

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 within banks, similarity between banks, and risks specifically associated with proprietary trading. We find that while the reduction in proprietary trading lowers systemic risk of targeted banks, an unintended consequence is that banks become more similar, which increases the risk that they default at the same time in a systemic event. Non-targeted banks that were not engaged in proprietary trading are affected by the Volcker Rule indirectly through this similarity channel.

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1. Introduction

Amidst the global effort to strengthen the financial system, the Volcker Rule was enacted as part of the Dodd-Frank Act in July 2010.² The Rule's objective is to limit the speculative activities of banks so as to reduce systemic threats to the financial system. As such, the Rule prohibits banks from conducting nonbanking activities such as proprietary trading, speculative transactions, and investments in hedge funds or private equity funds, among others.³

Has the Volcker Rule been successful in making the financial sector more stable by limiting speculative activity within banks? To date, there is no clear answer to this question. In part, this is because the effects of the Volcker Rule are complex, affecting systemic risk through a number of channels. Furthermore, empirical analysis is complicated by confounding effects and lack of control group. We contribute to answering this question by (i) identifying the relevant channels through which the Volcker Rule affects bank-level and systemic risk in a theoretical setting, and then (ii) empirically measuring the strength of each of the channels. In addition to the expected effects of the Rule such as reducing risk within investment banks by eliminating proprietary trading, our analysis highlights important unintended consequences of the Rule. The unintended consequences come from making banks more similar and thus more likely to default concurrently. We also show that banks that were not involved in proprietary trading and thus not directly affected by the Rule are affected indirectly through an increase in similarity between banks. Taking these additional effects into consideration is important for holistic evaluation of this regulatory intervention.

To identify the various effects of the Volcker Rule, build some intuition for these effects, and guide the empirical analysis, we develop a simple theoretical model. In the model, two representative banks engage in a combination of conventional banking (e.g., taking deposits and extending loans) and proprietary trading. One bank engages in only conventional banking, while the other does both, like many investment banks before the Volcker Rule. Both banks are risky as the payoffs of the two activities are uncertain and the banks are leveraged. We use the model to show that the Volcker Rule, which involves reducing or eliminating the proprietary trading activities of the investment bank, affects both banks through three channels. The first is that

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.

revenue diversification decreases at the investment bank, increasing its risk (both bank-specific default risk and its contribution to systemic risk). The second channel is that both banks become more similar once the investment bank abandons proprietary trading. This effect increases the probability that both banks default at the same time, thereby increasing systemic risk at both banks. Through this channel, even conventional banks that were not engaged in proprietary trading are affected by the Volcker Rule. Third, putting aside the previous two channels, eliminating the investment bank's proprietary trading may reduce the risk of the investment bank's assets (assuming proprietary trading is riskier than conventional banking) and lower its correlation with the broader financial system such as investment funds and capital markets. This can decrease bank-level and systemic risk at the investment bank. Therefore, the Volcker Rule can affect both investment and non-investment banks through three main channels, which have opposing effects.

We empirically test the three channels identified by the model. A recent report by the Securities and Exchange Commission (SEC, 2017) highlights several challenges that make it difficult to quantify the effects of regulatory reforms. First, it is difficult to isolate the effect of a single policy, especially when the post-implementation period of one reform 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 and natural control groups are often lacking.

To minimize the above concerns, we adopt a two-step approach to isolate the impacts of the Volcker Rule from other confounding factors. Rather than simply analyzing risk measures before and after the enactment of the Rule, we first examine how each of the different channels (diversification, similarity, proprietary trading) are related to bank-level and systemic risks. In this step we are able to use a longer sample period and instrumental variables to address endogeneity concerns, mitigate the post-crisis effects, and therefore more accurately measure the strength of each channel. We then turn to the period around the Volcker Rule and measure the Rule's effect on diversification, similarity, and proprietary trading. In this step, we can exploit

the Rule's heterogeneous effects on different banks to control for confounding factors, for example, using a difference-in-differences approach to measure the Rule's effect on diversification. Combining the results from the two stages provides a detailed characterization of the Rule's impact on bank-level and systemic risk, with two distinct advantages over other approaches: (i) our method clearly disentangles the individual mechanisms through which the Rule affects risks, and (ii) our approach explicitly characterizes the cross-sectional heterogeneity in how the Rule affects different banks.

Our first main finding is that banks that were presumably targeted by the Volcker Rule experienced a sharper decline in trading assets 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. This is perhaps the most direct and anticipated effect of the Volcker Rule. As proprietary trading makes 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 mitigates contagion of risks across sectors. This effect is in line with the Volcker Rule's intent to enhance financial system soundness.

Our second main finding is that the Volcker Rule is also likely to have unintended consequences, including effects 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. 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 key result 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 increase the similarity among banks. While limiting certain activities can have some benefits, these benefits must be weighed up against the increased systemic risk of having banks hold a more homogenous asset portfolio, which increases the likelihood of concurrent defaults. As restrictions on banking activity have a multitude of effects, we highlight the need to consider the various channels that give rise to the 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 several strands of the literature. First, our paper is broadly related to studies on financial system stability and systemic risk (e.g., Adrian and Brunnermeier, 2016; Acharya, Pedersen, Philippon, and Richardson, 2017; Brownlees and Engle, 2017). More specifically, it relates to studies that examine the relation between systemic risk and nonbanking activities (e.g., Stroh and Rumble, 2006; Brunnermeier, Dong, and Palia, 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. Our study adds to this literature by analyzing a major regulatory intervention designed to limit non-banking activities. Such natural experiments provide rare opportunities to examine the effects of non-banking activities. We provide the novel insight that limiting non-banking activities also carries significant unintended consequences, mainly by increasing the similarity of banks.

The second strand of the related literature focuses on the relation between diversification of a bank's activities and various risks. A central paper in this literature is Wagner (2010), who shows somewhat counterintuitively that diversification within banks can increase systemic risk. This counterintuitive effect of diversification arises because in Wagner's setup, diversification increases similarity among banks. We generalize Wagner's (2010) framework to separate the

effects of diversification and similarity and show it is similarity not diversification that drives systemic risk. Importantly, this allows us to examine scenarios such as the Volcker Rule in which diversification and similarity did not move in the same direction: diversification decreased at investment banks while similarity between banks increased. 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. Ibragimov, Jaffee, and Walden (2011) show that the negative effects of diversification within banks depends on the distribution of the risks that intermediaries take, and that it is most profound when these risks are moderately heavy-tailed. We extend this literature by highlighting that it is not diversification per se, but rather it is similarity between banks that increases systemic risk and the two factors need not move in the same direction. We consider a real scenario (the Volcker Rule) in which an increase in similarity is accompanied by a *decrease* in diversification. Thus, we are the first to formalize the effects of the Volcker Rule on risks using a model.

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. They show 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 to these studies, we isolate the effects of the Volcker Rule on bank risk taking by empirically examining the channels through which the 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, including the indirect effects on banks that were not engaged in proprietary trading. The analysis on the systemic stability rather than just directly affected banks is important, because enhancing financial sector’s stability has been the focus of various bank regulations, especially the Volcker Rule.

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 and presents 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 $\Phi(\cdot) \sim [0, s]$. 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:

$$v_A = (\alpha_1)x + (1 - \alpha_1)y, \quad (1)$$

$$v_B = (\alpha_2)x + (1 - \alpha_2)y, \quad (2)$$

where α_1 and α_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 $\alpha_1 > \alpha_2$. Furthermore, this setting also reveals that the payoffs of the banks are directly related to the asset composition of their portfolios. 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:

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

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

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 α_2 satisfies the condition specified in Eq. (5). We refer to Eq. (5) as a necessary condition:

$$\alpha_2 \leq 1 - \frac{d}{s_y}. \quad (5)$$

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

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.

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.

< Insert Figure 1 here >

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.

< Insert Figure 2 here >

Since bank A is now exposed to both X and Y, its probability of default moves from area $I+2$ to $I+4$, 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:

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

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:

$$\frac{d}{s_y} < \frac{1}{2}. \quad (7)$$

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 I). 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).

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

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.

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 α_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 α_2 in asset Y, while no change is made to bank A. Note that α_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:

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

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.

< Insert Figure 3 here >

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:

$$\alpha_2 < \frac{1}{2}, \quad (9)$$

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:

$$\frac{(2\alpha_2-1)d^2}{2(\alpha_2-1)\alpha_2s_y^2} > 0, \quad (10)$$

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 β , whereas there is no change in the portfolio composition of bank A. Note that β 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.

<Insert Figure 4 here>

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 α_2 (in Eq. (5)), we obtain the following interval in which the bank's debt level would fall within:

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

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 risk 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 seem 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:

$$\frac{\beta}{2} < \frac{d}{s_y}, \quad (13)$$

$$\beta < \frac{d}{s_y}, \quad (14)$$

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:

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

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.

<Insert Table 1 here>

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. As the targeted banks replace proprietary trading assets with conventional assets, they become more similar to the other commercial banks in the sector. Due to common asset portfolios, both the targeted and non-targeted banks are exposed to the same asset risks, thereby increasing the similarity between them. This leads us to the following hypotheses:

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

Hypothesis 5: The Volcker Rule increases similarity between banks.

Hypothesis 6: The Volcker Rule reduces trading activity of the targeted banks.

As shown in Section 2.5, the Volcker Rule brings about changes in different channels through which the effects on risks might 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 revenue diversification, bank 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 bank-level risk at targeted banks increases after Volcker Rule enactment due to lower revenue diversification.

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

Hypothesis 9: The Volcker Rule enactment decrease a) bank-level and b) systemic risks of targeted banks due to lower proprietary trading activity.

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. We take advantage of the extended sample to maximize the statistical

significance when estimating the relation between revenue diversification, bank similarity, trading activity, and the risks, which we then apply to investigate the effects of the Volcker Rule. For the analysis of the Rule, we use a shorter and balanced window to examine the enactment effects of the Volcker Rule on each channel and risk measures. 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. While the trading asset ratios are zero for most banks, 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 the Volcker Rule, we require banks to exist in the pre-enactment periods (from 2003(Q1) to 2007(Q4)) to classify their affectedness. This requirement reduces the data set to 546 BHCs, yielding 25,017 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-

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.

