# Does Dodd-Frank Wall Street Reform Act Changed Attitude of U.S. bank holding companies towards credit and interest derivatives?

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## Abstract

This paper investigates response of U.S. bank holding companies to introduction The Dodd-Frank Wall Street Reform Act (DFA). By examining 151 U.S. bank holding companies with total asset higher than 1 billion, we find that in post-DFA period, banks’ contribution to systemic risk was substantially reduced. Moreover, we found usage of credit and interest rate derivatives held for hedging have weakened impact on systemic risk. On other hand, our scrutiny reveals that the individual banks’ risks increase and performance decrease. Finally, we show that in regulator environment defined by DFA, the usage of interest and credit derivatives contribute less to the systemic risk.

*Keywords*: U.S. bank holding companies; Systemic risk; The Dodd-Frank Wall Street Reform Act (DFA); Credit derivatives; Interest derivatives; Hedging; Global Financial Crisis

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## Introduction

The popularity of derivative products among financial institutions has led to a substantial growth in derivative market. The notional principal amount of financial derivatives held by U.S. bank holding companies (BHCs) rose from less than $18 trillion in 1995 to nearly $270 trillion by the end of 2012, which was more than 10 times the total asset value of BHCs.[[1]](#footnote-1) Credit default swaps (CDSs) were used widely to transfer credit risk among financial institutions. The outstanding amount of CDSs grew from less than $1 trillion at the beginning of 2001 to over $6 trillion by the end of 2007. Empirical studies suggest that derivatives such as CDSs increase the correlations among banks, generate a wide net of linkages in the financial system, and make the financial market more vulnerable (Bedendo and Bruno, 2012). According to the Financial Crisis Inquiry Commission (2011), the significant systemic risk that fueled the GFC can be attributed to the size and complexity of the over-the-counter (OTC) derivative market. Millions of derivative contracts in such unregulated markets created interconnectedness among financial institutions and exposed the financial system to a contagion of losses and defaults via counterparty credit risk channel.

As the financial crisis unraveled in the U.S. in 2007, the Democratic-dominant Congress pushed for more restrictive regulations on Wall Street. The Dodd-Frank Wall Street Reform and Consumer Protection Act (DFA) was signed into the U.S. federal law on 21 July, 2010. Title VII of the DFA - Wall Street Transparency and Accountability, requires that financial derivatives be cleared through a derivative clearing organization. This title aims at improving market transparency and lowering the counterparty risk associated with financial derivative products via a central clearing channel. Unlike the previously unregulated OTC derivative market where the network of exposures is highly dispersed, derivative clearing organizations centralize the network of exposures and play a key role among counterparties involved in derivative contracts. Derivative clearing organizations are able to curtail the direct interconnectedness among banks by setting strict requirements on margin and collateral for cleared derivatives (Singh, 2010). Derivative clearing organizations also monitors the creditworthiness and risk of involved banks, and observes the prices of transactions. With relevant information, derivative clearing organizations can provide price quotes relying on involved banks for marking positions, which makes a cleared market less likely to freeze in states of market stress (Ghamami and Glasserman, 2017). Moreover, regulators are able to monitor the OTC derivatives market through derivative clearing organizations instead of a diffuse network of bilateral transactions. However, the central clearing channel has been criticized, since the central clearing organizations with concentrated risk might ultimately require government support in a crisis. Debates are also on the extent to which the intended benefits of central clearing could be achieved in practice. Another key part of the DFA is the proprietary trading restrictions, known as the Volcker rule, which prohibits government insured banks from making short-term risky trading of securities, derivatives, commodities futures and options. The Volcker rule directly reduces banks’ holdings of derivatives for speculation purposes, thereby mitigating their contributions to systemic risk (Li and Marinč, 2017).

Whether the DFA has achieved its intended objectives is a matter of controversy. On the one hand, the passing of the DFA paved the way to a regulatory scheme for previously unregulated over-the-counter derivatives. Consumer advocates who strongly support the DFA agree that banks should not use federally insured deposits to gamble and take risky bets, and banning proprietary trading will curtail risk taking activities in the financial system. On the other hand, financial institutions have criticized the DFA for inadequately address the problems that really push the financial market into turmoil (Kane, 2011). The Volcker rule requires the joint rulemaking from five different agencies and it is too complex to execute. The DFA is particularly too restrictive to smaller banks, which have assets in the range of $50 billion and are relatively small to threaten the soundness of the financial system. The DFA creates substantial compliance costs (Gorman, 2017) and fails to achieve its stated objectives (Calomiris, 2017).

In early 2017, the Financial CHOICE Act was introduced to the [115th U.S. Congress](https://en.wikipedia.org/wiki/115th_United_States_Congress) to repeal many parts of the DFA. The CHOICE Act has passed the Republican-led House on 8 June, 2017. While banking industry generally applauds the bill, the Democrats criticize the rolling back of the DFA as “a big bank-inspired wish list” (Schmidt and Dexheimer, 2017). The CHOICE Act will loosen the restrictions on banks’ investments in private equity and hedge funds, and allow smaller banks to increase lending by minimizing a rule about qualified mortgages. Proponents of the CHOICE Act, which will repel the Volcker rules completely, argue that distinguishing between speculation and market timing is not simple and easy. On the negative side, the CHOICE Act proposes “one-size-fits-all” solutions which are too weak to regulate large systemic banks. It exempts all banks, which have substantial tangible equities in relation to their assets (at least 10 percent), from many regulatory rules applied under the DFA. Large systemic banks are typically highly interconnected, have opaque financial leverage and large complicated off-balance-sheet derivative positions. The simple capital ratio requirement of 10 percent proposed in the Choice Act is too low to serve as a cushion for mega banks. Repelling the Volcker rule will also invite more risky bets from systemically important financial intuitions, which is likely to fuel a more severe crisis and heighten its potential damage.

The recent debate on deregulations in the financial system and the proposed dismantling of the key aspects of the DFA raises the need for an extensive study as to whether the DFA has been effective in mitigating bank’s risk and the degree of correlations among banks via derivative usage channels. Several studies have investigated the impacts of derivatives, for example, interest rate derivatives on bank’s risk and bank’s performance (Gunther and Siems, 2002; Li and Yu, 2010; Brewer, Deshmukh and Opiela, 2014). However, few studies on bank’s risk have examined the interactions between bank’s derivatives usage and the passage of the DFA. Li and Marinč (2017) explore the impact of the mandatory clearing requirement and place emphasis on bank’s holdings of interest rate derivatives.

In this study we conduct an extensive study of 151 large bank holding companies (BHCs) in the U.S. and focus on two types of derivatives which have been widely used in the financial market: credit derivatives and interest rate derivatives. Our analysis covers banks’ holding of credit derivatives and banks’ holdings of interest rate derivatives categorised by hedging and trading purposes, which allows us to test the effectiveness of the channel of restricting the proprietary trading in the Volcker rule. Our analysis also covers banks’ holdings of interest rate derivatives categorised by trading approaches of OTC trading and exchange trading, which allows to test the effectiveness of central clearing channel in Title VII of the DFA. We examine the effects of these derivative holdings, the passage of the DFA, and their joint effects on three aspects: (i) bank’s contribution to systemic risk; (ii) bank’s risk; and (ii) bank’s performance.

We find that excessive usage of interest rate derivatives held for hedging, interest derivatives traded on exchanges, and credit derivatives traded OTC substantially increased banks’ contribution to systemic risk. We also find that, in post-DFA periods, banks’ contribution to systemic risk was significantly lower within two out of three proxies employed for systemic risk. Moreover, we find usage of credit and interest rate derivatives held for hedging have weakened impact on systemic risk in post-DFA periods, while the use of interest rate derivatives held for trading does not exhibit significant impacts on systemic risk either before or after the introduction of the DFA. Part of our results also shows evidences that usage of derivatives and the DFA led to a higher individual risks, while banks’ performance decreased after the signing of DFA.

The research contribution is four-fold. First, we cover a long period of study from January 2007 to December 2014, and examine credit derivatives and interest rate holdings categorised by hedging and trading purposes and by trading approaches of OTC trading and exchange trading. We extend the evidence on the channels through which bank’s derivative usages affect its financial health and the wide net of linkages in the financial system. Second, by examining the effects of the DFA on systemic risk, bank’s risk and bank’s performance, we shed lights on whether the DFA has achieved its stated objectives in mitigating the degree of interconnectedness and improve the soundness of large financial institutions. Third, we explore the interactions between categories of derivative holdings and the DFA to test the effectiveness of the proprietary-trading and central-clearing channels through which the DFA intends to mitigate the impacts of derivatives on banks’ risk. Fourth, we use a more extensive set of variables than those have been used in prior work. We capture bank’s exposure to the housing market in each state and the degree of competition in the banking sector in each state. Our analysis also examines bank’s usages of the discount window borrowing and four special capital programs. The study contributes to the limited literature on derivative usages and risk management in the banking system following the coming into effect of the DFA. Our findings provide important implications to financial institutions, regulators, and legislators on the effectiveness of the DFA in regulating large systemic banks.

In the next section we discuss the literature and develop our hypotheses. Section 3 summarizes our methods and data, Section 4 presents empirical results, Section 5 reports sensitivity analyses, and Section 6 concludes.

## 2. Literature and Hypothesis

This paper is related to the two main streams of literature: first, to examine the effects of derivative holdings on systemic risk and bank’s risk; and second, to evaluate the effectiveness of the DFA in curtaining the degree of interconnectedness among banks and improving the financial soundness of individual banks. The following analysis will briefly discuss the two relevant streams of literature.

