# The intended and unintended effects of the Volcker Rule *

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**Abstract**

This paper examines the effect of banning proprietary trading by banks (the Volcker Rule) on financial stability. We identify three channels through which the Volcker Rule impacts bank-level and systemic risks: revenue diversification, bank similarity, and proprietary trading activity. We find that while the reduction in proprietary trading lowers the directly targeted banks' systemic risk, an unintended consequence is that greater similarity between banks increases the risk that they default at the same time and thus raises the probability of a systemic default. Banks that were not engaged in proprietary trading are also affected by the Volcker Rule through this similarity channel.

*JEL classification:* G01; G21; G28

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## 1. Introduction

Amidst the global effort to strengthen the financial system, the Volcker Rule was enacted as Section 619 of the Dodd-Frank Act in July 2010[2]. The objective is to limit the federal support to financial firms that carry out core banking functions, so that taxpayers' funds would not be gambled on speculative activities. As such, the Rule allows financial intermediaries to engage in commercial and investment banking activities but prohibits them from conducting nonbanking activities, such as proprietary trading, speculative transactions, and investments in hedge funds or private equity funds, among others[3]. Several academics and policy makers (e.g., Brunnermeier, Dong, and Palia, 2012; Diamond and Rajan, 2009; DeYoung and Torna, 2013; Whitehead, 2011) argue that bank involvement in nonbanking activities, particularly securitization and proprietary trading, played a role in the global financial crisis (GFC) in 2007–2009. Hence, the restriction is justified by the concerns that certain financial activities are too risky, and likely to expose banks to failing private equity or hedge funds, thereby leading to systemic defaults.

While the Volcker Rule aims to address a vital issue in the financial sector, a question remains as to what extent the regulation has achieved its objective. To date, there is no clear answer to this question. The assumption is that the Volcker Rule would directly affect banks with high trading asset ratios, as this indicates their participation in proprietary trading. We refer to these banks as the targeted banks. In the case of the Volcker Rule, there is no natural control group because those banks that had no trading assets were also indirectly affected by becoming more similar to the targeted banks. On the one hand, the ban on proprietary trading reduces the targeted banks' idiosyncratic risk by limiting their involvement in risky transactions, and thus lowers systemic risk. On the other hand, the shutting down of proprietary trading makes the targeted and non-targeted banks become more similar, which increases the probability of a systemic default.

Motivated by this puzzle, we analyze the intended and unintended effects of the Volcker Rule implementation on bank-level and systemic risks. We focus on identifying different mechanisms through which the Volcker Rule affects the risks and examine how they bring about

[2] The Dodd-Frank Act is fully known as the Dodd-Frank Wall Street Reform and Consumer Protection Act.
[3] These entities are prohibited from engaging in speculative trading where they use deposits to trade on their own accounts to gain profits in the short run due to market prices' fluctuations.

opposing effects on the risk measures. We refer to these mechanisms as the channels by which the Volcker Rule affects bank-level and systemic risks. Further, we explore the heterogeneity in these effects across the targeted and non-targeted banks. The affectedness of the Rule can differ between banks, as it depends on their exposure to the prohibited activities.

To formalize the intuition of the opposing effects, we develop a simple theoretical model that illustrates the independent effects of revenue diversification and bank similarity, by holding one constant at a time. We then consider the case of the Volcker Rule, which gives rise to a *decrease* in diversification but an *increase* in similarity. This is the case that has not been studied in the extant literature. The restriction on one bank's diversification raises its similarity with other banks since they now hold similar asset portfolios. The consequence of this situation is an increase in systemic risk, as low asset payoffs can lead to a bank's default while simultaneously triggering the defaults of other banks. Unlike what has previously been documented, the decomposition of these effects reveals that similarity and diversification do not necessarily increase in parallel for banks to experience higher systemic risk. Our model refines the existing theory by suggesting that a decline in diversification can result in higher similarity, which in turn increases the risk of the whole sector. The theory guides our empirical predictions in understanding how each of the channels interacts with the bank-level and systemic risks.

A recent report by the Securities and Exchange Commission (SEC, 2017) raises several challenges associated with quantifying the effects of the regulatory reforms. First, it is difficult to isolate the effect of a single policy, especially when one's post-implementation period overlaps with the pre-implementation period of another. Second, the rulemaking process takes place over an extended period, in which market participants could receive signals from the policy comments and change their behaviors in anticipation of the Rule. Third, for studies that look at financial regulations around the crisis, it is unclear whether the observed changes would have occurred absent the reforms since they could be due to changing market conditions during and after the crisis. Fourth, it is challenging to assess the impacts of any regulations because the counterfactuals are unobservable.

To overcome the above concerns, we propose a two-step approach to isolate the impacts of the Volcker Rule from other confounding factors. Rather than simply analyzing the risk measures before and after the enactment of the Rule, we first examine how different channels are related to bank-level and systemic risks. We also account for the banks' trading activity as another channel, since proprietary trading assets are directly affected by the Volcker Rule. We address the endogeneity concern by estimating a two-stage least square model with instrumental variables and, hence, are able reveal the causal relation between each of the channels and banks' risk measures. Second, we estimate a difference-in-differences model to investigate the effects on the channels after the regulation. Accordingly, the effects of the Volcker Rule can be computed by looking at the change in the risk measures resulting from the post-Volcker shifts in banks' diversification, similarity, and trading activity. The proposed method has two advantages. First, we identify and examine the mechanisms of why the Volcker Rule affects bank-level and systemic risks. This allows us to provide granular evidence of the effects on risks through various channels at the bank level. Second, we explore the cross-sectional heterogeneity in these effects, in which the interactions between the channels can give rise to opposing effects that make the combined effect ambiguous. More broadly, our method is useful for identifying the effects of a given regulation whilst addressing the contaminated data issues stated above.

Our first result is that banks that were presumably targeted by the Volcker Rule experienced a sharper decline in trading asset ratios relative to their counterparts. We find that trading activity is positively related to systemic risk, and thus a reduction in proprietary trading results in lower systemic risk for the targeted banks. As proprietary trading was criticized for making financial institutions (mainly investment banks) exposed to the failing hedge funds or private equity funds and other non-core banking risks (e.g., Whitehead, 2011), the ban on such activities would mitigate the contagion of risks across sectors. This finding supports the implementation of the Volcker Rule and its intended role in enhancing financial system soundness.

The second result is that the Volcker Rule might have unintended consequences on banks that are not engaged in proprietary trading. We document an increase in systemic risk of the non-targeted banks, suggesting that these banks have been indirectly affected by the regulatory ban. As the Rule carves out proprietary trading activities from the targeted banks' portfolio, it forces the targeted and non-targeted banks to become more similar by specializing in similar activities. Thus, the increase in similarity between these banks exposes them to common asset risks, thereby raising the probability that they would default jointly.

The last result of the paper is that the Volcker Rule's effects are not homogenous, even among the targeted banks. Our cross-sectional analysis reveals that the effects of the Rule vary in intensity depending on banks' trading asset ratios in the period prior to the Rule implementation. Banks that had higher level of trading assets in the pre-Volcker period would be affected by various channels to a greater extent, relative to those that did not. While the net effect might be small, the Volcker Rule results in substantial and opposing effects on risks through various channels, which offset each other's effect.

These findings yield important implications. First, regulations that limit bank involvement in certain activities would always increase the similarity among banks. While the intention was to reduce risks, the banks become more inclined to default systemically by holding a common asset portfolio. As restrictions on banking activity have a multitude of effects, we highlight the need to consider the various channels through which comes a net effect. Second, it is unclear whether the Volcker Rule has improved the soundness of the financial system by reducing systemic risk. Our results reveal that there is an implicitly adverse effect on banks that are not subject to the Rule. The ban on proprietary trading forces the targeted banks to cut back on their nonbanking operations and become more similar to the non-targeted banks. Consequently, higher similarity raises systemic risk of both the targeted and non-targeted banks. While this is a salient effect, bank similarity has been overlooked in the current policy discussions.

This paper contributes to a few strands of the literature. First, our paper is related to a broad set of studies on financial system stability in terms of measuring systemic risk (Adrian and Brunnermeier, 2016; Acharya, Pedersen, Philippon, and Richardson, 2017; Brownlees and Engle, 2017) and examining the relation between systemic risk and nonbanking activities (Stiroh and Rumble, 2006; Brunnermeier et al., 2012; Williams, 2016). Our definition of systemic risk is similar to that of Acharya et al. (2017) and the Extreme Value Theory (e.g., Longin and Solnik, 2001; Poon, Rockinger, and Tawn, 2004), whereby a bank's systemic risk is measured as the tendency that the given bank defaults conditioning on other banks are also in distress.

The second strand of the related literature builds on Wagner (2010) and focuses on the impacts of diversification on risk taking. De Jonghe (2010) uses a sample of European banks over the period 1997–2007 and finds that non-interest banking activities increase banks' systemic risk. In extension of Wagner (2010), Ibragimov, Jaffee, and Walden (2011) develop a model to show that this externality depends on the distribution of the risks that intermediaries take, and that it is most profound when these risks are moderately heavy-tailed. We refine the existing studies by showing that similarity is the underlying driver of systemic risk. This is consistent with the argument of Wagner (2010), whereby higher similarity between banks increases their inclination to fail at the same time. We consider a scenario (the Volcker Rule) where an increase in similarity can be due to a *decrease*, rather than an *increase*, in diversification. Thus, we are the first to formalize the effects of the Volcker Rule on risks.

Third, our paper is related to a growing literature that looks at the Volcker Rule and its implications for bank performance and risk taking. For example, Keppo and Korte (2016) find no effects on banks' overall risks, and those that were presumably affected by the Volcker Rule do not alter their risk targets following the regulation. Whereas, Chung, Keppo, and Yuan (2016) use a calibration of a structural model and show that the Volcker Rule raises banks' default probability and decreases equity value. More recently, Bao, O'Hara, and Zhou (2017) document an increase in the illiquidity of stressed bonds after the introduction of the Volcker Rule. Their finding shows that the increase in market liquidity of those non-Volcker-affected dealers is not sufficient to offset the decline in that of the affected dealers.

In contrast, we isolate the effects of the Volcker Rule on bank risk taking by empirically examining the channels through which these post-Volcker effects take place. Our paper is distinct from previous studies as it provides insights into the intended and unintended effects of the Volcker Rule on risks. We show that the non-targeted banks were indirectly affected by the Rule through the similarity channel. More importantly, we contrast the changes in the risk measures, including bank-level and systemic risks after the introduction of the Volcker Rule. The analysis on the systemic stability is important, because enhancing financial sector's stability has been the focus of various bank regulations, especially the Volcker Rule. For a policy to be optimal, financial institutions need to internalize the costs of their systemic risk and thus reduce the risks of these costs being passed on to the society (Richardson, Smith, and Walter, 2010).

The rest of this paper is organized as follows. Section 2 provides a theoretical framework and outlines our main hypotheses. Section 3 describes the data set and presents the descriptive statistics. Section 4 reports the main results of the paper and Section 5 concludes.

## 2. Theoretical framework

*2.1. Diversification, similarity, and risks*

The relation between diversification and bank risk taking has been well explored in the extant literature. According to standard portfolio theory (Markowitz, 1952), diversification reduces risks when individual assets are not perfectly correlated. As bank assets carry idiosyncratic risks, diversifying into other banks' assets can reduce the risk of the overall portfolio, and thus reduces the probability of failure at the bank level. However, diversification entails a cost. In Wagner's (2008) model, diversification leads to homogenization of financial firms that allows them to reduce idiosyncratic risk and the number of projects that they may have to discontinue in a crisis. At the same time, homogenization encourages these firms to invest in risky assets at the expense of liquidity holdings. As the costs of having riskier and less liquid institutions outweigh the benefits from fewer inefficient project discontinuations, homogenization would have a negative side effect on welfare. Wagner (2008) suggests that this negative effect can be fully mitigated by regulation that does not give capital support to more diversified institutions.

One of the ways through which diversification affects risk taking is bank similarity. According to previous studies, banks have incentives to invest in correlated assets as they do not want to internalize the costs of a joint failure (Acharya and Yorulmazer, 2005). The correlation between the assets increases the likelihood of a systemic collapse, which induces government bailout (Acharya and Yorulmazer, 2006; 2007). However, banks may not welcome this correlation. Wagner (2010) presents a model where more diversification increases similarities among banks with the assumption that they dislike being correlated. Since full diversification implies that banks invest in the same portfolio (that is the "market portfolio"), this makes their asset risks become perfectly correlated. As they are exposed to the same risks, diversification at financial institutions can be undesirable because it makes systemic crises more likely. Consequently, Wagner (2010) calls for regulation to limit diversification in the financial system.

*2.2. Model*

Our theoretical framework follows a similar structure to that of Wagner (2010) to investigate how diversification, similarity, and the Volcker Rule may impact banks' risk measures. We refer to diversification and similarity as the main channels through which the

Volcker Rule affects the risks. First, consider a market where two banks construct their asset portfolio by investing in different activities, one invests wholly in asset X and the other invests in both assets X and Y. We name the first bank as A and the second as B. We also refer to the first bank as a conventional bank and the latter as an investment bank, where X represents the conventional banking asset (which often consists of loans) and Y denotes proprietary trading asset. As in Wagner (2010), we assume that the asset payoffs follow a uniform distribution and their probability density function is defined as $\Phi(.) \sim [0, s]$. Assume that $x$ and $y$ are the payoff of assets X and Y, respectively; therefore, the payoff of each bank ($v_i$) can be written as:

$$v_A = (\alpha_1)x + (1 - \alpha_1)y, \tag{1}$$

$$v_B = (\alpha_2)x + (1 - \alpha_2)y, \tag{2}$$

where $\alpha_1$ and $\alpha_2$ are bank A's and bank B's portfolio weights invested in asset X, respectively. Note that in our setting, $\alpha_1 = 1$ since bank A is a purely commercial bank, and hence $\alpha_1 > \alpha_2$. Figure 1 portrays the baseline setting of our theoretical model. We outline the portfolio composition of each bank in Panel A, and illustrate the regions of banks' default and survival in Panel B.

A bank default would occur whenever $v_i$ is below $d$, where $d$ is the total debt amount. This is when the asset payoffs are insufficient to cover the debt amount; hence, the bank becomes insolvent and fails. Setting the expected payoff equal to the total debt, $d$, and solving for $y$, we can derive the minimum return function for each bank, where the given bank would face financial distress if their payoff falls below this minimum return threshold. These thresholds are:

$$y_A(x) = \frac{d}{1-\alpha_1} - \frac{\alpha_1}{1-\alpha_1}x, \tag{3}$$

$$y_B(x) = \frac{d}{1-\alpha_2} - \frac{\alpha_2}{1-\alpha_2}x. \tag{4}$$

By substituting $x = 0$, we obtain the y-intercept for $y_B(x)$ as $y_B(0) = \frac{d}{1-\alpha_2}$. The x-intercept is obtained by substituting $y = 0$, and thus $x_B(0) = \frac{d}{\alpha_2}$. Since $\alpha_1 = 1$, $y_A$ represents the exposure of bank A to the risk of asset X and, hence, $y_A$ is a vertical line that cuts the x-axis at $d$.

From Figure 1, the vertical line $y_A$ and the slanted line $y_B$ (more diversified) indicate the minimum return thresholds to avoid a bank default for banks A and B, respectively. The regions to the left of these lines represent the default areas of the respective banks. Thus, area *1* refers to the probability of both banks being in default while areas *2* and *4* represent the probability of individual bank default at banks A and B, respectively.

Similar to Wagner (2010), our model is based on the setting in which the y-intercepts are less than $s_y$ (that is, $\frac{d}{1-\alpha_2} < s_y$ as in Panel B of Figure 1), except the case in which a bank invests wholly in asset X (there is no y-intercept in such a scenario). To validate our results, we also use an alternative setting whereby the y-intercepts are above $s_y$ and, hence, do not touch the y-axis given the range of $[0, s_y]$. The alternative setting provides a more general set of results, so that a small shift in diversification can also be analyzed[4]. However, the alternative setting requires intensive mathematical derivations to account for the areas that are beyond the maximum value of the probability density function ($s_y$). We use the current setting for our analysis because it is consistent with Wagner's (2010) framework while yielding the same solutions as those obtained under the alternative setting[5]. Accordingly, under the assumption of $\frac{d}{1-\alpha_2} < s_y$ the results in our model would hold if $\alpha_2$ satisfies the condition specified in Eq. (5). We refer to Eq. (5) as a necessary condition:

$$\alpha_2 \leq 1 - \frac{d}{s_y}. \tag{5}$$

We now depart from Wagner (2010) by analyzing separately the effects of diversification and similarity on the risk measures. This separation is important in examining the independent effects of the channels, especially in the case in which diversification and similarity do not move in parallel. An example of this situation is the Volcker Rule, whereby the ban on proprietary trading decreases diversification but increases bank similarity. Note that for such a setting, the Wagner's (2010) model cannot account for the opposing directions of the channels, and hence is unable to assess the effects of this regulation.

We begin by considering two generalized scenarios in which one channel receives a treatment at a time, while holding the other constant. This is then followed by the last scenario where we illustrate the impact of a change in banks' asset composition as a result of the Volcker Rule. All detailed proofs are provided in Appendix A.

[4] Graphically, this would be when $y_B(x)$ is slightly slanted relative to $y_A(x)$, rather than touching the y-axis.
[5] The solutions derived using the alternative setting are similar to those reported in the paper. Proofs for these results are available upon request.

*2.3. Effect of diversification*

To examine the pure effect of diversification while holding similarity fixed, we refer to a scenario in which there are two periods, including pre- and post-treatment. The setting of the pre-treatment period is the same as the baseline case above, whereby two banks invest in two assets X and Y in different proportions. For the treatment, we switch the asset weights between the two banks so that bank A diversifies into asset Y (which it did not previously invest in), and thus reduces its investment in X, while bank B now becomes completely concentrated in asset X. An example of bank A in this scenario is when a commercial bank that is previously focused on commercial lending decides to pursue strategies toward diversification by undertaking mortgage lending or engaging in securitization to reduce credit risk concentration (Wagner, 2010; De Nicolo, Favara, and Ratnovski, 2012; Thakor, 2012). Note that in this case, the degree of bank similarity is unchanged between the two periods. Panel A of Figure 2 summarizes the portfolio composition of banks A and B in the pre- and post-treatment periods.