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.

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-Volcker 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 enactment (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 546 sample banks, there are 13 targeted banks.

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 overall bank-level risk (*BRISK*), we use the z-score that measures the distance from insolvency for each bank (Demirguc-Kunt and Huizinga, 2010; Laeven and Levine, 2009; Roy, 1952). The z-score can be computed as the sum of the return on assets and equity-to-assets ratio divided by the standard deviation of the return on assets over a year. As the z-score is highly skewed, we take the natural logarithm of this variable and use its inverse for interpretation purpose. Henceforth, we refer to this adjusted measure as z-score and thus, an increase in this variable implies higher bank-level risk.

While there is no consensus on what defines systemic risk, we refer to systemic risk as the relative risk that a given bank experiencing financial weakness when other banks are also in distress. Hence, we are not interested in the risk of the entire banking system being in crisis. Following Acharya et al. (2012; 2017), we use banks' marginal expected shortfall (MES) as the

proxy for systemic risk. We compute MES as the average stock return of each bank when the market return is in the lowest 5% quantile over the one-year horizon.¹¹

$$MES_i^{5\%} = \frac{1}{\# \text{ days}} \sum R_{i,\{t:\text{system is in its 5\% tail}\}} \quad (16)$$

Our choice of using MES as an indicator of systemic risk can be justified by the following reasons. First, Acharya et al. (2017) show that the individual banks' contribution to systemic risk (known as systemic expected shortfall (SES)) is related to its MES and leverage, whereby MES has a significant explanatory power of SES. Second, MES allows for extreme events and information in the “moderately bad days” rather than discarding those events that lie beyond the cut-off periods (Williams, 2016). Third, MES is directly proportional to SES and a good predictor of equity losses during the 2007-2009 financial crisis (Acharya et al., 2017; Engle, Sahgal, Moshirian, and Zhang, 2014; Williams, 2016). For interpretation purpose, we use the inverse of MES as our systemic risk measure (*SRISK*) and hence, a higher value of MES indicates higher systemic risk.

Referring to Section 2.2, our theoretical model shows that the composition of assets within the banks' portfolios would determine their payoffs, thereby affecting the likelihood of default depending on their relative leverage position. As banks generate income from the assets that they hold, we use revenue sources to construct the level of diversification and similarity between banks to better reflect and directly capture the dynamics of their asset diversification and similarity. 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:

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

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 .¹² This measure ranges between zero and one, with a value of zero meaning that the

¹¹ We also measure MES as the average loss on 1% worst-case days of the market over the last one year. The results remain qualitatively the same and available upon request.

¹² 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.

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:

$$DIV_{i,t} = \ln(DIVER_{i,t}), \quad (18)$$

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 returns move in line with the banking index (more synchronous). We prefer to use a market-based measure, rather than income data, especially for similarity 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:

$$RET_{i,d} = a_0 + a_1 \overline{RET}_d + e_{i,d}, \quad (19)$$

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).¹³ From this regression, we obtain the R-squared values. Consistent with the literature (Boubaker, Mansali, and Rjiba, 2014; Morck, Yeung, and Yu, 2000), we apply a logistic transformation of these values and, hence, the transformed values range from positive to negative infinity:

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

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 ($TRAD$) that is computed as the ratio of total trading assets to total assets to account for a bank's share of proprietary trading and the risk differential between

¹³ We use daily stock returns and estimate the regression at every quarter using the past one year of data.

asset classes.¹⁴ Since this variable 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).

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). Particularly, we use market leverage (*MKTLEV*) and non-performing loan (*NPL*) ratios to proxy for capital adequacy and asset quality, 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 leverage position.¹⁵

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 a priori 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, well performing banks are less likely to experience a bank default or pose greater threat to the banking system since they are financially sound. Regarding liquidity, banks with high asset 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

¹⁴ This is because trading accounts are riskier relative to other asset types such as residential real estate loans.

¹⁵ For robustness, we use equity-to-assets ratio rather than market leverage and obtain similar results.

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 government 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.

< Insert Table 2 here >

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. Comparing the risk measures of both bank groups, the targeted banks have higher bank-level risk (*BRISK*) and also contribute significantly to systemic risk as indicated by the mean *SRISK* of 2.71 relative to the mean of 1.43 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 asset liquidity ratio of 14.16%, while having a non-performing loan ratio of 1.72%. On average, the targeted banks have higher asset liquidity ratio (mean = 21.18%) but have lower real estate loan ratio (mean = 43.52%) compared to their counterparts. These statistics support the notion that the targeted 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 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 the targeted banks are more directly affected by the Volcker Rule.

< Insert Table 3 here >

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 revenue diversification, bank 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.

The first-stage bank-level IV regressions are:

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

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

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

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.

The second-stage regressions are:

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

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

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). Columns (1) and (2) report the estimates for the drivers of bank-level risk ($BRISK$), which test Hypotheses 1a, 2a, and 3a. From Column (1), the fitted value of diversification (\widehat{DIV}) has a negative coefficient of -0.257, which is statistically significant at the 1% level. This suggests that banks with more diversified operations tend to have lower level of bank risk. In Column (2), we include a set of bank-specific and macro-economic controls and obtain a coefficient of -0.311 on \widehat{DIV} . On average, a one standard deviation increase in revenue diversification is expected to decrease bank-level risk by 0.16.¹⁶ This result is consistent with our theoretical prediction and Hypothesis 1a, whereby diversification lowers individual banks' default probability, and thus is desirable at the bank level.

Considering Hypothesis 2a, Columns (1) and (2) show that the coefficients on \widehat{SIM} are statistically insignificant at the 10% level, which are in line with our prior expectation. Hence, Hypothesis 2a is supported and that means the similarity between banks has no impact on bank-level risk.

Consistent with the extant literature, \widehat{TRAD} obtains significantly positive coefficients in both Columns (1) and (2), implying that trading activities are risky and more volatile that can drive the riskiness of banks (Demirguc-Kunt and Huizinga, 2010; Williams, 2016). As we move from Column (1) to Column (2), the coefficient on \widehat{TRAD} decreases in magnitude from 4.302 to 2.152, suggesting that a bank's trading activity is closely related to other bank-specific factors, such as size and thus, its effect can be diluted after accounting for these variables.

< Insert Table 4 here >

Turning to the controls, banks with higher market leverage ($MKTLEV$) and non-performing loan ratios (NPL) tend to be riskier as they have higher default and credit risks, respectively. The coefficient on the liquidity ratio (LIQ) has a negative sign, which indicates that banks experience lower bank-level risk when they have a greater share of liquid assets. The negative estimate of LIQ supports the view that higher asset liquidity allows banks to avoid bank

¹⁶ The standard deviation of DIV is 0.52 and the standard deviation of $BRISK$ is 1.18. A one standard deviation increase in DIV leads to a decrease in $BRISK$ of $0.311 \times 0.52 = 0.162$.

default or liquidity shortage situations when short-term liabilities become due. Banks with high real estate loan ratios (*RELOAN*) might relax their lending standards to attract borrowers and thus, result in higher bank-level risk. The negative coefficients on profitability (*ROE*) and GDP growth rate are also in line with the intuition that banks are safer when their financial performance is sound or when the economy is in a good state. Finally, large banks are more likely to engage in riskier transactions and thus, tend to have higher bank-level risk.

We turn to the third and fourth columns of Table 4, which test Hypotheses 1b, 2b, and 3b to examine the drivers of banks' systemic risk (*SRISK*). Consistent with Hypothesis 1b, the results in Columns (3)–(4) indicate that diversification is negatively associated with systemic risk, though the effect is small. The coefficient on \widehat{DIV} of -0.137 from Column (4) suggests that, on average, a one standard deviation decrease in diversification increases systemic risk by 0.07. We also find support for Hypothesis 2b, as the variable \widehat{STM} has a significantly positive coefficient that implies that systemic risk increases when banks are more similar to each other. The effect of similarity on systemic risk is both statistically and economically significant. For an average bank, the coefficient on \widehat{STM} of 0.358 implies that a one standard deviation increase in similarity is expected to increase systemic risk by 0.963. 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 contribution.

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, thereby supporting Hypothesis 3b. From Column (4) of Table 4, the significant coefficient on \widehat{TRAD} of 2.217 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 0.17.¹⁷ These results are qualitatively similar with and without the inclusion of bank specific and macro-economic controls.

Regarding the controls, banks that hold more liquid assets and residential loans are associated with lower systemic risk. Consistent with the moral hazard and too-big-to-fail concerns (Black and Hazelwood, 2013; Duchin and Sosyura, 2014), large banks or those that

¹⁷ 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 2.32 for *TRAD* and *SRISK*, respectively.

received the TARP funds tend to have higher contribution of systemic risk. As expected, leverage and non-performing loan ratios are also positively related to banks' contribution to systemic risk. These results indicate that banks that are heavily leveraged and experience deteriorating loan portfolio performance are more inclined to fail in a systemic default.

Overall, the IV regression results are in line with our model's predictions and hypotheses. First, diversification has risk reduction benefits 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 no effect on bank-level risk, high similarity among banks increases asset correlation and exposes banks to common asset risks, thereby raising the probability of a systemic default. Finally, banks' involvement in trading activities serves as a mechanism through which the 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 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:

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

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 enactment 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, γ_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 enactment of the Volcker Rule. Thus, our sample data is not contaminated by the pre-Volcker enactment noises and crisis effects,

thereby mitigating the data issues documented in most policy studies (SEC, 2017). Keppo and Korte (2016) show that major affected banks in the US have repeatedly announced reconfigurations of their business models and have even shut down proprietary trading desks and sold their shares in hedge funds prior to the full compliance period. For these reasons, we use the time window from 2012 to 2016 in the baseline regressions to fully capture the changes in banks' behavior following the Rule's enactment.

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 enactment, 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 enactment of 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.

< Insert Table 5 here >

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 in the periods following the Rule enactment. By restricting proprietary trading, the Volcker Rule makes banks become more similar to each other as 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. These findings support Hypothesis 5. While all banks have higher similarity after the enactment 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, which we will discuss in the next section.