### 2.1. Derivative holdings, systemic risk and DFA

The strong growth of derivative holdings among banks has been a key driver of intra-financial system activities (Mayordomo, Rodriguez-Moreno and Pena, 2014). Previous studies suggest that derivatives build up the correlations and leads to a higher degree of interdependence among banks (Nijskens and Wagner, 2010; Bedendo and Bruno, 2012; Mayordomo, Rodriguez-Moreno and Pena, 2014). Calmes and Theoret (2010) present evidence that banks’ off-balance-sheet activities reduce their average returns, increase the volatility of their operating revenues and raise their contributions to systemic risk. Nijskens and Wagner (2010) examine banks trading Credit Default Swaps (CDS) and issuing Collateralized Loan Obligations (CLO) prior to the crisis. They report that the risk transfer via CDS and CLO channels increases banks’ systemic risk. Mayordomo et al (2014) extend previous studies and analyze the impacts of different derivative categories held among banks. They find that the five classes of derivatives[[2]](#footnote-2) exhibit different impacts on bank’s contributions to systemic risk. Specifically, holdings of foreign exchange and credit derivatives increase bank’s contributions to systemic risk while holdings of interest rate derivatives decrease it. They further posit that non-performing loans and leverage ratio have greater impacts on systemic risk than derivatives holdings. In light of the literature discussed above, we propose the following hypothesis:

**H1: *Banks’ holdings of derivatives increase their contributions to systemic risk.***

Several studies have examined the impacts of derivative holdings on systemic risk following the passing of the DFA. Giancarlo (2015) analyzes flaws in the implementation of derivative trading regulation under the DFA. They state that those flaws would actually increase market fragility and the systemic risk. Li and Marinč (2017) present evidence that bank’s usage of interest rate derivatives is associated with a higher contribution to systemic risk. Following the introduction of the mandatory clearing requirement, a larger drop in systemic risk has been observed among the heavy users of derivatives.

A number of studies focus on testing the influence of central clearing on the risks associated with OTC derivatives trading. Acharya and Bisin (2013) theoretically show that the lack of position transparency in OTC derivatives leads to higher counterparty and systemic risks, and central clearing with collateral requirements can effectively limit such risks. [Aminiy](https://scholar.google.co.nz/citations?user=3oiQwWkAAAAJ&hl=en&oi=sra), [Filipovic](https://scholar.google.co.nz/citations?user=5-y36GEAAAAJ&hl=en&oi=sra), [and Minca](https://scholar.google.co.nz/citations?user=ILs-K8kAAAAJ&hl=en&oi=sra) (2013) test the effects of central clearing on a financial network and find that central clearing decreases banks' liquidation and shortfall losses and can reduce systemic risk. Loon and Zhong (2014) examine the impact of central clearing on CDS market with data on voluntarily cleared CDS contracts and find evidences that central clearing decreases counterparty risk as well as systemic risk of clearing members.

However, some studies argue the central clearing in OTC derivatives might not be able to mitigate counterparty and systemic risk as intended. [Pirrong (2009)](https://www-sciencedirect-com.ezproxy.canterbury.ac.nz/science/article/pii/S0304405X13003012?_rdoc=1&_fmt=high&_origin=gateway&_docanchor=&md5=b8429449ccfc9c30159a5f9aeaa92ffb&ccp=y#bib51) argues that central clearing could increase the counterparty risk because of the information asymmetries between central clearing counterparties and large financial institutions, since CCPs have the disadvantage in evaluating clearing members’ risk and therefore could underestimate the risk and therefore, weaken its guarantee. [Duffie and Zhu (2009)](https://www.sciencedirect.com/science/article/pii/S0304405X11002327#bib12) investigate the impact of central clearing counterparty in CDS market and find that central clearing might increase the counterparty credit risk. [Arora, Gandhi, and Longstaff (2012)](https://www-sciencedirect-com.ezproxy.canterbury.ac.nz/science/article/pii/S0304405X13003012?_rdoc=1&_fmt=high&_origin=gateway&_docanchor=&md5=b8429449ccfc9c30159a5f9aeaa92ffb&ccp=y#bib5) suggest that central clearing might not be able to further lower the counterparty risk if the existing arrangements in the OTC derivative market (e.g. posting of collateral by both counterparties, use of International Swaps and Derivatives Association (ISDA), master agreements and credit support annexes,) can effectively deal with counterparty risk.

We conjecture that the implementation of the DFA, specifically the Volcker rule, leads to a lower degree of derivative usage, thereby reducing the interdependence among banks. We share the same view as Singh (2010) and Li and Marinč (2017) that implementing mandatory clearing requirement improves the transparency in the derivative markets, thereby curtailing the effects of banks’ derivative holdings on systemic risk. Thus, we put forward the following hypothesis:

**H1a: *The implementation of the DFA mitigates bank’s contribution to systemic risk***

**H1b: *The implementation of the DFA reduces the impacts of derivatives holdings on bank’s contribution to systemic risk (in H1)***

### 2.2. Derivative holdings, bank’s risk and bank’s performance

2.2a. **Derivative holdings and bank risk**

Derivatives have been widely used by financial institutions to hedge against unfavourable changes in the value of their cash flows. Derivatives help mitigate cash flow volatility, lower external funding cost, and reduce banks’ overall risk (Koppenhaver, 1985; Froot, Scharfstein and Stein, 1993; Duffee and Zhou, 2001; Jaffe, 2003; Norden, Silva Buston, and Wagner, 2014; Bartram, 2017; Deng, Elyasiani and Mao, 2017; Huang, Kabir and Zhang, 2017).

Previous studies, however, show that banks are more likely to use financial derivatives for trading motives rather than for hedging purposes (Stulz and Willamson, 2005; Li and Marinč, 2014). This tendency makes them more vulnerable to financial distress. Without proper oversight, derivative traders may take a position which is substantially larger than their risk absorbing capacity (Biais, Heider, and Hoerova, 2012). Derivatives used for regulatory arbitrage to decrease capital requirements may also lead to excessive risk taking (Yorulmazer, 2013). Li and Marinč (2014) find supportive evidences that derivative holdings for speculation increases banks’ risk exposure. In light of the above literature, we propose the following hypothesis:

**H2a: *Interest rate derivatives used for hedging decreases banks’ risk while interest rate derivatives used for trading increases banks’ risk***

Credit derivatives such as CDSs and CLOs have been widely used among financial institutions to transfer counterparty credit risks. Despite being powerful hedging tools, they are like two-edge knifes. Credit derivatives, which serve similar to an insurance policy, may increase moral hazards as it lowers banks’ motivations to thoroughly review loan applications and regularly monitor bank loans (Parlour and Winton, 2013). Banks which hold CDSs to hedge against potential credit loss tend to make more profits by raising loan volumes while taking a higher degree of risk (Acharya and Naqvi, 2012; Shan, Tang and Yan, 2014). According to Instefjord (2005), credit derivatives enhance risk sharing as well as making further acquisition of risk more attractive, and the latter effect may be dominant, if the price elasticity of the underlying credit markets is high. In light of the literature above, we propose the following hypothesis:

**H2b: *Credit derivatives* *increases banks’ risk***

While few studies in the empirical literature link banks’ individual risk to derivatives traded in OTC market and on exchanges, banks with derivatives traded in OTC markets are more likely to get exposed to higher risks. There might be two reasons behind it. First, derivatives used for speculating and trading purpose in OTC markets could increase banks’ risk exposure, which is consistent with Li and Marinč (2014) discussed in previous section. Second, if banks use OTC derivatives to hedge instead of other more transparent approaches, those banks are expected to show higher risks. The low position transparency with lower supervision and monitoring in OTC markets allows banks to hedge very risky positions, which are likely to be not allowed or extremely costly to hedge with more transparent approaches. On the other hand, derivatives traded on exchanges with higher level of transparency are more likely to be used for hedging purpose by banks. Thus, we put forward the following hypothesis:

**H2c: *Derivatives traded in OTC markets increase banks’ risk while derivatives traded on exchanges decrease increases banks’ risk***

A few studies have examined the effects of the DFA on banks’ risk.[[3]](#footnote-3) Keppo and Korte (2016) present evidence that banks reduce the size of their trading books and exhibit higher volatility in asset returns after the passing of the Volcker rule. Chung, Keppo and Yuan (2016) suggest that the Volcker rule raises banks’ illiquid book portfolios which are hard to control. We are of the view that liquidity reduction hinders banks’ ability to meet short-term obligations and make them more susceptible to financial distress. Thus, we propose the following hypothesis:

**H3A:** ***The implementation of the DFA increases bank’s risk***

**H3B: *The implementation of the DFA lessens the effects of derivative holdings on bank’s risk (in H2a, H2b and H2c).***

2.2b. **Derivative holdings and bank performance**

Banks used derivatives for speculation purposes tend to achieve higher returns though those trading activities expose banks to a higher degree of risk (Li and Yu, 2010; Lau, 2016). Said (2011) examines the impact of derivative holdings on U.S. bank performance prior to and during the GFC. He documents a positive relationship between derivative holdings and bank performance. On the other hand, Egly and Sun (2014) find that the derivative holdings for trading impose very small effects on bank performance and the trading income does not contribute to banks’ overall income during the crisis. Keffala and De Peretti (2016) investigate banks’ derivative usage in both emerging and developed countries, and find that derivatives decreased banks’ performance. We share a similar view with Said, and propose the following hypothesis:

**H4: *Derivative holdings improve bank performance***

The DFA restricts consumer credit, makes mortgages and bank transactions more expensive, increases banks’ compliance costs, and reduces banks’ liquidity. It also limits the financial sector’s ability to renovate. Previous studies suggest that the DFA decreases the capacity and quality of banks' market-making services (Chow and Surti, 2011; Whitehead, 2011; Duffie, 2012), therefore lowering banks’ performance. Schäfer, Schnabel and Weder (2013) present evidence that the DFA significantly reduces banks’ share returns. Chung and Keppo (2014) and Keppo and Korte (2016) also find that the DFA decreases banks’ earnings. In light of the literature discussed above, we propose the following hypothesis:

**H5a: *The implementation of the DFA decreases banks performance***

***H5b: The implementation of the DFA hampers the positive effects of derivative holdings on bank performance (as in H4)***

## 3. Methodology

In this section, we present the models used to test the null hypothesis formulated earlier. We would like to get better understanding what are the determinants of banks’ systemic risk and what factors influence risk and performance of individual companies from banking sector. The section is divided into two parts, and each of them focuses on one of the above topic.