Consider the impact of diversification at bank A, which receives the diversification treatment (becoming more diversified). To quantify the impacts on the risks, we use two main risk measures, including individual banks' default risk and banks' systemic risk. We define the former as the probability of the individual banks being insolvent, while the latter is the conditional probability of default at bank $i$ given that bank $j$ is also insolvent. An alternative measure for systemic risk is the aggregate systemic default, which is the probability of a joint default where both banks are insolvent. We illustrate these post-treatment changes in Panel B of Figure 2.

Since bank A is now exposed to both X and Y, its probability of default moves from area *1+2* to *1+4*, as its minimum return threshold shifts from $y_A$ to $y_B$ during the post-treatment period. The white and black arrows indicate the shift in asset allocation of banks A and B after receiving the treatment, respectively. Based on the belief that diversification reduces banks' idiosyncratic risks, we expect to see a reduction in bank A's default probability in the post-period. This implies that area *2* has a higher probability mass relative to area *4* (see Figure 2). We derive the condition in which this result holds and provide the proofs in Section 1 of Appendix A. Under the assumption of a uniform distribution, we compute the probability of default as suggested by the specified areas in Figure 2 and solve for $d$. The condition in which diversification reduces individual bank risk is given by:

$$\frac{d}{s_y} < 2\alpha_2(1-\alpha_2). \tag{6}$$

Referring to the necessary condition of $\alpha_2 \leq 1 - \frac{d}{s_y}$ (as outlined in Eq. (5)), we can simplify the above result to:

$$\frac{d}{s_y} < \frac{1}{2}. \tag{7}$$

The intuition is that when banks have a default probability of less than 50%, they would gain risk saving by diversifying their activities. This is a reasonable condition to assume for banks to remain functional and, henceforth, we refer to Eq. (7) as a reasonable condition and will use this condition throughout the discussion of the later sections. Therefore, diversification is desirable at the bank level as it reduces individual banks' default probability.

We test the impact of diversification on systemic risk by examining the aggregate systemic risk (probability of systemic default) and banks' systemic risk (conditional probability of a systemic default)[6]. Interestingly, the region in which both banks will be simultaneously insolvent remains the same after the treatment (area *1*). The result implies that when holding similarity fixed, there is no evidence that diversification would increase the probability of a joint default. However, the banks' systemic risk will be different due to the change in their individual default probabilities (in Panel B of Figure 2, bank A's individual default region moves from area *2* to area *4*, and vice versa for bank B).

Under the reasonable condition that $\frac{d}{s_y} < \frac{1}{2}$ (Eq. (7)), it reveals that bank A's systemic risk in the post-period is, in fact, lower than that in the period before the diversification treatment. Hence, it follows that as long as $\frac{d}{s_y} < \frac{1}{2}$, diversification (ceteris paribus) would not *increase*, but rather *decrease* banks' systemic risk. We conclude that when banks have less than 50% default probability, diversification would reduce the default risk at the bank and system-wide levels, holding other channels constant. While this might seem to contradict Wagner's (2010) predictions, we need to consider the effects on risks driven by another channel that is similarity.

[6] We use the terms banks' systemic risk and banks' conditional probability of a systemic default interchangeably.

*2.4. Effect of similarity*

Next, we examine the pure effect of similarity, holding diversification constant. Recall that in the baseline setting, bank B invests $\alpha_2$ in asset X and $(1-\alpha_2)$ in asset Y. Consider the treatment for similarity where bank B switches its asset weights and now invests $(1-\alpha_2)$ in asset X and $\alpha_2$ in asset Y, while no change is made to bank A. Note that $\alpha_2$ is less than $(1-\alpha_2)$ to ensure that bank B will become more similar to bank A, after having the treatment. Hence, bank B's new minimum return threshold in the post-treatment period becomes:

$$y_B^{post}(x) = \frac{d}{\alpha_2} - \frac{1-\alpha_2}{\alpha_2} x. \tag{8}$$

Figure 3 shows the post-treatment changes in portfolio composition and default regions of two banks in Panel A and B, respectively. The treatment changes the slope of line $y_B$, shifting it to $y_B^{post}$. Accordingly, area *2*, which is the default area of bank A in the pre-period, becomes the increment in systemic default after the shift while the region where both banks survive is also increased by area *5*. As shown in Figure 3, there is no change in the default probability of bank A. However, the default probability of bank B has changed, from areas *1+5+6* to areas *1+2+6*. To examine this effect, we compare the probability mass between areas *5* and *2*. For similarity to increase bank B's individual default probability, area *2* has to be greater than area *5*. Panel B shows that these areas are the same by symmetry, and hence we can infer that similarity has no effect on bank risk taking.

From Panel B, the systemic risk of each bank differs between the pre- and post-periods. This is because the similarity among banks increases as bank B becomes similar to bank A by having invested more in asset X. Recall that we impose the condition:

$$\alpha_2 < \frac{1}{2}, \tag{9}$$

so that bank B will have more share of asset X after the similarity treatment. By comparing the systemic risks between the pre- and post-periods, we find that the systemic risks of both banks increase in the post-period (see Section 2 of Appendix A for details).

The interpretation is that if the conventional asset makes up less than 50% of bank B's asset portfolio in the pre-period, bank similarity will always increase when it switches the weights and invests more in asset X after the treatment (since bank B will become more similar to the conventional bank in the post-period). Accordingly, an increase in similarity leads to higher systemic risk. The aggregate systemic risk is also increased by area *2*, as the probability of a joint default extends from area *1* to areas *1+2*. This increment can be represented by the probability mass of area *2*:

$$\frac{(2\alpha_2-1)d^2}{2(\alpha_2-1)\alpha_2 s_y^2} > 0, \quad (10)$$

which is always positive when $\alpha_2 < \frac{1}{2}$.

Taken together, we conclude that bank similarity increases systemic risk, both in terms of aggregate systemic default and banks' conditional systemic default, while having no effect on individual banks' default probability. The results indicate that similarity, rather than diversification, is the main driver of systemic risk. Wagner (2010) argues that diversification increases systemic crisis, yet the effect that he is referring to is, in fact, similarity as in his model set-up both diversification and similarity increase in parallel. Consequently, diversification increases systemic risk only when it is accompanied by higher similarity. From our model, we are able to disentangle the independent effects of the two channels.

### *2.5. Effect of the Volcker Rule*

So far, we have looked at how each channel affects the risk measures individually. The introduction of the Volcker Rule as a regulatory restriction on banks' proprietary trading brings about changes in both diversification and similarity, making the net effect ambiguous. The Wagner's (2010) model cannot fully assess the effects of the Volcker Rule, since his model only examines the cases in which diversification and similarity co-move. Consider the same baseline setting for the pre-Volcker period, the treatment for the last scenario is where the Volcker Rule restricts proprietary trading (asset Y) by banks. Consequently, bank B decreases its investment in asset Y by $\beta$, whereas there is no change in the portfolio composition of bank A. Note that $\beta$ represents a reduction in the level of proprietary trading asset and an increase in the share of conventional asset in bank B's portfolio following the Rule. We illustrate the setting and default probability of both banks in this scenario in Figure 4.

The reduction in diversification at bank B makes it more exposed to the risk of asset X, which changes the minimum return threshold to avoid bank default:

$$y_B^{Volcker}(x) = \frac{d}{1-\alpha_2-\beta} - \frac{(\alpha_2+\beta)}{1-\alpha_2-\beta}x. \quad (11)$$

From Figure 4, the line $y_B^{Volcker}$ is steeper and closer to $y_A$ than $y_B$, which portrays the increase in the level of asset X at bank B. As a result, the shutting down of proprietary trading causes banks to become more similar (bank B is to invest more in asset X, and thus is similar to bank A) that in turn increases the probability of a systemic default, from area *1* to areas *1+2*. Consider the individual default probability of bank A, which is the total of areas *2+3* in the pre-Volcker period and area *3* in the post-Volcker period (holding the default probability of bank B constant). The decrease in individual bank's default becomes an increment in the systemic default, where both banks will be insolvent. Area *5* represents the reduction in bank B's individual default probability (from areas *5+6* to area *6*), which then becomes the additional probability that both banks will survive after the Rule.

We derive the condition in which the Volcker Rule would increase bank risks by setting the difference between the post- and pre-default probabilities of bank B to be greater than 0. Applying the necessary condition of $\alpha_2$ (in Eq. (5)), we obtain the following interval in which the bank's debt level would fall within:

$$\beta < \frac{d}{s_y} < \frac{1}{2}(1+\beta). \tag{12}$$

Since $\frac{d}{s_y} < \frac{1}{2}$, it follows that the upper bound always holds under the reasonable condition. Regarding the lower bound, it implies that $\beta < \frac{1}{2}$ as $\beta < \frac{d}{s_y}$ (see Section 3 of Appendix A). The intuition is that the Volcker Rule would result in higher bank-level riskin even when the targeted banks cut back a small share of proprietary trading asset. As diversification is beneficial at the bank level (lowering bank risk), a constraint on diversification would deem to increase bank risk taking.

While the Volcker Rule does not change the asset composition of bank A (non-targeted), it can have implications on this bank via the similarity channel (as both groups become more similar). Using the same approach, the Volcker Rule would lead to higher systemic default risk under the following conditions:

$$\frac{\beta}{2} < \frac{d}{s_y}, \tag{13}$$

$$\beta < \frac{d}{s_y}, \tag{14}$$

for bank A (untreated) and bank B (treated), respectively.

Note that the condition in Eq. (14) is the same as the lower bound of $\frac{d}{s_y}$ specified in Eq. (12). Following the results in Eqs. (12) and (14), Eq. (13) is always true since $\beta < \frac{d}{s_y}$. Thus, we confirm that the Volcker Rule would increase the treated banks' individual risk as well as raising the systemic risk of the treated and untreated banks.

To further investigate this result, we turn to our aggregate systemic probability of default that is represented by area *1* and areas *1+2* in the pre- and post-Volcker periods, respectively. It is evident that the aggregate systemic default probability would increase by the probability mass of area *2*, which is defined as:

$$\frac{\beta d^2}{2s_y^2(-1+\alpha_2)(-1+\alpha_2+\beta)} > 0. \tag{15}$$

To summarize, the Volcker Rule results in no change in the individual risk at bank A but increases the likelihood of default at bank B due to the constraint on diversification. Interestingly, we show that the Volcker Rule increases the systemic risk of the targeted and non-targeted banks as well as their aggregate systemic default through the similarity channel.

Table 1 summarizes the changes in default probabilities as the banks move from pre- to post-treatment periods in the three scenarios above.

### *2.6. Trading activity channel*

Apart from diversification and similarity channels, the riskiness of bank activity is also an important mechanism by which the Volcker Rule affects risks. We refer to banks' trading activity as the third channel. So far, we assume that the risk and probability density functions of assets X and Y are the same, and thus the change in asset allocation at these banks does not alter their risk profile. However, it is often argued that trading activities are more volatile and are likely to expose banks to higher systemic risk (Brunnermeier et al., 2012; King et al., 2013; Williams, 2016). If the proprietary trading asset (denoted as asset Y) is risky, increasing a bank's share of this asset class would make the bank riskier, thereby raising the probability of its default as well as a systemic default. Ibragimov et al. (2011) also note that the higher the asset correlation and the heavier the tails of the risk distribution, the less beneficial risk-sharing is to banks. As such, we anticipate that the trading risk is positively associated with both the bank-level and systemic risks. This view complements the objective of the Volcker Rule to restrict banks' engagement in proprietary trading activities. By prohibiting proprietary trading by banks, the targeted banks would reduce their investments in risky assets and, hence, decrease their risk profile. The restriction also aims to limit those banks' exposure to volatile fluctuations in the stock prices, shield banks from losses incurred elsewhere (failing hedge funds), and lower the risk of a systemic default (Gambacorta and van Rixtel, 2013).

### *2.7. Main hypotheses*

Motivated by our theoretical predictions, we propose the following hypotheses to examine the effects of diversification, similarity, and trading activity on the risk measures.

*Hypothesis 1*: Revenue diversification (a) reduces bank-level and (b) systemic risks.

*Hypothesis 2*: Bank similarity (a) has no effect on bank-level risk but (b) increases systemic risk.

*Hypothesis 3*: Trading activity (a) increases bank-level risk and (b) systemic risk.

To understand how the Volcker Rule affects the risk measures, we formulate additional hypotheses to study the effects of the Volcker Rule on each of the channels. Since the Rule imposes constraint on banks' trading activity, the targeted banks would be unable to pursue full diversification of financial activities. Consequently, the regulatory restriction on proprietary trading forces these targeted banks to cut back on proprietary trading assets and, hence, reduces the trading activity of these banks. This leads us to the next two hypotheses:

*Hypothesis 4*: The Volcker Rule reduces diversification of the targeted banks.

*Hypothesis 5*: The Volcker Rule reduces trading activity of the targeted banks.

By replacing investment in proprietary trading assets with conventional assets, the targeted banks become more similar to the other conventional banks in the sector. Due to their common asset portfolios, the targeted and non-targeted banks have the same exposure to asset risks, which increases the similarity between banks. Hence, we propose the following hypothesis:

*Hypothesis 6*: The Volcker Rule increases similarity between banks.

As shown in Section 2.5, the Volcker Rule brings about changes in different channels through which the effects on risks can be in opposing directions. According to our model, the restriction on a particular trading activity would always decrease revenue diversification. Since the targeted banks would have less capacity to diversify their idiosyncratic risk, the Volcker Rule would lead to an increase in bank-level risk of these banks. We also theoretically show that banks would experience an increase in systemic risk from higher similarity between banks in the

Volcker Rule scenario. As the targeted and non-targeted banks hold similar asset portfolios, they are more likely to fail together when asset payoffs fall below the minimum return threshold. By examining the independent effects of diversification, similarity, and trading activity, we expect that the Volcker Rule would increase systemic risk through the similarity channel. Guided by our theoretical model, the last hypotheses are as follows:

*Hypothesis 7*: The targeted banks' risk level increases after Volcker Rule implementation due to lower revenue diversification.

*Hypothesis 8*: The systemic risk of the targeted and non-targeted banks increases after Volcker Rule implementation due to higher bank similarity.

## 3. Data and descriptive statistics

### *3.1. Data*

Our study uses data from 1993 to 2016, which covers the period before the introduction of the Volcker Rule. The extension of the sample period allows us to empirically estimate the relation between diversification, similarity, trading activity, and risk measures, which we then apply to investigate the effects of the Volcker Rule. We take the advantage of the long sample to maximize the statistical significance when examining the relation between each channel and the risks but use a shorter and balanced window to examine the effects of Volcker Rule implementation. We construct a data set containing all listed bank holding companies (BHCs) in the US during the sample period. We collect the quarterly financial data at the BHC level from the Consolidated Report of Condition and Income (FR-Y9C) of the Federal Reserve of Chicago website[7]. We normalize level variables using seasonally adjusted Gross Domestic Product (GDP) deflator as of 2016(Q4). We winsorize all financial variables at the top and bottom 1% except the trading asset ratio, since the values are zero for most banks, whereas some banks hold a significant amount of trading asset in their portfolio (the highest ratio reaches about 38%)[8]. We then match the financial data with the daily stock price information collected from the Center of Research on Security Prices (CRSP) for the full sample. We are able to match 997 BHCs with the stock price data. To determine the effects of Volcker Rule implementation, we require banks

[7] The BHCs whose assets are above $500 million are required to file their financial statements on a consolidated basis at a quarterly (half-yearly) frequency.

[8] The minimum and maximum values of the variables are not reported and are available upon request.

to exist in the pre-implementation periods (from 2003(Q1) to 2007(Q4)) to classify their affectedness. This requirement reduces the number of observations in the data set to 547 BHCs (yielding 25,019 BHC-quarter observations).

All depository institutions, BHCs, and their subsidiaries, as well as those systemically important non-bank financial firms are subject to the Volcker Rule. While it prohibits these financial institutions from engaging in proprietary trading and having relationships with hedge funds or private equity funds, the Rule also sets a broad range of exemptions such as market making and hedging activities[9]. Accordingly, we classify the BHCs that are engaged in proprietary trading activities as the targeted banks since these would be presumably affected by the Volcker Rule[10]. Although the targeted banks are mainly investment banks, other non-investment banks can also have proprietary trading assets, and thus might be affected by the Rule.

To formally define the banks' affectedness, we refer to their trading asset ratios in the period prior to the introduction of the Volcker Rule. Similar to Keppo and Korte (2016), we use two variables to measure the extent to which a bank is affected by the Volcker Rule, including pre-trading asset ratio ($PRETRAD$) and an indicator variable ($TARGETEDBHC$). The former refers to a continuous measure that is computed as the average trading asset ratio over the periods prior to Volcker Rule implementation (from 2003(Q1) to 2007(Q4)), while the latter assigns a value of one for banks that had a pre-Volcker trading asset ratio above 3% and zero otherwise. Since $PRETRAD$ is a more granular measure of banks' affectedness, we rely on this variable for the main analysis and use the affectedness' indicator variable in robustness tests. Table 2 provides a full description and measurement of the variables used in the paper. Out of the 547 sample banks, there are 13 targeted banks.

[9] Other exemptions include investments in small business investment companies, seed investments for the purpose of establishing a fund, and de minimis investments, i.e., less than 3% of the total ownership of a fund provided that the aggregate does not exceed 3% of the banking entity's Tier 1 capital (Keppo and Korte, 2016; Bao et al., 2017). Although the rule would not be applied on the non-bank financial firms, these firms are subject to higher capital and quantitative requirements proposed by the relevant regulatory bodies.

[10] Henceforth, we refer to BHCs as banks for brevity throughout the paper.

*3.2. Main variables*

Our main variables of interest are measures of revenue diversification, bank similarity, and trading activity as well as the risks. To proxy for the bank-level risk ($BRISK$), we use the stock return volatility that is computed as the standard deviation of the daily prices over the last one-year horizon. This is a reasonable market-based indicator of banks' default probability because their stock returns are more likely to be volatile when banks have high default risk or are facing financial distress (Campbell, Hilscher, and Szilagyi, 2008).