The last column tests Hypothesis 6, which examines the effect of the Volcker Rule on banks' trading activity. Consistent with Keppo and Korte (2016), we obtain a 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 6 and complements the negative effect of the Rule on the targeted banks' diversification in Column (1).

As an alternative specification, we replace the pre-Volcker trading asset ratio with an indicator variable, *TARGETEDBHC*. The alternative indicator 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 note that they are qualitatively similar to those reported above. From Column (1), the negative coefficient on the DID term indicates that the targeted banks decrease revenue diversification, while the variable *POST* and DID term from Column (2) confirm that bank similarity increases following the Volcker Rule. 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. For the targeted banks' average *PRETRAD* of 10.76%, this is a reduction of 13% relative to their pre-Volcker trading asset ratios.¹⁸

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 similar to our previous discussions and are reported in Columns (4)–(9) of Table 6.

<Insert Table 6 here>

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 decline in the level of diversification and share of trading assets for the Volcker-targeted banks, the increase in similarity between 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 are independently related to bank-level and systemic risks, and how the Volcker Rule affect these channels. We now combine these results to estimate the effects of the Volcker Rule on the two risk measures to test Hypotheses 7, 8, and 9. We compute the effects at the bank level using the estimated coefficients obtained from Columns (2)–(4) in Table 4 and Columns (1)–(3) in Table

¹⁸ 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.

5. For example, the effect of the Volcker Rule on bank i 's bank-level risk from the diversification channel is calculated as $\delta_3 \times PRETRAD_i \times \beta_1$.¹⁹ This estimate represents the change in bank i 's risk due to the change in revenue diversification driven by the Volcker Rule enactment. Similarly, the effect of the Rule on bank i 's risk via the trading activity channel is computed as $\delta_3 \times PRETRAD_i \times \beta_3$. To also account for the indirect impact on the non-targeted banks via the similarity channel, we compute the Volcker Rule's effect on bank-level risk as $(\delta_3 \times PRETRAD_i \times \beta_2) + \delta_1$. That is, those that do not hold trading assets on their book would yet be affected by the coefficient on $POST_t$ (δ_1). The effects of the Volcker Rule on bank i 's systemic risk from each channel are computed in a similar way, except the estimates β_1 , β_2 , and β_3 (from Eq. (24)) are replaced with γ_1 , γ_2 , and γ_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' z-score, whereas the systemic risk (*SRISK*) is measured as the banks' MES. 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 just before the Volcker Rule's enactment, that is, the first two quarters of 2010.²⁰

< Insert Figure 5 here >

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 enactment period, the ban on proprietary trading decreases the targeted banks' diversification that in turns raises bank-level risk by about 1% (relative to their pre-Volcker *BRISK* of -3.96). Hence, we find supporting evidence for Hypothesis 7,

¹⁹ Note that δ_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.

²⁰ 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.

whereby the Volcker Rule decreases the targeted banks' capacity to diversify idiosyncratic risk, hence, increases their risk level. Next, we test Hypothesis 9a that anticipates that the Volcker Rule limits proprietary trading, thereby decreasing bank risk. As evident by the negative bar for *TRAD*, our result strongly implies that the Volcker Rule is successful in reducing the bank-level risk of individual banks through the trading activity channel by about 3%. Consistent with our theoretical model, the Volcker Rule has a marginal or no effect on the bank-level risk of non-targeted banks.

Overall, the Volcker Rule has a weak impact on individual banks' risk level (a net decrease in bank-level risk of 0–1.8%). 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 Hypotheses 8 and 9b, which predict that the Volcker Rule would increase banks' contribution to systemic risk due to higher bank similarity while decrease systemic risk via lower trading activity, respectively. As intended by the Volcker Rule, the negative bar for *TRAD* confirms that the reduction in proprietary trading activity lowers the systemic risk of the targeted banks. At an average pre-Volcker systemic risk (*SRISK*) of 3.66 for targeted banks, the trading activity channel results in a decrease of more than 3% in systemic risk in the post-Volcker enactment period. The results lend support to our Hypothesis 9b.

However, there is a substantial increase in systemic risk of the targeted banks by 20% via 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. While the ban on banks' proprietary trading leads to a reduction in systemic risk, greater similarity among banks makes them exposed to higher probability of a systemic default. 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. There is an increase in systemic risk for the non-targeted banks of 22% relative to their average level of 2.27 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 concurrently since they invest in similar or 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 50th percentile (median value); the range for Group 2 is between the 50th and 90th percentiles, followed by Group 3 that ranges from the 90th to 95th percentiles. Banks in Group 4 have pre-trading asset ratios ranging between the 95th and 99th 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.

< Insert Figure 6 here >

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 -4.11 during the period just before the introduction of the Rule (*PREBRISK*), while Panel B reports the change in systemic risk, relative to the average pre-Volcker systemic risk (*PRESRISK*) of 2.31.²¹ 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 enactment. 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. Following the Volcker Rule, bank-level risk is expected to fall by 0% to 2.2% (see Panel A), depending on which group the banks are in. 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.

²¹ The descriptive statistics of *PREBRISK* and *PRESRISK* are from an unreported table and are available upon request.

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. However, the independent effects from each channel are of larger magnitude. For example, an increase in Group 5's bank-level risk of 1.3% (relative to *PREBRISK*) from lower diversification that is offset by a decline in bank risk of more than 3.5% due to lower trading activity, through which comes the net decline of about 2%. 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, Panel B confirms that bank similarity is a dominating channel that drives systemic risk. At the average *PRESRISK* of 2.31, 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. It is interesting that banks that are not targeted by the Volcker Rule are also significantly affected by greater similarity between banks. 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 nearly 7%, which is offset by an increase of 35% (relative to *PRESRISK*) via higher similarity.

5. Robustness

5.1. Alternative risk measures

We use several measures of bank-level and systemic risk to examine the robustness of our results. Following the literature (Campbell, Hilscher, and Szilagyi, 2008; Demirguc-Kunt and Huizinga, 2010; Duchin and Sosyura, 2014), we use the stock return volatility (*RETVOL*) 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. Further, we use the standard deviations of net operating income (*SDREV*) and return on assets (*SDROA*) as other proxies for bank-level risk. The volatility of revenue reflects the fluctuations in the revenue portfolio while the volatility of return on total assets captures the effects of changes in leverage and asset composition (Duchin and Sosyura, 2014).

In addition to our primary proxy for *SRISK* (that is, *MES*) that captures the average stock return of each bank when the return of the market index is in the lowest 5% quantile, we measure

$MES^{1\%}$ as the average loss on 1% worst-case days of the market over the last one year. We also compute $FMES$ by replacing the CRSP value-weighted index return as the market return with the financial industry return data on 30 industry portfolios provided by Kenneth French (Acharya et al., 2017). For further robustness, we follow Van Oordt and Zhou (2012) and construct an alternative systemic risk measure, tail beta ($TBETA$), by extracting the OLS estimate of the slope coefficient from the following indicator regression:

$$I_{i,d} = \beta_I I_{market,d} + \varepsilon_t, \quad (16)$$

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 β_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. We run the 2SLS IV regression model (Eqs. (24) and (25)) using alternative risk proxies as the dependent variables and report the regression results in Table 7.

Columns (1)–(3) of Table 7 display the results for bank-level risk. As indicated by the significantly negative coefficients on DIV , we show evidence for Hypothesis 1a that suggests the existence of diversification benefits of at the bank-level. Similarly, there is a robust positive relation between trading activity and bank risk (Hypothesis 3a). Surprisingly, the coefficients on SIM across Columns (1)–(3) are significant but with differing signs, implying that similarity between banks might lead to changes in bank-level risk. We note that the effect of SIM is economically small relative to the other two channels where the most pronounced channel of bank-level risk is trading activity. On average, a one standard deviation increase in SIM and DIV decreases stock return volatility (revenue volatility) by 0.04% (0.04%) and 0.12% (0.23%), respectively, while a one standard deviation increase in $TRAD$ results in an increase of 2.82% (7.64%) in stock return volatility (revenue volatility). From Column (3), the effect of SIM is even smaller in magnitude as a one standard deviation increase in SIM leads to an increase of 0.02% in ROA volatility, on average.

The evidence across Columns (4)–(6) further confirm our baseline results and Hypotheses 1b, 2b, and 3b. As such, we conclude that bank similarity and trading activity are positively related to systemic risk, while banks with higher diversification are likely to have lower systemic risk contribution.

5.2. Use of the Volcker Rule's post-implementation period

Despite the enactment in July 2010, the Volcker Rule came into effect on April 1, 2014 with the conformance period extending until July 21, 2015. Banks were also given extensions up to further two years for them to exit their investments in private equity and hedge funds. Accordingly, our definition of *POST* might also capture the pre-implementation noises or other effects of simultaneous regulations other than the Volcker Rule. As a robustness check, we redefine the Post-Volcker period as those quarters from 2014 onwards ($POST_{VOLCKER}$). To further examine the changes in diversification, similarity, and trading activity around the effective and compliance dates of the Volcker Rule, we follow Bao et al. (2018) and split up $POST_{VOLCKER}$ into two periods using respective binary variables, including $POST_{VOLCKER-EARLY}$ and $POST_{VOLCKER-LATE}$. The former binary variable refers to the quarters from 2014(Q1) to 2015(Q1) while the latter refers to the period from 2015(Q2) onwards.

Referring to Columns (1)–(3) of Table 8, the interaction terms between $POST_{VOLCKER}$ and *PRETRAD* are statistically significant and are consistent with our expectations across various specifications. Similar to the results reported in Table 5, we find robust evidence that banks reduced their diversification and trading activity while became more similar following the introduction of the Volcker Rule. In addition, we also repeat the DID estimation using the dummy *TARGETEDBHC* and reach similar conclusions in Columns (4)–(6). We note that these effects are more pronounced compared to the baseline results, and thus, the effects that we documented in the main results are quite conservative relative to what they would have been if the alternative regressions' estimates were used.

