.535435	0.568976	0.514551	0.009012	0.002646
8	1068762	0	17.428902	0.111515	0.003359	0.138654	0.249106	0.366019	0.634348	0.004448	0.241432
22	1131787	1	18.945129	0.098125	0.002791	0.026055	0.473088	0.587738	0.448842	0.011262	0.240203
23	1199563	0	16.849295	0.097834	0.003582	0.018513	0.478164	0.706010	0.357780	0.014888	0.061500
14	1094640	1	17.430975	0.059120	0.002840	0.024599	0.479826	0.785421	0.536421	0.014529	0.060122
19	1120754	0	19.890814	0.089416	0.004393	0.036310	0.412157	0.628391	0.480767	0.022974	0.407470
3	1032473	1	17.842522	0.074628	0.000939	0.135845	0.105737	0.037500	0.457071	0.008376	0.681403
39	2337045	0	16.333740	0.063193	0.003633	0.002716	0.258604	0.000000	0.486520	0.000000	0.315365
0	1020201	1	18.788057	0.078767	0.001485	0.046566	0.362995	0.642943	0.372252	0.015216	0.313860
18	1119794	0	19.133537	0.097178	0.005571	0.030687	0.423236	0.455451	0.388848	0.011844	0.391849
48	3232325	1	19.735331	0.079888	0.002137	0.029474	0.143461	0.598670	0.339739	0.041571	0.729646
37	2277860	0	17.858492	0.172174	0.009431	0.046289	0.421833	0.004669	0.453919	0.035858	0.367646
6	1042351	1	20.694307	0.102694	0.004287	0.052629	0.171628	0.394569	0.380156	0.029583	0.865452
31	1871159	0	17.959209	0.205157	0.010158	0.102150	0.432136	0.032327	0.468029	0.034416	0.336761
5	1039502	1	20.881365	0.089686	0.000846	0.041456	0.231952	0.377931	0.581872	0.017612	0.814823
25	1199769	0	18.515608	0.100083	0.002323	0.019826	0.339165	0.584409	0.426992	0.020807	0.307424
17	1111435	1	18.462543	0.060044	0.002152	0.215532	0.031881	0.000000	0.560026	0.000627	0.796612
46	3157473	0	13.318555	0.071282	0.006014	0.229175	0.435291	0.721389	0.363915	0.010547	0.005371
45	3123638	1	13.447393	0.075220	0.001735	0.050186	0.428885	0.786206	0.477902	0.012982	0.005373
15	1099195	0	12.462415	0.076690	0.001715	0.027110	0.750313	0.568126	0.493310	0.015532	0.001038

	bankcode	affected_bhc	ln_assets	leverage	roa	liquidity	deposit_ratio	loans_re_ratio	cir	credit_risk	propensity_score
34	1966783	1	13.743006	0.113653	0.001953	0.011962	0.839936	0.910883	0.337947	0.004537	0.001037
24	1199611	0	17.649693	0.072409	0.003193	0.282666	0.193571	0.489207	0.489704	0.009975	0.285449
42	2872407	1	19.029060	0.063594	0.001521	0.054621	0.285618	0.584844	0.370109	0.015526	0.463363
1	1026632	0	17.654425	0.092517	0.004015	0.199894	0.238526	0.351391	0.624425	0.000836	0.279059
40	2549857	1	18.882008	0.076467	0.003832	0.005296	0.188380	0.954187	0.322106	0.028070	0.381563
9	1069125	0	18.785152	0.090043	0.004390	0.030019	0.384507	0.678725	0.415080	0.023358	0.265984
43	2914521	1	19.101725	0.008295	-0.000384	0.001783	0.000044	0.602681	0.135487	0.007053	0.829590
10	1070345	0	18.451788	0.088603	0.004053	0.026123	0.446401	0.465619	0.396521	0.012836	0.262223
13	1073757	1	20.947247	0.081251	0.003778	0.031590	0.328332	0.564487	0.332699	0.013440	0.750053
28	1247633	0	15.673128	0.096584	0.002872	0.023960	0.485257	0.731421	0.477090	0.015180	0.021747
16	1107205	1	14.289759	0.114801	0.005516	0.088232	0.460365	0.308047	0.455065	0.010776	0.021690
36	2132932	0	17.042768	0.129429	0.003471	0.008691	0.435450	0.995349	0.163761	0.003345	0.061771
32	1883693	1	16.582712	0.093626	0.003263	0.038549	0.522941	0.464167	0.433559	0.013803	0.061079
2	1029884	0	15.635015	0.083345	0.002338	0.023162	0.570075	0.713714	0.456684	0.010456	0.015840
27	1246159	1	13.845728	0.242339	0.006794	0.076357	0.489068	0.000000	0.774996	0.000000	0.015644
49	3305461	0	18.436378	0.114703	0.000586	0.012080	0.004264	0.999932	0.977789	0.000004	0.254368
4	1033470	1	18.451307	0.094177	0.003986	0.106141	0.199772	0.183077	0.548293	0.014208	0.582712
7	1068025	0	18.326481	0.080213	0.003211	0.038120	0.443305	0.451304	0.490092	0.012867	0.227023
29	1379552	1	18.792414	0.033219	0.000590	0.021261	0.258267	0.579356	0.457749	0.020735	0.436171
20	1123223	0	12.391140	0.071524	0.003771	0.021078	0.746084	0.357300	0.469456	0.017898	0.001635
35	2052601	1	12.565323	0.102095	0.003648	0.040101	0.642622	0.593971	0.500832	0.009094	0.001634
26	1199844	0	17.824869	0.092850	0.003964	0.033733	0.435105	0.366475	0.439939	0.007661	0.217069
12	1073551	1	20.053522	0.092641	0.003240	0.026945	0.482483	0.573823	0.443495	0.010443	0.404020
21	1129382	0	17.644478	0.069479	0.002903	0.019324	0.389612	0.552075	0.387097	0.043705	0.182426
47	3232316	1	19.735893	0.080011	0.002130	0.029452	0.143380	0.599122	0.339904	0.041602	0.729545

