1. Introduction & Problem Statement

The 2008 financial crisis was considered by many as the worst financial crisis since the Great Depression due to its ripple effects worldwide. Following the crisis, the U.S market regulators scrambled to impose strict regulations on the financial sector to maintain risk level. **The Volcker Rule (TVR)** was deployed as a part of the most important regulations, the **Dodd-Frank Act (DFA)**, to restrict banks' risky activities and reduce risk-taking by banks - specifically focusing on limiting proprietary trading and investments.

This report aims to analyse the effectiveness and impact of TVR on U.S **Bank Holding Companies (BHC)**. To quantify the impact, we measured the change in **Trading Asset Ratio (TAR)** before and after the TVR announcement in 2010. We expect that TAR would decrease if TVR is effective as banks would decrease risky trading activities. We introduced four robustness tests to ensure that our baseline model holds when some of our assumptions are tweaked.

Understanding how TVR affects different banks is also important, especially since the aim of the rule is to halt activities of banks that previously indulge in risky trading activities. As such, we further investigated how different banks reacted to TVR by segmenting banks based on their trading ratio in 2007 (pre-DFA announcement period) and measuring the impact of TVR on the TAR of different segments.

2. Data & Features

The dataset used was of the 2,473 BHCs selected financial data - mostly from balance sheet and income statement. The dataset has 81,560 entries and 14 features, and gives panel data covering the Q3 2004 to Q2 2009, and then from Q3 2010 to Q2 2015.

To maintain consistency throughout the report, we have created a table of all the variables used, and how they would address it moving forward **(*See Appendix A*)**.

2.1 Exploratory Data Analysis (EDA)

Through our EDA, we found these relevant insights:

- **Unbalanced treatment group**. We found that the treated group only represents 1.25% (1,018 observations) of the datasets; this could increase the risk of facing unobserved bias.

- **Missing values.** We identified that half of the data (around 50.9% or 41,534 observations) are missing values in one or more columns. We however did not drop any rows as our models will automatically exclude missing values.

- **Defunct or new BHCs.** We identified that many BHCs do not have data before or after a certain period (either because they went defunct or they were newly established). We filtered these data according to our models.

- **Control Variables.** Out of the 14 features, we found that 9 features (return on assets, leverage ratio, total assets, non-performing loan ratio, cost-income ratio, deposit ratio, real estate loan ratio, liquidity ratio and CPP recipient indicator) are highly correlated with TAR. They will be used as control variables in our models to account for covariates that might influence bank business models and risk appetite. Correlation matrix available for reference **(*See Appendix B & E*)**

2.2 Feature Engineering

Since our focus is on creating robust models and measuring the banks' responsiveness, we created 5 new features:

- **Propensity matching score**. To minimise bias and better estimate intervention effect due to unbalanced sample (discussed in part 2.1), we did propensity score matching for treated banks versus unaffected banks to test for robustness of our models. As we were matching based on 2007 TAR, we excluded BHCs which were not active before 2007 or after 2007. We found that matching did improve the separability between our groups **(*See Appendix H*)**. The propensity score column was merged to our dataset.

- **Creating interaction variables.** We created 2 interaction variables for our baseline models. *Affect* is the average TAR between Q3 2004 - Q2 2009. Meanwhile, *Affect (pre-2007)* is the average TAR between Q3 2003 - Q4 2006. These variables are times with a post announcement variable to measure the treatment effect.

- **Categorising data and creating dummy variables.** We created 2 dummy variables: Top 10 and Bottom 10, which identify the Affected BHCs with the highest and lowest TAR in 2007 to measure responsiveness between the groups.

The rationale of adopting these variables into our models will be explained in part 3.

2.3 Feature Selection

We selected TAR as our dependent variable. Affected BHC dummy variable was adopted to define the entity fixed effect, and the post announcement dummy to define the time fixed effect.

As mentioned in part 2.1, we also included 9 selected features as control variables. These variables remove endogeneity that are not captured by fixed effects in the model.

3. Model

As discussed in part 1 and 2, our baseline models will measure the effect of TVR on TAR.

3.1 Assumptions

A few assumptions we adopted for our models:

- Banks have not adjusted their TAR in 2007 as new regulations and financial crisis have not occured.
- BHC that has a TAR equal or higher than 3% is considered a high trader and is thus most affected by TVR.
- Control variables capture covariates that might affect banks' trading and risk appetite.
- There is no major economic or regulatory shock to BHCs throughout the time period except TVR.
- Trading BHCs were geared towards trading activities which are now banned or limited by TVR.