In Columns (7)–(12), we also replace $POST_{VOLCKER}$ with $POST_{VOLCKER-EARLY}$ and $POST_{VOLCKER-LATE}$ to capture the compliance effect of the Volcker Rule. Across these specifications, the DID terms are significant and have expected signs for those between $POST_{VOLCKER-LATE}$ and banks' affectedness (*PRETRAD* and *TARGETEDBHC*). Interestingly, the coefficients on $POST_{VOLCKER-EARLY}$ are statistically significant in most specifications, especially for the diversification. While we note that the effects on the banks' similarity and trading activity are stronger during the compliance phase, the significance of $POST_{VOLCKER-EARLY}$ suggests that banks began to reallocate their portfolios (changing their portfolio mix) in response to the announcement of the Rule rather than waiting until the

compliance period. This evidence supports our use of a longer time window for post-enactment period of the Volcker Rule.

5.3. Control for capital requirements

The Basel III capital requirements were one of the regulatory reforms passed in 2014 to combat the crisis. According to the Basel III framework, banks are required to hold larger shares of high quality capital (that is, common equity). Regarding the banks' trading portfolios, Alexander, Baptista, and Yan (2015) find that the Basel framework was ineffective in preventing banks from taking substantive tail risk in such portfolios and argue that the Volcker Rule can reduce this ineffectiveness partially. As such, a key challenge is to examine whether the effects documented are driven by other reforms during the period. While we mitigate this concern by adopting a two-stage approach to clearly identify the independent effects from individual channels of the Volcker Rule, one could argue that banks might change their behaviors in response to the enforcement of the Basel III's higher capital requirements. For example, banks that are subject to stricter capital requirements might choose to contract their lending, rather than recapitalizing more capital during economic downturns (Shim, 2013). Similarly, Duffie (2012) and Thakor (2012) argue that the limitation on banks' trading activity could affect the liquidity of many securities, thereby affecting their ability to raise capital and increasing cost of capital. By making banks more capital constrained with stress tests and Basel III requirements, this could make them change their market-making businesses (Bao et al., 2017). From this view, banks could shift their asset allocation in the portfolios by cutting back on their risky activities (becoming less diversified and more similar) to raise their capital ratios. Consequently, the reduction in revenue diversification and trading activity, and increased level of similarity between banks could be driven by their responsiveness to the Basel III framework.

We test this scenario in two ways. First, we conduct a subsample test whereby we split banks into high-capitalization and low-capitalization samples based on their common equity ratios. A bank is classified as highly capitalized if its common equity ratio is greater than the median value. If banks are likely to change their behaviors due to capital requirements, the expectation is that the effects on the three channels are present only in the high-capitalization sample.

Second, we control for banks' capital buffers (*CAPBUFFER*) in the DID regressions. While banks are required to hold a regulatory minimum capital level for viability, they should hold a capital buffer to absorb unexpected losses. We define capital buffer as the excess capital that banks hold in addition to the required regulatory capital level. As such, the variable *CAPBUFFER* can be computed as the difference between the actual capital (sum of Tier 1 and Tier 2 capital) that banks hold and the minimum required capital level, which is 8% of the risk-weighted assets (Shim, 2013; Thakor, 2014). In support of our theory, we would expect that the effects on revenue diversification, similarity, and trading activity remain the same as those reported above after accounting for capital buffers.

Panel A of Table 8 reports the results with the inclusion of banks' capital buffers while Panel B reports those of subsample tests. From Columns (1)–(3) of Panel A, the DID coefficient estimates are statistically significant and are of similar magnitude, if not stronger, relative to those discussed in the baseline results, implying that there is a robust decrease in revenue diversification and trading activity at the targeted banks following the Volcker Rule. Hence, our results still hold in the inclusion of banks' capital buffers.

In Columns (4)–(9) of Panel B, we obtain similar trends as those in the baseline results for banks that have low capital ratio. By contrast, the results for banks in the high-capitalization group have unexpected and opposing signs. The subsample results suggest that targeted banks with high capital ratio are likely to be more diversified and less similar to other banks after the Rule's enactment, which is the opposite of our anticipation if the alternative explanation holds. Due to the limited number of observations in the subsamples, we note that the statistical significance and magnitude of some estimates will be adversely affected. In Columns (5)–(6), the decline in trading activity in both subsamples, and even more pronounced for the low-capitalization group, suggests that banks did not cut back on risky trading activities as a means of hoarding capital. Hence, the explanation that banks reduced diversification and limited trading activities in response to stricter capital standards is not supported.

5.4. Did the Volcker Rule make banks safer?

The intent of the Volcker Rule is to limit risky transactions, namely proprietary trading activities by banks. Accordingly, one could argue that by cutting back on these risky activities

and replacing them with less risky activities, banks would become more similar, but they would be more similar by holding *safer* assets after the Volcker Rule. If so, the increase in similarity between banks should be welcomed by the regulators, rather than discouraged, as it implies higher safety net. We note that the analysis regarding this aspect is beyond the scope of our paper. However, in the presence of such a situation it would lend more support to our findings, as this provides an upper bound for the documented effects on risks. That is, even when banks became safer with higher share of non-proprietary trading assets, we still observe an increase in systemic risk as there are dominant channels that have opposing effects. As such, the decline in bank-level and systemic risks via lower trading activity would not be able to take the full advantage of the risk savings when banks switch to less risky assets. Hence, if anything, this view would make our results more conservative. In line with our findings, Keppo and Korte (2016) show that the affected banks did not become safer, rather they maintained their overall risk targets and did not reduce the risks as strongly as the unaffected banks following the announcement of the Volcker Rule.

6. 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:

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

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

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,

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

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

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 π 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 $\Phi(\cdot) \sim [0, s]$. 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:

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

$$\begin{aligned} Pr(D_B) &= \pi_{1+4} \\ &= \int_0^d \int_0^{\frac{d-\alpha_2x}{1-\alpha_2}} \frac{1}{s^2} dy dx + \int_0^{\frac{d}{\alpha_2}} \int_0^{\frac{d-\alpha_2x}{1-\alpha_2}} \frac{1}{s^2} dy dx \\ &= \frac{d^2}{2\alpha_2s^2 - 2\alpha_2^2s^2}, \end{aligned} \quad (\text{A.6})$$

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

$$\begin{aligned}\pi_{1+4} - \pi_{1+2} &< 0 \\ \frac{d^2}{2\alpha_2 s^2 - 2\alpha_2^2 s^2} - \frac{d}{s} &< 0 \\ \frac{d}{s} &< 2\alpha_2(1 - \alpha_2).\end{aligned}\tag{A.7}$$

To simplify this result, we apply the condition on α_2 where $\alpha_2 \leq 1 - \frac{d}{s}$. Hence, the final result can be simplified as:

$$\begin{aligned}\frac{d}{s} &< 2\alpha_2(1 - \alpha_2) \\ &< 2\left(1 - \frac{d}{s}\right)\left(1 - \left(1 - \frac{d}{s}\right)\right) \\ &< \frac{1}{2}.\end{aligned}\tag{A.8}$$

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

$\pi_1 = \int_0^d \int_0^{\frac{d-\alpha_2 x}{1-\alpha_2}} \frac{1}{s^2} dy dx$. This follows that:

$$\begin{aligned}\frac{\pi_1}{\pi_{1+4}} - \frac{\pi_1}{\pi_{1+2}} &> 0 \\ \frac{1}{2}(-2 + \alpha_2)\left(2\alpha_2 + \frac{d}{(-1 + \alpha_2)s}\right) &> 0 \\ \frac{d}{s} &> 2\alpha_2(1 - \alpha_2).\end{aligned}\tag{A.9}$$

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:

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

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: $\pi_{1+2+3} = \frac{d}{s}$, $\pi_1 = \int_0^d \int_0^{\frac{d-\alpha_2 x}{1-\alpha_2}} \frac{1}{s^2} dy dx$, and $\pi_{1+2} = \int_0^d \int_0^{\frac{d-(1-\alpha_2)x}{\alpha_2}} \frac{1}{s^2} dy dx$. 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:

$$\begin{aligned} Pr(D_B|D_A)^{post} - Pr(D_B|D_A)^{pre} &> 0 \\ \frac{\pi_{1+2}}{\pi_{1+2+3}} - \frac{\pi_1}{\pi_{1+2+3}} &> 0 \\ \frac{(1+\alpha_2)d}{2\alpha_2 s} - \frac{(-2+\alpha_2)d}{2(-1+\alpha_2)s} &> 0 \\ \frac{d-2\alpha_2 d}{2\alpha_2 s - 2\alpha_2^2 s} &> 0 \end{aligned}$$

Simplifying the expression yields a solution of:

$$\alpha_2 < \frac{1}{2}. \quad (\text{A.11})$$

We verify that this result is the same as the pre-determined condition on α_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:

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

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 $\pi_2 = \frac{(2\alpha_2-1)d^2}{2(\alpha_2-1)\alpha_2s^2}$. Note that π_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:

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

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:

$$\begin{aligned}
Pr(D_B)^{Volcker} - Pr(D_B) &> 0 \\
\pi_{1+5+6} - \pi_{1+2+6} &> 0 \\
\left(-\frac{d^2}{2(-1+\alpha_2+\beta)(\alpha_2+\beta)s^2}\right) - \left(\frac{d^2}{2\alpha_2s^2-2\alpha_2^2s^2}\right) &> 0 \\
\frac{\beta d^2(-1+2\alpha_2+\beta)}{2\alpha_2s^2(-1+\alpha_2)(-1+\alpha_2+\beta)(\alpha_2+\beta)s^2} &> 0.
\end{aligned} \tag{A.14}$$

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

$$\begin{aligned}
Pr(D_B|D_A)^{Volcker} - Pr(D_B|D_A)^{pre} &> 0 \\
\frac{\pi_{1+2}}{\pi_{1+2+3}} - \frac{\pi_1}{\pi_{1+2+3}} &> 0 \\
\frac{(-2+\alpha_2+\beta)d}{2(-1+\alpha_2+\beta)s} - \frac{(-2+\alpha_2)d}{2(-1+\alpha_2)s} &> 0 \\
\frac{\beta d}{2(-1+\alpha_2)(-1+\alpha_2+\beta)s} &> 0.
\end{aligned} \tag{A.16}$$

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 α_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:

$$\begin{aligned}
Pr(D_B|D_A)^{Volcker} - Pr(D_B|D_A)^{pre} &> 0 \\
\frac{\pi_{1+2}}{\pi_{1+2+6}} - \frac{\pi_1}{\pi_{1+5+6}} &> 0
\end{aligned}$$

$$\begin{aligned}
-(-2 + \alpha_2 + \beta)(\alpha_2 + \beta) - (2 - \alpha_2)\alpha_2 &> 0 \\
-\beta(-2 + 2\alpha_2 + \beta) &> 0.
\end{aligned} \tag{A.19}$$

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

$$\begin{aligned}
\beta &< 2(1 - \alpha_2) \\
\frac{\beta}{2} &< \frac{d}{s}.
\end{aligned} \tag{A.20}$$

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

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

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 δ_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. Full descriptions of the variables are provided in Table 2.