In [27]:
```
# Find all banks where affected_bhc = 0 and NOT selected as control from the larger df dataset
df_control = df_b2[df_b2['affected_bhc'] == 0]
df_treated = df_b2[df_b2['affected_bhc'] == 1]
matched_control = matched_df[matched_df['affected_bhc'] == 0]['bankcode']

# Use inner join to filter out only matched banks' data
df_control_new = pd.merge(df_control, matched_control, on='bankcode')

# Now regression can be run as per normal using df_matched
df_matched = pd.concat([df_control_new,df_treated])

# Total number of records left after propensity score matching
print(len(df_matched))
df_matched.head()
```

```
1228
```

Out[27]:

	bankcode	date	trading_ratio	affected_bhc	after_dfa	roa	leverage	ln_assets	credit_risk	cir	...	qtr	roa_vol	affect_2007	nontrading_bhc	post_fin_crisis	affect	affectpfc	afterdfa*affe

	bankcode	date	trading_ratio	affected_bhc	after_dfa	roa	leverage	ln_assets	credit_risk	cir	...	qtr	roa_vol	affect_2007	nontrading_bhc	post_fin_crisis	affect	affectpfc	afterdfa*affe
0	1026632	2004-09-30	0.016441	0	0	-0.000870	0.099590	17.642731	0.000499	0.855045	...	Q1	NaN	0	0	0	0.008199	0.008124	0
1	1026632	2004-12-31	0.012458	0	0	0.001124	0.096071	17.668482	0.003892	0.778730	...	Q2	0.000237	0	0	0	0.008199	0.008124	0
2	1026632	2005-03-31	0.010848	0	0	0.003098	0.092590	17.652916	0.002742	0.675167	...	Q3	0.000205	0	0	0	0.008199	0.008124	0
3	1026632	2005-06-30	0.006535	0	0	0.004015	0.092517	17.654425	0.000836	0.624425	...	Q4	0.000251	0	0	0	0.008199	0.008124	0
4	1026632	2005-09-30	0.005510	0	0	0.004498	0.094363	17.630426	0.000541	0.615542	...	Q5	0.000239	0	0	0	0.008199	0.008124	0

5 rows × 24 columns

Run Model 4 with matched sample and After_DFA * AffectedBHC.