### 3.1. Bank’s systemic risk

We consider conditional value at risk as a proxy for the contribution of each bank to the systemic risk. Our approach is in line of study by Adrian and Brunnermeier (2011), we calculate the Value at Risk of banking system conditional on the distress of the bank *i* with a confidence level of 95% (*CoVaR*) and also the *CoVaR* of banking system with a confidence level of 50%, which is conditional on the median state of the bank. Therefore, bank *i*’s contribution to systemic risk is estimated as the difference between those two *CoVaRs* of banking system.

, (1)

where *CoVaR(q*) and *VaR(q)* are defined

 (2)

The estimation of quantile regression (Koenker and Bassett, 1978) allows to estimated parameters α and γ input for equation (2) for each bank *i* and the whole banking system. More precisely, we estimate the growth rate of the market value of total assets, *Xi* that defined as the growth rate of market valued assets, where market valued assets is defined as the product between the market value of equity of institution *i* and its ratio of total assets to book equity. We consider the following quantile regression:

 (3)

where *Mt-1* is a set of state variables describing the current market situation[[4]](#footnote-4). The above constructed proxy of bank’s systemic risk is a dependent variable in the panel regression design to examine the effect of derivatives usage and the introduction of the DFA on banks’ contribution to systemic risk, the following model was estimated:

, (4)

where *SRi,t*, is the measure on banks’ contribution to systemic risk initially measured by the change in conditional value at risk (ΔCoVaR); *Yi,t* is the notional value of and credit derivatives and interest rate derivatives, categorized either by holding purpose (trading or hedging) or by trading approach (OTC or exchange); the event dummy, *PostDFA*, which is set to one after the introduction of the DFA and zero otherwise; *Ci,t-1*is the set of firm characteristics variables including banks’ exposure to housing market, HHI index, and government bailout programs dummy. According to the statement of Financial Crisis Inquiry Commission (2011), as financial derivatives expose the financial system to a contagion of spreading losses and defaults, we expect negative signs for variables measuring the use of derivatives, *Yi,t*, which suggest that derivative use by banks increase banks’ contribution to systemic risk. If the DFA effectively controls the impact of financial derivatives on systemic risk, we then expect positive signs for the interactions between the DFA dummy and derivative variables.

In order to address the potential critique that our results related to the DFA are driven by selection of proxy of banks’ contribution to systemic risk, we consider two alterative measures as dependent variable in panel regression (4).

One of them is marginal expected shortfall (MES) defined as the average return of bank *i* on days when the banking industry (S&P Banks Selected Industry Index return, *Rm*, is among its lowest 5% level in one-quarter period:

 (5)

where *q* stands for the quantile of S&P Banks Selected Industry Index return, which is set as 5%. Accordingly, lower negative value in MES indicates a higher marginal contribution to systemic risk. In addition toΔCoVaR and MES, we apply banking industry beta as a third measure of systemic risk. Accordingly, a bank’s industry beta is calculated as the sensitivity of stock return to the return of S&P Banks Selected Industry Index in one-year time window. Higher industry beta could imply higher systemic risk (Nijskens and Wolf, 2011).

### 3.2. Bank’s risk and performance

In order to test the impact of the DFA on risk of individual U.S. bank holding companies, we consider different type of risks and their measures. As proxies of credit risk of US banks, we use Z-score and distance to default (DD). The Z-score is defined as the sum of the mean return on assets and the mean ratios of equity to assets, divided by the standard deviation of the return on assets:

. (6)

Z score indicates the number of standard deviations that a bank’s rate of return on assets can fall in a single period before it becomes insolvent. A higher Z score signals a lower probability of bank insolvency. The other proxy of credit risk on individual bank’s level is distance to default (DD), measures the number of standard deviation the asset value is away from the default point. DD is defined as:

 (7)

*V* is the market value of total assets; *K* is the value of debt, calculated as short-term debt plus half of the long-term debt and *σv*is the annualized standard deviation in the market value of assets. Higher DD indicates less chance for default.

In addition to credit risk we calculate measures allowing us to determine banks’ individual risks, namely the worst loss and the level of overall risk for each bank respectively. Specifically, we calculate bank *i’*s Value at Risk (VaR) to measure banks’ worst loss and volatility of daily stock return with a six-month rolling window to capture overall risk . A lower negative VaR or higher volatility indicates a higher risk.

In order to evaluate the impacts of derivatives usage in *pre* and *post* DFA regulatory environments on the banks’ credit and overall risk, we consider the model

 (8)

*IRi,t* is the individual banks’ risk measures such as Z-score, DD, VaR and stock return volatility for bank holding company *i* and time *t*.; *Yi,t* is the notional value of and credit derivatives and interest rate derivatives, categorized either by holding purpose (trading or hedging) or by trading approach (OTC or exchange);; *PostDFA*, which is equal to one after the DFA has become a law and zero otherwise; *Ci,t-1* is the set of firm specific variables and can differ across regressions as some variables can be used to calculate the dependent variable therefore cannot be included as explanatory variables any more.

Our analysis of implication of the DFA on US bank’s risk-return profile would be incomplete without performance analysis. As proxies for banks’ performance, we consider: Tobin’s Q, returns on assets, cost to income ratio, and quarterly return of market shares. Higher values in a bank’s Tobin’s Q, returns on assets (ROA) or quarterly return of market shares imply better performance while higher cost to income ratio suggests a lower operating efficiency and therefore a worse performance. The regression (8) is use for examination of performance, where *IRi,t* is replaced with a bank’s performance measures, namely, Tobin’s Q, ROA, quarterly return of market shares and cost to income ratio.

## 4. Data

### 4.1. Sample and data

This study examines large and publically listed bank holding companies in the U.S. from January 2007 to December 2014. Our study covers the subprime crisis 2007-2009 and roughly equal pre-DFA and post-DFA sub-periods. We focus on bank holding companies because these large financial institutions are more likely to use derivatives for both hedging and trading purposes. Our main sample is restricted to banks which have at least USD1 billion in assets at the end of 2006, and have derivative holdings reported in Y9 call report as well as stock prices reported in CRSP. The main sample consists of 151 bank holding companies, which captures more than 70% of the total market capitalization of U.S. publically traded bank holding companies at the end of 2006.

Two other samples were also created for robustness testing. The first alternative sample includes 52 bank holding companies; each had total assets above USD5 billion in both the first quarter of 2006 and the first quarter of 2009. This approach was similar to that of Mayordomo, Rodriguez-Moreno and Pena (2014). An advantage of this screening criterion is that it incorporates both pre-crisis and ongoing crisis-period time spots, thereby avoiding potential bias. The second alternative sample includes 18[[5]](#footnote-5) banks that underwent stress tests during the study period. We examine stress test banks for three reasons. First, stress tests can uncover threats to the financial system as a whole when mega banks are collectively undercapitalized. Second, these large banks were heavy users of derivatives prior to and during the GFC, and subject to heightened regulations from 2010 onwards (Panel D, E, F of Figure 1). Third, these too-big-to-fail banks may exhibit a different relationship between derivatives holdings and bank’s risk and performance because of the government bailout expectations. The market was certainly able to identify these banks as too-big-to-fail at the beginning of the GFC which is also the commencement of our study.

Bank-specific data were collected from SNL Financial database (SNL). The volatility of equity returns, which is based on 6 months of daily data, was calculated using stock prices data from CRSP. The banking industry index (S&P Banks Selected Industry Index) returns and macro-economic variables used to calculate *△CoVaR* were downloaded from *Datastream*.

### 4.2. Independent variables

We focus on two types of derivatives namely interest rate derivatives and credit derivatives, which have been widely used by banks and subject to heightened regulations following the coming into effect of the GFC (Li and Marinč, 2017). According to the Accounting Standards SFAS133, banks must classify derivatives into two sub-categories: for hedging and for trading purposes[[6]](#footnote-6). We therefore examine separately bank’s interest derivative holdings for trading and interest derivative holdings for hedging; each is measured as the notional amount of the relevant off-balance-sheet contracts reported in Y9 call report, and then scaled by bank’s assets. Unlike interest rate derivatives, -credit derivative holdings are not categorised based on the purposes. Thus, we follow a similar approach as in Li and Marinč (2014) and examine the net notional amount of credit derivatives (scaled by bank’s assets). By categorising derivatives for trading or hedging purpose, we are allowed to test the effectiveness of the propitiatory trading channel by Volcker rule of the DFA on mitigating the systemic risk associated with derivatives. On the other hand, we calculate the total net notional amounts of interest rate derivatives categorised by trading approaches of OTC or on exchanges[[7]](#footnote-7), and then scale with bank's assets. By doing this, we are allowed to examine the effectiveness of central clearing channel of mitigating the systemic risk associated with derivatives by Title VII of the DFA as well.