Following Van Oordt and Zhou (2012), we construct our systemic risk measure ($SRISK$) by extracting the OLS estimate of the slope coefficient from the following indicator regression:

$$I_{i,d} = \beta_I I_{market,d} + \varepsilon_t, \tag{16}$$

where the indicator for extreme values of market index returns ($I_{market,d}$) is regressed on the indicator for extreme values of bank *i*'s stock returns ($I_{i,d}$) on day $d$. The estimated $\beta_I$ can be interpreted as the tail beta, which is the sensitivity of individual bank's returns being in extreme events to the market index given that the market returns are also in extreme events.

To proxy for the banks' revenue diversification ($DIV$), we follow previous literature (Stiroh and Rumble, 2006) and compute the diversification measure using the Herfindahl-Hirschman Index approach:

$$DIVER_{i,t} = 2 \times \left[1 - \left(\left(\frac{NET_{i,t}}{NET_{i,t}+NON_{i,t}}\right)^2 + \left(\frac{NON_{i,t}}{NET_{i,t}+NON_{i,t}}\right)^2\right)\right], \tag{17}$$

where $NET_{i,t}$ is the share of net interest income and $NON_{i,t}$ is the share of non-interest income in quarter $t$[11]. This measure ranges between zero and one, with a value of zero meaning that the bank is highly concentrated with revenues generated from one income source, while a value of one refers to a fully diversified bank where the revenues are split evenly between net interest and non-interest income streams. Since the variable $DIVER_{i,t}$ is bounded within the unit interval, we apply the following logistic transformation so that it can be used a dependent variable:

$$DIV_{i,t} = \ln\left(DIVER_{i,t}\right), \tag{18}$$

[11] Net interest income is calculated as the difference between total interest income and interest expense. Total interest income includes interest and fee on loans, income from leases, interest income from balance due from depository institutions, interest income from trading assets, interest income on federal funds sold and securities purchased under agreements to sell, and other interest income. Interest expense includes interest paid on deposits, expense on fed funds purchased, interest on trading liabilities and subordinated notes, and other interest expense. Non-interest income includes fiduciary income, fees and charges, trading revenue, and other non-interest income.

where $DIVER_{i,t}$ is the revenue diversification index of bank $i$ in quarter $t$.

We capture the similarity ($SIM$) among banks by calculating the synchronicity index of banks' stock returns. The intuition is that since the returns on assets are closely related to the stock returns, a bank would be similar to other banks in the market if its stock return moves in line with the banking index (more synchronous). One could argue that using banks' accounting data (such as income) would capture the degree of banks' revenue similarity more effectively than using stock prices data. However, we prefer to use a market-based measure, especially for this similarity index for two reasons. First, the share of non-interest income is zero for most of the banks, and thus the accounting data fail to capture much of the differences between banks. Second, the stock market data are available on a more frequent and up-to-date basis, and thus better reflect the current state of the banks. We follow the extant literature (e.g., Hutton, Marcus, and Tehranian, 2009) on stock price synchronicity and estimate a modified regression model for each bank-quarter as follows:

$$RET_{i,d} \ = \ a_0 + a_1\overline{RET_d} + e_{i,d}, \tag{19}$$

where $RET_{i,d}$ is the stock return of bank $i$ on day $d$ and $\overline{RET_d}$ is the return on the banking index (which is computed as the average of all the banks' stock returns in the banking sector on day $d$)[12]. From this regression, we obtain the R-squared values. Consistent with the literature (Morck, Yeung, and Yu, 2000; Boubaker, Mansali, and Rjiba, 2014), we apply a logistic transformation of these values and, hence, the transformed values range from positive to negative infinity:

$$SIM_{i,t} = \ln\left(\frac{R_{i,t}^2}{1-R_{i,t}^2}\right), \tag{20}$$

where $R_{i,t}^2$ is the R-squared values obtained from Eq. (19) for bank $i$ in quarter $t$.

We use trading asset ratio ($TRAD$) to account for banks' share of proprietary trading and the risk differential between asset classes[13]. Since this captures the riskiness of proprietary trading activities, we anticipate that $TRAD$ would be positively related to bank-level and systemic risk (Brunnermeier et al., 2012; Williams, 2016).

[12] We use daily stock returns and estimate the regression at every quarter using the past one year of data.

[13] This is because trading accounts are riskier relative to other asset types such as residential real estate loans. The measurement of the variable is provided in Table 2.

*3.3. Controls*

To control for other factors that might affect the risk measures, we include several bank-level and macro-economic variables that are widely used in the banking literature. For bank characteristics, we use a selection of financial ratios that capture the constituents of the CAMELS rating. The US authorities have adopted this rating index for stress testing because it reflects various important aspects of a bank's operational performance and business model (De Jonghe, 2010; Cornett, Li, Tehranian, 2013; among others). We use market leverage ratio ($MKTLEV$) and non-performing loan ($NPL$) to proxy for capital adequacy and asset quality using, respectively. We predict that both variables would be positively related to the risk measures, given that they indicate the default and credit risks of a bank. We prefer to use market leverage, instead of the book value equity ratio, because it better reflects the banks' current state and leverage position.

Management quality is proxied by the banks' share of non-interest expense ($NONIE$), which captures manager's ability in controlling non-interest expenses. Since the bank risks are also likely to be related to profitability (earnings) and liquidity position, we control for these factors using return to equity ratio ($ROE$) and liquidity ratio ($LIQ$). We have no prior regarding the sign of the coefficients on profitability and liquidity. On the one hand, profitability tends to co-move with bank-level risk, as riskier investments often entail higher payoffs. On the other hand, banks with sound financial performance are less likely to experience high bank risk or pose greater threat to the banking system. Regarding liquidity, banks that have high liquidity would be seen as safer relative to those that hold more illiquid assets. However, the liquid banks might take advantage of their favorable liquidity position to engage in riskier activities, which could lead to greater bank-level and systemic risk.

Furthermore, past studies also show that size is an important factor in determining the degree of bank risk taking and systemic risk (Laeven, Ratnovski, and Tong, 2016). Large banks are likely to take on more risks and have higher contribution to banking system crashes. Hence, we control for bank size ($SIZE$).

Apart from these standard bank-level variables, we account for bank participation in the government bailout programs. As documented by extant literature (Black and Hazelwood, 2013; Duchin and Sosyura, 2014), bank access to the Capital Purchase Program (CPP) as part of the Trouble Asset Relief Program (TARP) gave rise to a moral hazard problem, whereby banks shifted to riskier investments following the support. The Federal Reserve injected about $700 billion into the banking sector through TARP, of which $250 billion was allocated for CPP. We include an indicator variable, $TARP\_BANK$, to control for bank participation in the TARP funding. Lastly, we control for the business cycle by including the GDP growth rate as a macro-economic factor.

*3.4. Descriptive statistics*

Table 3 reports the summary statistics of the variables in our study. The targeted banks have an average diversification index ($DIV$) of -0.26 and trading asset ratio ($TRAD$) of 9.47%. These measures are relatively higher compared to the non-targeted banks, which have an average of -0.48 and 0.18% for $DIV$ and $TRAD$, respectively. The similarity index ($SIM$) is also higher for the targeted banks, suggesting that those banks appear more synchronous to the banking industry. This could be due to their larger size, as these are mainly large investment banks. While the bank-level risk ($BRISK$) of both bank groups is similar, the targeted banks contribute significantly to systemic risk as indicated by the mean $SRISK$ of 0.70 relative to the mean of 0.44 for the non-targeted banks.

Looking at the controls and proxies for the CAMELS ratings, an average bank has a leverage ratio of 85.54% and deposit ratio of 75.63%, while having a non-performing loan ratio of 1.72%. On average, the targeted banks are less reliant on deposit funding (mean = 56.42%) and have lower real estate loan ratio (mean = 43.52%) compared to their counterparts. These statistics support the notion that these banks diversify their financial activities and are engaged in non-core banking operations, other than commercial lending. Further, the targeted banks tend to be large, liquid, and mostly recipients of the TARP bailout funding. The average trading asset ratio over the pre-Volcker period ($PRETRAD$) is also higher at the targeted banks than the non-targeted banks, which confirms that these banks are directly affected by the Volcker Rule.

## 4. Empirical analysis

*4.1. Relation between diversification, similarity, trading activity, and risk measures*

In this section, we study the relation between the three channels and (i) bank risk, as well as (ii) systemic risk. To address the possible endogeneity between the risk measures and diversification, similarity, and trading activity, we use a two-stage least square (2SLS) model with instrumental variables (IV). In the first-stage regressions, we follow the approach used in Hasbrouck and Saar (2013) and instrument the degree of each channel for a given bank-quarter with the average level of that channel in the same quarter in all other banks with corresponding size (market capitalization) quartile and bank type (investment versus non-investment banks). The intuition is that a given bank's diversification, similarity, and trading activity are correlated with the corresponding channel of other similar banks, but other banks' channels are unlikely to be indirectly influenced by the risk in the given bank. The 2SLS IV model is estimated as follows.

Stage 1 bank-level IV regressions:

$$DIV_{i,t} = b_0 + b_1 DIV_{not,t} + b_2 controls_{\,i,t} + u_{i,t}, \tag{21}$$

$$SIM_{i,t} = c_0 + c_1 SIM_{not,t} + c_2 controls_{\,i,t} + u_{i,t}, \tag{22}$$

$$TRAD_{i,t} = d_0 + d_1 TRAD_{not,t} + d_2 controls_{\,i,t} + u_{i,t}, \tag{23}$$

where $DIV_{not,t}$, $SIM_{not,t}$, and $TRAD_{not,t}$ are the quarterly average level of revenue diversification, bank similarity, and trading activity in other comparable banks, except bank *i*, respectively.

Stage 2 regression:

$$BRISK_{i,t} = \beta_0 + \beta_1 \widehat{DIV}_{i,t} + \beta_2 \widehat{SIM}_{i,t} + \beta_3 \widehat{TRAD}_{i,t} + \beta_4 controls_{i,t} + \varepsilon_{i,t}, \tag{24}$$

$$SRISK_{i,t} = \gamma_0 + \gamma_1 \widehat{DIV}_{i,t} + \gamma_2 \widehat{SIM}_{i,t} + \gamma_3 \widehat{TRAD}_{i,t} + \gamma_4 controls_{i,t} + \varepsilon_{i,t}, \tag{25}$$

where $\widehat{DIV}_{i,t}$, $\widehat{SIM}_{i,t}$, and $\widehat{TRAD}_{i,t}$ are the fitted values of diversification, similarity, and trading activity obtained from the first stage regressions, respectively.

Table 4 displays our second-stage regression results for Eqs. (24) and (25) in Columns (1) and (2), respectively. Column (1) reports the marginal effects from a IV regression for the drivers of bank-level risk ($BRISK$), which tests Hypotheses 1a, 2a, and 3a. From Column (1), the fitted values of diversification ($\widehat{DIV}$) have a negative coefficient of -0.156, which is statistically significant at the 1% level. This suggests that banks with more diversified operations tend to have less fluctuations in value and lower level of bank risk. On average, a one standard deviation increase in revenue diversification leads to a 0.08% decrease in bank-level risk[14]. This result is consistent with our theoretical prediction and Hypothesis 1a, whereby diversification lowers

[14] The standard deviation of $DIV$ is 0.52 and the standard deviation of $BRISK$ is 1.12%. A one standard deviation increase in $DIV$ is expected to decrease $BRISK$ by 0.156 × 0.52 = 0.08112%.

individual banks' risk, and thus is desirable at the bank level. The negative coefficient on $\widehat{SIM}$ of -0.016 implies that banks that are more similar to each other have lower bank risk. While we expect that similarity has no impact on bank-level risk, this effect is economically small. For a one standard deviation increase in similarity, the bank-level risk is expected to decrease by 0.04%. While Hypothesis 2a is not clearly supported by the empirical result, the small effect is still consistent with our model whereby similarity has no effect on individual banks' default risk.

The variable $\widehat{TRAD}$ obtains a negative but insignificant coefficient of -0.103. The direction of the effect suggests that banks that have higher ratios of trading assets tend to have lower bank-level risk. This is quite surprising, as the common belief is that trading activities are risky and more volatile that can drive the riskiness of banks (Williams, 2016). One explanation is that trading activity is highly correlated with other bank-specific factors, such as size and, hence, its effect can be diluted after controlling for these variables. Further, Lepetit, Nys, Rous, and Tarazi (2008) show that banks' higher reliance on non-interest activities is associated with higher risk but that higher risk is more correlated with commission and fee income than trading activities. Lepetit et al. (2008) also argue that a larger share of trading income is associated with a lower risk exposure and default risk for small listed banks.

Turning to the controls, banks with higher market leverage ($MKTLEV$) and non-performing loan ratios ($NPL$) tend to be more volatile as they have higher default and credit risks, respectively. The coefficients on the liquidity ($LIQ$) and real estate loan ratios ($RELOAN$) both have negative signs, which indicate that banks experience lower bank-level risk when they have a greater share of liquid assets and residential loans. These estimates are consistent with the perception that these are regarded as safe asset classes. The negative coefficient on profitability ($ROE$) is also in line with the intuition that banks are less volatile when their financial performance is sound. Finally, banks are safer when they are more reliant on deposit funding or when the economy is in a good state.

We turn to the second column of Table 4, which tests Hypotheses 1b, 2b, and 3b to examine the drivers of banks' systemic risk ($SRISK$). Consistent with Hypothesis 1b, the results in Column (2) indicate that diversification is negatively associated with systemic risk. We also find support for Hypothesis 2b, as the variable $\widehat{SIM}$ has a significantly positive coefficient that implies that systemic risk increases when banks are more similar to each other. The effects of revenue diversification and similarity on systemic risk are both statistically and economically significant. The coefficients on $\widehat{DIV}$ of -0.036 and $\widehat{SIM}$ of 0.063 suggest that, on average, a one standard deviation increase in diversification and similarity decreases systemic risk by 0.02 while increases systemic risk by 0.17, respectively. All else equal, banks with higher diversification tend to have lower systemic risk, whereas those that are more similar to others have higher systemic risk.

In line with previous studies (e.g. Brunnermeier et al., 2012; Williams, 2016), we also find a positive relation between trading activity and systemic risk. From Column (2) of Table 4, the significant coefficient on $\widehat{TRAD}$ of 0.339 suggests that banks that are more active in proprietary trading tend to have higher systemic risk. For an average targeted bank with the standard deviation of $TRAD$ of 0.08, a one standard deviation increase in trading asset ratio is expected to increase systemic risk by 0.03[15].

Regarding the controls, banks that hold more liquid assets and residential loans have lower systemic risk. Consistent with the documented moral hazard and too-big-to-fail concerns (Black and Hazelwood, 2013; Duchin and Sosyura, 2014), large banks or those that received the TARP funds tend to have higher systemic risk. As expected, leverage and non-performing loan ratios are also positively related to banks' systemic risk.

These results are consistent with our model's predictions and hypotheses. First, diversification has risk reduction benefit as banks can diversify idiosyncratic risks by spreading their investments across different asset classes (Markowitz, 1952). Second, we confirm that when holding other channels constant, higher diversification leads to lower risk at the system-wide level and, hence, is not the main driver of systemic risk. Third, while similarity has small effect on bank risk, high similarity among banks increases asset correlation and exposes them to common risks, thereby raising the probability of a systemic default. Finally, banks' involvement in trading activities serves as a mechanism through which risks are transmitted across sectors, leading to the build-up of systemic risk.

### *4.2. Effects of the Volcker Rule on risk measures*

This section investigates the effects of the Volcker Rule. To do this, we employ a two-stage approach. In the first stage, we estimate a difference-in-differences (DID) model for each

[15] The standard deviations of $TRAD$ and $SRISK$ for the targeted banks are in an unreported table, which is available upon request. These values are 0.08 and 0.225 for $TRAD$ and $SRISK$, respectively.

of the channels to quantify the effects of the Volcker Rule on diversification, similarity, and trading activity. Our difference-in-differences model is estimated as follows:

$$y_{i,t} = \delta_0 + \delta_1 POST_t + \delta_2 PRETRAD_i + \delta_3 POST_t \times PRETRAD_i + \epsilon_{i,t}, \tag{26}$$

where $y_{i,t}$ is a vector of the measures of bank $i$'s revenue diversification ($DIV_{i,t}$), bank similarity ($SIM_{i,t}$), and trading asset ratio ($TRAD_{i,t}$) in quarter $t$; $POST_t$ is the indicator variable that takes a value of one for the post-Volcker period (from 2012 to 2016) and zero for the pre-Volcker period (from 2003 to 2007); $PRETRAD_i$ is bank $i$'s average trading asset ratio over the pre-Volcker period (from 2003 to 2007); $POST_t \times PRETRAD_i$ is an interaction term (henceforth, DID term) that serves as a continuous treatment variable that takes a higher value when the Volcker Rule is more binding on bank $i$. The estimated coefficients on the DID term, $\gamma_3$, allow us to examine the effect of the Volcker Rule on the targeted banks' revenue diversification, similarity, and trading activity. For the estimation stage, we use a balanced sample period that contains data of five years before and five years after the implementation of the Volcker Rule. Thus, our sample data is not contaminated by the pre-Volcker implementation noises and crisis effects, thereby mitigating the data issues documented in most policy studies (SEC, 2017).

In the second stage, we compute the effects of the Volcker Rule on the risk measures via each of the channels by which the Rule affects risks. Note that this cannot be done directly with the standard DID method. The reason is because by simply analyzing the risks before and after the Rule implementation, we cannot disentangle the effects of the Volcker Rule from other factors that occurred during that time. Hence, this stage involves multiplying the DID coefficients obtained in the first stage (Eq. (26)) by the 2SLS regression coefficients estimated from Eqs. (24) and (25). That is, we separately compute the effects of the Volcker Rule on revenue diversification, similarity, and trading activity to assess how each of these channels influence the risk measures at the bank level.

The proposed method has two main advantages. First, we clearly identify the channels for the effects, and thus provide more granular evidence on the impacts of the Volcker Rule at the individual bank level. By estimating the consequences of the Volcker Rule on each of the channels, we can isolate the effects of the Volcker Rule from other regulations and confounding factors that were simultaneously implemented during the crisis as well as understand the mechanisms of how the Volcker Rule affects risks. Second, we conduct the analysis at the bank level rather than at the aggregate level to capture the cross-sectional heterogeneity among banks.