In [28]:
```
df_fe=df_matched.copy()
df_fe['bankcodecluster'] = df_fe['bankcode']

keep=['afterdfa*affectbhc','ln_assets', 'roa', 'leverage', 'liquidity', 'deposit_ratio',
      'credit_risk','loans_re_ratio', 'cir', 'cpp', 'bankcode','date', 'bankcodecluster']

X_clean = df_fe[keep]
X_clean=pd.get_dummies(data=X_clean,columns=['bankcode','date'])

X = X_clean.drop(['bankcodecluster'], axis = 1)

y=df_fe['trading_ratio']

# Specify clustering to ensure standard errors are clustered by bankcode
propscore_fe = sm.OLS(y,X).fit(cov_type = 'cluster', cov_kwds={'groups': X_clean['bankcodecluster']})
sm_summary(propscore_fe)
```

```
Results (fixed effects parameters not shown):
R-squared:0.9372
Number of observations:1228.0
Errors clustered at the entity level.
```

Out[28]:

	beta	std_error	p-value	tstat
afterdfa*affectbhc	-0.0291	0.0096	0.0025	-3.0259
ln_assets	-0.0005	0.0095	0.9607	-0.0493
roa	-0.4521	0.2680	0.0916	-1.6871
leverage	0.0490	0.1540	0.7505	0.3180
liquidity	-0.0182	0.0581	0.7544	-0.3129
deposit_ratio	0.0807	0.0494	0.1026	1.6323
credit_risk	0.1018	0.0731	0.1638	1.3924
loans_re_ratio	-0.0996	0.0425	0.0191	-2.3441
cir	0.0007	0.0005	0.1662	1.3845
cpp	-0.0040	0.0075	0.5994	-0.5252

2.2.3 Pre-2007 Affectedness Ratio

Run Model 4 with After_DFA *Affect (pre-2007) (known as afterdfa*affectpfc).

In [29]:
```
drop_b3_nancols=['affectpfc','afterdfa*affectpfc']

df_b3=df_b2.dropna(subset=drop_b3_nancols)
```

In [30]:
```
df_fe=df_b3.copy()
df_fe['bankcodecluster'] = df_fe['bankcode']

keep=['afterdfa*affectpfc','ln_assets', 'roa', 'leverage', 'liquidity', 'deposit_ratio',
      'credit_risk','loans_re_ratio', 'cir', 'cpp', 'bankcode','date', 'bankcodecluster']

X_clean = df_fe[keep]
X_clean=pd.get_dummies(data=X_clean,columns=['bankcode','date'])

X = X_clean.drop(['bankcodecluster'], axis = 1)

y=df_fe['trading_ratio']

# Specify clustering to ensure standard errors are clustered by bankcode
pfc_fe = sm.OLS(y,X).fit(cov_type = 'cluster', cov_kwds={'groups': X_clean['bankcodecluster']})

sm_summary(pfc_fe)
```

```
Results (fixed effects parameters not shown):
R-squared:0.8939
Number of observations:38783.0
Errors clustered at the entity level.
```

Out[30]:

	beta	std_error	p-value	tstat
afterdfa*affectpfc	-0.2052	0.0578	0.0004	-3.5530
ln_assets	-0.0002	0.0005	0.6499	-0.4539
roa	0.0123	0.0079	0.1196	1.5566
leverage	0.0056	0.0040	0.1609	1.4021
liquidity	-0.0024	0.0029	0.4054	-0.8321
deposit_ratio	0.0004	0.0011	0.7427	0.3282
credit_risk	0.0021	0.0020	0.2933	1.0508
loans_re_ratio	-0.0068	0.0037	0.0618	-1.8677
cir	0.0004	0.0002	0.0356	2.1015
cpp	0.0001	0.0004	0.7676	0.2955

2.2.4 Excluding non-trading BHCs

Run Model 4 with After_DFA *Affect (pre-2007) (known as afterdfa*affectpfc), excluding non-trading BHCs.

In [31]:
```
df_fe=df_b3.copy()
df_fe = df_fe[df_fe['nontrading_bhc']==0]
df_fe['bankcodecluster'] = df_fe['bankcode']

keep=['afterdfa*affectpfc','ln_assets', 'roa', 'leverage', 'liquidity', 'deposit_ratio',
      'credit_risk','loans_re_ratio', 'cir', 'cpp', 'bankcode','date', 'bankcodecluster']

X_clean = df_fe[keep]
X_clean=pd.get_dummies(data=X_clean,columns=['bankcode','date'])
```

```
X = X_clean.drop(['bankcodecluster'], axis = 1)

y=df_fe['trading_ratio']

# Specify clustering to ensure standard errors are clustered by bankcode
ntbhc_fe = sm.OLS(y,X).fit(cov_type = 'cluster', cov_kwds={'groups': X_clean['bankcodecluster']})

sm_summary(ntbhc_fe)
```

```
Results (fixed effects parameters not shown):
R-squared:0.9108
Number of observations:4493.0
Errors clustered at the entity level.
```