3.2 Baseline Models

To test whether TVR announcement reduce the TAR of affected banks, we run the regression model outlined below. The model includes **after_DFA_1,** a dummy variable which equals '1' for the quarters post-DFA announcement (Q3 2010 - Q2 2015) and '0' prior (Q3 2004 - Q2 2009). It represents the status of the BHCs prior to and after the announcement to obtain a better idea of TVR on TAR.

Baseline Model 1

The first baseline model shown in **Appendix F, Table 1 - Column(1)** is a basic regression running **TAR** against **after_dfa_1** without control variables or fixed effect.

$$\text{bhc\_avgtradingratio}_{i,t} = 0.00051 \times \text{after\_DFA\_1} + 0.0024$$

The coefficient obtained, 0.00051 (0.05%), is close to 0 with R^2 = 0, indicating no strong reduction in TAR.

Baseline Model 2

We ran the same again but added control variables (the 9 features chosen in part 2.3) to remove endogeneity and ensured that the relationship observed was indeed due to the regressed variables.

The result is as shown in **Appendix F, Table 1 - Column (2).**

$$\text{bhc\_avgtradingratio}_{i,t} = -0.0010 \times \text{after\_DFA\_1} + X_{i,t} + -0.0207$$

X = set of control variables
i = indicates a BHC
t = time - indicates a quarter

Similar to baseline model 1, the coefficient, 0.0010 (0.1%), is close to 0 with R^2 = 0.234 suggests that there is no significant reduction in TAR, even when control variables are considered.

Baseline Model 3

Not all or the majority of the banks would have high TAR prior to the DFA announcement, thus TVR would have minimal effect on them. To obtain a more accurate picture on how banks with high TAR would be affected, we used the **affect** variable.

We run another model (**Appendix F, Table 1 - Column (3)**) with an interaction between **after DFA 1** & **affect,** which captures the varying degree of exposure to activities banned by TVR.

$$\text{bhc\_avgtradingratio}_{i,t} = -0.00002 \times \text{after\_DFA\_1} + 0.993 \times \text{Affect} - 0.161 \times (\text{after\_DFA\_1} * \text{Affect}) + X_{i,t} - 0.002968$$

X = set of control variables
i = indicates a BHC
t = time - indicates a quarter

The results obtained - with R^2 = 0.902 illustrate a few key points:

- Firstly, ***after_DFA_1***, with coefficient, -0.00002 (-0.002%) has a negative but virtually insignificant effect;
- Next, ***affect*** was highly significant and positive, 0.993 (99.3%). This was expected as banks that had high TAR pre-DFA announcement were expected to still have a relatively high TAR post announcement (i.e. even if they reduced the TAR after announcement, it would still be higher than the typical BHC).
- The interaction **affect * after DFA 1** was highly significant and negative, - 0.161 (-16.1%), suggesting that the banks that were mostly affected (i.e. had higher TAR prior) did reduce their TAR more after the announcement.

Baseline Model 4

We ran model 3 again, but controlling for fixed effects, both time and entity. The results are shown in **Appendix F, Table 1 - Column (4).**

$$\text{bhc\_avgtradingratio}_{i,t} = 0.2024 \times (\text{after\_DFA\_1} * \text{Affect}) + \gamma_i + \delta_t + X_{i,t} + 0.0065$$

X = set of control variables
γ_i = entity fixed effects
δ_t = time fixed effects
i = indicates a BHC
t = time - indicates a quarter

Accounting for fixed effects, the values were highly significant and even more negative with coefficient -0.202 (-20.2%), further strengthening the expectation that the affected banks reduced their TAR post DFA announcement.

3.3 Robustness Test

To validate that the discussion of TVR impacted TAR, we ran a 'robustness check' - comparing changes in the coefficient and p-values against 4 different scenarios described below.

Fixed effects for both time and entity are accounted for in all of our robustness test models.