Hence, our method is able to account for the fact that different banks are affected by the Rule in different ways. Further, this method also allows us to investigate the interactions between different channels through which the effects take place, which could have opposing directions.

Table 5 reports the first stage DID estimation results. We estimate the model with the control variables because it is likely that revenue diversification, similarity, and trading activity are affected by other bank-level characteristics. In Column (1), we test Hypothesis 4 that examines the Volcker Rule's effect on diversification of the targeted banks. We obtain a negative coefficient on $POST$, indicating that, on average, revenue diversification declines following the Volcker Rule. The negative coefficient on the DID term is in line with our prior expectations. Banks that had a high level of pre-Volcker trading asset ratio reduce their diversification level more than their counterparts during the post-Volcker period. By banning proprietary trading, the Volcker Rule limits banks' capacity to diversify their financial activities, and thus leads to a decline in revenue diversification of the targeted banks. This finding supports our Hypothesis 4.

Turning to Column (2), we assess the effects of the Volcker Rule on bank similarity. The coefficient on $POST$ is positive and statistically significant, implying that all banks, on average, exhibit an increase in similarity after the introduction of the Volcker Rule. As anticipated, the variable $PRETRAD$ is significantly negative, which indicates that banks that were engaged in proprietary trading (more diversified) and other nonbanking activities during the pre-Volcker period tend to be less similar or synchronous with other conventional banks in the banking sector. Interestingly, the positive coefficient on the DID interaction term (significant at the 1% level) suggests that Volcker-targeted banks become more similar to other banks following the implementation of the Volcker Rule. These findings support Hypothesis 6. By restricting proprietary trading, the Volcker Rule makes banks become more similar to each other. This is because the targeted banks are forced to cut back on their proprietary trading activities, and thus become specialized in similar operations as the non-targeted banks. While all banks have higher similarity after the implementation of the Volcker Rule, the targeted banks are more affected than the non-targeted banks. This suggests that there is heterogeneity in the Rule's effects across banks.

The last column tests Hypothesis 5, which examines the effect of the Volcker Rule on banks' trading activity. Consistent with Keppo and Korte (2016), we obtain significant and negative coefficient on the DID term for the $TRAD$ regression. Banks with a relatively high pre-

Volcker trading asset ratio experience a stronger reduction in their trading asset ratios following the Volcker Rule. This finding supports our Hypothesis 5 and complements the negative effect of the Rule on the targeted banks' diversification in Column (1).

As an alternative specification, we replace the pre-trading ratio with a binary variable, $TARGETEDBHC$. The alternative binary variable assigns a value of one for banks that had a trading asset ratio of 3% or above during the pre-Volcker period (from 2003 to 2007) and zero otherwise. We report the results in the first three columns of Table 6 and they are qualitatively similar to those reported above. From Column (1), the negative coefficient on the DID interaction term indicates that the targeted banks decrease revenue diversification after the implementation of the Rule. The variable $POST$ in the $SIM$ regression (Column (2)) has a coefficient of 1.291 that confirms Hypothesis 6, in that bank similarity increase following the Volcker Rule. Note that this coefficient is similar in magnitude with our results in Column (2) of Table 5. The coefficient on the DID term in Column (3) of -0.014 implies that the targeted banks experience a decrease in the trading asset ratio of 1.4% more than the non-targeted banks. At an $PRETRAD$ of 10% for the targeted banks, this is a reduction of 14% in trading assets of the targeted banks[16]. Taken together, the Volcker Rule has the largest impact on the similarity channel.

For further robustness, we use other alternative variables to classify the targeted banks. The first measure is the dummy variable $TARGETEDBHC\_P99$, where we consider the targeted banks to be those with the top 1% average trading asset ratio during the pre-Volcker period. The second alternative measure is $TARGETEDBHC\_TOP10$ that takes a value of one if a bank is among the top 10 banks in terms of their pre-Volcker trading asset ratio and zero otherwise. The results are consistent with our previous discussions and are reported in Columns (4)–(9) of Table 6.

Overall, we find evidence that the Volcker Rule has implications on different channels, which can have opposing effects on bank-level and systemic risks. While we document a strong decline in the level of diversification and share of trading assets for the Volcker-targeted banks,

[16] For robustness, we also estimate a DID model with the inclusion of bank and time fixed effects. In this specification, the coefficients on the interaction term in the trading asset ratio equation have similar magnitudes as those reported in Keppo and Korte (2016). The results are available upon request.

the increase in similarity among banks reveals that the Volcker Rule can also have significant effects on the non-targeted banks via the similarity channel.

So far, we have estimated how diversification, similarity, and trading activity independently affects bank-level and systemic risks, and how the Volcker Rule impacts these channels. We now combine these results to estimate the effects of the Volcker Rule on the two risk measures to test Hypotheses 7 and 8. We compute the effects by using the estimated coefficients obtained from Columns (1)–(2) in Table 4 and Columns (1)–(3) in Table 5 at the bank level. For example, the effect of the Volcker Rule on bank $i$'s bank-level risk from the diversification channel is calculated as $\delta_3 \times PRETRAD_i \times \beta_1$[17]. This estimate represents the change in banks' risk measures due to the change in revenue diversification caused by the Volcker Rule. Similarly, the effect of the Rule on bank $i$'s risk from the trading activity channel is computed as $\delta_3 \times PRETRAD_i \times \beta_3$. For the similarity channel, we compute the effect of the Volcker Rule on bank-level risk of bank $i$ as $(\delta_3 \times PRETRAD_i \times \beta_2) + \delta_1$ to also account for the indirect impact on the non-targeted banks. The effects of the Volcker Rule on bank $i$'s systemic risk from each channel are computed in a similar way, except the estimates $\beta_1$, $\beta_2$, and $\beta_3$ (from Eq. (24)) are replaced with $\gamma_1$, $\gamma_2$, and $\gamma_3$ (from Eq. (25)), respectively.

Figure 5 presents the effects of the Volcker Rule on bank-level and systemic risks in Panels A and B, respectively. In addition to our computations for the aggregate banking sector, we separately report the effects on the risk measures for the targeted and non-targeted banks. The bank-level risk ($BRISK$) is measured as the banks' annualized stock return volatility, whereas the systemic risk ($SRISK$) is measured as the banks' systemic tail beta. The bars in Figure 5 refer to the percentage changes in the risk measures of each bank group relative to their respective average bank-level and systemic risks during the periods before the Volcker Rule's enactment[18].

We test Hypothesis 7 that proposes that the Volcker Rule reduces diversification by which it raises bank-level risk of the targeted banks. From Panel A, which illustrates the change in bank-level risk in the post-Volcker period, the ban on proprietary trading decreases the

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[17] Note that $\delta_3$ is the coefficient on the interaction term $POST \times PRETRAD$ in Eq. (26). This estimated coefficient varies as the dependent variable takes turn to be $DIV$, $SIM$, and $TRAD$ at a time.

[18] We report the absolute changes in the risk measures in Appendix B. Note that we calculate the value-weighted averages of these effects to account for the size differential across banks, which might affect the magnitude of the effects. The average pre-Volcker bank-level and systemic risks are defined as $PREBRISK$ and $PRESRISK$ in Table 2. We report the descriptive statistics of these variables in Table 3 for reference purposes. The number of banks in this section drops due to some banks no longer existing after 2011.

targeted banks' trading activity and diversification and, hence, raises bank-level risk by about 0.3% and 1.5% (relative to their pre-Volcker $BRISK$ of 1.76%), respectively. While the independent effect of similarity on bank-level risk is small (from Table 4), a sharp rise in similarity due to the Rule implementation magnifies its effect for the targeted banks. This effect is of similar magnitude to the one via the diversification channel, thereby offsetting the increase in bank risk from a lower diversification level. We find supporting evidence for Hypothesis 7, whereby the Volcker Rule decreases the targeted banks' capacity to diversify idiosyncratic risk, hence, increases their risk level. As evident by the slight effect of the bar $TRAD$, our result suggests that the Volcker Rule does not influence the riskiness of individual banks through the trading activity as we expected.

By contrast, the non-targeted banks have a greater net bank-level risk reduction relative to the targeted banks. Given that these banks had low or zero trading asset ratios, a decrease of 1% in their bank-level risk relative to their average pre-Volcker $BRISK$ of 1.86% is driven mostly by the similarity channel.

Overall, the Volcker Rule has a weak impact on individual banks' risk level (a decrease of about 0–1% for the targeted and non-targeted banks). A surprising result is that the bank-level risk of non-targeted banks decreases more relative to that of the targeted banks. As the goal of this regulation is to strengthen the stability of financial markets, we continue to examine the effect that the Volcker Rule has on systemic risk in Panel B.

The results in Panel B test Hypothesis 8, which predicts that the Volcker Rule would increase the systemic risk due to high bank similarity. As intended by the Volcker Rule, the negative bar for $TRAD$ indicates that the reduction in proprietary trading activity lowers the systemic risk of the targeted banks. At an average pre-Volcker systemic risk ($SRISK$) of 0.60 for targeted banks, the trading activity channel results in a decrease of about 3% in systemic risk in the post-Volcker period. However, there is a substantial increase in systemic risk of the targeted banks because of higher bank similarity. Interestingly, this suggests that the Volcker Rule can have an unintended consequence on banks' systemic risk through the similarity channel, and thus makes the combined effect ambiguous. The effect from bank similarity is also economically meaningful, which implies an increase of more than 20% of the targeted banks' average pre-Volcker systemic risk. While the decrease in trading activity lowers systemic risk, greater similarity among banks makes them exposed to higher probability of a systemic default. We find that this is the case with the ban on banks' proprietary trading. Accordingly, it is unclear whether the Volcker Rule can enhance financial stability by decreasing systemic risk, since there are strong channels that result in the opposite effect.

Another striking result is that the Volcker Rule can have an adverse effect on banks that are not subject to the regulation. As shown in Panel B of Figure 5, the non-targeted banks are also unintendedly affected by the Rule through higher bank similarity and, hence, increase systemic risk in the post-Volcker period. There is an increase in systemic risk for the non-targeted banks of 22% relative to their average level of 0.38 before the Rule's enactment. This is because when two banks hold a common asset portfolio, a shock to the asset payoffs is likely to cause both banks to default at the same time since they invest in similar and correlated assets. Hence, Hypothesis 8 is strongly supported by our empirical results.

Recognizing that the effects are not homogenous, we further analyze the cross-sectional heterogeneity of the effects on risks in Figure 6. We stratify the sample banks into five groups according to the level of their pre-Volcker trading asset ratios ($PRETRAD$). The ratio range for Group 1 is between zero and the 50$^{th}$ percentile (median value); the range for Group 2 is between the 50$^{th}$ and 90$^{th}$ percentiles, followed by Group 3 that ranges from the 90$^{th}$ to 95$^{th}$ percentiles. Banks in Group 4 have pre-trading asset ratios ranging between the 95$^{th}$ and 99$^{th}$ percentiles, and Group 5 is for ratios that are in the top 1% of the distribution. Since most banks have trading asset ratios of 0%, Group 1 accounts for 72% of the banks in our study (consisting of 198 banks) while Groups 4 and 5 consist of 13 banks in total. Our expectation is that the Volcker Rule would have the strongest effects on banks with large holdings of trading assets as they would be directly targeted by the regulation.

Figure 6 displays the percentage changes in the risk measures after the Volcker Rule for five ranges of trading ratios relative to the average pre-Volcker risk levels. Panel A reports the results for bank-level risk, relative to the sample average bank risk of 1.86% during the pre-Volcker period, while Panel B reports the change in systemic risk, relative to the average pre-Volcker systemic risk of 0.38 (from Table 3). There are three key findings from this figure. First, the intensity of the effects on risks from individual channels is positively related to banks' trading asset ratios prior to the Volcker Rule implementation. From Panel A, the magnitude of the relative change in bank-level risks from diversification, similarity, and trading activity increases as we move from Groups 1 to 5. For banks in Group 5, at an average pre-Volcker

BRISK of 1.86% the Volcker Rule increases bank-level risk by 0.4% and 0.1% via diversification and trading activity channels, respectively. As expected, there is little change in bank-level risk via diversification and trading activity channels for banks with lower pre-Volcker trading ratio range. The same pattern can be drawn from Panel B, which examines the relative change in banks' systemic risk.

Second, the Volcker Rule affects various channels that result in opposing effects on risks. Referring to the net combined effect, it seems that the Volcker Rule does not significantly influence the risk measures. Following the Volcker Rule, bank-level risk is expected to change by -1% to 0.3% (see Panel A), depending on which group the banks are in. However, the independent effects from each channel are of larger magnitude. For example, an increase in Group 5's bank-level risk of 1.7% and 0.4% from diversification and trading activity are offset by a decrease in bank risk of about 1.8% from similarity, through which comes the net effect of 0.3%. Further, the opposing effects of the Volcker Rule on the risk measures are most prominent for banks that had high trading asset ratios (which are in Groups 4 and 5).

Third, we confirm that bank similarity is a dominating channel that drives systemic risk in Panel B. The average systemic risk during the pre-Volcker period is 0.38, and banks in Group 1 raise systemic risk by more than 20% due to higher similarity while being unaffected by the trading activity and diversification channels. The magnitude of these effects is even larger for banks in Group 5. For these banks, the reduction in trading activity decreases systemic risk by 6%, which is offset by an increase of 35% from higher similarity. It is interesting that banks that are not targeted by the Volcker Rule are also significantly affected by the increased similarity between banks.

## 5. Conclusion

As part of the Dodd-Frank Act, the Volcker Rule aims to limit bank risk taking by restricting commercial banks from engaging in proprietary trading and excessively speculative activities. We find that the Volcker Rule has an intended effect on the targeted banks, as these banks reduced trading asset ratios more than their counterparts following the Rule. Hence, the reduction in proprietary trading results in a decline in systemic risk of the targeted banks through the trading activity channel. However, we also find an unintended effect of the Volcker Rule on banks that are not subject to the regulation. Because the Rule bans proprietary trading by the targeted banks, this makes the targeted and non-targeted banks become more similar, and thus having common risk exposure. As such, the similarity between banks increases the probability that they default at the same time, thereby raising systemic risk.

We also show that the effects of the Volcker Rule are heterogenous across banks. The intensity of the effects is positively related to the targeted banks' trading asset ratios in the period before the Volcker Rule implementation. Banks that had a pre-Volcker trading asset ratio in the top 1% of the distribution experience a significant increase in bank-level and systemic risks, which is mostly attributed to less diversification and higher similarity with other banks. While the targeted banks decrease systemic risk through the trading activity channel, there is an increase in systemic risk of both the targeted and non-targeted banks through the similarity channel. Our model refines the theory of Wagner (2010) in that an increase in bank similarity can arise due to a decrease, rather than an increase in diversification. By analyzing the independent effects of each channel separately, we are the first to theoretically assess the effects of the Volcker Rule on risks since diversification and similarity do not go hand in hand in this setting.

The results of this paper have important implications for policymakers. First and foremost, regulation that limits bank involvement in certain activities can have a multitude of effects that make the net effect ambiguous. While policymakers might have focused on the anticipated risk reduction from restricting a particularly risky activity, we show that empirically this is not the dominant effect. Our findings are relevant for several advanced economies that are adopting structural bank regulations. Similar to the Volcker Rule in the US, the proposals of the Vickers Commission in the United Kingdom, and the adaptations of the Liikanen Report in recent French and German reform proposals (Gambacorta and van Rixtel, 2013). Similar to the Volcker Rule in the US, these structural reform proposals seek to limit the high-risk trading activities by banks but with broader scope and varying degree of strictness. By design, the constraint on the targeted banks' activities would always make them more similar to other banks, which in turn amplifies the probability of a systemic default. Our results suggest that regulators need to consider carefully the salient effects that bank similarity has on systemic risk.

Second, regulation can often impact entities that are not the direct targets of the regulation. We find that this is the case with the Volcker Rule. Banks that are not engaged in proprietary trading are not directly affected but are indirectly affected by the Volcker Rule by becoming more similar to the targeted banks. While the ban on proprietary trading does not influence the bank-level risk of the non-targeted banks, their systemic risk increases due to higher similarity. Given the large number of indirectly affected commercial banks, our results imply that these unintended costs on the non-targeted banks are substantial. Accordingly, regulators need to be mindful of the collateral damage costs when evaluating regulations.

On the basis of our results, it is not clear that the Volcker Rule has had its intended effect of decreasing systemic risk. In fact, the mechanisms that we examine and quantify provide several reasons why the effects could go in the opposite direction. Future research should investigate whether there are other channels of relevance that might offset the negative effects documented in the paper. The effects of Volcker Rule implementation on risks are only a part of current policy discussions in addressing financial fragility. Thus, further research on other potential implications of this reform are needed to evaluate its effectiveness.

## Appendix A: Proofs

This section provides the proofs for derivations discussed in Section 2.

### 1. Proof of diversification's effects

Recall that the minimum return thresholds to avoid bank default for banks A and B in the baseline setting are as follows:

$$y_A(x) = \frac{d}{1-\alpha_1} - \frac{\alpha_1}{1-\alpha_1} x, \tag{A.1}$$

$$y_B(x) = \frac{d}{1-\alpha_2} - \frac{\alpha_2}{1-\alpha_2} x. \tag{A.2}$$

After receiving the treatment, bank A becomes more diversified and has a new minimum return threshold that is equal to that of bank B in the pre-treatment period, and vice versa. Hence,

$$y_A^{post}(x) = \frac{d}{1-\alpha_2} - \frac{\alpha_2}{1-\alpha_2} x, \tag{A.3}$$

$$y_B^{post}(x) = \frac{d}{1-\alpha_1} - \frac{\alpha_1}{1-\alpha_1} x. \tag{A.4}$$

We examine the probability of individual banks' default and systemic default by computing the probability mass of the areas specified in Panel B of Figure 2.