Out[31]:

	beta	std_error	p-value	tstat
afterdfa*affectpfc	-0.1858	0.0601	0.0020	-3.0938
ln_assets	0.0014	0.0044	0.7451	0.3251
roa	0.0431	0.0520	0.4070	0.8292
leverage	0.0361	0.0498	0.4690	0.7241
liquidity	-0.0107	0.0162	0.5092	-0.6601
deposit_ratio	0.0012	0.0078	0.8743	0.1582
credit_risk	0.0328	0.0226	0.1461	1.4536
loans_re_ratio	-0.0315	0.0214	0.1400	-1.4757
cir	0.0012	0.0005	0.0132	2.4787
cpp	-0.0006	0.0024	0.7898	-0.2666

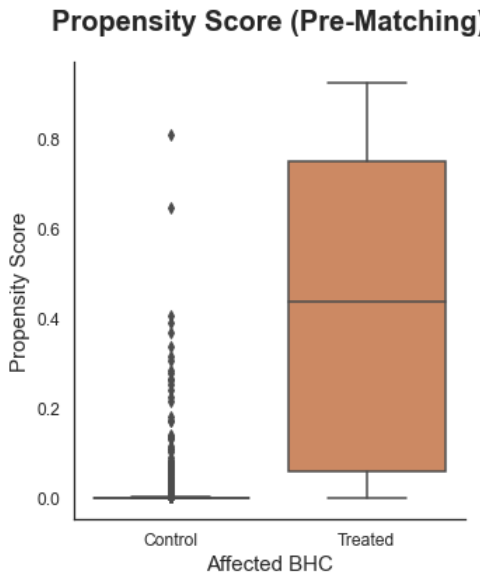
4. Appendix

4.1 Propensity Scoring: Comparison of Sample Statistics Before & After Matching

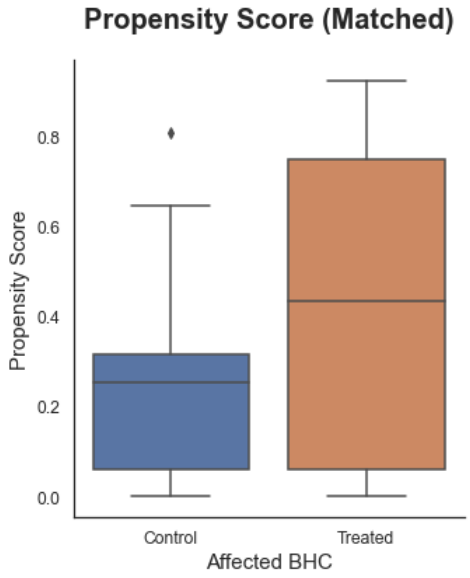
The following plots show that the matched sample has much closer propensity scores to the treated sample, which can help to control for confounding variables between both samples despite loss of data.

In [32]:

```
fig = plt.figure(figsize=[5,6])
ax = sns.boxplot(x="affected_bhc", y="propensity_score", data=df_prop)
ax.set_xticklabels(['Control','Treated'])
plt.xlabel('Affected BHC', fontsize = 15)
plt.ylabel('Propensity Score', fontsize = 15)
plt.title('Propensity Score (Pre-Matching)', weight='bold', fontsize = 20, y=1.05)
sns.despine()
```



In [33]:
```
fig = plt.figure(figsize=[5,6])
ax = sns.boxplot(x="affected_bhc", y="propensity_score", data=matched_df)
ax.set_xticklabels(['Control','Treated'])
plt.xlabel('Affected BHC', fontsize = 15)
plt.ylabel('Propensity Score', fontsize = 15)
plt.title('Propensity Score (Matched)', weight='bold', fontsize = 20, y=1.05)
sns.despine()
```



Prior to matching, control and treated groups were significantly different (at $p < 0.05$) for **ln_assets, liquidity, deposit_ratio and loans_re_ratio**.

After matching, only **roa** is significantly different.