Channel	Panel A: Bank-level risk			Panel B: Systemic risk		
	All	Non-targeted	Targeted	All	Non-targeted	Targeted
Revenue diversification	0.02	0.00	0.05	0.01	0.00	0.02
Bank similarity	0.00	0.00	0.00	0.62	0.51	0.75
Trading activity	-0.06	-0.01	-0.12	-0.06	-0.01	-0.12
Net effect	-0.04	-0.01	-0.07	0.57	0.50	0.65
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 δ_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. Full descriptions of the variables are provided in Table 2.

Panel A: Bank-level risk					
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	0.00	0.01	0.06
Bank similarity	0.00	0.00	0.00	0.00	0.00
Proprietary trading	0.00	0.00	-0.01	-0.03	-0.15
Net effect	0.00	0.00	-0.01	-0.02	-0.09
No. of banks	198	50	14	11	2

Panel B: Systemic risk					
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	0.00	0.01	0.03
Bank similarity	0.49	0.49	0.51	0.56	0.82
Proprietary trading	0.00	0.00	-0.01	-0.03	-0.15
Net effect	0.49	0.49	0.50	0.54	0.70
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 $\Phi(\cdot) \sim [0, s]$. 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: α_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 β 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 Bank B: ↑ $\beta < \frac{d}{s_y}$	Bank A: ↑ $\frac{\beta}{2} < \frac{d}{s_y}$ 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
<i>DIV</i>	Revenue diversification	Logs	<p>$DIV_{i,t} = \ln(DIVER_{i,t})$, where $DIVER_{i,t}$ is the revenue diversification index of bank i in quarter t. The variable $DIVER_{i,t}$ is computed as follows:</p> $DIVER_{i,t} = 2 \times \left[1 - \left(\left(\frac{NET_{i,t}}{NET_{i,t} + NON_{i,t}} \right)^2 + \left(\frac{NON_{i,t}}{NET_{i,t} + NON_{i,t}} \right)^2 \right) \right]$ <p>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.</p>
<i>SIM</i>	Bank similarity	Logs	<p>$SIM_{i,t} = \ln \left(\frac{R_{i,t}^2}{1 - R_{i,t}^2} \right)$,</p> <p>where $R_{i,t}^2$ 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).</p>
<i>TRAD</i>	Banks' trading asset ratio	Percent	Total trading assets to total book assets.
<i>BRISK</i>	Bank-level risk	Logs	Distance to default, z-score, which is measured as the sum of return on assets and equity-to-asset ratio divided by the standard deviation of asset return (<i>SDROA</i>) over the last one-year horizon. For interpretation purposes, we use the inverse of the natural logarithm of this ratio.
<i>SRISK</i>	Banks' systemic risk		<p>Marginal Expected Shortfall (MES), which is measured as the average stock return of each bank when the market return is in the lowest 5% quantile over a one-year horizon, calculated as:</p> $MES_i^{5\%} = \frac{1}{\# \text{ days}} \sum R_{i,\{t:\text{system is in its 5\% tail}\}}$ <p>We take the inverse of this measure and multiply by 100 to express in percent.</p>
<i>MKT_LEV</i>	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 value of equity and total liabilities.
<i>NPL</i>	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.
<i>LIQ</i>	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.
<i>RELOAN</i>	Banks' real estate loan ratio	Percent	Total real estate loans to total loans. Total real estate loans include residential and commercial real estate loans.
<i>SIZE</i>	Bank size	Logs	Natural logarithm of total book assets, deflated using GDP deflator as at 2016(Q4).
<i>NONIE</i>	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.).
<i>TARP_BK</i>	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.
<i>IBANK</i>	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.
<i>GDP_GR</i>	Current Gross Domestic Product (GDP) growth rate	Percent	Difference between the current and last year's GDP indices, seasonally adjusted and annualized.
<i>POST_VOLCKER</i>	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.
<i>PRETRAD</i>	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.
<i>PREBRISK</i>	Banks' average bank-level risk	Percent	Average of z-score over the period just before the Volcker Rule enactment (from 2010 (Q1) to 2010(Q2)). The measure is calculated at the bank level.
<i>PRESRISK</i>	Banks' average systemic risk	Percent	Average of MES over the period just before the Volcker Rule enactment (from 2010 (Q1) to 2010(Q2)). The measure is calculated at the bank level.
<i>TARGETED_BHC</i>	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 (<i>PRETRAD</i>) above or equal to 3%.
<i>TARGETEDBHC_P99</i>	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.
<i>TARGETEDBHC_TOP10</i>	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).
<i>RETVOL</i>	Banks' stock return volatility	Percent	The standard deviation of the daily stock prices over the last one-year horizon.
<i>SDREV</i>	Banks' revenue volatility	Percent	The standard deviation of banks' net operating income (including net interest income

			and noninterest income) over the last one-year horizon.
<i>TBETA</i>	Banks' tail beta		The estimated β_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 ($I_{i,d}$)
<i>CAPBUFFER</i>	Banks' capital buffer	Percent	The difference between the actual capital (sum of Tier 1 and Tier 2 capital) that banks hold and the minimum required capital level, which is 8% of the risk-weighted assets.
<i>HIGH_EQUITY</i>	A binary variable for high capitalization	Dummy	A binary variable that is equal to one for banks with common equity to total assets ratio above the median value.

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).

Variable	All banks						Affected banks		Non-affected banks		Difference	
	Obs.	Mean	Median	Std. dev.	p1	p99	Obs.	Mean	Obs.	Mean		
<i>DIV</i>	25,017	-0.47	-0.37	0.52	-2.09	0.00	744	-0.26	24,273	-0.48	0.22	***
<i>SIM</i>	25,017	-2.34	-1.80	2.69	-10.20	1.42	744	-0.72	24,273	-2.39	1.67	***
<i>TRAD</i>	24,529	0.46	0.00	2.35	0.00	13.75	720	9.47	23,809	0.18	9.28	***
<i>BRISK</i>	24,117	-5.18	-5.26	1.18	-7.66	-1.84	711	-4.75	23,406	-5.19	0.45	***
<i>SRISK</i>	25,017	1.47	1.22	1.65	-1.29	6.86	744	2.71	24,273	1.43	1.28	***
<i>MKTLEV</i>	25,017	85.54	86.27	7.24	65.94	96.49	744	86.08	24,273	85.53	0.55	**
<i>NPL</i>	25,017	1.72	1.21	1.86	0.00	9.17	744	2.25	24,273	1.70	0.55	***
<i>LIQ</i>	25,017	14.16	11.89	9.35	2.10	47.64	744	21.18	24,273	13.95	7.23	***
<i>RELOAN</i>	25,016	69.12	72.10	17.74	11.09	98.32	743	43.52	24,273	69.90	-26.38	***
<i>NONIE</i>	24,629	3.24	3.04	1.16	1.39	9.28	726	4.04	23,903	3.22	0.82	***
<i>SIZE</i>	25,017	14.93	14.62	1.52	12.52	18.78	744	17.83	24,273	14.84	2.99	***
<i>TARP_BK</i>	25,017	0.18	0.00	0.38	0.00	1.00	744	0.28	24,273	0.18	0.10	***
<i>IBANK</i>	25,017	0.05	0.00	0.21	0.00	1.00	744	0.52	24,273	0.03	0.49	***
<i>GDP_GR</i>	24,427	0.05	0.05	0.02	-0.03	0.08	723	4.59	23,704	4.57	0.02	
<i>POST_VOLCKER</i>	25,017	0.21	0.00	0.41	0.00	1.00	744	0.23	24,273	0.21	0.02	
<i>AFFECTEDBHC</i>	25,017	0.03	0.00	0.17	0.00	1.00	744	1.00	24,273	0.00	1.00	***
<i>PRETRAD</i>	25,017	0.47	0.00	2.32	0.00	12.56	744	10.76	24,273	0.15	10.60	***

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' distance to default (that is, the z-score measure). The dependent variable in Column (2) is systemic risk (*SRISK*), which is measured as the banks' marginal expected shortfall (MES). 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*), non-interest expense ratio (*NONIE*), bank size (*SIZE*), an indicator variable that takes a value of one if 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. We report the values of adjusted R-squared 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. The sample period is from 1993(Q1) to 2016(Q4).

