Measuring the Efficacy of Financial Regulations

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Abstract

> *We think of a cause as something that makes a difference, and the difference it makes must be a difference from what would have happened without it. Had it been absent, its effects – some of them, at least, and usually all – would have been absent as well.*
>
> –David Lewis

As the American philosopher David Lewis explained in his seminal work *Counterfactuals* (1973), causality is perhaps best understood by comparing an experiential account where some event occurred to its counterfactual narrative, consisting of the imponderable states of the world where such an event never came to pass. In an empirical setting, recovering complete information about the counterfactual chain of events is a formidable task, but it is a useful paradigm to think about when designing experiments and testing hypotheses. In particular, it is generally insufficient to ascribe a cause without access to rigorous cross-sectional data, where the effects can be individually determined – or at least approximated – in both the presence and absence of the instigating event.

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1. Executive Summary

1.1 Overview of Findings

To understand and evaluate the impact of the Volcker Rule, a statute promulgated by the Dodd-Frank Act which sought to place limits on proprietary trading activity among commercial banks in the fallout of the 2008 financial crisis, data is collected from the financial statements of nearly 2,500 banking institutions over 20 quarters-end. A difference in differences (DiD) model is adopted to show that the average trading ratio of banks subject to the regulation drastically reduced in the time period following the announcement of the provision. Key findings are reported as follows:

- The banks that were most inclined to reduce or eliminate their proprietary trading portfolios were in fact those targeted by the Volcker Rule which, prior to its announcement, tended to invest more than 3% of their total book assets in trading accounts.
- On average, affected banks reduced their trading ratios by as much as 20.2% following the announcement of the legislation.
- The phenomenon is statistically robust in the sense that, even after controlling for other variables that might portend selection bias, the treatment effect persists.

Regarding the last point, an essential technique for separating treatment effects from incidental factors is propensity score matching, which attempts to pair observations in the treatment group with those in the control group having similar characteristics. This is used to claim that the effects of the Volcker Rule are not attributable to mere luck or endogenous factors common among the affected banks, even in the absence of true counterfactual data. However, it is argued that even though banks may have reduced their proprietary trading activity to comply with the letter of the law, the potential to engage in high-risk activity is not eliminated.

2. Introduction

Over the past few decades, perhaps no topic concerning the regulation of financial markets has been more intensely studied than the 2008 financial crisis and the attendant reforms legislated in its aftermath. In response to the crisis, governments, supranational organizations and regulatory authorities enacted numerous policy proposals to promote a stable and robust financial system. In the European Union, major milestones include the European Market Infrastructure Regulation with enhanced scrutiny of the OTC derivatives markets and, more recently, the Markets in Financial Instruments Directive II with expanded investor protections. In the United States, various regulations and bills were passed in response to the financial crisis, of which the Dodd-Frank Act (DFA) stands among the most prominent.

The DFA represents a decisive governmental intervention, conceivably intended to address the conditions giving rise to the crisis, and encompasses several key rules and regulations. Since many market players have been subjected to the sweeping mandate of the DFA, it is natural to question whether the legislation was indeed successful in achieving its original goals, chief among which is to prevent financial services firms from engaging in inappropriately high-risk activities and transactions. This paper attempts to critically evaluate the success of the DFA by analyzing observational data in the context of one of its most controversial aspects: the Volcker Rule.

2.1 The Volcker Rule

The Volcker Rule, named after former Federal Reserve Chairman Paul Volcker, is a federal regulation that places restrictions on US-based commercial banks conducting proprietary trades on their own accounts and limits transactions involving hedge funds and private equity, otherwise known as covered funds.

2.2 Difference in Differences

To measure the effects of the Volcker Rule on regulated commercial banks, the trading activity for a firm is examined with respect to its total book value of assets. This evaluation criteria follows a DiD approach, which ensures that conclusions are drawn in a statistically robust and objective manner. This method involves establishing a treatment group as well as a control group, which differ only by the presence of a particular treatment but are otherwise unremarkable.[1] Practically, the groups must divide along two distinct time periods, since the counterfactual narrative (i.e. an alternative timeline under which the Volcker Rule had not been introduced) is unobservable. The development of each group is then monitored over time, and any response to the intervention for the treatment group is noted and compared against that of the control group.