In addition to derivative holdings we employ two additional variables which capture the extent of interconnectedness among financial institutions: *Loan to depository institutions* and *Balance due from depository institutions* (scaled by gross loans and leases)[[8]](#footnote-8).Mayordomo, Rodriguez-Moreno and Pena (2014) found that *Balance due from depository institutions* increased banks’ systemic risk while the impacts of *Loan to depository institutions* were insignifican.

We create a dummy variable, *PostDFA*, for bank-quarter observations in the period following the signing of the DFA (July 21, 2010). To explore the joint effects between derivatives and the DFA, we construct three interaction terms between interest rate derivatives held for hedging, interest rate derivatives held for trading, net credit derivatives, and the dummy, *PostDFA* to test the effectiveness of proprietary trading channel. We then construct the interaction terms between interest rate derivatives traded OTC, interest rate derivatives traded on exchanges, net credit derivatives (traded OTC), and *PostDFA* to test the central clearing channel of the DFA.

In terms of control variables, we include *assets* to control for bank’s size, *return on average assets* to account for profitability, and *short-term borrowings* (scaled by assets) which have often been blamed for precipitating financial crises. We also add *book-to-market* and *equity return volatility* in our models to capture bank’s health and uncertainty.

Mayordomo et al (2014) present evidence that *Non-performing loans* and *Leverage ratio* have greater impacts on systemic risk than derivatives holdings. In light of their findings, we incorporate *Loan loss provisions and Tier 1 risk ratio* in our models. We use *Loan loss provisions* as this measure is an allowance for potential loan losses whereas *Non-performing loan* only accounts for uncollected loans in the past. *Tier 1 risk ratio* is also a better measure than *Leverage ratio*. The latter simply sets the same risk weight across all assets while *Tier 1 risk ratio* is derived based on risk weighted assets, that is, it captures the quality of bank’s asset portfolio.[[9]](#footnote-9)

The study period witnesses several failures and a number of mergers among financial institutions. We include merged banks in the sample as long as SNL reports its balance sheet and income items. For an acquirer, taking over near failed firms will substantially raise its leverage and loan loss provisions. To capture this effect, we create a dummy variable for banks that made an acquisition in the quarter examined.

During the subprime crisis many banks experienced financial distress due to their exposures to housing bust and their substantial losses on real-estate related investments (Cole and White, 2012). We account for bank’s exposure to the downturn in the real estate market in each state where it operates. We calculate a weighted average housing return index for each bank-quarter. Housing returns are derived from the Fannie Mae house price index for each state. The weighted average is derived by using the proportion of deposits a bank has in each state, which is available from branch deposit and branch location data in SNL.

To capture the degree of market concentration in the banking sector, we construct a weighted average Herfindahl-Hirschman Index (HHI) following Berger and Roman (2015) for each bank-year in a similar manner. The weighted average HHI for each bank-year is derived by using the proportion of deposits a bank has in each state.

We also consider banks’ usage of the discount window borrowing and four special capital programs namely troubled asset relief program (TARP), term securities lending facility, term auction facility and primary dealer credit facility. The data on special capital programs and discount window borrowing were collected from the Federal Reserve System[[10]](#footnote-10).

### 4.3. Statistics

Figure 1 features the average derivative holdings (scaled by total assets) across quarters for the main sample of 151 banks (Panel A, B, C) and the alternative sample of 18 stress test banks (Panel D, E, F). Panel A and Panel D feature the average derivative holdings for trading and for hedging purpose while Panel B and Panel E show the average derivatives traded in the OTC market and in the Exchange.[[11]](#footnote-11) Panel C and Panel F depict the average net credit derivative holdings.

FIGURE 1 HERE

As presented in Figure 1, banks in both samples use a greater proportion of interest rate derivatives for trading than for hedging, and most of interest rate derivatives were traded in the OTC market. From mid-to-end 2011 onwards, interest rate derivatives held for trading and interest rate derivatives traded in the OTC market declined while interest rate derivatives in the Exchange increased, particularly for the main sample. Credit derivative holdings increased substantially during 2007-2008 but were markedly lower as of 2009, the trend is more pronounced for stress test banks.

On average, a stress test bank holds substantially larger derivative positions than a typical bank in the main sample. Stress test bank’s interest rate derivatives held for trading and derivatives traded in the OTC increased sharply in the last two quarters of 2008 and leveled off afterwards.

The statistics of the dependent variables and key independent variables are presented in Panel A and Panel B of Table 1 respectively.

TABLE 1 HERE

Due to the data availability of 151 banks in the main sample, the sample used for systemic risk analysis includes 3414 quarter-bank observations while the sample used for bank-risk and bank-performance analysis includes 3724 quarter-bank observations. As presented in Panel A of Table 1, on average, a bank in the main sample has a △CoVaR of -2.8 percent, marginal expected shortfall (MES) of -3.5 percent and a beta of 0.8 (benchmarked against S&P Banks Selected Industry Index). △CoVaR varies between -19.4 and 7.3 percent while MES spread over a wider range between -26.3 percent and 16.3 percent.

In terms of bank’s risk and bank performance, a typical bank, on average, has a Z-score of 3.5, 95% VaR of -7.92 percent, equity return volatility of 2.74 percent, return on assets of 0.7 percent and Tobin Q of 23. These measures also vary widely. For example, Z score ranges between -0.86 and 32.6, *VaR* varies between -42.5 and -0.9 percent, and Tobin Q spread over a larger range between 3.7 and 62.5. In an untabulated analysis, we find that the means and medians of all dependent variables in Panel A, except *Net interest rate margin,* are statistically different for the two sub-periods: prior to and after the signing of the DFA.

As shown in Panel B of Table 1, on average, a bank has USD 58.9 billion in assets, a tier 1 risk capital ratio of 9.24 percent and loan loss provision of 19.4 percent. The average loan to depository institutions is USD 349.3 million and the average Balance due from depository institutions is USD 6.3 million.

The average interest rate derivative holdings for hedging and for trading (scaled by bank’s assets) are 4.6 percent and 48 percent. Derivatives held for trading varies markedly between 0 and 51.2 percent while net credit derivatives spread between -6.4 and 12.2 percent. In an untabulated analysis, we document that the mean and median derivatives held for trading, the median derivatives held for hedging, and the mean credit derivatives are statistically different for the two sub-periods: prior to and after the signing of the DFA.

## 5. Results

### 5.1. Derivatives, DFA, and systemic risk

We investigate (H1), (H1a), and (H1b) with three measures of systemic risk: (1)*△CoVaR*, (2) *Marginal Expected Shortfall* (*MES*), and (3) *industry beta.* *△CoVaR* is the difference between the financial system’s *VaR* conditional on bank *i’*s being in distress and the financial system’s *VaR* in the median state of bank *i.* Bank *i’*s *MES* is its mean return on days when the S&P Banks Selected Industry Index return reaches its lowest 5 percent level over a quarter period. Bank *i’*s industry beta captures the sensitivity of its stock returns to the returns of the S&P Banks Selected Industry Index over a one-year period. Recall that *△CoVaR* and *MES* have negative values on average (Panel A Table 1). A lower negative value of *△CoVaR* and *MES* and a higher *industry beta* indicate a higher marginal contribution by bank *i* to systemic risk.

Table 2 and Table 3 report the systemic regression results for Equation (4). Bank-quarter observations have both a time series and a cross-sectional dimension. We estimate Equation (4) as a panel regression with firm and time fixed effects. We control for clustering in standard errors at the bank level. In each regression in Table 2, three measures of derivatives catergorised by holding purposes (then scaled by bank’s assets) are employed, while each regression in Table 3 reports regressions with measures of derivatives catergorised by trading approaches (then scaled by bank’s assets). In both Table 2 and Table 3, Columns (1), (2) and (3) respectively show the effects of derivative holdings, without considering the DFA, on *△CoVaR*, *MES* and *industry beta*. Columns (4), (5) and (6) respectively extend columns (1), (2) and (3); each features *PostDFA* and three interaction terms between derivative categories and *PostDFA*.

TABLE 2 HERE

As shown in Table 2, interest rate (IR) derivative holdings for hedging is significant in every estimated model. Its negative (positive) coefficients when *△CoVaR* and *MES* (*industry beta*) were used to capture systemic risk indicate that its usage results in a larger contribution to systemic risk. This finding is consistent with hypothesis (H1). The magnitudes of its coefficients are quite large in models (3) and (6) where systemic risk is proxied by *industry beta*.

*IR derivatives for trading* is marginal significant when *△CoVaR* is the dependent variable (model (1)) and is not significant when *Post\_DFA* is added to the models. Using *IR derivatives for trading* also increases systemic risk but its effect is much smaller compared with the effect of *IR derivatives for hedging*.