#### *1.1. Bank risk*

Let $\pi$ denote the probability mass of the default areas, and its subscripts represent the specified areas in Panel B of Figure 2. Note that the asset payoffs have a uniform distribution with a probability density function of $\Phi(.) \sim [0, s]$. Since the assets have the same probability density function, we refer to $s_y$ as $s$ for short. For individual bank risks, we obtain the probability of bank A's and bank B's default to be:

$$\begin{aligned} Pr(D_A) &= \pi_{1+2} \\ &= \frac{d}{s}, \end{aligned} \tag{A.5}$$

$$\begin{aligned} Pr(D_B) &= \pi_{1+4} \\ &= \int_0^d \int_0^{\frac{d-\alpha_2 x}{1-\alpha_2}} \frac{1}{s^2} dydx + \int_0^{\frac{d}{\alpha_2}} \int_0^{\frac{d-\alpha_2 x}{1-\alpha_2}} \frac{1}{s^2} dydx \\ &= \frac{d^2}{2\alpha_2 s^2 - 2\alpha_2^2 s^2}, \end{aligned} \tag{A.6}$$

respectively. Note also that diversification decreases bank risk when $\pi_{1+2} > \pi_{1+4}$, and thus, the expression can be written as:

$$\pi_{1+4} - \pi_{1+2} < 0$$

$$\frac{d^2}{2\alpha_2 s^2 - 2\alpha_2^2 s^2} - \frac{d}{s} < 0$$

$$\tfrac{d}{s} < 2\alpha_2(1 - \alpha_2). \quad \text{(A.7)}$$

To simplify this result, we apply the condition on $\alpha_2$ where $\alpha_2 \leq 1 - \frac{d}{s}$. Hence, the final result can be simplified as:

$$\frac{d}{s} < 2\alpha_2(1 - \alpha_2)$$

$$< 2\left(1 - \frac{d}{s}\right)\left(1 - \left(1 - \frac{d}{s}\right)\right)$$

$$< \tfrac{1}{2}. \quad \text{(A.8)}$$

The intuition is that as long as banks have less than 50% probability of default, diversification has risk saving benefit at the bank level. We refer to this as a reasonable condition, which will be used in the derivations of the later sections.

*1.2. Systemic risk*

Diversification makes systemic default more likely when the default probability of bank A conditional on bank B's default (($Pr(D_A|D_B)$) is higher in the post-treatment period, that is $Pr(D_A|D_B)^{pre} < Pr(D_A|D_B)^{post}$. The former is defined as $\frac{\pi_1}{\pi_{1+2}}$ while the latter is $\frac{\pi_1}{\pi_{1+4}}$, where $\pi_1 = \int_0^d \int_0^{\frac{d-\alpha_2 x}{1-\alpha_2}} \frac{1}{s^2} dydx$. This follows that:

$$\frac{\pi_1}{\pi_{1+4}} - \frac{\pi_1}{\pi_{1+2}} > 0$$

$$\frac{1}{2}(-2 + \alpha_2)\left(2\alpha_2 + \frac{d}{(-1 + \alpha_2)s}\right) > 0$$

$$\tfrac{d}{s} > 2\alpha_2(1 - \alpha_2). \quad \text{(A.9)}$$

Recall from Eq. (A7), diversification results in a risk saving at the bank level when $\frac{d}{s} < 2\alpha_2(1 - \alpha_2)$. This suggests that the banks would have no incentive to hold a debt amount higher than the threshold should they want to seek the benefits of diversification. As such, the condition required for diversification to reduce individual bank risk does not hold in the case where diversification will increase systemic risk. We also verify the result by using the reasonable condition of $\frac{d}{s} < \frac{1}{2}$ (Eq. (A.8)), whereby under this condition on $\frac{d}{s}$, the post-treatment systemic risk of bank A is lower relative to the one in the pre-treatment period. Thus, it follows that diversification leads to a reduction in both the bank-level and systemic risk when $\frac{d}{s} < \frac{1}{2}$.

## 2. Proof of bank similarity's effects

*2.1. Bank risk*

Here, bank B receives the treatment by switching its investment between assets X and Y. The new minimum return threshold to avoid bank default for bank B becomes:

$$y_B^{post}(x) = \frac{d}{\alpha_2} - \frac{1-\alpha_2}{\alpha_2} x. \tag{A.10}$$

Following a similar approach to that in the previous section, the probability of bank B's default in the pre- and post-period can be expressed as $Pr(D_B)^{pre} = \pi_{1+5+6}$ and $Pr(D_B)^{post} = \pi_{1+2+6}$, respectively. As areas 5 and 2 are the same by symmetry, there is no change to bank B's individual default. Hence, similarity has no effect on individual bank risk.

*2.2. Systemic risk*

First, consider bank B that becomes more similar to bank A after receiving the treatment. The conditional probabilities of default are $Pr(D_B|D_A)^{pre} = \frac{\pi_1}{\pi_{1+2+3}}$ and $Pr(D_B|D_A)^{post} = \frac{\pi_{1+2}}{\pi_{1+2+3}}$ for the pre- and post-periods, respectively. Using double integrals, we obtain the following: $\pi_{1+2+3} = \frac{d}{s}, \pi_1 = \int_0^d \int_0^{\frac{d-\alpha_2 x}{1-\alpha_2}} \frac{1}{s^2} dydx,$ and $\pi_{1+2} = \int_0^d \int_0^{\frac{d-(1-\alpha_2)x}{\alpha_2}} \frac{1}{s^2} dydx$. By computing the probability mass of the specified areas in Panel B of Figure 3, we set $Pr(D_B|D_A)^{post} > Pr(D_B|D_A)^{pre}$ to test whether bank similarity results in higher systemic risk. Hence, we have:

$$Pr(D_B|D_A)^{post} - Pr(D_B|D_A)^{pre} > 0$$

$$\frac{\pi_{1+2}}{\pi_{1+2+3}} - \frac{\pi_1}{\pi_{1+2+3}} > 0$$

$$\frac{(1+\alpha_2)d}{2\alpha_2 s} - \frac{(-2+\alpha_2)d}{2(-1+\alpha_2)s} > 0$$

$$\frac{d-2\alpha_2 d}{2\alpha_2 s - 2\alpha_2^2 s} > 0$$

Simplifying the expression yields a solution of:

$$\alpha_2 < \frac{1}{2}. \tag{A.11}$$

We verify that this result is the same as the pre-determined condition on $\alpha_2$ in the scenario setting in Panel A of Figure 3. This is to ensure that bank B will become more similar to bank A, as it holds greater weight in asset X in the post-treatment period.

As similarity affects both the treated and control groups, we then compute the bank A's risk differential between the pre- and post-periods. The conditional probabilities of default are $Pr(D_A|D_B)^{pre} = \frac{\pi_1}{\pi_{1+2+6}}$ and $Pr(D_B|D_A)^{post} = \frac{\pi_{1+2}}{\pi_{1+5+6}}$ for the pre- and post-periods, respectively. We compute the systemic risk differential, yielding a solution of:

$$\begin{aligned} \frac{\pi_{1+2}}{\pi_{1+2+6}} - \frac{\pi_1}{\pi_{1+5+6}} &> 0 \\ (1-\alpha_2^2) - (2-\alpha_2)\alpha_2 &> 0 \\ 1 - 2\alpha_2 &> 0 \\ \alpha_2 &< \frac{1}{2}. \end{aligned} \tag{A.12}$$

and hence, we obtain the same condition as in (A.11).

For the aggregate systemic risk, the increase in similarity implies a higher value for this measure that is represented by the probability mass of area *2*, defined as $\pi_2 = \frac{(2\alpha_2-1)d^2}{2(\alpha_2-1)\alpha_2 s^2}$. Note that $\pi_2$ is strictly positive given that $0 < \alpha_2 < 1$.

## 3. Proof of the Volcker Rule's effects

When the Volcker Rule was implemented, it affected both the diversification and similarity channels. In particular, the Volcker Rule increases the similarity among banks A and B, but decreases the diversification of bank B. The new minimum return threshold for bank B is defined as:

$$y_B^{Volcker}(x) = \frac{d}{1-\alpha_2-\beta} - \frac{(\alpha_2+\beta)}{1-\alpha_2-\beta}x. \tag{A.13}$$

### *3.1. Bank risk*

The reduction in diversification would be expected to have an adverse effect on individual banks' riskiness. This follows that the Volcker Rule would result in an increase in the targeted bank's default probability while there would be no change to the risk taking of the non-targeted bank. As such, the change in bank B's default probability is given by:

$$Pr(D_B)^{Volcker} - Pr(D_B) > 0$$

$$\pi_{1+5+6} - \pi_{1+2+6} > 0$$

$$\left(-\frac{d^2}{2(-1+\alpha_2+\beta)(\alpha_2+\beta)s^2}\right) - \left(\frac{d^2}{2\alpha_2 s^2 - 2\alpha_2^2 s^2}\right) > 0$$

$$\frac{\beta d^2(-1+2\alpha_2+\beta)}{2\alpha_2 s^2(-1+\alpha_2)(-1+\alpha_2+\beta)(\alpha_2+\beta)s^2} > 0. \tag{A.14}$$

Hence, by substituting the condition on $\alpha_2 \leq 1 - \frac{d}{s}$ into Eq. (A.14) and solving for $\frac{d}{s_y}$, we have:

$$\beta < \frac{d}{s} < \frac{1}{2}(1+\beta). \tag{A.15}$$

*3.2. Systemic risk*

The Volcker Rule leads to opposing effects on the diversification and similarity. This is a situation where the treated banks would experience an increase in systemic risk due to lower diversification, while the treated and untreated banks would anticipate an increase in systemic risk as a result of higher similarity. Proceeding exactly as before, we obtain:

$$Pr(D_B|D_A)^{Volcker} - Pr(D_B|D_A)^{pre} > 0$$

$$\frac{\pi_{1+2}}{\pi_{1+2+3}} - \frac{\pi_1}{\pi_{1+2+3}} > 0$$

$$\frac{(-2+\alpha_2+\beta)d}{2(-1+\alpha_2+\beta)s} - \frac{(-2+\alpha_2)d}{2(-1+\alpha_2)s} > 0$$

$$\frac{\beta d}{2(-1+\alpha_2)(-1+\alpha_2+\beta)s} > 0. \tag{A.16}$$

This yields two sets of solutions, of which the following solution holds:

$$\alpha_2 < 1 \text{ and } (\alpha_2 + \beta) < 1. \tag{A.17}$$

Applying the condition on $\alpha_2$ again, this set of solutions can be rewritten as:

$$\frac{d}{s} > 0 \text{ and } \beta < \frac{d}{s}. \tag{A.18}$$

Similar to Section 2.2 of Appendix A, the Volcker Rule would also have implications on the systemic risk of the non-targeted bank through the similarity channel. Our prediction is that bank A (conventional bank) would exhibit higher systemic risk as it is exposed to similar risks as bank B (diversified bank). Thus, we repeat the steps for bank A, and obtain:

$$Pr(D_B|D_A)^{Volcker} - Pr(D_B|D_A)^{pre} > 0$$

$$\frac{\pi_{1+2}}{\pi_{1+2+6}} - \frac{\pi_1}{\pi_{1+5+6}} > 0$$

$$-(-2+\alpha_2+\beta)(\alpha_2+\beta)-(2-\alpha_2)\alpha_2 > 0$$
$$-\beta(-2+2\alpha_2\ +\beta)\ \ > 0. \qquad \text{(A.19)}$$

By rearranging and solving for $\beta$, we have the following condition in terms of $\frac{d}{s}$:

$$\beta < 2(1-\alpha_2)$$
$$\frac{\beta}{2} < \frac{d}{s}. \qquad \text{(A.20)}$$

Using the aggregate systemic risk, there is an increment of area *2* in the post-treatment period that is defined as:

$$\frac{\beta d^2}{2s^2(-1+\alpha_2)(-1+\alpha_2+\beta)} > 0. \qquad \text{(A.21)}$$

Note that this probability mass is the same as the solution obtained in Eqs. (A.16)–(A.18), and is always positive.

## Appendix B: Extension results

**Table B.1**
**Effects of Volcker Rule on risk measures – by channel**

This table presents the effects of the Volcker Rule on bank-level ($BRISK$) and systemic risk ($SRISK$) in Panels A and B, respectively. We report separately the results for non-targeted, targeted, and all banks, as well as the effects on risks by different channels (including diversification ($DIV$), similarity ($SIM$), and trading activity ($TRAD$)). $NET$ is the net effect of the Volcker Rule on risks, which is calculated as the sum of the effects by three individual channels following the Rule implementation (that is, $NET = DIV + SIM + TRAD$). The absolute effects are computed at the bank level using the estimated coefficients obtained from the 2SLS regressions (in Columns (1) and (2) in Table 4) and the difference-in-differences models (Columns (1)–(3) in Table 5). The absolute effects of the Volcker Rule on diversification, similarity, and trading activity are computed as $\delta_3 \times PRETRAD$, where $\delta_3$ is the coefficient on the interaction term $POST \times PRETRAD$ in Eq. (26) where the dependent variable is $DIV$, $SIM$, and $TRAD$, respectively. $POST$ is the indicator variable that equals one for periods 2012(Q1)–2016(Q4) and zero for periods 2003(Q1)–2007(Q4). $PRETRAD$ is the average trading asset ratio of bank $i$ during the pre-Volcker period (2003(Q1)–2007(Q4)). $POST \times PRETRAD$ is the interaction term between $POST$ and $PRETRAD$, which serves as a continuous treatment variable that takes a higher value when the Volcker Rule is more binding on bank $i$. We then quantify the effects of the Volcker Rule on risks by multiplying the computed Volcker-effects on the channels ($\delta_3 \times PRETRAD$) by the 2SLS models' coefficients that capture the relation between each channel and the risk measures (for bank-level and systemic risks in Eqs. (24) and (25), respectively). We aggregate these bank-level effects by calculating value-weighted averages. The number of banks drops in this analysis as some banks no longer existing after 2011. The reported results for bank-level risk is in percent, and those for systemic risk are scaled by 100. Full descriptions of the variables are provided in Table 2.

| | Panel A: Bank-level risk (in percent) | | | Panel B: Systemic risk (scaled by 100) | | |
|---|---|---|---|---|---|---|
| Channel | All | Non-targeted | Targeted | All | Non-targeted | Targeted |
| Revenue diversification | 1.21 | 0.16 | 2.50 | 0.28 | 0.04 | 0.58 |
| Bank similarity | -2.59 | -2.14 | -3.13 | 10.10 | 8.36 | 12.24 |
| Trading activity | 0.27 | 0.04 | 0.55 | -0.88 | -0.12 | -1.81 |
| Net effect | -1.11 | -1.95 | -0.08 | 9.50 | 8.28 | 11.00 |
| No. of banks | 275 | 267 | 8 | 275 | 267 | 8 |

**Table B.2**
**Effects of Volcker Rule on risk measures – Cross-sectional results**

This table presents the effects of the Volcker Rule on bank-level ($BRISK$) and systemic risk ($SRISK$) in Panels A and B, respectively. We report separately the results for various channels (diversification ($DIV$), similarity ($SIM$), and trading activity ($TRAD$)) through which the Volcker Rule affects risks. $NET$ is the net effect of the Volcker Rule on risks, which is calculated as the sum of the effects by three individual channels following the Rule (that is, $NET = DIV + SIM + TRAD$). We further stratify the effects by the level of trading assets that banks had during the period before the Volcker Rule (2003(Q1)–2007(Q4)). Banks are stratified into five ranges of pre-Volcker trading asset ratios' percentiles (<50th percentile, 50–90th percentiles, 90–95th percentiles, 95–99th percentiles, and >99th percentile). We name these ranges as Groups 1–5, respectively. The absolute effects are computed at the bank level using the estimated coefficients obtained from the 2SLS regressions (in Columns (1) and (2) in Table 4) and the difference-in-differences models (Columns (1)–(3) in Table 5). The absolute effects of the Volcker Rule on diversification, similarity, and trading activity are computed as $\delta_3 \times PRETRAD$, where $\delta_3$ is the coefficient on the DID interaction term in Eq. (26), which serves as a continuous treatment variable that takes a higher value when the Volcker Rule is more binding on bank $i$. $PRETRAD$ is the average trading asset ratio of bank $i$ during the pre-Volcker period (2003(Q1)–2007(Q4)). We then quantify the effects of the Volcker Rule on risks by multiplying the computed Volcker-effects on the channels ($\delta_3 \times PRETRAD$) by the 2SLS models' coefficients that capture the relation between each channel and the risk measures (for bank-level and systemic risks in Eqs. (24) and (25), respectively). We aggregate these bank-level effects by calculating value-weighted averages. For interpretation purposes, we compute the change in risks (by each channel) relative to the average risk levels during the pre-Volcker period ($PREBRISK$ and $PRESRISK$). The number of banks drops in this analysis as some banks no longer existing after 2011. The reported results for bank-level risk is in percent, and those for systemic risk are scaled by 100. Full descriptions of the variables are provided in Table 2.

| | Panel A: Bank-level risk (in percent) | | | | |
|---|---|---|---|---|---|
| Channel | Group 1 (<p50) | Group 2 (p50–p90) | Group 3 (p90–p95) | Group 4 (p95–p99) | Group 5 (>p99) |
| Revenue diversity | 0.00 | 0.02 | 0.17 | 0.72 | 3.19 |
| Bank similarity | -2.07 | -2.08 | -2.15 | -2.38 | -3.42 |
| Proprietary trading | 0.00 | 0.00 | 0.04 | 0.16 | 0.70 |
| Net effect | -2.07 | -2.06 | -1.93 | -1.50 | 0.47 |
| No. of banks | 198 | 50 | 14 | 11 | 2 |

| | Panel B: Systemic risk (scaled by 100) | | | | |
|---|---|---|---|---|---|
| Channel | Group 1 (<p50) | Group 2 (p50–p90) | Group 3 (p90–p95) | Group 4 (p95–p99) | Group 5 (>p99) |
| Revenue diversity | 0.00 | 0.00 | 0.04 | 0.16 | 0.73 |
| Bank similarity | 8.09 | 8.12 | 8.38 | 9.28 | 13.38 |
| Proprietary trading | 0.00 | -0.01 | -0.13 | -0.52 | -2.31 |
| Net effect | 8.09 | 8.11 | 8.29 | 8.93 | 11.80 |
| No. of banks | 198 | 50 | 14 | 11 | 2 |