In [34]:
```
# Summary Statistics Before Matching
prop_control = df_prop[df_prop['affected_bhc'] == 0]
prop_treated = df_prop[df_prop['affected_bhc'] == 1]

summary_cols = ['ln_assets', 'leverage', 'roa', 'liquidity', 'deposit_ratio', 'loans_re_ratio', 'cir', 'credit_risk']
mean_control = prop_control[summary_cols].mean()
std_control = prop_control[summary_cols].std()
mean_treated = prop_treated[summary_cols].mean()
std_treated = prop_treated[summary_cols].std()
summary_statistics = {'mean_control':mean_control, 'std_control': std_control,
                      'mean_treated': mean_treated, 'std_treated': std_treated}

# Create DataFrame
df_summary = pd.DataFrame(summary_statistics)
df_summary['mean_diff'] = df_summary['mean_control'] - df_summary['mean_treated']

# T-test to calculate significance of difference in means
pval = []
tstat = []

for i in range(2,10):
    tstat_calc = ttest_ind(prop_control.iloc[:,i], prop_treated.iloc[:,i])[0]
    tstat.append(tstat_calc)
    pval_calc = ttest_ind(prop_control.iloc[:,i], prop_treated.iloc[:,i])[1]
    pval.append(pval_calc)

df_summary['diff_pval'] = pval
df_summary['diff_tstat'] = tstat
df_summary['diff_stderr'] = df_summary['mean_diff']/df_summary['diff_tstat']

df_summary = df_summary.round(decimals = 3)
print('Summary Statistics Before Matching:')
df_summary
```

```
Summary Statistics Before Matching:
```

Out[34]:

	mean_control	std_control	mean_treated	std_treated	mean_diff	diff_pval	diff_tstat	diff_stderr
ln_assets	13.063	1.116	17.824	2.774	-4.761	0.000	-20.648	0.231
leverage	0.090	0.034	0.083	0.043	0.008	0.256	1.136	0.007
roa	0.003	0.002	0.003	0.002	0.000	0.422	0.804	0.000
liquidity	0.037	0.028	0.052	0.047	-0.015	0.009	-2.633	0.006
deposit_ratio	0.672	0.106	0.317	0.214	0.355	0.000	16.411	0.022
loans_re_ratio	0.727	0.148	0.495	0.256	0.233	0.000	7.758	0.030
cir	0.462	0.108	0.429	0.128	0.033	0.132	1.508	0.022
credit_risk	0.015	0.014	0.016	0.011	-0.001	0.824	-0.223	0.003

In [35]:
```
# Summary Statistics After Matching
matched_control = matched_df[matched_df['affected_bhc'] == 0]

mean_control = matched_control[summary_cols].mean()
std_control = matched_control[summary_cols].std()
mean_treated = prop_treated[summary_cols].mean()
std_treated = prop_treated[summary_cols].std()
summary_statistics = {'mean_control':mean_control, 'std_control': std_control,
                      'mean_treated': mean_treated, 'std_treated': std_treated}
```

```
# Create DataFrame
df_summary = pd.DataFrame(summary_statistics)
df_summary['mean_diff'] = df_summary['mean_control'] - df_summary['mean_treated']

# T-test to calculate significance of difference in means
pval = []
tstat = []

for i in range(2,10):
    tstat_calc = ttest_ind(matched_control.iloc[:,i], prop_treated.iloc[:,i])[0]
    tstat.append(tstat_calc)
    pval_calc = ttest_ind(matched_control.iloc[:,i], prop_treated.iloc[:,i])[1]
    pval.append(pval_calc)

df_summary['diff_pval'] = pval
df_summary['diff_tstat'] = tstat
df_summary['diff_stderr'] = df_summary['mean_diff']/df_summary['diff_tstat']

df_summary = df_summary.round(decimals = 3)
print('Summary Statistics After Matching:')
df_summary
```

```
Summary Statistics After Matching:
```

Out[35]:

	mean_control	std_control	mean_treated	std_treated	mean_diff	diff_pval	diff_tstat	diff_stderr
ln_assets	17.052	2.111	17.824	2.774	-0.771	0.274	-1.106	0.697
leverage	0.094	0.035	0.083	0.043	0.011	0.305	1.036	0.011
roa	0.004	0.002	0.003	0.002	0.001	0.019	2.423	0.001
liquidity	0.058	0.075	0.052	0.047	0.006	0.738	0.336	0.018
deposit_ratio	0.388	0.199	0.317	0.214	0.071	0.232	1.211	0.058
loans_re_ratio	0.509	0.273	0.495	0.256	0.014	0.853	0.186	0.075
cir	0.471	0.167	0.429	0.128	0.042	0.320	1.005	0.042
credit_risk	0.014	0.011	0.016	0.011	-0.002	0.616	-0.505	0.003