Without considering the DFA, *net credit derivatives* is marginal significant in model (2) when *MES* is employed to capture systemic risk. However, it is significant in models (4) and (5) which feature *Post\_DFA* and the interaction terms. Consistent with hypothesis (H1), the use of credit derivatives raises bank’s contribution to systemic risk. The effects of credit derivatives are stronger than the effects of interest rate derivatives, and become more pronounced in the presence of *Post\_DFA* and the interaction terms (models (4) and (5)).

Overall, *IR derivatives held for hedging* is the only category which is significant in every estimated model. *Net credit derivatives* exhibits the strongest effect while *IR derivatives held for trading* shows the weakest impact on systemic risk. The effects of significant derivative variables are consistent with hypothesis (H1) and in line with the findings of Calmes and Theoret (2010), Nijskens and Wagner (2010) that banks’ use of derivatives led to higher systemic risk.

*Post\_DFA* represents the period after the DFA came into effect. Itis significant in all three models (4), (5), and (6). Consistent with hypothesis (H1a), the implementation of the DFA lowers bank’s contribution to systemic risk which is measured by *△CoVaR* (model (4)) and *industry beta* (model (6)). However, the coefficient of *Post\_DFA* flips sign when *MES* is the dependent variable (model (5)).

None of models (4), (5) and (6) features all three significant interaction terms between derivative holdings and *Post\_DFA.* The two interaction terms between *net credit derivatives, IR derivatives held for hedging* and *Post\_DFA* are significant when *△CoVaR* and *MES* are used to capture systemic risk. The positive coefficient signs in models (4) and (5) support hypothesis (H1b) that the implementation of the DFA reduces the hampering effects of these derivatives on systemic risk, although the interaction terms between *IR derivatives held for trading* and *PostDFA* feature no significant coefficients. The results on *IR derivatives for hedging* are consistent with Li and Marinč (2017) while the findings on *credit derivatives* and the DFA show contrary results.

Overall, the results in Table 2 confirm hypothesis (H1), (H1a) and partly support hypothesis (H1b) for two out of the three derivative categorises examined (*credit derivatives* and *IR derivatives for hedging*). However, the insignificant results on *IR derivative for trading* as well as the interaction terms between *IR derivative for trading* and *PostDFA* did not provide supportive evidences for the effectiveness of proprietary trading approach by Volcker rule of the DFA.

In addition to the three derivative variables discussed above, *loan to depositary institutions* and *balances due from depository institutions* also capture the extent of interconnectedness among banks. *Loan to depositary institutions* is not significant in any models which is consistent with Mayordomo, Rodriguez-Moreno and Pena (2014), while *balances due from depository institutions* is significant in four out of six models (models (1), (2), (4), (5)). However, the coefficient sign in models (1) and (4) is not consistent with the coefficient sign in models (2) and (5). If *MES* is a more relevant measure to capture systemic risk then its negative sign in models (2) and (5) suggests a higher degree of systemic risk.

Adding *Post\_DFA* and the interaction terms in models (4), (5), (6) in Table 2 does not change the significance of any control variables (compared with models (1), (2), (3)). The *standard deviation of stock returns* is the only variable which is significant in every model in Table 2. *Short-term borrowing* and *loan loss provision* are significant in four out of six models (models (1), (2), (4), (5)). As expected, the negative sign of the coefficients of these three variables, when significant, indicates that a higher degree of uncertainty, insufficient liquid assets and poor asset quality increase systemic risk. Bank’s *size* is significant in four out of six models (models (2), (3), (5), (6)). *Book to market ratio, Tier 1 risk ratio* and dummy *acquisition* are significant in models (3) and (6) while *real estate exposure* is significant in model (2) and (5). The results suggest that large banks, healthier banks (higher *Tier 1 risk ratio*), or those with a small *book-to market ratio* are more likely to do business with a number of financial institutions and thereby raise systemic risk. In contrast, *acquisitions* or a large exposure to the real estate market diminish bank’s contribution to systemic risk.

TABLE 3 HERE

Table 3 presents the results with derivatives catergorised by trading approaches of OTC or exchanges. As shown in Table 3, without considering the DFA, *IR derivatives traded on exchanges* is significant when industry beta is used to capture systemic risk (model 3). It is significant in all models (4), (5) and (6) when *Post\_DFA* and the interaction terms were added. Its negative (positive) coefficients when *△CoVaR* and *MES* (*industry beta*) were used to capture systemic risk indicate that derivatives traded on exchanges results in a larger contribution to systemic risk. This finding is consistent with hypothesis (H1). On the other hand, none of models in Table 3 features significance for the coefficient of *IR derivatives traded OTC*.

*Net credit derivatives* (traded OTC) is significant in models (4) and (5) in Table 3, where *Post\_DFA* dummy and the interaction terms are added. In addition, *Net credit derivatives* shows marginal significance in both model (2) and (6). Its negative coefficient sign in models (2) (4) (5) and positive coefficient sign in models (6) suggest that the use of OTC-traded credit derivatives raises bank’s contribution to systemic risk, which is consist with the findings in Table 2 and hypothesis (H1).

Overall, *IR derivatives traded on exchanges* and *credit derivatives traded OTC* show significant impact on banks’ contribution to systemic risk while *IR derivatives traded OTC* presents insignificant effects.

As shown in Table 3, the interaction term between *IR derivatives traded OTC* and *Post\_DFA* is marginal significant only when *industry beta* is used the capture systemic risk (model (6)). The positive coefficient sign, however, suggests after the implementation of the DFA, *IR derivatives trade OTC* marginally increases systemic risk, which is contrary to hypothesis (H1b). The interaction term between *IR derivatives traded on exchanges* and *Post\_DFA* is also marginal significant in model (6) but with a negative sign, which suggests that the implementation of the DFA marginally migrated the hampering effect of I*R derivatives trade on exchanges* on systemic risk. The two interaction term between *net credit derivatives* and *Post\_DFA* is significant when *△CoVaR* and *MES* are used to capture systemic risk. The positive coefficient signs in models (4) and (5) support hypothesis (H1b) that the implementation of the DFA reduces the hampering effects of *credit derivatives trade OTC* on systemic risk.

Overall, the results on *IR derivative traded on exchanges,* *credit derivatives* (*traded OTC*) and their interaction terms in Table 3 confirm hypothesis (H1), (H1a) and (H1b), while the results on *IR derivative traded OTC* show it has insignificant impacts on systemic rik. However, interaction term between *IR derivative traded OTC* and *PostDFA* indicates, after the signing of the DFA, *IR derivatives trade OTC* marginally increases systemic risk when *industry beta* in used to capture systemic risk. The findings on *credit derivatives* (*traded OTC*) provide supportive evidences that the central clearing channel of the DFA effectively lower banks’ systemic risk associated with OTC credit derivatives. On the other hand, the findings on *IR derivative traded OTC* suggest that the central clearing channel of the DFA might not work out appropriately for *IR derivatives traded OTC*. All the other control variables in Table 3 present consistent significance and signs as in Table 2.

### 5.2. Derivatives, DFA and bank’s risk.

We investigate (H2a), (H2b), (H2c), (H3a) and (H3b) with three measures of bank risk: (1) *Z-score*, as calculated by Laeven and Levine (2009), (2) *distance to default*, (3) *VaR* and (4) *stock return volatility*,. *Z-score* and *distance to default* captures bank’s credit risk and *Z-score* is calculated using the past 16 quarters of data. Standard deviation of stock return and 95% *VaR* capture bank’s overall risk and bank’s worst loss respectively. *Stock return volatility* and *VaR* are calculated using six months and three months of daily stock return data, respectively.

Table 4 and Table 5 report the regression results for Equation (8). Models (1), (2), (3) and (4) respectively show the effects of derivative categories, without considering the DFA, on *Z-score*, *distance to default,* 95% *VaR,* and *stock return volatility*,. Models (5), (6), (7) and (8) respectively extend models (1), (2), (3) and (4) by adding *PostDFA* and three interaction terms between three derivative categories and *PostDFA*.

TABLE 4 HERE

As shown in Table 4, without considering the DFA, net credit derivatives is significant in model (1) and model (4).The negative sign of *net credit derivatives* coefficient in model (1) suggests that the use of credit derivatives lowers banks’ *Z-score*, and raises bank’s credit risk. Consistently, the positive sign of *net credit derivatives* coefficient in model (4) suggests the use of credit derivatives increases stock volatility and overall risk. There findings are consistent with hypothesis (H2b) and in line with Keppo and Korte (2016). *IR derivatives for trading* is significant in model (4) with a negative coefficient sign, which suggests the use of IR derivatives for trading somehow lowers banks’ *stock return volatility* and overall risks. The negative sign of *IR derivatives for hedging* in model (2) indicates that holdings of *IR derivatives for hedging* decreases banks’ *distance to default* and therefore increases banks’ credit risk. These findings on IR derivatives for trading or hedging do not support hypothesis (H2a).

As *PostDFA* and the three interaction terms are added in models (5), (6), (7) and (8) in Table 4, *net credit derivatives* is significantly negative (posiotive) in model (6) (model (8)), suggesting the use of credit derivatives increases banks’ *distance to default* (*stock return volatility*) and credit risk (overall risk) *IR derivatives for trading* is significant in model (8) while *IR derivatives for hedging* becomes significant in models (6), (7) and (8). The negative coefficient sign of *IR derivatives for hedging* in model (6) and (7), and its positive coefficient sign in model (8) suggest that holdings of *IR derivatives for hedging* hamper bank’s credit risk, worst loss and overall risk, as measured by *distance to default, VaR* and *stock return volatility* respectively. In contrast, the use of *IR derivatives for trading* lowers bank’s overall risk, as evidenced by its significant negative coefficient in model (8). The significant effects of both IR derivative categories do not support hypothesis (H2a).