While other classes of models may be suitable, this paper focuses on multiple linear regression for its interpretability and clean decomposition. The model is derived using traditional maximum likelihood techniques, evaluated according to certain robustness criteria, and discussed in the context of how it may be leveraged to design meaningful regulations in the future.

[1] That is, in the absence of treatment, each group would exhibit similar, if not identical, outcomes.

3. Model Formulation

3.1 Data

The dataset provided contains observations for 2,473 financial institutions, each assigned a unique identification code. The following columns, as reported on that entity's quarter-end financial statements from September 2004 to June 2015, are of particular interest:

- $TR_i(t)$ is the trading ratio, or the value of any trading accounts divided by the value of total assets, at time t for bank i. Also based on this ratio, $\overline{TR}_i$ is the average trading ratio for each bank i over all quarters prior to the announcement of the Volcker Rule.

- $Post_i(t) \in \{0,1\}$ is an indicator for whether bank i, operating at some time t, is made aware of the Volcker Rule ($Post_i(t) = 1$ if affirmative).

- $V_i \in \{0,1\}$ is an indicator for whether bank i belongs to the treatment group ($V_i = 1$ if affirmative); a bank is presumed to be affected by the implementation of the Volcker Rule if $\overline{TR}_i > 3\%$.

- Other attributes (e.g. return on assets, leverage ratio, total assets) are regarded as control variables. These not only serve to increase the statistical power of the model, but also enable the modeler to ascertain whether some set of characteristics differs between the control and treatment groups, which may undermine or distort the treatment effect.

A simple time series of the average trading ratios over over all banks belonging to the control and treatment groups, respectively, is presented in Figure 1. The shaded region represents the time period during which the Volcker Rule was in the public discourse.

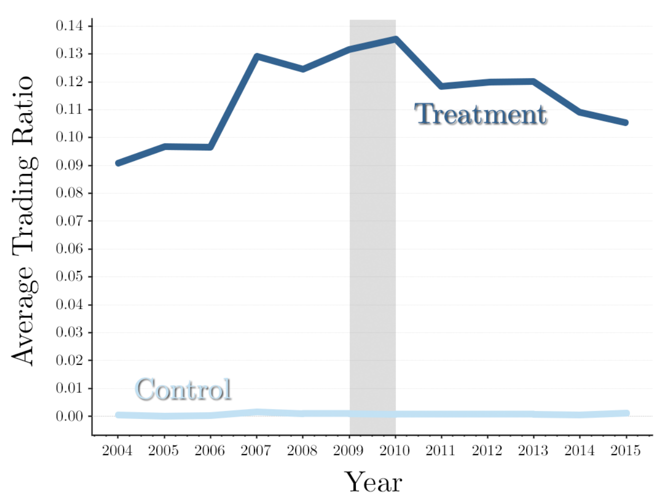

Figure 1. Average Trading Ratios

3.2 Approach

A reasonable starting point for assessing whether the Volcker Rule had any meaningful effect on the behavior of financial institutions is to consider the naïve case where $Post_i(t)$ is the main explanatory variable of interest. After adding relevant control variables $X_k(t)$, the model is specified as follows:

$$TR_i(t) = \beta_0 + \beta_1 Post_i(t) + \gamma_{0,i}(t) + \sum_k \gamma_{k,i} X_{k,i}(t) + \varepsilon_{i,t} \quad (1)$$

In this simple approach, β_1 can be interpreted as the average amount that an estimate of $TR_i(t)$ would need to change upon learning that bank i is operating at some time t past the announcement of the Volcker Rule. In other words, after incorporating fixed effects $\gamma_{0,i}(t)$ and control variables $X_{k,i}(t)$, what is the average before-and-after difference in trading ratio?