Robustness Test Model 1

We added the interaction variable, **treat_3_b_avg * after_DFA_1**, to measure the effect of TVR on BHCs with TAR equal or greater than 3% post announcement period .

$$\text{bhc\_avgtradingratio}_{i,t} = -0.0234 \times (\text{treat\_3\_b\_avg*after\_DFA\_1}) + \gamma_i + \delta_t + X_{i,t} + 0.0058$$

We affirm that the TAR changes are significant (p = 0.000) when including a treatment dummy (***See Appendix F, Table 2 - Column (1)***). In fact, this test shows that BHCs with higher TAR prior to DFA announcement reduced their TAR by 2.34% more as compared to other BHCs.

Robustness Test Model 2

We further improved model 1 by balancing the treated group through propensity score matching.

$$\text{bhc\_avgtradingratio}_{i,t} = -0.0256 \times (\text{treat\_3\_b\_avg*after\_DFA\_1}) + \gamma_i + \delta_t + X_{i,t} + 0.1759$$

After broadcasting the propensity score matrix (**weight**) into the larger dataset, we also find that the Volcker Rule discussion resulted in a reduction of TAR, with a very low p-value returned (p = 0.000). See (***Appendix F, Table 2 - Column (2)***).

Robustness Test Model 3

We ran a robustness test to replicate our findings in the pre-DFA announcement period by using the average of the TAR pre-DFA period (**Affect pre-2007** variable).

$$\text{bhc\_avgtradingratio}_{i,t} = -0.2053 \times (\text{affect\_2007*after\_DFA\_1}) + \gamma_i + \delta_t + X_{i,t} + 0.0057$$

Like before, we had a low p-value (p = 0.000). See (***Appendix F, Table 2 - Column (3)***).

Robustness Test Model 4

We excluded non-trading BHC from the model then ran model 3 again.

$$\text{bhc\_avgtradingratio}_{i,t} = -0.2114 \times (\text{affect\_2007*after\_DFA\_1}) + \gamma_i + \delta_t + X_{i,t} + 0.0628$$

Narrowing to only BHCs with any trading activity, the result remains statistically significant (p = 0.000). See (***Appendix F, Table 2 - Column (4)***).

3.4 Measuring Responsiveness between BHCs

To measure the different responsiveness between banks, we adopted 2 different approaches:

1. Segmentation based on TAR Reduction. We identified BHCs which responded either most negatively or positively to the DFA announcement, and BHCs which responded the least (i.e: DFA announcement had minimal effect on their TAR). We then compared these bank segments to the Affected BHC group to observe whether our understanding of the effect of TVR on Affected BHC's TAR remains.

To determine the BHCs that responded the most and least, we ranked the top 10 most positive, top 10 most negative, and the middle 10 BHCs based on the difference between TAR after and before 2007 for each bank. We used 2007 TAR to avoid endogeneity as it is in pre-DFA announcement period. The middle 10 BHCs – BHCs with TAR difference close to 0 – represent the least responsive BHCs. The specific 10 BHCs for each ranking can be found in ***Appendix I.***

We found that 7 out of 10 most negative BHCs were affected BHCs pre-2007 (***see Appendix I, Graph IB***). Unsurprisingly, this finding is consistent with our findings from before – high trading BHCs pre-2007 declined their trading activity significantly.

Out of the top 10 most positive BHCs, only 1 was an affected BHCs pre-2007. Thus, BHCs that actually increased trading after 2007 were mostly BHCs that didn't trade much or at all pre-2007 (**see Appendix I, Graph IC**).

It is to no surprise that the middle 10 BHCs are all unaffected BHCs - the most unresponsive BHCs were BHCs that simply do not trade.

2. OLS and Dummy variables introduction for top and least trading BHCs. We identified BHCs which traded most and least in 2007 (pre-DFA announcement period) and created dummy variables Top 10 and Bottom 10 (see part 2.2). We then measured the interaction effect of these dummy variables with the post-DFA announcement. We also tested the robustness of these models by doing propensity score matching to control for imbalance test samples.

Top 10 and Bottom 10 BHCs Models

Here, instead of defining top 10 and bottom 10 like in the first method, we ranked the top 10 or bottom 10 BHCs based on their TAR pre-2007 (see part 2.2 for more details). The baseline models are as follows:

Top 10 Baseline Model

$$\text{bhc\_avgtradingratio}_{i,t} = -0.0293 \times (\text{after\_DFA\_1*top10}) + \gamma_i + \delta_t + X_{i,t} + 0.0107$$

Bottom 10 Baseline Model

$$\text{bhc\_avgtradingratio}_{i,t} = 0.0004 \times (\text{after\_DFA\_1*btm10}) + \gamma_i + \delta_t + X_{i,t} + 0.0061$$

Most notably, the coefficient of **after_DFA_1 * top10** was -0.0293 (-2.93%) and the coefficient for **after_DFA_1 * btm10** was 0.0004 (0.04%) (***See Appendix J, Top 10 Baseline Model, Bottom 10 Baseline Model***).