*PostDFA* is significant in all four models in Table 4 (models (5), (6), (7), (8)). The positive sign of its coefficient in model (7) implies that the signing of the DFA lowers the extent of bank’s worst loss. In contrast, its significant negative coefficient in model (5) (6) and its significant positive coefficient in model (8) confirm hypothesis (H3a). In line with Chung, Keppo and Yuan (2016), these results indicate that the coming into effect of the DFA raises bank’s credit risk, as measured by *Z-score*, *distance to default*, and bank’s overall risk, as measured by bank’s *stock return volatility*.

In Table 4, the interaction terms between *IR derivatives for hedging* and *PostDFA* is significant in models (7) and (8). Its coefficient signs in these two models confirm hypothesis (H3b) that the signing of the DFA reduces the hampering effects of IR derivatives for hedging on bank’s volatility and the extent of bank’s worst loss. The interaction term between *IR derivatives for trading* and *PostDFA* is significant in models (6) and the negative coefficient sign suggests that signing of the DFA even worsened the hampering effects of *IR derivatives for trading* on credit risk, as measured by *distance to default*. The interaction term between *net credit derivatives* and *PostDFA* is significant in model (6), (7) and (8)and its coefficient signs confirm hypothesis (H3b) that implementation of the DFA lessened the hampering effects of credit derivatives on banks risk as well. The magnitudes of the coefficients for credit derivatives and its interaction term with *PostDFA* are found much larger than the magnitudes of the coefficients for IR derivatives and their interaction terms.

Overall, the empirical evidence in Table 4 are consistent with hypothesis (H2b), (H3a) and partially support hypothesis (H3b) for two out of the three derivative categories examined (*net credit derivatives* and *IR derivatives for hedging*). The results on *IR derivatives for trading* and its interaction term with *PostDFA* do not support hypothesis (H2a) and (H3b)

Adding *PostDFA* and the interaction terms in models (5), (6), (7) and (8) in Table 4 does not change the significance of any control variables (compared with models (1), (2), (3) and (4)). Table 4 features only one significant control variable in all models, which is *short-term borrowing.* However, the positive coefficient sign in models (1) and (5) are not consistent with the findings in other models. Results in models (2), (3), (4), (6), (7) and (8) suggest that *short-term borrowing* hampers bank’s credit risk, worst loss, and overall risk as measured by *distance to default, VaR* and *stock return volatility* respectively. *Loan loss provisions* and *book to market ratio* are significant in models (2), (3), (4), (6), (7), (8). Their negative coefficient sign in models (2), (3), (6), (7) and positive sign in (4), (8) suggest that banks with poor asset quality (*loan loss provisions*) and higher *book to market ratio* tend to experience higher credit risk, worst loss and overall risk. Similarly, the significantly negative coefficient sign of *stock volatility in 6 months* in models (2), (3), (6), (7) indicates that banks with higher *stock returns volatility* are likely to get higher credit risk and worst loss. *Return on assets* and *special capital program* dummy are significant only in models (4) and (8) when *stock return volatility* is used to capture banks’ risk. Banks which achieve lower profitability (*return on assets*) and those who use one of the special capital programs or the discount window borrowing show more volatility and higher overall risk. *Tier 1 risk capital* *ratio* is significant in (2), (4), (6), (8) and assets (*size*) significant in (2) and (6). In contrast, large banks and healthy banks with strong capital (*Tier 1 risk ratio*) exhibit less credit risk measured by *distance to default* and large banks show a lower degree of volatility in their stock returns. *Exposures to real estate market* is significant in (3), (7) and the positive sign suggests that banks with higher *exposures to real estate market* tend to experience lower *worst loss.*

TABLE 5 HERE

Table 5 presents results on bank’s risk with derivatives categorised by trading approach of OTC-traded and exchange-traded. Without considering the DFA, *IR derivatives traded OTC* is significant in model (4) with a negative coefficient sign, which suggests banks with more *IR derivatives traded OTC* exhibit less *stock return volatility* and overall risk. *IR derivative trade on exchanges* is significant in models (2) and (3) and its negative coefficient sign indicates that the use of exchange-traded IR derivative hampers bank’s credit risk (*distance to default*) and worst loss (*VaR*)*.* The findings on IR derivative provide evidences against hypothesis (H2c). *Credit derivatives* (*traded OTC*) is significantly negative in model (1) and significantly positive in model (4), suggesting that banks’ use of *credit derivative traded OTC* raises credit risk (*Z-score*)and overall risk (*stock return volatility*)*.* These findings on credit derivatives support hypothesis (H2c).

Adding *PostDFA* and the three interaction terms in Table 5 does not change the significance and sign for *IR derivatives traded OTC* or *on exchanges*, while *credit derivatives* (*traded OTC*) becomes significant in models (6), (7) and (8). The negative sign in models (6), (7) and positive sign in model (8) again show that the use of *credit derivatives traded OTC* lowers banks’ credit risk, worst loss and overall risk. *PostDFA* dummy is significant in all four models in Table 5 (models (5), (6), (7), (8)), and the results on *PostDFA* dummy is consistent with those in Table 4, that signing of the DFA raises bank’s credit risk, as measured by *Z-score*, *distance to default*, and bank’s overall risk, as measured by bank’s *stock return volatility*, while lowers worst loss measured by *VaR.* The results on *PostDFA* dummy in models (5), (6), (8) support hypothesis (H3a).

As shown in Table 5, the interaction terms between *IR derivatives traded OTC* and *PostDFA* is significant in models (6) and (7). Its negative coefficient sign suggests that the coming into effect of the DFA even increased the hampering effects of *IR derivatives traded OTC* on bank’s credit risk (*distance to default*) and the extent of bank’s worst loss (*VaR*). These findings do not support hypothesis (H3b). The interaction terms between *IR derivatives traded on exchanges* and *PostDFA* is significantly positive in model (7), showing that the DFA lessens the hampering impact of exchange-traded IR derivatives on bank’s worst loss. The interaction terms between *credit derivatives* (*traded OTC*) and *PostDFA* is significant in models (6), (7) and (8). Its positive coefficient sign in (6), (7) and positive coefficient sign in (8) suggest that the signing of the DFA lessens the hampering effects of *credit derivatives traded OTC* on banks’ risk. These findings on interaction terms between *IR derivatives traded on exchanges*, *net credit derivatives* (*traded OTC*) and *PostDFA* confirm hypothesis (H3b).

Overall, the empirical evidences from *credit derivatives* (*traded OTC*) in Table 5 are consistent with hypothesis (H3a), and partially support hypothesis (H3b) for two out of the three derivative categories examined (*credit derivatives* *traded OTC* and *IR derivatives traded on exchanges*). The findings on interaction term between *IR derivatives traded OTC* do not support (H3b). Although the results on *credit derivative* confirm hypothesis (H2c), those on *IR derivatives trade OTC* and *on exchanges* do not support hypothesis (H2c). Other control variables are found with consistent significance and signs as in Table 4.

### 5.3. Derivatives, DFA and bank’s performance

We investigate (H4), (H5a) and (H5b) with *Tobin’s Q, return on asset, cost to income ratio, and market equity returns*. Table 6 and Table 7 report the regression results for Equation (9). Similarly, models (1), (2), (3) report the effects of derivative holdings, without considering the DFA and models (4), (5), (6) extend by adding *PostDFA* and interaction terms between three derivative categories and *PostDFA* dummy.

TABLE 6 HERE

As shown in Table 6, without considering the DFA and interaction terms, only *IR derivatives for hedging* is significant in models (1) when *Tobin’s Q* is used to capture banks’ performance. The positive coefficient sign suggests that the use of *IR derivatives for hedging* improves bank’s performance. As the *PostDFA* dummy and interaction terms added in models (4), (5), (6), *IR derivatives for hedging* still exhibits positive significance when *Tobin’s Q* is used to capture banks’ performance (model (4)), and confirms hypothesis (H4). *Net credit derivatives* becomes significant in model (4) and its negative coefficient sign indicates that use of credit derivatives hampers banks’ performance, which is contrary to hypothesis (H4), however, in line with the findings from Keffala and De Peretti (2016). *IR derivatives for trading* is not found significant in any models in Table 6.

As noted in model (4) Table 6, *Tobin’s Q* is negatively affected by *PostDFA*, which is consistent with hypothesis (H5a). *PostDFA* is also found marginal significant in model (5), however its positive sign does not support hypothesis (H5a). Of the three interaction terms included in models (4), (5), (6), the interaction term between *IR derivatives for trading* and *PostDFA* is the only one that presents significance. The negative sign of this interaction term coefficient in models (4) (5) and positive sign in model (6) suggest after the signing of the DFA, the use of *IR derivatives held for trading* hampers bank’s performance (*Tobin’s Q* and *ROA*), and operating efficiency (*cost to income ratio*). These evidences from *IR derivatives held for trading* partly support hypothesis (H5b).