Dependent variable	Bank-level risk (<i>BRISK</i>)		Systemic risk (<i>SRISK</i>)	
	(1)	(2)	(3)	(4)
<i>DIV</i>	-0.257*** (-10.880)	-0.311*** (-13.840)	-0.128*** (-5.070)	-0.137*** (-5.590)
<i>SIM</i>	-0.005 (-1.610)	-0.002 (-0.480)	0.434*** (112.450)	0.358*** (67.020)
<i>TRAD</i>	4.302*** (15.140)	2.152*** (6.140)	4.831*** (9.310)	2.217*** (4.990)
<i>MKTLEV</i>		3.035*** (17.370)		0.469*** (3.060)
<i>NPL</i>		12.197*** (24.640)		10.485*** (15.980)
<i>ROE</i>		-2.588*** (-12.240)		-1.444*** (-6.150)
<i>LIQ</i>		-0.584*** (-7.570)		-0.078 (-0.860)
<i>RELOAN</i>		0.468*** (9.020)		-0.350*** (-6.460)
<i>NONIE</i>		25.206*** (30.690)		9.595*** (11.410)
<i>SIZE</i>		0.029*** (3.770)		0.061*** (6.670)
<i>TARP_BANK</i>		0.001 (0.030)		0.216*** (7.360)
<i>GDP_GR</i>		-3.551*** (-8.820)		-19.350*** (-31.420)
Adj. R-squared (%)	1.38	22.05	40.58	52.73
Observations	23,643	23,053	24,147	23,557

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* × *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*), non-interest expense ratio (*NONIE*), bank size (*SIZE*), and an indicator variable that takes a value of one if 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-squared 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	<i>DIV</i>	<i>SIM</i>	<i>TRAD</i>
	(1)	(2)	(3)
<i>POST</i>	-0.085*** (-4.50)	1.365*** (27.330)	0.001*** (3.740)
<i>PRETRAD</i>	-0.834*** (-4.490)	-14.561*** (-12.180)	0.991*** (64.420)
<i>POST</i> × <i>PRETRAD</i>	-0.831* (-1.90)	3.946*** (2.950)	-0.291*** (-12.970)
<i>MKTLEV</i>	2.677*** (11.60)	-7.834*** (-18.760)	-0.019*** (-3.130)
<i>NPL</i>	-3.080*** (-4.530)	-5.579*** (-4.480)	0.020*** (3.280)
<i>ROE</i>	1.263*** (6.320)	0.813** (2.360)	-0.002 (-1.150)
<i>LIQ</i>	0.037 (0.680)	-1.058*** (-5.250)	0.001 (0.950)
<i>RELOAN</i>	-0.188*** (-5.610)	0.567*** (4.230)	-0.001*** (-2.90)
<i>NONIE</i>	11.306*** (15.750)	-23.529*** (-12.40)	0.031*** (2.850)
<i>SIZE</i>	0.070*** (17.990)	1.190*** (71.180)	0.000*** (3.740)
<i>TARP_BANK</i>	0.021 (1.010)	-0.245*** (-4.60)	0.000 (-0.650)
Adj. R-squared (%)	13.48	48.44	87.46
Observations	11,966	11,966	11,964

Table 6

Robustness tests – Alternative difference-in-differences specifications

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* × *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’s enactment. *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* × *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* × *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*), non-interest expense ratio (*NONIE*), bank size (*SIZE*), and an indicator variable that takes a value of one if 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-squared 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	Panel A			Panel B			Panel C		
	<i>DIV</i>	<i>SIM</i>	<i>TRAD</i>	<i>DIV</i>	<i>SIM</i>	<i>TRAD</i>	<i>DIV</i>	<i>SIM</i>	<i>TRAD</i>
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
<i>POST</i>	-0.085*** (-4.480)	1.373*** (27.410)	0.000 (-0.40)	-0.082*** (-4.290)	-0.082*** (-4.290)	-0.001*** (-3.510)	-0.082*** (-4.30)	1.387*** (27.740)	-0.001 (-1.460)
<i>TARGETEDBHC</i>	-0.087** (-2.10)	-1.720*** (-16.910)	0.096*** (15.860)						
<i>POST</i> × <i>TARGETEDBHC</i>	-0.234*** (-3.160)	0.505*** (3.460)	-0.014* (-1.870)						
<i>TARGETEDBHC_P99</i>				-0.056** (-2.060)	-2.051*** (-16.570)	0.166*** (20.980)			
<i>POST</i> × <i>TARGETEDBHC_P99</i>				-0.262*** (-2.990)	0.985*** (5.190)	-0.045*** (-5.250)			
<i>TARGETEDBHC_TOP10</i>							-0.009 (-0.20)	-1.632*** (-15.980)	0.110*** (16.570)
<i>POST</i> × <i>TARGETEDBHC_TOP10</i>							-0.237** (-2.550)	0.835*** (5.120)	-0.008 (-1.010)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared (%)	13.61	48.23	59.08	13.45	47.96	72.63	13.39	48.01	65.92
Observations	11,966	11,966	11,964	11,966	11,966	11,964	11,966	11,966	11,964

Table 7
Robustness tests – Alternative risk proxies

The table reports second stage regression results of the two-stage least squares (2SLS) model using instrumental variables. The dependent variables in Columns (1)-(3) are proxies for bank-level risk, which are stock return volatility, revenue volatility, and ROA volatility. Note that these measures are expressed in percent. The dependent variables in Columns (2)-(5) are the proxies for systemic risk, namely banks' marginal expected shortfall (MES) at 1%, MES using financial industry market index (F-MES), and 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*), non-interest expense ratio (*NONIE*), bank size (*SIZE*), an indicator variable that takes a value of one if 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. We report the values of adjusted R-squared 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. The sample period is from 1993(Q1) to 2016(Q4).

Dependent variable	Panel A: Bank-level risk			Panel B: Systemic risk		
	Stock return volatility	Revenue volatility	ROA volatility	MES ^{1%}	F-MES	Tail beta
	(1)	(2)	(3)	(4)	(5)	(6)
\widehat{DIV}	-0.224*** (-11.580)	-0.449*** (-14.170)	-0.084*** (-12.480)	-0.137*** (-5.590)	-0.109*** (-3.70)	-0.041*** (-13.230)
\widehat{SIM}	-0.015*** (-3.940)	-0.016*** (-4.30)	0.009*** (7.650)	0.358*** (67.020)	0.431*** (70.340)	0.063*** (77.430)
\widehat{TRAD}	1.199*** (3.320)	3.252*** (7.460)	0.422*** (2.740)	2.217*** (4.990)	0.795* (1.70)	0.328*** (6.030)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared (%)	33.98	64.12	17.41	52.73	49.06	49.26
Observations	23,557	23,020	23,020	23,557	23,557	23,557

Table 8

Robustness tests – Alternative post-Volcker Rule definitions

The table reports coefficient estimates from the difference-in-differences regression. The dependent variables are revenue diversification (*DIV*), bank similarity (*SIM*), and trading activity (*TRAD*). In Panels A and B, $POST_{VOLCKER}$ is the indicator variable that equals one for periods 2014(Q1)–2016(Q4) and zero for periods 2005(Q1)–2007(Q4). In Panels C and D, we split $POST_{VOLCKER}$ into two subsample periods: $POST_{VOLCKER-EARLY}$ and $POST_{VOLCKER-LATE}$. $POST_{VOLCKER-EARLY}$ is the indicator variable that equals one for periods 2014(Q1)–2015(Q1) and zero otherwise. $POST_{VOLCKER-LATE}$ is the indicator variable that equals one for periods 2015(Q2)–2016(Q4) and zero otherwise. $PRETRAD$ is the average trading asset ratio of bank *i* during the pre-Volcker period (from 2005(Q1) to 2007(Q4)). $TARGETEDBHC$ 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. For Panel A, we control for banks' capital buffer (*CAPBUFFER*). We also include control variables, which comprise market leverage ratio (*MKTLEV*), non-performing loan ratio (*NPL*), profitability (*ROE*), liquidity (*LIQ*), real estate loan ratio (*RELOAN*), 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 $POST_{VOLCKER}$, $POST_{VOLCKER-EARLY}$, and $POST_{VOLCKER-LATE}$, time fixed effects are omitted to avoid multicollinearity. We report the values of adjusted R-squared 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	Panel A			Panel B			Panel C			Panel D		
	<i>DIV</i>	<i>SIM</i>	<i>TRAD</i>	<i>DIV</i>	<i>SIM</i>	<i>TRAD</i>	<i>DIV</i>	<i>SIM</i>	<i>TRAD</i>	<i>DIV</i>	<i>SIM</i>	<i>TRAD</i>
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$POST_{VOLCKER}$	-0.008 (-0.450)	1.108*** (19.260)	0.000** (2.30)	-0.010 (-0.530)	1.118*** (19.360)	0.0 (-1.470)						
$POST_{VOLCKER-EARLY}$							-0.059** (-2.040)	1.231*** (16.120)	0.000 (0.590)	-0.061** (-2.10)	1.241*** (16.170)	-0.001** (-2.180)
$POST_{VOLCKER-LATE}$							0.022 (1.270)	1.531*** (23.410)	0.0 (0.590)	0.018 (1.060)	1.550*** (23.660)	-0.001*** (-2.180)
$PRETRAD$	-1.030*** (-3.550)	-15.861*** (-10.980)	0.995*** (43.960)				-0.859*** (-4.280)	-15.917*** (-10.530)	1.009*** (46.410)			
$POST_{VOLCKER} \times PRETRAD$	-1.038* (-1.740)	4.545*** (2.710)	-0.338*** (-12.90)									
$POST_{VOLCKER-EARLY} \times PRETRAD$							-1.20 (-1.460)	3.581* (1.760)	-0.308*** (-9.420)			
$POST_{VOLCKER-LATE} \times PRETRAD$							-1.217* (-1.750)	7.237*** (4.10)	-0.383*** (-14.10)			
$AFFECTEDBHC$				-0.168*** (-2.580)	-1.732*** (-14.380)	0.102*** (13.320)				-0.145** (-2.190)	-1.712*** (-14.230)	0.103*** (12.480)
$POST_{VOLCKER} \times AFFECTEDBHC$				-0.273** (-2.50)	0.347* (1.910)	-0.025** (-2.550)						
$POST_{VOLCKER-EARLY} \times AFFECTEDBHC$										-0.312* (-1.750)	0.335 (1.100)	-0.022* (-1.750)

										(-1.790)	(1.430)	(-1.830)
<i>POSTVOLCKER-LATE</i> × <i>AFFECTEDBHC</i>										-0.281**	0.694***	-0.029**
										(-2.570)	(3.440)	(-2.570)
Controls	Yes	Yes	Yes									
Adj. R-squared (%)	15.26	47.69	88.80	15.67	47.34	60.16	15.94	49.20	88.76	16.38	48.85	60.16
Observations	6,932	6,932	6,932	6,932	6,932	6,932	6,932	6,932	6,932	6,932	6,932	6,932