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**Table 1**

**Summary of the effects of the Volcker Rule by channel**

This table summarizes the theoretical predictions of the independent effects on bank-level risk, bank-level and aggregate systemic risks of diversification, similarity, and the Volcker Rule. Bank A is a commercial bank that invests wholly in asset X (a conventional asset), while Bank B is a diversified bank that is engaged in proprietary trading, which invests in assets X and Y (proprietary trading asset). We assume that the assets' payoffs follow a uniform distribution with a probability density function of $\Phi(.) \sim [0, s]$. Bank-level risk is the probability of bank $i$'s default ($\Pr(D_i)$). Bank-level systemic risk is a bank's systemic risk, which is defined as the probability of bank $i$ default conditioning on other banks (bank $j$) also default ($\Pr(D_i | D_j)$). Aggregate systemic risk is the probability of a joint default ($\Pr(D_i \cap D_j)$), where all banks fail at the same time. The arrow indicates the direction of the change in risks after a given bank receives a treatment (in each scenario). The notations are defined as: $\alpha_2$ is bank B's portfolio weight invested in asset X, which is a conventional asset; $d$ is the banks' debt level; $\frac{d}{s_y}$ is the default probability of banks; and $\beta$ is the reduction in bank B's investment in asset Y that is also the increment in its investment of asset X following the ban on proprietary trading (in the Volcker Rule scenario).

| Scenario | Bank-level risk $\Pr(D_i)$ | Bank-level systemic risk $\Pr(D_i \| D_j)$ | Aggregate systemic risk $\Pr(D_i \cap D_j)$ |
|---|---|---|---|
| Increase in diversification (similarity is fixed) | Bank A: ↓ $\frac{d}{s_y} < \frac{1}{2}$ | Bank A: ↓ $\frac{d}{s_y} < \frac{1}{2}$ | No effect |
| Increase in similarity (diversification is fixed) | No effect | Banks A and B: ↑ $\alpha_2 < \frac{1}{2}$ | Banks A and B: ↑ by $\frac{(2\alpha_2 - 1)d^2}{2(\alpha_2 - 1)\alpha_2 s_y^2} > 0$ |
| Volcker Rule (increase in similarity and decrease in diversification) | Bank A: No effect<br>Bank B: ↑ $\beta < \frac{d}{s_y}$ | Bank A: ↑ $\frac{\beta}{2} < \frac{d}{s_y}$<br>Bank B: ↑ $\beta < \frac{d}{s_y}$ | Banks A and B: ↑ by $\frac{\beta d^2}{2s_y^2(-1+\alpha_2)(-1+\alpha_2+\beta)} > 0$ |

**Table 2**
**Description of variables**

This table defines and describes the measurement of the variables used in the paper.

| Variables | Definition | Unit | Measurement |
|---|---|---|---|
| $DIV$ | Revenue diversification | Logs | $DIV_{i,t} = \ln(DIVER_{i,t})$, where $DIVER_{i,t}$ is the revenue diversification index of bank $i$ in quarter $t$. The variable $DIVER_{i,t}$ is computed as follows: $DIVER_{i,t} = 2 \times \left[1 - \left(\left(\frac{NET_{i,t}}{NET_{i,t}+NON_{i,t}}\right)^2 + \left(\frac{NON_{i,t}}{NET_{i,t}+NON_{i,t}}\right)^2\right)\right]$, where $NET_{i,t}$ is the share of net interest income and $NON_{i,t}$ is the share of non-interest income in quarter $t$. Net interest income is calculated as the difference between total interest income and interest expense. Non-interest income includes fiduciary income, fees and charges, trading revenue, and other non-interest income. |
| $SIM$ | Bank similarity | Logs | $SIM_{i,t} = \ln\left(\frac{R^2_{i,t}}{1-R^2_{i,t}}\right)$, where $R^2_{i,t}$ is the R-squared value for bank $i$ in quarter $t$ obtained from the model $RET_{i,d} = a_0 + a_1\overline{RET_d} + e_{i,d}$, in which $RET_{i,d}$ is the daily stock return of bank $i$ on day $d$, and $\overline{RET_d}$ is the return on the banking index (computed as the average of all the banks' stock returns in the banking sector on day $d$). |
| $TRAD$ | Banks' trading asset ratio | Percent | Total trading assets to total book assets. |
| $BRISK$ | Banks' risk (bank-level) | Percent | Stock return volatility (annualized), which is measured as the standard deviation of the daily stock prices over the last one-year horizon. |
| $SRISK$ | Banks' systemic risk | | The estimated $\beta_I$ of the following model can be interpreted as the sensitivity of individual banks' returns being in extreme events to the market index given that the market returns are also in extreme events. $I_{i,d} = \beta_I I_{market,d} + \varepsilon_t$, where the indicator for extreme values of market index returns ($I_{market,d}$) is regressed on the indicator for extreme values of bank $i$'s stock returns ($I_{i,d}$). |
| $MKT\_LEV$ | Banks' market leverage ratio | Percent | Total liabilities to total market value of assets. Total liabilities include deposits from domestic and foreign offices, federal funds purchased, and securities sold under agreements to repurchase, trading liabilities, other borrowed money, subordinated notes and debentures, and other liabilities. Total market value of assets is computed as the sum of market capitalization and total liabilities. |
| $NPL$ | Banks' non-performing loan ratio | Percent | Total non-performing loans to total loans. Total non-performing loans include loans that are nonaccrual, past due 90 days or more, and past due 30 through 89 days and still accruing. Total loans include loans and leases, net of unearned income. |

| | | | |
|---|---|---|---|
| $LIQ$ | Banks' liquidity ratio | Percent | Total liquid assets to total assets. Total liquid assets include cash, due balances, repurchase agreements, US treasuries, non mortgage-backed securities, non asset-backed securities, and investment securities issued by states and political sub-divisions in US. |
| $RELOAN$ | Banks' real estate loan ratio | Percent | Total real estate loans to total loans. Total real estate loans include residential and commercial real estate loans. |
| $SIZE$ | Bank size | Logs | Natural logarithm of total book assets, deflated using GDP deflator as at 2016(Q4). |
| $DEP$ | Banks' deposit ratio | Percent | Total deposits to total book assets. Total deposits include deposits in domestic and foreign offices, including those that are interest and noninterest bearing. |
| $NONIE$ | Banks' non-interest expense ratio | Percent | Total non-interest expense to total book assets. Total non-interest expense includes non-interest expense (e.g., salaries, employee benefits, expenses of premises and fixed assets, goodwill impairment losses, and amortization expense) and other non-interest expense (e.g., administrative fees, advertising, and marketing expenses, etc.). |
| $TARP\_BK$ | A binary variable for the recipient banks of the Troubled Asset Relief Program (TARP) | Dummy | A binary variable that takes a value of one if a bank received the government bailout funding under the TARP during its implementation, and zero otherwise. |
| $IBANK$ | A binary variable for the investment banks | Dummy | A binary variable that takes a value of one if a bank is classified as an investment bank, and zero otherwise. |
| $GDP\_GR$ | Current Gross Domestic Product (GDP) growth rate | Percent | Difference between the current and last year's GDP indices, seasonally adjusted and annualized. |
| $POST\_VOLCKER$ | A binary variable for periods after the implementation of the Volcker Rule | Dummy | A binary variable that takes a value of one from 2012(Q1) to 2016(Q4), and zero otherwise. |
| $PRETRAD$ | Banks' average pre-trading asset ratio | Percent | Average of trading asset ratio over the period before the Volcker Rule implementation (from 2003(Q1) to 2007(Q4)). The measure is calculated at the bank level. |
| $PREBRISK$ | Banks' average bank-level risk | Percent | Average of stock return volatility over the period before the Volcker Rule implementation (from 2003(Q1) to 2007(Q4)). The measure is calculated at the bank level. |
| $PRESRISK$ | Banks' average systemic risk | | Average of systemic tail beta over the period before the Volcker Rule implementation (from 2003(Q1) to 2007(Q4)). The measure is calculated at the bank level. |
| $TARGETED\_BHC$ | A binary variable for the targeted BHCs | Dummy | A binary variable that takes a value of one if a bank has an average pre-trading asset ratio ($PRETRAD$) above or equal to 3%. |
| $TARGETEDBHC\_P99$ | An alternative binary variable for the targeted BHCs | Dummy | A binary variable that takes a value of one if the average trading asset ratio during the pre-Volcker period (2003(Q1)-2007(Q4)) was in the top 1% of the distribution. |
| $TARGETEDBHC\_TOP10$ | An alternative binary variable for the targeted BHCs | Dummy | A binary variable that is equal to one for 10 banks that had the highest average trading asset ratio during the period 2003(Q1)-2007(Q4). |

**Table 3**

**Descriptive statistics of main variables**

This table reports the means, medians, standard deviations (Std. dev.), 1st and 99th percentiles (p1, p99), and the number of observations (Obs.) of the main variables in the paper. The descriptive statistics are reported for all banks (N = 547), targeted banks (N = 13), and non-targeted banks (N = 534), where N refers to the number of banks in each category. The targeted banks are those that are directly affected by the Volcker Rule, as they had a trading asset ratio of 3% or above in the pre-Volcker period (2003(Q1)─2007(Q4)). The non-targeted banks are those who had a low trading asset ratio (below 3%) or zero trading assets in the pre-Volcker period. To avoid outliers, the financial ratios are winsorized at the 1st and 99th percentiles, except trading asset ratio ($TRAD$). Financial ratios and bank-level risk are expressed in percent. Full definitions of the variables are provided in Table 2. Column 4 reports the test of difference with double clustered standard errors by bank and by date. All observations are at bank-quarter level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The data set covers the full period from 1993(Q4)─2016(4).

| | (1) All banks | | | | | | (2) Targeted banks | | (3) Non-targeted banks | | Diff (2) - (3) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Variable | Obs. | Mean | Median | Std. dev. | p1 | p99 | Obs. | Mean | Obs. | Mean | | Signif. |
| $DIV$ | 25,019 | -0.47 | -0.37 | 0.52 | -2.09 | 0.00 | 744 | -0.26 | 24,275 | -0.48 | 0.22 | *** |
| $SIM$ | 25,019 | -2.34 | -1.80 | 2.69 | -10.20 | 1.42 | 744 | -0.72 | 24,275 | -2.39 | 1.67 | *** |
| $TRAD$ | 24,531 | 0.46 | 0.00 | 2.35 | 0.00 | 13.75 | 720 | 9.47 | 23,811 | 0.18 | 9.28 | *** |
| $BRISK$ | 25,019 | 2.30 | 2.00 | 1.12 | 0.92 | 6.48 | 744 | 2.21 | 24,275 | 2.30 | -0.09 | * |
| $SRISK$ | 25,019 | 0.45 | 0.42 | 0.27 | 0.00 | 1.00 | 744 | 0.70 | 24,275 | 0.44 | 0.26 | *** |
| $MKTLEV$ | 25,019 | 85.54 | 86.27 | 7.23 | 65.94 | 96.49 | 744 | 86.08 | 24,275 | 85.53 | 0.55 | ** |
| $NPL$ | 25,019 | 1.72 | 1.21 | 1.86 | 0.00 | 9.17 | 744 | 2.25 | 24,275 | 1.70 | 0.55 | *** |
| $LIQ$ | 25,019 | 14.16 | 11.89 | 9.35 | 2.10 | 47.64 | 744 | 21.18 | 24,275 | 13.95 | 7.23 | *** |
| $RELOAN$ | 25,018 | 69.12 | 72.10 | 17.74 | 11.09 | 98.32 | 743 | 43.52 | 24,275 | 69.90 | -26.39 | *** |
| $DEP$ | 25,019 | 75.63 | 77.85 | 10.22 | 36.04 | 90.38 | 744 | 56.42 | 24,275 | 76.22 | -19.80 | *** |
| $NONIE$ | 24,629 | 3.24 | 3.04 | 1.16 | 1.39 | 9.28 | 726 | 4.04 | 23,903 | 3.22 | 0.82 | *** |
| $SIZE$ | 25,019 | 14.93 | 14.62 | 1.52 | 12.52 | 18.78 | 744 | 17.83 | 24,275 | 14.84 | 2.99 | *** |
| $TARP\_BK$ | 25,019 | 0.18 | 0.00 | 0.38 | 0.00 | 1.00 | 744 | 0.28 | 24,275 | 0.18 | 0.10 | *** |
| $IBANK$ | 25,019 | 0.05 | 0.00 | 0.21 | 0.00 | 1.00 | 744 | 0.52 | 24,275 | 0.03 | 0.49 | *** |
| $GDP\_GR$ | 24,429 | 4.57 | 4.80 | 2.01 | -3.10 | 7.50 | 723 | 4.59 | 23,706 | 4.57 | 0.02 | |
| $POST\_VOLCKER$ | 25,019 | 0.21 | 0.00 | 0.41 | 0.00 | 1.00 | 744 | 0.23 | 24,275 | 0.21 | 0.02 | |
| $AFFECTEDBHC$ | 25,019 | 0.03 | 0.00 | 0.17 | 0.00 | 1.00 | 744 | 1.00 | 24,275 | 0.00 | 1.00 | *** |
| $PRETRAD$ | 547 | 0.33 | 0.00 | 1.84 | 0.00 | 8.60 | 13 | 9.52 | 534 | 0.11 | 9.42 | *** |
| $PREBRISK$ | 547 | 1.86 | 1.80 | 0.53 | 1.00 | 4.03 | 13 | 1.76 | 534 | 1.86 | -0.10 | |
| $PRESRISK$ | 547 | 0.38 | 0.37 | 0.20 | 0.05 | 0.79 | 13 | 0.60 | 534 | 0.38 | 0.22 | *** |

**Table 4**

**Effects of diversification, similarity, and trading activity on risks**

The table reports second stage regression results of the two-stage least squares (2SLS) model using instrumental variables. The dependent variable in Column (1) is bank-level risk ($BRISK$), which is measured as the banks' stock return volatility (that is, the standard deviation of stock return over the one-year horizon, in percent). The dependent variable in Column (2) is systemic risk ($SRISK$), which is measured as the systemic tail beta. The main independent variables are the measures of three channels, including: revenue diversification ($DIV$), bank similarity ($SIM$), and trading activity ($TRAD$). Full definitions of the variables are provided in Table 2. In the first stage of the 2SLS models, we regress the degree of $DIV$, $SIM$, and $TRAD$ for a given bank on the instrumental variables and other controls. The instruments for bank $i$'s $DIV$, $SIM$, and $TRAD$ are the average level of $DIV$, $SIM$, and $TRAD$ in the same quarter in all other banks with corresponding size quartile and bank type (investment versus non-investment banks)), respectively. Control variables comprise market leverage ratio ($MKTLEV$), non-performing loan ratio ($NPL$), profitability ($ROE$), liquidity ($LIQ$), real estate loan ratio ($RELOAN$), deposit ratio ($DEP$), non-interest expense ratio ($NONIE$), bank size ($SIZE$), an indicator variable that takes a value of one of the bank was a participating bank in the TARP CPP program during the implementation period and zero otherwise ($TARP\_BANK$), and GDP growth rate ($GDP\_GR$). Since we control for the macro-economic factor (GDP growth rate), time fixed effects are omitted to avoid multicollinearity. Standard errors are clustered both by bank and by date, and t-values are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is from 1993(Q1) to 2016(Q4).

| Dependent variable | Bank-level risk | Systemic risk |
|---|---|---|
| | (1) | (2) |
| $\widehat{DIV}$ | -0.156*** | -0.036*** |
| | (-9.330) | (-12.910) |
| $\widehat{SIM}$ | -0.016*** | 0.063*** |
| | (-4.320) | (82.650) |
| $\widehat{TRAD}$ | -0.103 | 0.339*** |
| | (-0.510) | (8.930) |
| $MKTLEV$ | 1.890*** | 0.183*** |
| | (15.40) | (8.480) |
| $NPL$ | 6.071*** | 0.662*** |
| | (13.010) | (8.670) |
| $ROE$ | -1.154*** | -0.117*** |
| | (-7.970) | (-5.340) |
| $LIQ$ | -1.199*** | -0.043*** |
| | (-19.110) | (-3.490) |
| $RELOAN$ | -0.823*** | -0.091*** |
| | (-20.850) | (-11.830) |
| $DEP$ | -0.558*** | 0.021 |
| | (-8.360) | (1.560) |
| $NONIE$ | 10.862*** | 1.732*** |
| | (17.980) | (15.480) |
| $SIZE$ | -0.197*** | 0.022*** |
| | (-30.040) | (17.410) |
| $TARP\_BANK$ | 0.006 | 0.057*** |
| | (0.270) | (16.060) |
| $GDP\_GR$ | -21.846*** | 0.454*** |
| | (-47.090) | (6.740) |
| Adj. R-square (%) | 31.86 | 47.81 |
| Observations | 26,412 | 26,412 |