The results of other control variables suggest that large banks with poor asset quality (*loan loss provisions*), high *book to market ratio*, *stock return volatility*, market competition (*HHI*), and low *exposure to real estate market*, and *short-term borrowings* tend to exhibit worse performance. Overall, the results in Table 6 weakly support hypothesis (H5b) for t *IR derivatives for trading*, but not for *IR derivatives for hedging* or *net credit derivatives*. However, empirical findings for hypothesis (H4) and (H5a) are mixed.

Table 7 presents results on bank’s performance with derivatives categorised by trading approach of OTC-traded and exchange-traded. Without considering the DFA, *IR derivatives traded on exchanges* is the only significant. Its negative coefficient sign in model (2) suggest that the use of exchange-traded IR derivatives hampers bank’s performance, although the significance is marginal. As the *PostDFA* dummy and interaction terms added in models (4), (5), (6), *IR derivatives traded on exchange* becomes significantly positive when *Tobin’s Q* is used to capture banks’ performance (model (4)), and confirms hypothesis (H4). *Net credit derivatives* (*traded OTC*) becomes significant in model 4 and its negative coefficient sign indicates that use of credit derivatives hampers banks’ performance, which is contrary to hypothesis (H4). *IR derivatives traded OTC* is not significant in any models in Table 7.

As shown in model (4) Table 7, *PostDFA* negatively affects *Tobin’s Q* , which is in line with hypothesis (H5a). Itis marginal significant in model (5) when *VaR* is used to capture banks’ worst loss. The positive sign of *PostDFA* in model (5) does not support hypothesis (H5a). The interaction term between *IR derivatives traded OTC* and *PostDFA* is the significant in models (5), (6), and the negative sign in model (5) with the positive sign in model (6) indicate that after the DFA came into effect, banks’ use of *IR derivatives traded OTC* hampers bank’s performance (*ROA*) and operation efficiency (*cost to income ratio*). These evidences are partly in line with hypothesis (H5b). The interaction term between *IR derivatives traded on exchanges* and *PostDFA* is significant in model (6) and the negatives sign suggests that the use of exchanged-traded IR derivatives in post-DFA period improves banks’ operation efficiency as measured by *cost to income ratio*, which does not support hypothesis (H5b)*.* Other control variables are consistent as in Table 6 in terms of significance and signs. Overall, the empirical results in Table 7 present mixed evidences for hypothesis (H4), (H5a) and (H5b) with derivatives categorized by traded approach.

## 6. Robustness Test

In this section, we discuss several sensitivity tests to check the robustness of results presented above. First, we test our results in another sample with the criterion applied by Mayordomo, Rodriguez-Moreno and Pena, (2014). Second, we test our results for banks that are involved in the Stress Test by Federal Reserve. Third, we apply alternative measurements for several important variables.

**6.1. Sample of bigger banks**

We set up the main threshold as $1 billion in total assets as of year-end 2006, by which we can capture the effects of derivatives for more BHCs and also for those banks that got defunct during the GFC. We could instead raise the size threshold and add more time spots in the criterion. Similar to the approach of Mayordomo, Rodriguez-Moreno and Pena, (2014), we construct another sample consist of 52 BHCs with total assets above $5billion in both the first quarter of 2006 and the first quarter of 2009. One benefit of this criterion is to avoid potential bias as it incorporates both pre-crisis and ongoing crisis-period time spot. The untabulated results with those 52 Banks indicate that the findings on systemic risk are not changed by a different sample criterion. The results still show that banks’ use of interest rate derivatives for hedging and credit derivatives increases their contribution to systemic risk, and the DFA effectively mitigates the effectiveness of those derivatives. The results of tests on banks’ individual overall risk and performance also remain consistent with the main results presented in section 5.

**6.2. Stress Tested Banks**

As a response to the “too-big-to-fail’ issue, the DFA requires the Federal Reserve to conduct an annual supervisory stress test for those systemically important financial institution (SIFIs). Meanwhile, those institutions subject to the supervisory stress test are also required to conduct their own stress tests and report the test results to the Federal Reserve twice a year. Considering the importance of monitoring the financial health of those SIFIs, our second sensitivity test examines the impacts of derivatives use and the DFA among those stress tested banks. We include banks that are required to report the stress test results as year-end 2015 and get another sample of 18 BHCs. Findings on systemic risk and banks’ risk and performance for stress tested banks present similar impacts of interest rate derivatives for hedging and credit derivatives, although the results are slightly weaker.

**6.3. Alternative measurements**

In our models, we employ *tier 1 ratio* and *loan loss provision* as proxies for banks’ capital adequacy and loan loss risk respectively. Alternative measures for those two are the *leverage ratio* and *non-performing loans.* As reported by Mayordomo, Rodriguez-Moreno and Pena, (2014), *leverage* and *non-performing loans* have much stronger impact on systemic risk than derivatives holdings. Following Mayordomo, Rodriguez-Moreno and Pena, (2014), we replace *tier 1 ratio* and *loan loss provision* with *leverage* and *non-performing loans* respectively in each model as a third sensitivity test. In addition, we replace *return on assets* with *return on equity*, both of which are proxies for banks’ performance. We also test with variables calculated with different confidence levels (*△CoVaR*, *MES* and *VaR*) and different time window (*Z-score* and *stock return volatility*). We find consistent results on derivatives use and the DFA in untabulated tests.[[12]](#footnote-12)

## 7. Conclusions

Our study provides comprehensive examination of The Dodd-Frank Wall Street Reform and Consumer Protection Act (DFA) and how it impacted the usage of derivative products by U.S. banks. Our sample consists of 151 U.S. bank holding companies with total asset higher than 1 billion at the end of 2006. We cover the period from the first quarter 2007 to the last quarter 2014. In the line of past studies prior to the DFA, we find that excessive usage of interest rate derivatives held for hedging, exchange-traded interest rate derivatives and credit derivatives (traded OTC), substantially increased banks’ contribution to systemic risk. We also find that in post-DFA periods, banks’ contribution to systemic risk was substantially reduced. Moreover, we find usage of credit derivatives (traded OTC) and interest rate derivatives held for hedging have weakened impact on systemic risk in post-DFA periods. These findings provide supportive evidences on the effectiveness of central clearing channel, showing that the implementation of the DFA mitigated systemic risk associated with credit derivatives (traded OTC). However, the effectiveness of proprietary trading channel in the DFA might be questioned with the results on interest rate derivatives held for trading.

Our paper is an important voice in the debate about consequences of the implementation of the DFA on banking sector. There are empirical findings showing that banks reduce the size of their trading books as a response to the introduction of the DFA, while empirical evidences also show that the DFA made individual banks risker. Therefore, we move on to examine bank’s individual risk and performance. Our analysis reviews the usage of credit derivatives (traded OTC), exchange-traded interest rate derivatives and interest rate derivatives held for hedging increased banks’ individual risks. We show that in post-DFA time, those effects are weaker.

In order to shed the light on risk-return profile of U.S. banking sector, we scrutinize banks’ performance measured by *Tobin’s Q, return on asset, cost to income ratio, and market equity returns*.. We find that usage of interest rate derivatives enhances bank’s performance while usage of credit derivatives hampered bank’s performance. In addition, there are mixed evidences that post-crisis period combined with the DFA regulatory environment resulted in a lower performance for holding companies from banking sector.

Our results remain robust for alternative measurements and sample selection of U.S. bank holding companies. For example the reported results are consistent for banks that are subject of DFA stress testing and big banks that reported asset higher than 5 billion at the first quarter of 2006, and the first quarter of 2009.

Overall, the DFA achieved one of its objectives, namely, mitigating the impact of derivatives usage on systemic risk. Post-DFA periods show less interconnectedness between banks caused by credit derivatives. On the other hand, introduction of the DFA seemed to be a great illustration for well-known statement that the “risks do not disappear”, as we show that bank’s individual risks increased at the same time when systemic risk goes down. The regulators face a tradeoff between the decreasing systemic risk and the increase of individual bank risks.

Our results are tangible and important to banking regulators around the world. However, we have no doubt the debate on optional regulation of financial market (banking sector) is far from over. As a natural extension of our study, further research should examine the channels in which banks’ systemic risks affect and interact with their individual risks.

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### **Table 1** Summary Statistics

This able present the statistics of variables calculated from the 151 banks in the sample using quarterly data from 2007Q1 to 2014Q4. Statistics of depend variables are presented in Panel A. *△CoVaR* is the difference between *Value at Risk* of banking system conditional on the distress of a bank and *Value at Risk* of banking system conditional on the median state of the bank. *MES* is bank’s marginal expected shortfall calculated as the average return of a bank on days when the S&P Banks Selected Industry Index return is among its lowest 5% level. *Banking industry beta* is calculated as the sensitivity of stock return to the return of banking industry index in one-year time window. The *Z-score* is the sum of the mean return on assets and the mean ratios of equity to assets, divided by the standard deviation of the return on assets. *Distance to default* is the ratio of market capitalization to the product of market value of assets. *Volatility* is the volatility of daily stock return with a six-month rolling window. *Tobin’Q* is defined as the market value of a bank’s assets over the book value of assets. *Net interest margin* is calculated as the ratio of interest margin to average earning assets. *Return on Asset* is the ratio of net income to book value of total assets. *Cost to Income* is the ratio of operating cost to net interest income, which measures banks’ operating efficiency. *Market cap Return* is the quarterly percentage change in market capitalization.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Panel A** |  |  |  |  |  |  |
| **Dependent Variables** | Obs | Mean | Median | SD | Min | Max |
| △CoVaR  | 3414 | -0.0279 | -0.0229 | 0.0216 | -0.1942 | 0.0726 |
| MES | 3414 | -0.0348 | -0.0261 | 0.0329 | -0.2626 | 0.1626 |
| Banking industry beta | 3414 | 0.7865 | 0.8197 | 0.3044 | 0.0016 | 1.9287 |
| Z-score | 3724 | 3.5242 | 2.1242 | 4.3596 | -0.8562 | 32.5934 |
| Distance to Default | 3724 | 2.9855 | 2.7561 | 1.6730 | 0.0671 | 14.6817 |
| Value at Risk | 3724 | -0.0792 | -0.0689 | 0.0424 | -0.4248 | -0.0090 |
| Volatility | 3724 | 0.0270 | 0.0211 | 0.0174 | 0.0052 | 0.1310 |
| Tobin’s Q | 3724 | 0.2310 | 0.2213 | 0.0813 | 0.0372 | 0.6251 |
| Net interest margin  | 3724 | 3.6439 | 3.6178 | 0.7337 | -0.4457 | 8.9082 |
| Return on Asset | 3724 | 0.0066 | 0.0088 | 0.0143 | -0.1511 | 0.1779 |
| Cost to Income | 3724 | 0.6705 | 0.6461 | 0.2194 | 0.2500 | 3.9750 |
| △Market cap  | 3724 | 0.0495 | 0.0151 | 0.4215 | -0.7801 | 18.2456 |