Table 9

Robustness tests – Control for capital requirements

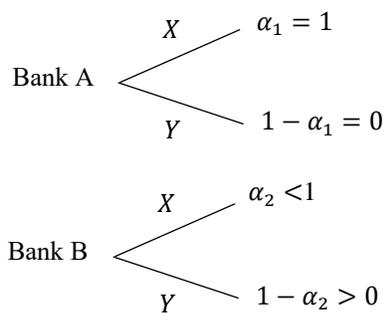
The table reports coefficient estimates from the difference-in-differences regression. The dependent variables in Columns (1), (2), and (3) are revenue diversification (*DIV*), bank similarity (*SIM*), and trading activity (*TRAD*), respectively. *POST* is the indicator variable that equals one for periods 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* × *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*. For Panel A, we control for banks’ capital buffer (*CAPBUFFER*). We also include control variables, which comprise market leverage ratio (*MKTLEV*), non-performing loan ratio (*NPL*), profitability (*ROE*), liquidity (*LIQ*), real estate loan ratio (*RELOAN*), non-interest expense ratio (*NONIE*), bank size (*SIZE*), and an indicator variable that takes a value of one if 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-squared 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	Panel A: Inclusion of capital buffer			Panel B: Subsample tests by bank capitalization					
	<i>DIV</i>	<i>SIM</i>	<i>TRAD</i>	<i>HIGH_EQUITY</i> = 0			<i>HIGH_EQUITY</i> = 1		
				<i>DIV</i>	<i>SIM</i>	<i>TRAD</i>	<i>DIV</i>	<i>SIM</i>	<i>TRAD</i>
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
<i>POST</i>	-0.085*** (-4.320)	1.410*** (27.670)	0.001*** (3.730)	-0.112*** (-4.930)	1.348*** (24.130)	0.001*** (3.830)	0.031 (1.480)	1.454*** (14.120)	0.0 (-0.230)
<i>PRETRAD</i>	-0.835*** (-4.480)	-14.490*** (-12.180)	0.991*** (64.40)	-0.580*** (-3.020)	-13.270*** (-11.710)	0.989*** (67.040)	-1.308 (-0.780)	-62.601*** (-5.570)	1.015*** (3.190)
<i>POST</i> × <i>PRETRAD</i>	-0.831* (-1.910)	4.009*** (2.990)	-0.291*** (-12.950)	-0.707* (-1.670)	4.108*** (3.290)	-0.293*** (-13.230)	-6.909 (-1.410)	-409.684*** (-12.90)	-0.233** (-2.010)
<i>CAPBUFFER</i>	0.004 (0.020)	-2.158*** (-3.060)	-0.003 (-1.140)						
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared (%)	13.48	48.47	87.46	12.94	49	89.64	25.88	50.22	28.81
Observations	11,966	11,966	11,964	8,741	8,741	8,740	3,225	3,225	3,224

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: α_1 and α_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 α_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 $\Phi(\cdot) \sim [0, s]$. 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

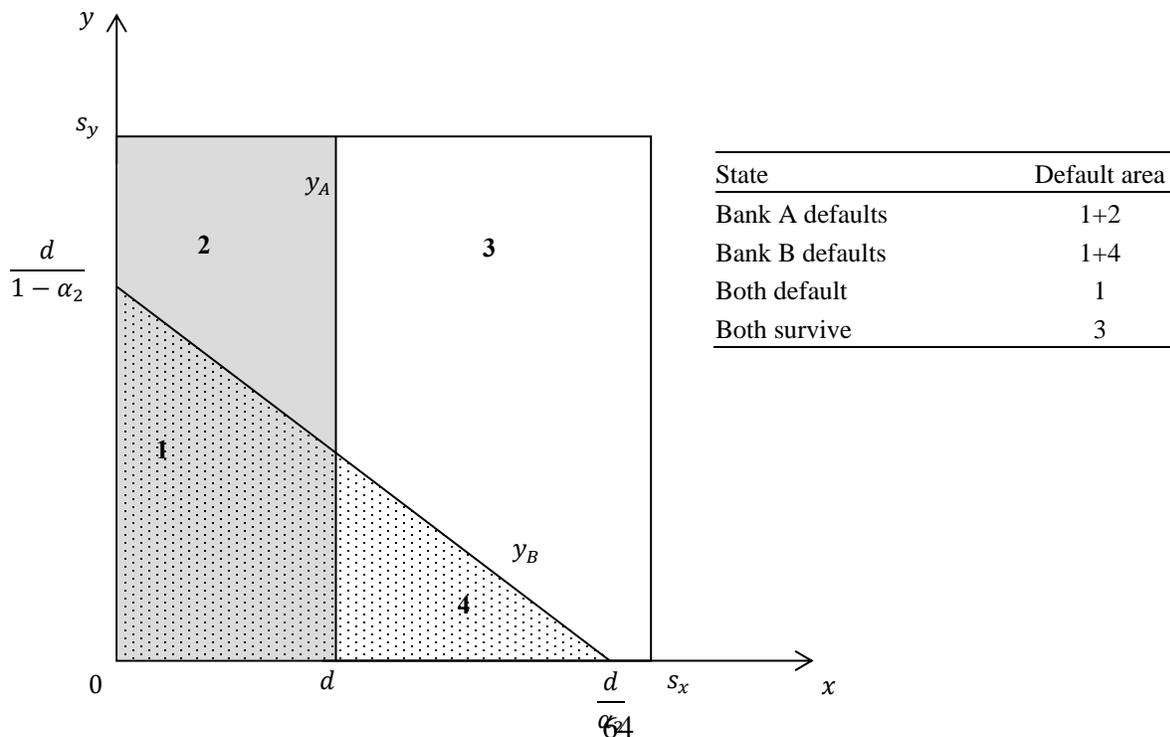
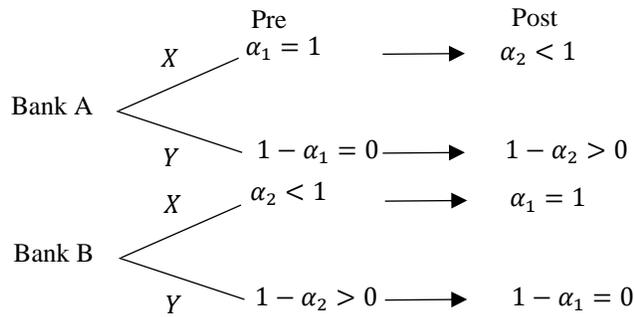


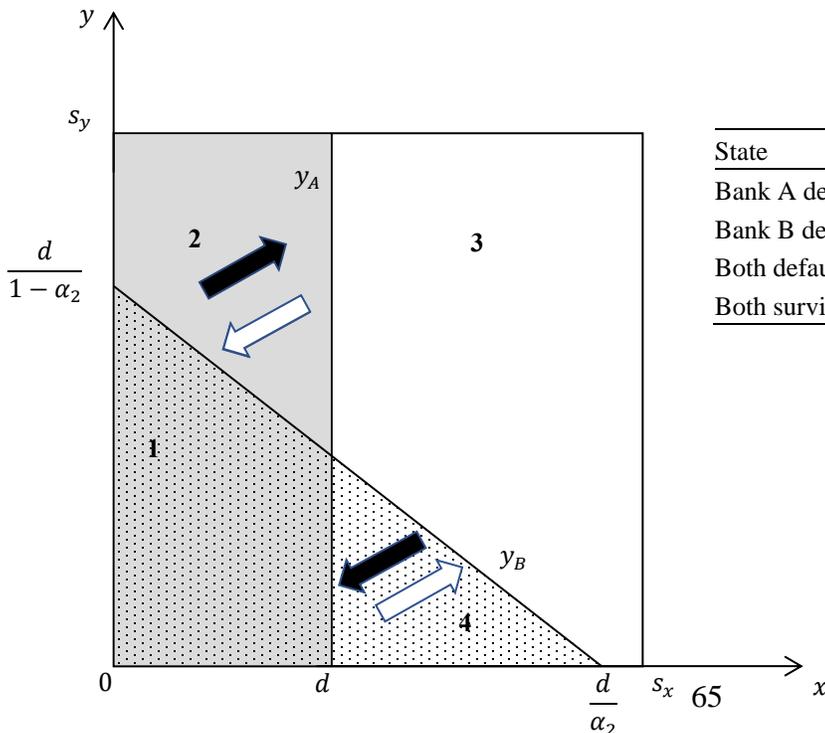
Figure 2: Effects of diversification on banks' default probability.

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: α_1 and α_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 α_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 $\Phi(\cdot) \sim [0, s]$. 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 $\Phi(\cdot) \sim [0, s]$. 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

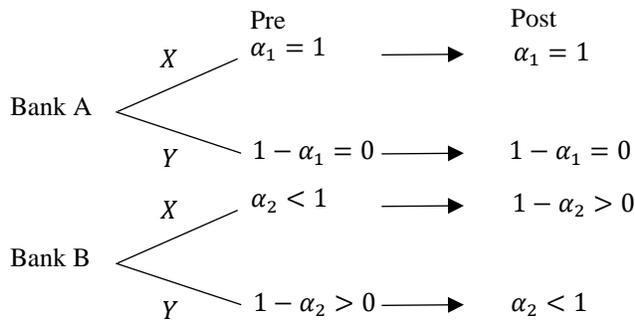


State	Pre-treatment	Post-treatment
Bank A defaults	1+2	1+4
Bank B defaults	1+4	1+2
Both default	1	1
Both survive	3	3

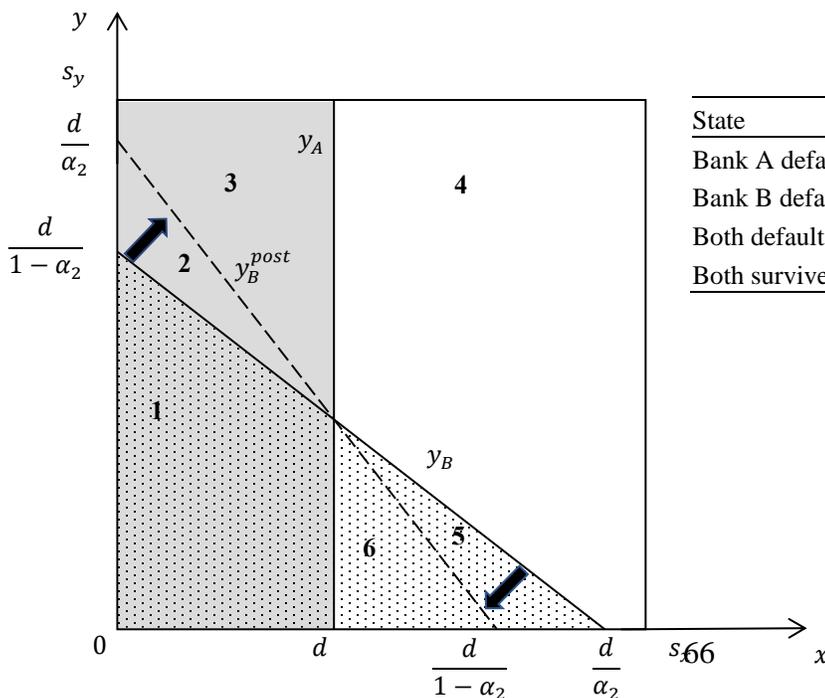
Figure 3: Effects of similarity on banks' default probability.