**Table 5**

**Effects of the Volcker Rule on revenue diversification, similarity, and proprietary trading**

The table reports coefficient estimates from the difference-in-differences regression. The dependent variables in Columns (1), (2), and (3) are revenue diversification ($DIV$), bank similarity ($SIM$), and trading activity ($TRAD$), respectively. $POST$ is the indicator variable that equals one for periods 2012(Q1)–2016(Q4) and zero for periods 2003(Q1)–2007(Q4). $PRETRAD$ is the average trading asset ratio of bank $i$ during the pre-Volcker period (from 2003(Q1) to 2007(Q4)). $POST \times PRETRAD$ is the interaction term between $POST$ and $PRETRAD$, which serves as a continuous treatment variable that takes a higher value when the Volcker Rule is more binding on bank $i$. We include control variables, which comprise market leverage ratio ($MKTLEV$), non-performing loan ratio ($NPL$), profitability ($ROE$), liquidity ($LIQ$), real estate loan ratio ($RELOAN$), deposit ratio ($DEP$), non-interest expense ratio ($NONIE$), bank size ($SIZE$), and an indicator variable that takes a value of one of the bank was a participating bank in the TARP CPP program during the implementation period and zero otherwise ($TARP\_BANK$). Full definitions of the variables are provided in Table 2. Since we include $POST$, time fixed effects are omitted to avoid multicollinearity. We report the values of adjusted R-square in percent. Standard errors are clustered both by bank and by date, and t-values are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

| Dependent variable | $DIV$ | $SIM$ | $TRAD$ |
|---|---|---|---|
| | (1) | (2) | (3) |
| $POST$ | -0.094*** | 1.293*** | 0.001*** |
| | (-4.790) | (25.010) | (4.030) |
| $PRETRAD$ | -0.589*** | -12.437*** | 0.983*** |
| | (-3.260) | (-10.540) | (63.80) |
| $POST \times PRETRAD$ | -0.872** | 3.590*** | -0.290*** |
| | (-2.020) | (2.790) | (-13.0) |
| $MKTLEV$ | 2.636*** | -8.192*** | -0.017*** |
| | (11.80) | (-20.840) | (-3.050) |
| $NPL$ | -2.951*** | -4.464*** | 0.016*** |
| | (-4.310) | (-3.550) | (2.790) |
| $ROE$ | 1.257*** | 0.755** | -0.002 |
| | (6.260) | (2.210) | (-1.020) |
| $LIQ$ | 0.040 | -1.027*** | 0.001 |
| | (0.760) | (-5.140) | (0.840) |
| $RELOAN$ | -0.175*** | 0.674*** | -0.002*** |
| | (-5.080) | (5.030) | (-1.020) |
| $DEP$ | 0.188** | 1.626*** | -0.006*** |
| | (2.420) | (7.040) | (-4.150) |
| $NONIE$ | 11.412*** | -22.608*** | 0.027*** |
| | (16.130) | (-11.950) | (2.620) |
| $SIZE$ | 0.075*** | 1.229*** | 0.000 |
| | (15.490) | (70.670) | (0.710) |
| $TARP\_BANK$ | 0.018 | -0.271*** | 0.000 |
| | (0.860) | (-5.090) | (0.710) |
| Adj. R-square (%) | 13.56 | 48.64 | 87.51 |
| Observations | 11,966 | 11,966 | 11,964 |

**Table 6**
**Robustness tests**

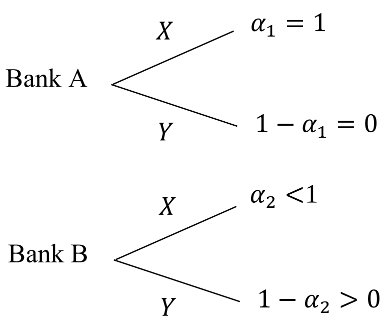
The table reports robustness tests for the difference-in-difference estimation results. The dependent variable in Columns (1), (4), and (7) is revenue diversification ($DIV$). The dependent variable in Columns (2), (5), and (8) is bank similarity ($SIM$). The dependent variable in Columns (3), (6), and (9) is trading activity ($TRAD$). $POST$ is the indicator variable that equals one for periods 2012(Q1)–2016(Q4) and zero for periods 2003(Q1)–2007(Q4). We use several definitions of the targeted banks to measure banks' affectedness of the Volcker Rule. $TARGETEDBHC$ is an indicator variable that equals one if the average trading asset ratio of bank $i$ during the pre-Volcker period (from 2003(Q1) to 2007(Q4)) was equal to or greater than 3% and zero otherwise. $POST \times TARGETEDBHC$ is the interaction term between $POST$ and $TARGETEDBHC$, which serves as a binary treatment variable that takes a value of one if bank $i$ is the targeted bank for the quarters following the Rule implementation. $TARGETEDBHC\_P99$ takes a value of one if the average trading asset ratio during the pre-Volcker period (2003(Q1)–2007(Q4)) was in the top 1% of the distribution. $POST \times TARGETEDBHC\_P99$ is the interaction term between $POST$ and $TARGETEDBHC\_P99$. $TARGETEDBHC\_TOP10$ is equal to one for 10 banks that had the highest average trading asset ratio during the period 2003(Q1)–2007(Q4). $POST \times TARGETEDBHC\_TOP10$ is the interaction term between $POST$ and $TARGETEDBHC\_TOP10$. We include control variables, which comprise market leverage ratio ($MKTLEV$), non-performing loan ratio ($NPL$), profitability ($ROE$), liquidity ($LIQ$), real estate loan ratio ($RELOAN$), deposit ratio ($DEP$), non-interest expense ratio ($NONIE$), bank size ($SIZE$), and an indicator variable that takes a value of one of the bank was a participating bank in the TARP CPP program during the implementation period and zero otherwise ($TARP\_BANK$). Full definitions of the variables are provided in Table 2. Since we include $POST$, time fixed effects are omitted to avoid multicollinearity. We report the values of adjusted R-square in percent. Standard errors are clustered both by bank and by date, and t-values are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

| Dependent variable | DIV | SIM | TRAD | DIV | SIM | TRAD | DIV | SIM | TRAD |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| $POST$ | -0.094*** | 1.291*** | 0.001*** | -0.092*** | -0.092*** | -0.001 | -0.092*** | 1.297*** | 0.0 |
| | (-4.750) | (24.880) | (2.70) | (-4.660) | (-4.660) | (-1.280) | (-4.670) | (25.040) | (0.860) |
| $TARGETEDBHC$ | -0.060 | -1.449*** | 0.092*** | | | | | | |
| | (-1.470) | (-13.510) | (15.610) | | | | | | |
| $POST \times TARGETEDBHC$ | -0.235*** | 0.495*** | -0.014* | | | | | | |
| | (-3.190) | (3.360) | (-1.90) | | | | | | |
| $TARGETEDBHC\_P99$ | | | | -0.010 | -1.605*** | 0.162*** | | | |
| | | | | (-0.330) | (-11.860) | (20.560) | | | |
| $POST \times TARGETEDBHC\_P99$ | | | | -0.264*** | 0.963*** | -0.045*** | | | |
| | | | | (-3.030) | (4.950) | (-5.240) | | | |
| $TARGETEDBHC\_TOP10$ | | | | | | | 0.029 | -1.296*** | 0.107*** |
| | | | | | | | (0.650) | (-12.270) | (16.310) |
| $POST \times TARGETEDBHC\_TOP10$ | | | | | | | -0.236** | 0.849*** | -0.008 |
| | | | | | | | (-2.550) | (5.310) | (-1.050) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Adj. R-square (%) | 13.69 | 48.50 | 60.15 | 13.54 | 48.28 | 73.03 | 13.50 | 48.32 | 66.45 |
| Observations | 11,966 | 11,966 | 11,964 | 11,966 | 11,966 | 11,964 | 11,966 | 11,966 | 11,964 |

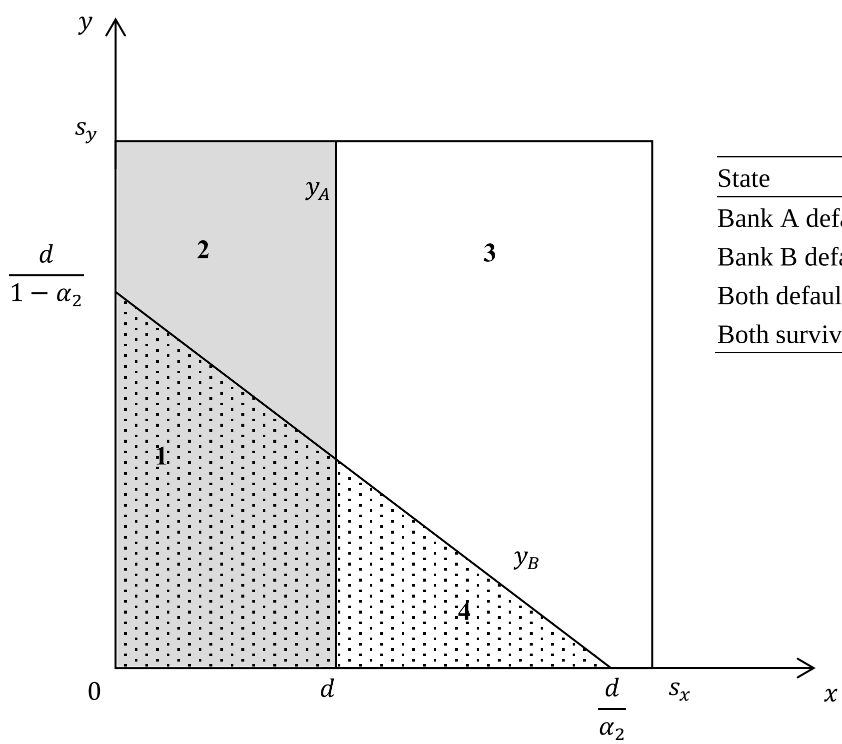
**Figure 1: Model set-up – Baseline setting**

This figure outlines the baseline setting for our theoretical model. Panel A portrays the asset composition of two banks A and B. The notations are defined as: $\alpha_1$ and $\alpha_2$ are banks A and B's portfolio weights invested in asset $X$ (conventional asset), respectively; and $d$ is the debt level. In the baseline setting, Bank A is a commercial bank that invests wholly in asset X (a conventional asset, so $\alpha_1 = 1$), while Bank B is a diversified bank that is engaged in proprietary trading, which invests in assets X and Y (proprietary trading asset). Bank B forms its asset portfolio by investing $\alpha_2$ of their wealth in asset $X$ and $1 - \alpha_2$ in asset $Y$. Note that $\alpha_1 > \alpha_2$. We assume that the assets' payoffs follow a uniform distribution with a probability density function of $\Phi(.) \sim [0, s]$. Panel B illustrates the areas of individual banks' and systemic default, as well as their survival, indicated by the numbers. The lines $y_A$ and $y_B$ denote the minimum return thresholds to prevent bank default at banks A and B, respectively. The slanted line $y_B$ has a y-intercept at $y = \frac{d}{1-\alpha_2}$ and a x-intercept at $x = \frac{d}{\alpha_2}$, while the line $y_A$ has a x-intercept at $x = d$, which is the debt level. The regions to the left of these thresholds indicate areas where the respective banks will be insolvent. For example, since bank A invests wholly in asset $X$, the bank will only be exposed to the risk of asset $X$ and thus, will default when its minimum return falls below $d$. Accordingly, bank A's default region includes areas *1* and *2*. Similarly, bank B is a diversified bank that invests in both assets $X$ and $Y$ and hence, will be exposed to the risk of both assets. For this bank, the default region is areas *1* and *4*. As area *1* is where both banks will default when the assets' returns are below the debt level, this is referred to as the region of a systemic default. Area *3* represents the survival region where both banks survive. For example, the grey shaded and dotted areas represent the default regions of banks A and B in the pre-treatment period, respectively.

**Panel A: Portfolio composition**




**Panel B: Changes in the banks' probability of default**

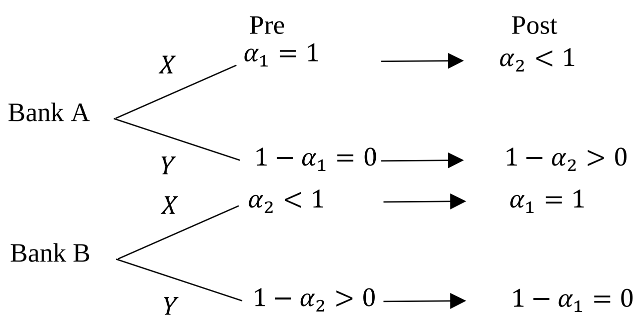



| State | Default area |
|---|---|
| Bank A defaults | 1+2 |
| Bank B defaults | 1+4 |
| Both default | 1 |
| Both survive | 3 |

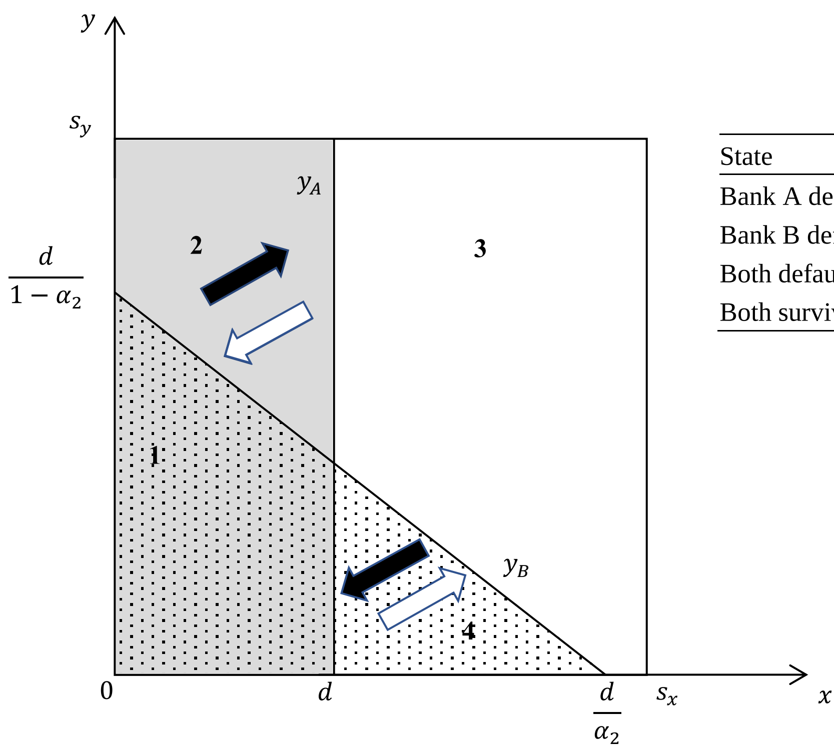
**Figure 2: Effects of diversification on banks' default probability.**

This figure outlines the scenario setting to test the effect of diversification on risks, holding similarity constant. In this scenario, both banks receive the treatment. Panel A portrays the asset composition of each bank in the periods before and after the treatment. The notations are defined as: $\alpha_1$ and $\alpha_2$ are banks A and B's portfolio weights invested in asset $X$ (conventional asset), respectively; and $d$ is the debt level. In the pre-treatment period, bank A is a commercial bank that invests wholly in asset X (hence, $\alpha_1 = 1$), while Bank B is a diversified bank that is engaged in proprietary trading, which invests in assets X and Y (proprietary trading asset). Bank B forms its asset portfolio by investing $\alpha_2$ of their wealth in asset $X$ and $1 - \alpha_2$ in asset $Y$. Note that $\alpha_1 > \alpha_2$. We assume that the assets' payoffs follow a uniform distribution with a probability density function of $\Phi(.) \sim [0, s]$. For the treatment, we switch the asset weights between the two banks so that bank A diversifies into asset $Y$ and reduces its investment in asset $X$, while bank B becomes a concentrated bank that invests all its wealth in asset $X$. Note that the degree of similarity is unchanged between the two periods. Panel B illustrates the change in the banks' survival and default probabilities between the pre- and post-treatment periods, as indicated by the numbers. The lines $y_A$ and $y_B$ denote the minimum return thresholds to prevent bank default at banks A and B, respectively. The slanted line $y_B$ has a y-intercept at $y = \frac{d}{1-\alpha_2}$ and a x-intercept at $x = \frac{d}{\alpha_2}$, while the line $y_A$ has a x-intercept at $x = d$, which is the bank's debt level. Hence, after the treatment bank A's minimum return threshold shifts from $y_A$ to $y_B$ in the post-period, and vice versa for bank B. The regions to the left of these thresholds indicate areas where the respective banks will be insolvent. For example, the grey and dotted areas represent the default regions of banks A and B in the pre-period, respectively. Assume that the assets' payoffs follow a uniform distribution with a probability density function of $\Phi(.) \sim [0, s]$. The white and black arrows indicate the shift in asset allocation of banks A and B after receiving the treatment, respectively.

**Panel A: Portfolio composition**



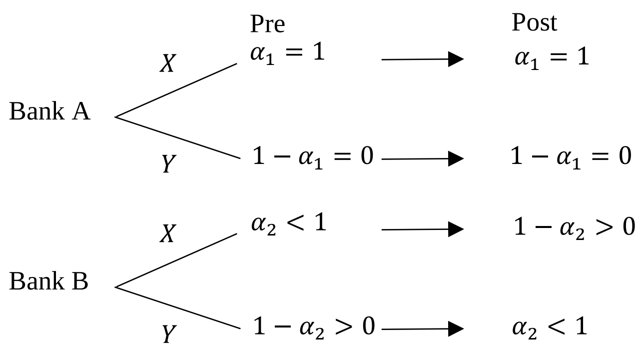

**Panel B: Changes in the banks' probability of default**



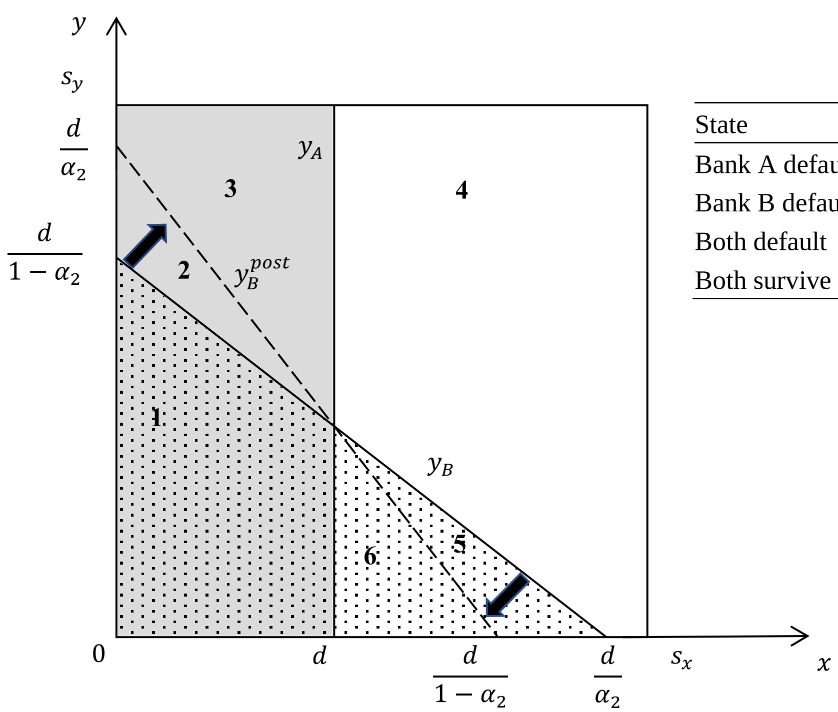

| State | Pre-treatment | Post-treatment |
|---|---|---|
| Bank A defaults | 1+2 | 1+4 |
| Bank B defaults | 1+4 | 1+2 |
| Both default | 1 | 1 |
| Both survive | 3 | 3 |

**Figure 3: Effects of similarity on banks' default probability.**
This figure outlines the scenario setting to test the effect of similarity on risks, holding diversification constant. In this scenario, bank A is the untreated bank while bank B is the treated bank. Panel A portrays the asset composition of each bank in the periods before and after the treatment. The notations are defined as follows: $X$ denotes conventional asset; $Y$ denotes proprietary trading asset; $\alpha_1$ and $\alpha_2$ are banks A and B's portfolio weights invested in asset $X$, respectively; and $d$ is the debt level. In the pre-treatment period, bank A is a commercial bank that invests wholly in asset X (hence, $\alpha_1 = 1$), while Bank B is a diversified bank that is engaged in proprietary trading, which invests in assets X and Y (proprietary trading asset). Bank B forms its asset portfolio by investing $\alpha_2$ of their wealth in asset $X$ and $1 - \alpha_2$ in asset $Y$. Note that $\alpha_1 > \alpha_2$. We assume that the assets' payoffs follow a uniform distribution with a probability density function of $\Phi(.) \sim [0, s]$. For the treatment, bank B switches its portfolio weights and invests $1 - \alpha_2$ in asset $X$ and $\alpha_2$ in asset $Y$, while bank A' portfolio is the same. The degree of diversification is unchanged between the two periods. Note that $\alpha_2$ is set to be less than $1 - \alpha_2$ for bank B to become more similar to bank A after the treatment. Panel B illustrates the change in the banks' survival and default probabilities between the pre- and post-treatment periods, as indicated by the numbers. The lines $y_A$ and $y_B$ denote the minimum return thresholds to prevent bank default at banks A and B, respectively. After the treatment, bank B has a new minimum return threshold of $y_B^{post}$ that reflects its higher share of asset $X$ in the portfolio, and hence, $y_B^{post}$ is steeper and closer to $y_A$ than $y_B$. The points indicated on the axes are the y-intercepts and x-intercepts of the corresponding lines. The line $y_A$ has a x-intercept at $x = d$, which is the bank's debt level. The regions to the left of these thresholds indicate areas where the respective banks will be insolvent. For example, the grey and dotted areas represent the default regions of banks A and B in the pre-period, respectively. Assume that the assets' payoffs follow a uniform distribution with a probability density function of $\Phi(.) \sim [0, s]$. The black arrow indicates the shift in asset allocation of bank B after receiving the treatment.