It is important to understand that $\beta_1 \neq 0$ does not imply a causal link between the Volcker Rule and trading ratios. For instance, macroeconomic factors omitted from the model may have coincided with the DFA, giving rise to an apparent link between banking activity and the regulatory change. In the absence of pure counterfactual data, the options for affirming a causal relationship are limited; however, a DiD model can attempt to bridge this disconnect.

The hypothesis of the analysis to follow is that a bank belonging to the treatment group exhibits a stronger decline in its trading ratio in response to the Volcker Rule as compared to a bank in the control group. In order to quantify this effect, (1) is expanded to include an interaction term, which captures the compound effect of two explanatory variables. This quantifies the excess change that one explanatory variable produces in the context of another; it is particularly useful for distilling treatment effects when one of these is tied to the treatment indicator.

Thus, while (1) simply asserts that $TR_i(t)$ depends upon the announcement of the Volcker Rule, (2) further postulates that the response is even higher in magnitude for the treatment group, where $V_i = 1$ if $\overline{TR}_i > 3\%$:

$$\begin{aligned} TR_i = \beta_0 + \beta_1 Post_i + \beta_2 \overline{TR}_i + \beta_3 \left(Post_i \times \overline{TR}_i\right) \\ + \gamma_{0,i}(t) + \sum_k \gamma_{k,i} X_{k,i}(t) + \varepsilon_{i,t} \end{aligned} \quad (2)$$

In (2), β_3 is the coefficient of the interaction term and the main parameter of interest. If $\beta_3 \neq 0$, then affected banks are prone to disproportionate changes in $TR_i(t)$ once the Volcker Rule is made public.

4. Results

4.1 Regression

Table 1 summarizes the parameterizations of the models formulated in Section 3.2. For completeness, (1) is also examined without and with the usage of control variables. In the former case, $\hat{\beta}_1$ is positive, a counterintuitive suggestion that the revelation of the Volcker Rule is associated with an increase in $TR_i(t)$; however, this lacks statistical significance. Upon introducing the control variables, $\hat{\beta}_1$ becomes negative and, while statistically significant, is close to zero, indicating a very mild effect on $TR_i(t)$. This may be due to the fact that in the absence of segmentation, banks with low $\overline{TR}_i$ dilute the overall effect. This also suggests that the majority of banks have a low volume of trading activity, and are likely already in compliance with the Volcker Rule.

Table 1. Comparison of Regression Results

Parameters	Model (1) Naïve Approach		Model (2) DiD Approach	
$\hat{\beta}_1$	0.0005	−0.001	−0.00002	
$SE_{\hat{\beta}_1}$	0.0002	0.0002	0.0001	
$\hat{\beta}_2$			0.9925	
$SE_{\hat{\beta}_2}$			0.0025	
$\hat{\beta}_3$			−0.1611	−0.2019
$SE_{\hat{\beta}_3}$			0.0031	0.0036
Control Variables?	No	Yes	Yes	Yes
Fixed Effects?	No	No	No	Yes
Observations	41,442	40,026	40,026	40,026
R^2	0.0002	0.234	0.9018	0.921

Hence, it is necessary to consider the impact to banks most affected (i.e. those with comparatively high values of $\overline{TR}_i$) separately from those least affected (having zero or low $\overline{TR}_i$). This is straightforwardly determined using the DiD method and examining the coefficient of the interaction term $\hat{\beta}_3 = -0.1611$, which is negative, high in magnitude, and statistically significant. Adding fixed effects strengthens this relationship even further with $\hat{\beta}_3 = -0.2019$. This result provides compelling support to the contention that banks engaging in high volumes of proprietary trading also experienced the most drastic reductions in such activity upon the disclosure of the Volcker Rule.