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; α_1 and α_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 α_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 $\Phi(\cdot) \sim [0, s]$. For the treatment, bank B switches its portfolio weights and invests $1 - \alpha_2$ in asset X and α_2 in asset Y , while bank A's portfolio is the same. The degree of diversification is unchanged between the two periods. Note that α_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 $\Phi(\cdot) \sim [0, s]$. 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

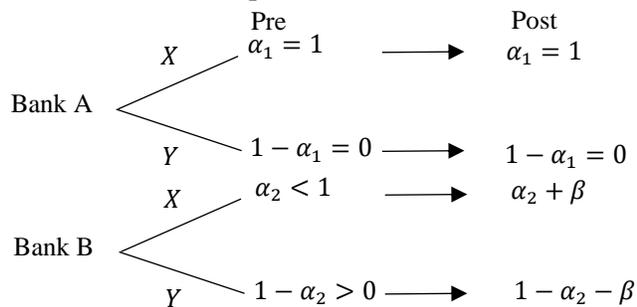


State	Pre-treatment	Post-treatment
Bank A defaults	1+2+3	1+2+3
Bank B defaults	1+5+6	1+2+6
Both default	1	1+2
Both survive	4	4+5

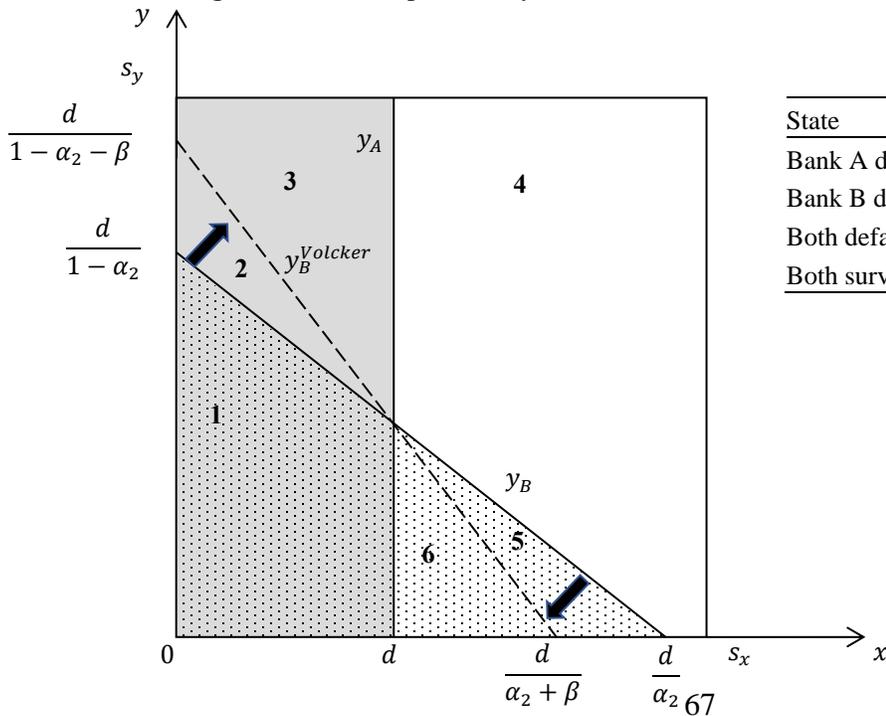
Figure 4: Effects of Volcker Rule implementation on banks' default probability.

This figure outlines the scenario setting to test the effect of the Volcker Rule on risks, whereby 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; α_1 and α_2 are banks A and B's portfolio weights invested in asset X, respectively; d is the debt level; and β 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 α_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 $\Phi(\cdot) \sim [0, s]$. For the treatment, bank B reduces its investment in asset Y by β , 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 $\Phi(\cdot) \sim [0, s]$. 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

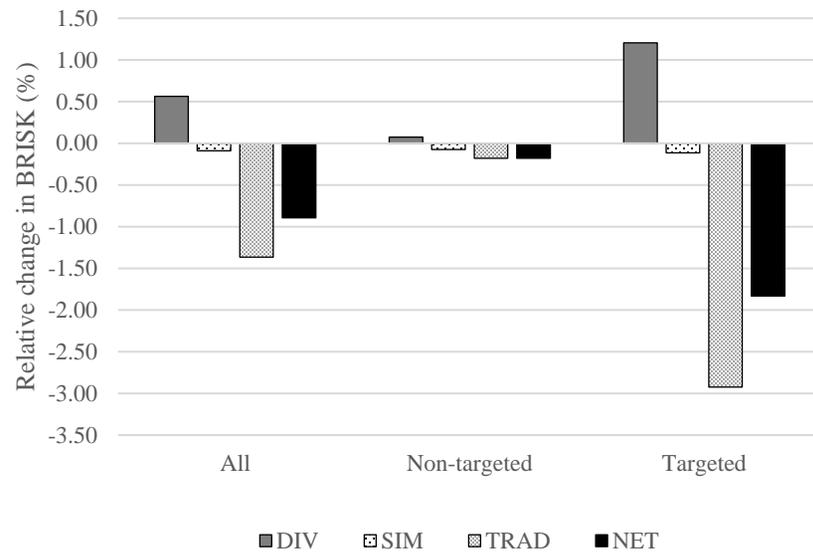


State	Pre-treatment	Post-treatment
Bank A defaults	1+2+3	1+2+3
Bank B defaults	1+5+6	1+2+6
Both default	1	1+2
Both survive	4	4+5

Figure 5: Effects of the Volcker Rule enactment 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 δ_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 2010(Q1)–2010(Q2) (*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*)

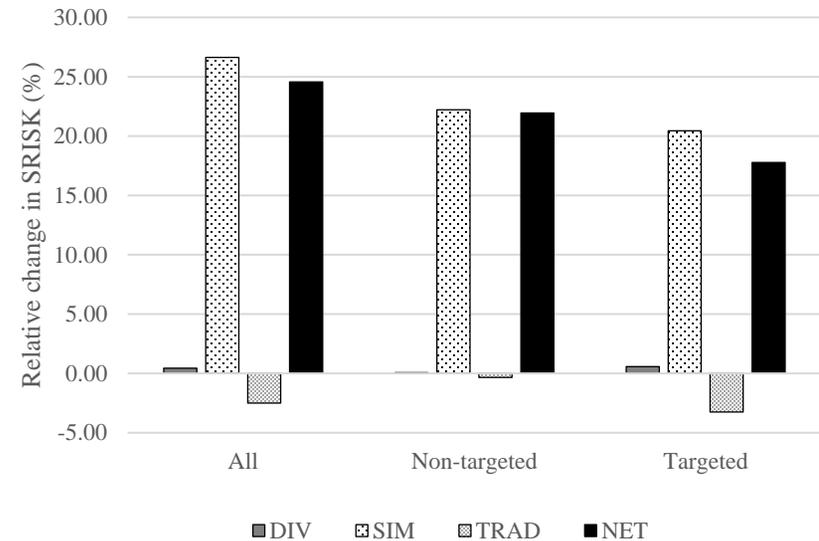
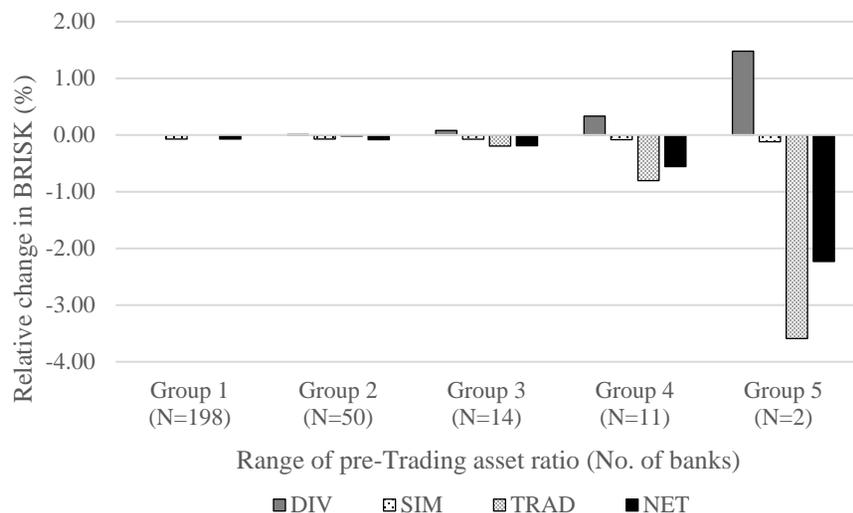


Figure 6: Cross-sectional effects of the Volcker Rule enactment on (A) bank risk and (B) systemic risk

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 (<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 δ_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 2010(Q1)-2010(Q2) (*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*)