**Panel A: Portfolio composition**




**Panel B: Changes in the banks' probability of default**

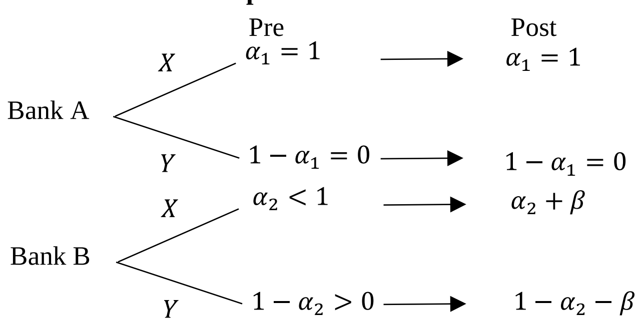



| State | Pre-treatment | Post-treatment |
|---|---|---|
| Bank A defaults | 1+2+3 | 1+2+3 |
| Bank B defaults | 1+5+6 | 1+2+6 |
| Both default | 1 | 1+2 |
| Both survive | 4 | 4+5 |

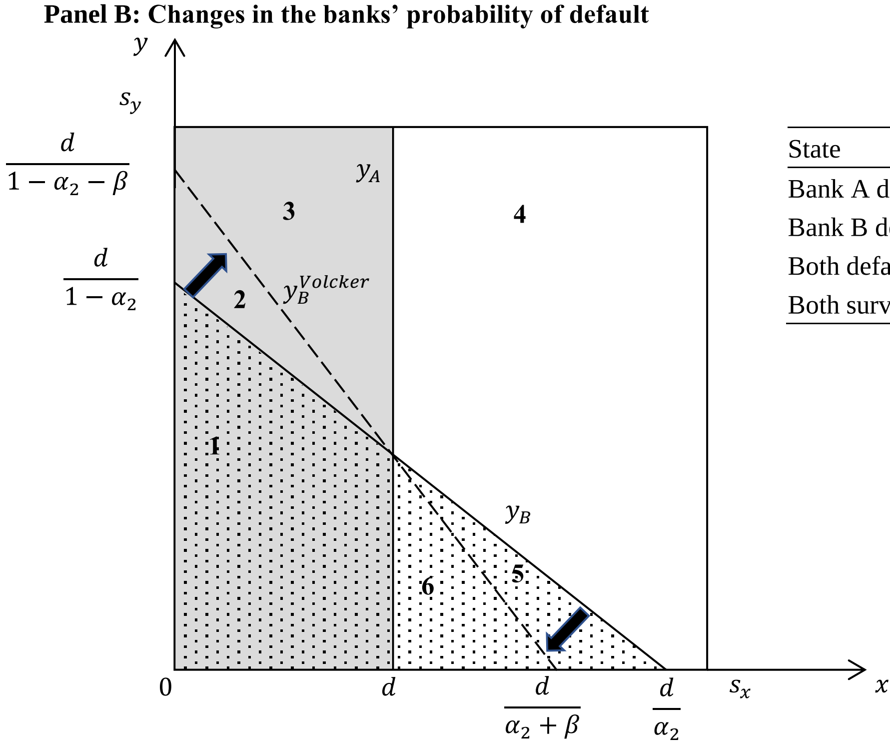
**Figure 4: Effects of Volcker Rule implementation on banks' default probability.**

This figure outlines the scenario setting to test the effect of the Volcker Rule on risks, whereby where there are changes in both diversification (decrease) and similarity (increase) channels. In this scenario, bank A is the untreated bank while bank B experiences a decrease in diversification but an increase in similarity. Panel A portrays the asset composition of each bank in the periods before and after the treatment. The notations are defined as follows: $X$ denotes conventional asset; $Y$ denotes proprietary trading asset; $\alpha_1$ and $\alpha_2$ are banks A and B's portfolio weights invested in asset $X$, respectively; $d$ is the debt level; and $\beta$ is the reduction in bank B's investment in asset $Y$ that is also the increment in its share of asset X following the ban on proprietary trading. In the pre-treatment period, bank A is a commercial bank that invests wholly in asset X (hence, $\alpha_1 = 1$), while Bank B is a diversified bank that is engaged in proprietary trading, which invests in assets X and Y (proprietary trading asset). Bank B forms its asset portfolio by investing $\alpha_2$ of their wealth in asset $X$ and $1 - \alpha_2$ in asset $Y$. Note that $\alpha_1 > \alpha_2$. We assume that the assets' payoffs follow a uniform distribution with a probability density function of $\Phi(.) \sim [0, s]$. For the treatment, bank B reduces its investment in asset $Y$ by $\beta$, and replace this portion with asset $X$. Hence, diversification is reduced while there is an increase in similarity, and there is no change in bank A's portfolio composition. Note that $\alpha_2 + \beta$ is greater than $1 - \alpha_2 - \beta$ for bank B to become more similar to bank A after the treatment. Panel B illustrates the change in the banks' survival and default probabilities between the pre- and post-treatment periods, as indicated by the numbers. The lines $y_A$ and $y_B$ denote the minimum return thresholds to prevent bank default at banks A and B, respectively. After the treatment, bank B has a new minimum return threshold of $y_B^{Volcker}$ that reflects its higher level of asset $X$ in its portfolio and hence, $y_B^{Volcker}$ is steeper and closer to $y_A$ than $y_B$. The points indicated on the axes are the y-intercepts and x-intercepts of the corresponding lines. The line $y_A$ has a x-intercept at $x = d$, which is the bank's debt level. The regions to the left of these thresholds indicate areas where the respective banks will be insolvent. For example, the grey and dotted areas represent the default regions of banks A and B in the pre-period, respectively. Assume that the assets' payoffs follow a uniform distribution with a probability density function of $\Phi(.) \sim [0, s]$. The black arrow indicates the shift in asset allocation of bank B after the treatment.

**Panel A: Portfolio composition**




**Panel B: Changes in the banks' probability of default**

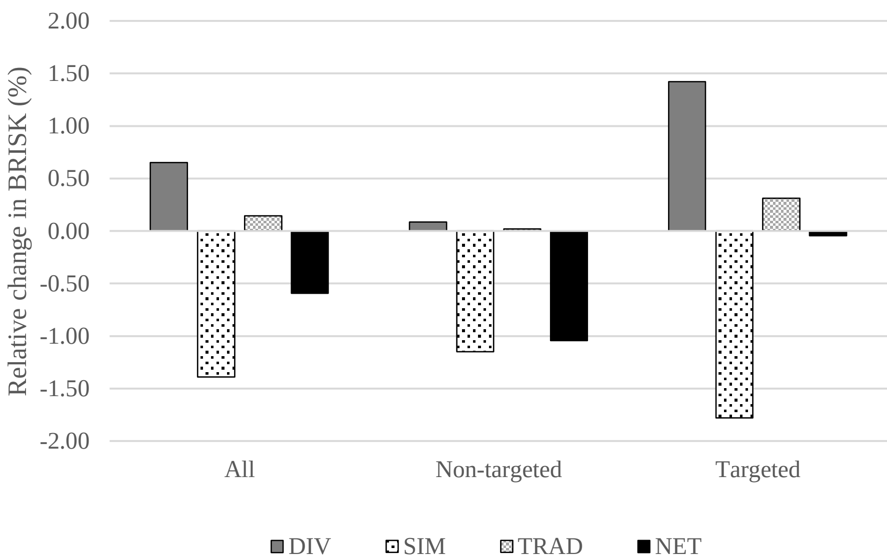



| State | Pre-treatment | Post-treatment |
|---|---|---|
| Bank A defaults | 1+2+3 | 1+2+3 |
| Bank B defaults | 1+5+6 | 1+2+6 |
| Both default | 1 | 1+2 |
| Both survive | 4 | 4+5 |

**Figure 5: Effects of the Volcker Rule on (A) bank-level risk and (B) systemic risk – by bank group**

This figure presents the effects of the Volcker Rule on bank-level ($BRISK$) and systemic risk ($SRISK$) in Panels A and B, respectively. We report separately the results for non-targeted, targeted and all banks, as well as the effects on risks by different channels (including diversification ($DIV$), similarity ($SIM$), and trading activity ($TRAD$)). $NET$ is the net effect of the Volcker Rule on risks, which is calculated as the sum of the effects by three individual channels following the Rule implementation (that is, $NET = DIV + SIM + TRAD$). The absolute effects are computed at the bank level using the estimated coefficients obtained from the 2SLS regressions (in Columns (1) and (2) in Table 4) and the difference-in-differences models (Columns (1)–(3) in Table 5). The absolute effects of the Volcker Rule on diversification, similarity, and trading activity are computed as $\delta_3 \times PRETRAD$, where $\delta_3$ is the coefficient on the interaction term $POST \times PRETRAD$ in Eq. (26) in which the dependent variable is $DIV$, $SIM$, and $TRAD$, respectively. $POST$ is the indicator variable that equals one for periods 2012(Q1)–2016(Q4) and zero for periods 2003(Q1)–2007(Q4). $PRETRAD$ is the average trading asset ratio of bank $i$ during the pre-Volcker period (2003(Q1)–2007(Q4)). $POST \times PRETRAD$ is the interaction term between $POST$ and $PRETRAD$, which serves as a continuous treatment variable that takes a higher value when the Volcker Rule is more binding on bank $i$. We then quantify the effects of the Volcker Rule on risks by multiplying the computed Volcker-effects on the channels ($\delta_3 \times PRETRAD$) by the 2SLS models' coefficients that capture the relation between each channel and the risk measures (for bank-level and systemic risks in Eqs. (24) and (25), respectively). We aggregate these bank-level effects by calculating value-weighted averages. For interpretation purposes, we compute the change in risks (by each channel) relative to the average risk levels during the pre-Volcker period ($PREBRISK$ and $PRESRISK$) of each group. Full descriptions of the variables are provided in Table 2, and absolute effects are reported in Appendix B.

**Panel A: Relative change in bank-level risk ($BRISK$)**




**Panel B: Relative change in systemic risk ($SRISK$)**

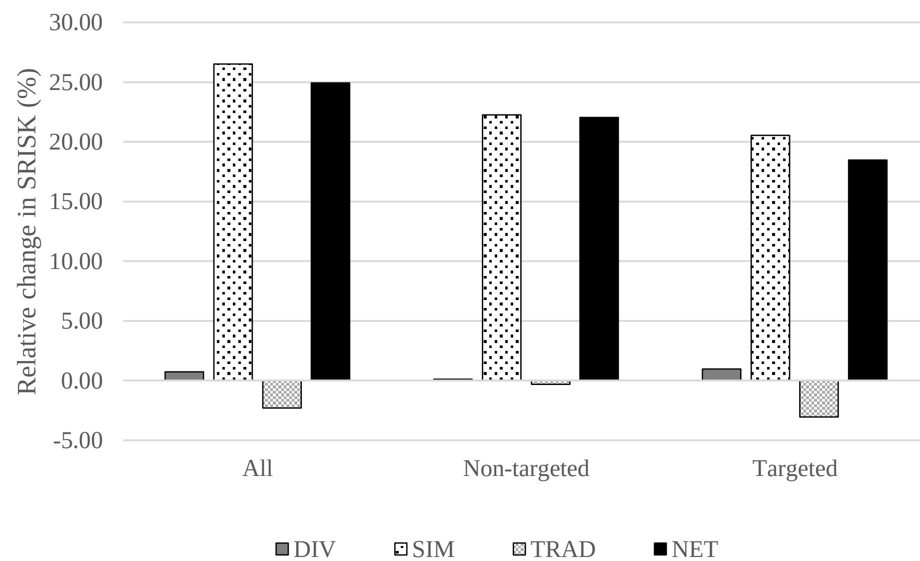
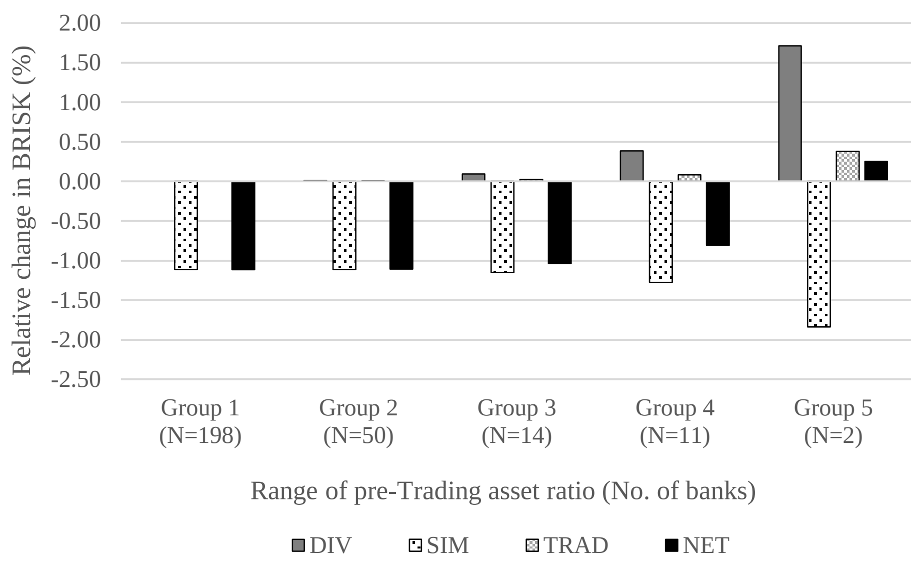


**Figure 6: Cross-sectional effects of the Volcker Rule on (A) bank risk and (B) systemic risk**

This figure presents the cross-sectional effects of the Volcker Rule on bank-level ($BRISK$) and systemic risk ($SRISK$) in Panels A and B, respectively. We report separately the results for various channels (diversification ($DIV$), similarity ($SIM$), and trading activity ($TRAD$)) through which that the Volcker Rule affects risks. $NET$ is the net effect of the Volcker Rule on risks, which is calculated as the sum of the effects by three individual channels following the Rule (that is, $NET = DIV + SIM + TRAD$). We further stratify the effects by the level of trading assets that banks had during the period before the Volcker Rule (2003(Q1)–2007(Q4)). Banks are stratified into five ranges of pre-Volcker trading asset ratios' percentiles (<50$^{th}$ percentile, 50–90$^{th}$ percentiles, 90–95$^{th}$ percentiles, 95–99$^{th}$ percentiles, and >99$^{th}$ percentile). We name these ranges as Groups 1–5, respectively. The absolute effects are computed at the bank level using the estimated coefficients obtained from the 2SLS regressions (in Columns (1) and (2) in Table 4) and the difference-in-differences models (Columns (1)–(3) in Table 5). The absolute effects of the Volcker Rule on diversification, similarity, and trading activity are computed as $\delta_3 \times PRETRAD$, where $\delta_3$ is the coefficient on the DID interaction term in Eq. (26), which serves as a continuous treatment variable that takes a higher value when the Volcker Rule is more binding on bank $i$. $PRETRAD$ is the average trading asset ratio of bank $i$ during the pre-Volcker period (2003(Q1)–2007(Q4)). We then quantify the effects of the Volcker Rule on risks by multiplying the computed Volcker-effects on the channels ($\delta_3 \times PRETRAD$) by the 2SLS models' coefficients that capture the relation between each channel and the risk measures (for bank-level and systemic risks in Eqs. (24) and (25), respectively). We aggregate these bank-level effects by calculating value-weighted averages. For interpretation purposes, we compute the change in risks (by each channel) relative to the average risk levels during the pre-Volcker period ($PREBRISK$ and $PRESRISK$). We report the number of banks in each range in parentheses. Full descriptions of the variables are provided in Table 2, and absolute effects are provided in Appendix B.

**Panel A: Relative change in bank-level risk ($BRISK$)**




**Panel B: Relative change in systemic risk ($SRISK$)**