4.2 Robustness

The concept of statistical robustness can be used to challenge whether a model has adequately mitigated possible forms of bias. Propensity score matching is one common technique for checking the robustness of DiD models. This procedure attempts to pair one or more observation in the control group with "similar" observations in the treatment group based on a propensity score, mimicking the conditions of a randomized controlled trial. In this study, logistic regression is performed on the control variables to obtain a propensity score for each observation, which can be interpreted as the probability that a bank is assigned to the treatment group based on its underlying characteristics. A comparison of means within each group before and after the matching by propensity score is provided in Table 2. The scores are then used to match one bank in the treatment group to three comparable banks in the

Table 2. Comparison of Means Before and After Propensity Score Matching

	Treatment Group	Control Group		Differences	
Control Variable		*Before*	*After*	*Before*	*After*
Total Assets	17.83	13.24	16.33	-4.59	-1.50
Leverage Ratio	0.08	0.09	0.08	0.01	0.00
Return on Assets	0.00	0.00	0.00	0.00	0.00
Liquidity Ratio	0.05	0.04	0.04	-0.01	-0.01
Deposit Ratio	0.36	0.66	0.48	0.30	0.13
Real Estate Ratio	0.52	0.70	0.60	0.17	0.08
Cost-Income Ratio	0.47	0.51	0.48	0.03	0.00

control group,[2] and reapplying model (2) from Section 3.2 on the transformed dataset. Table 3 shows the parameters of this model alongside those corresponding to the original dataset. The results are directionally consistent with the previous findings and, if anything, strengthen support for the hypothesis that $\hat{\beta}_3 \neq 0$.

Table 3. Regression Results with Propensity Score Matching

Parameters	**Full Sample**	**Matched Sample**
$\hat{\beta}_3$	-0.0234	-0.0300
$SE_{\hat{\beta}_3}$	0.0365	0.0022
$\hat{\beta}_3$ p-value	< 0.001	< 0.001
Control Variables?	Yes	Yes
Fixed Effects?	Yes	Yes
Observations	40,026	1,580
R^2	0.0531	0.1878

4.3 Implications

A cursory glance at the preceding results may lead one to believe that the Volcker Rule has been generally successful in achieving its aims; after all, the banks most affected by the regulation experienced the sharpest declines in their average trading ratios. However, economic theory posits that such intervention strategies often have unintended consequences, and the stated goal of reigning in high-risk activities among commercial banks relies on the appropriateness of using proprietary trading activity as the sole measure of risk. A holistic view suggests that there are methods for a bank to remain nominally compliant under the Volcker Rule while still achieving its desired investment objectives; for instance, by leveraging its portfolio of risky assets (e.g. speculative bonds) to compensate for the dearth of investment in covered funds.[3] Such an outcome would undermine the spirit of the regulation and circumvent the desire for lessening total asset risk.

Lawmakers and regulators should therefore be cautioned that, while financial institutions may outwardly appear to comply with the Volcker Rule, it is dangerous to assume banks' natural alignment with the governing bodies' core guiding principles. One need only look as far as another example from the 2008 financial crisis – namely, the credit bubble brought upon by collateralized mortgage obligations, and the failure of rating agencies to envision their contagion effects – to understand that the preponderance of risks rarely collapses into a single yet comprehensive metric. It is therefore incumbent upon policymakers to appreciate the incentives and tactics of banking institutions and anticipate the behavioral responses that a new statute might provoke.

References

Keppo, Jussi and Korte, Josef (2018), *Risk Targeting and Policy Illusions – Evidence from the Announcement of the Volcker Rule*, Management Science, vol. 64, no. 1, pp. 215-234.

Lewis, David (1973). *Counterfactuals.* Blackwell Publishers.

[2] To more fully utilize available data, the matching process need not restrict itself to one-to-one assignments, especially for imbalanced datasets.

[3] The capital asset pricing model (CAPM) suggests that a bank could freely borrow funds to invest in an optimal market portfolio along the efficient frontier to achieve a higher expected return in exchange for a concomitant increase in risk.