To test for robustness, we did a propensity score matching to accommodate for the imbalance of top 10 or bottom 10 BHCs. The coefficient of **after_DFA_1 * top10** in the top 10 model grew more negative to - 4.03% and the coefficient of **after_DFA_1 * btm10** in the bottom 10 propensity model dropped to 0.02%.

Top 10 Baseline Model with Propensity Score Matching

$$\text{bhc\_avgtradingratio}_{i,t} = -0.0403 \times (\text{after\_DFA\_1*top10}_{propensity}) + \gamma_i + \delta_t + X_{i,t} + 0.0829$$

Bottom 10 Baseline Model with Propensity Score Matching

$$\text{bhc\_avgtradingratio}_{i,t} = 0.0002 \times (\text{after\_DFA\_1*btm10}_{propensity}) + \gamma_i + \delta_t + X_{i,t} + 0.0056$$

It is worth noting that the **after_DFA_1 * top10** coefficient in this model is more negative than the same coefficient in the baseline model and the Robustness Test Model 3, which implies that the higher a BHC's pre-2007 TAR, the bigger the decline of TAR. Similarly, the **after_DFA_1 * btm10** appears to be closer to 0 which implies that the lower the bank's TAR before 2007, the more unresponsive the bank is after DFA.

4. Conclusion

Based on our analysis on TVR announcement effects on BHCs, we conclude that TVR did reduce the TAR of BHCs from pre-announcement period by 20.1%; this remains significant after controlling for fixed effects and control variables. We further found that BHCs that are affected by TVR (defined as those with TAR greater than 3% in the pre-announcement period) reduce their TAR 2.34% more than other BHCs. Our findings are robust considering various robustness tests, such as including dummy variables to identify affected BHCs and excluding non trading BHCs.

We further investigated the responsiveness of BHCs using two methods. From the first method, we observed that the biggest trading declines consisted of mainly affected BHCs and the biggest trading increases predominantly consisted of unaffected BHCs. The top 10 unresponsive BHCs were, as expected, all unaffected BHCs that did not trade.

A second method was used to compare the responsiveness between affected and unaffected BHCs. Based on our models, we found that the most affected BHCs declined more heavily than the least affected BHCs - supporting our initial findings.

4.1 Insights & Application from Results

There exists a limitation to this report. The time period covered in this report ends in Q2 2015; TVR has not been fully rolled out by then. As such, there might be other long term effects which could not be observed in this report.

Our findings indicated that TVR indeed reduced trading activities as we saw a reduction of TAR. However, this does not necessarily reflect a reduction in risks. BHCs can simply increase the riskiness of the permitted trading activities, as the line between the permitted and proprietary trading is not clearly defined in TVR. An example could include using privately owned investment firms to carry on proprietary trading. As such, we propose suggestions whereby regulators could potentially increase TVR effectiveness below.

4.2 Considerations for Regulators

It is highly intuitive as BHCs would comply with government and market regulator's rules within the governed region and reduce their TAR post-DFA period. However, as discussed in part 5.1, BHCs have more than one way to comply with TVR. BHCs can still - and will likely - maintain their set riskiness level despite complying.

Market regulators and policy makers need to consider strengthened approaches as it is their shared mission to make sure the rule achieves its effectiveness:

1. Strict enforcement should be a priority when a new rule is introduced.

2. Define structured and clear definitions on what investment activities are permitted. This is to effectively narrow the BHCs' methods of finding interchangeable risky activities, and eliminate the possible loopholes altogether.

3. Lastly, policy makers should make sure to implement the rule with a high level of coordination. With the joint effort between different parties, regulators and BHCs can establish a clear and strict understanding of prohibited risky tradings and better standardize financial derivatives that might disrupt the market as a whole, and therefore accomplish a stable and healthy economy.

Reference:

Dombalagian, O. H. (2015). The Volcker Rule and regulatory complementarity. Capital Markets Law Journal, 10(4), 469–487. doi:10.1093/cmlj/kmv034