**Table 1 Summary Statistics (Cont’d)**

Statistics of key explanatory variables are presented in Panel B. *IR derivatives held for trading* is defined as the notional amount of interest rate derivatives held for trading purpose scaled by asset. *IR derivatives held for hedging* is defined as the notional amount of interest rate derivatives held not for trading purpose scaled by asset. *Net credit derivatives* is defined as the credit derivatives bought minus credits derivative sold, then scaled by asset. *IR Derivatives OTC* is the notional amount of net long positions in interest rate derivatives traded OTC scaled by asset. *IR Derivatives exchange* is the notional amount of net long positions in interest rate derivatives traded on exchange scaled by asset. *Credit Derivatives OTC* is the notional amount of net long positions in credit derivatives traded OTC scaled by asset. *Credit Derivatives Exchange* is the notional amount of net long positions in credit rate derivatives traded on exchange scaled by asset. *Total asset*, *Loan to depository institutions* and *Balance due from depository institutions* are reported in billion USD[[13]](#footnote-13). *Loan loss provision* is the ratio of loan loss provision to net interest income. *Tier 1 ratio* is tier 1 capital as a percent of total risk-weighted assets. *Exposure to housing price change* is calculated as average weighted housing price changes derived by using the proportion of deposits a bank has in each state. *HHI index* is the logarithm value of the average weighted Herfindahl-Hirschman Index derived by using the proportion of deposits a bank has in each state.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Panel B** |  |  |  |  |  |  |
| **Key Independent Variables** | 　 | 　 | 　 | 　 | 　 | 　 |
| IR Derivatives trading | 3724 | 0.4804 | 0.0000 | 3.3438 | 0.0000 | 51.1553 |
| IR Derivatives hedging | 3724 | 0.0456 | 0.0103 | 0.1044 | 0.0000 | 1.5314 |
| Net credit derivatives | 3724 | 0.0002 | 0.0000 | 0.0059 | -0.0640 | 0.1217 |
| IR Derivatives OTC | 3724 | 0.4267 | 0.0110 | 2.8096 | -0.0329 | 42.3556 |
| IR Derivatives Exchange | 3724 | 0.0193 | 0.0000 | 0.1052 | -0.0359 | 1.4426 |
| Credit Derivatives OTC  | 3724 | 0.0005 | 0.0000 | 0.0055 | -0.0540 | 0.1118 |
| Credit Derivatives exchange | 3724 | 0.0000 | 0.0000 | 0.0004 | -0.0113 | 0.0088 |
| Loan to depository institutions | 3414 | 0.3493 | 0.0000 | 2.2351 | 0.0000 | 25.8000 |
| Balance due from depository institutions | 3414 | 0.0063 | 0.0001 | 0.0424 | -0.0202 | 1.0370 |
| Total asset | 3724 | 58.9375 | 4.4191 | 279.0158 | 0.8761 | 2572.2740 |
| Loan loss provision | 3724 | 0.1937 | 0.0883 | 0.3284 | -0.6409 | 4.9213 |
| Tier 1 ratio | 3724 | 0.0924 | 0.0910 | 0.0188 | 0.0313 | 0.1937 |
| Exposure to housing price change | 3724 | -0.0015 | -0.0015 | 0.0241 | -0.0989 | 0.0849 |
| HHI index | 3724 | 6.5846 | 6.6281 | 0.5303 | 3.4417 | 8.0995 |

### Table 2 The Effects of Derivative Use and DFA on Systemic Risk

The dependent variables in the regressions are change in conditional Value at Risk at 95%, marginal expected shortfall at 95% and banking industry beta calculated using 1 year of daily stock price. All regressions include unreported time fixed effects and firm fixed effects. *PostDFA* is a dummy set to one after Dodd-Frank Act is issued and zero otherwise. *Size* is calculated as the logarithm of total asset. *Exposure to housing price change* is a weighted average of the returns on the state-specific Fannie Mae real estate index where the weights are the fraction of bank deposits in the various states. *HHI* is a weighted average of the Herfindahl-Hirschman index where the weights are the fraction of bank deposits in the various states. *Special capital* is a dummy set to one if the bank uses any of the government bailout special capital programs. *Acquisition* is a dummy set to one if the bank acquires other banks in that quarter. Standard errors are heteroskedasticity-consistent

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| 　 | (1) | (2) | (3) | (4) | (5) | (6) |
|  | △CoVaR | MES | Bank beta | △CoVaR | MES | Bank beta |
| IR Derivatives trading | -0.0003\* | -0.0001 | 0.0046 | -0.0001 | 0.0001 | 0.0043 |
| IR Derivatives hedging | -0.0121\* | -0.0134\*\* | 0.2269\*\*\* | -0.0155\*\*\* | -0.0209\*\*\* | 0.2248\*\*\* |
| Net credit derivatives | -0.0643 | -0.1139\* | 0.5826 | -0.2027\*\*\* | -0.2199\*\*\* | 1.2956 |
| Loan to depository institutions | 0.1013 | 0.0920 | 1.1042 | 0.0740 | 0.0242 | 0.9290 |
| Balance due from depository institutions | 0.6468\*\* | -1.4026\*\*\* | 3.5906 | 0.7120\*\* | -1.4006\*\*\* | 2.8682 |
| Post DFA dummy |  |  |  | 0.0112\*\*\* | -0.0050\*\*\* | -0.4275\*\*\* |
| IR Derivatives trading \* PostDFA |  |  |  | -0.0001 | -0.0002 | 0.0028 |
| IR Derivatives hedging \* PostDFA |  |  |  | 0.0115\*\*\* | 0.0282\*\*\* | -0.0456 |
| Net Credit Derivatives \* PostDFA |  |  |  | 0.4773\*\*\* | 0.2911\*\*\* | -2.1118 |
| Size | -0.0003 | -0.0062\*\* | 0.2211\*\*\* | -0.0005 | -0.0065\*\* | 0.2215\*\*\* |
| Tier 1 ratio | -0.0293 | -0.0638 | 1.7109\*\*\* | -0.0309 | -0.0673 | 1.7191\*\*\* |
| Loan Loss Provision | -0.0022\*\*\* | -0.0050\*\*\* | 0.0089 | -0.0020\*\*\* | -0.0045\*\* | 0.0086 |
| Book to market ratio | -0.0002 | 0.0013 | -0.0322\*\*\* | -0.0003 | 0.0011 | -0.0323\*\*\* |
| Return on average assets | -0.0148 | -0.0016 | 0.2833 | -0.0127 | 0.0025 | 0.2818 |
| Short-term borrowing | -0.0841\*\*\* | -0.0771\*\* | -0.1128 | -0.0803\*\*\* | -0.0673\*\* | -0.1068 |
| Stock price volatility in 6 months | -0.1448\*\*\* | -0.4982\*\*\* | 9.7276\*\*\* | -0.1310\*\*\* | -0.4756\*\*\* | 9.6896\*\*\* |
| Acquisition | 0.0006 | -0.0002 | -0.0422\*\*\* | 0.0006 | -0.0004 | -0.0422\*\*\* |
| Special capital users dummy | -0.0008 | -0.0005 | -0.0021 | -0.0006 | -0.0003 | -0.0024 |
| Exposure to housing price change | 0.0077 | 0.0706\* | -0.1144 | 0.0062 | 0.0685\* | -0.1093 |
| HHI index | 0.0016 | 0.0050 | 0.0059 | 0.0011 | 0.0044 | 0.0054 |
| Intercept | -0.0287 | 0.0243 | -1.1709\*\* | -0.0236 | 0.0310 | -1.1708\*\* |
| Adj.R-squared | 0.627 | 0.641 | 0.404 | 0.631 | 0.642 | 0.404 |
| N | 3414 | 3414 | 3414 | 3414 | 3414 | 3414 |

### Table 3 The Effects of Derivative Use and DFA on Systemic Risk

The dependent variables in the regressions are change in conditional Value at Risk at 95%, marginal expected shortfall at 95% and banking industry beta calculated using 1 year of daily stock price. All regressions include unreported time fixed effects and firm fixed effects. PostDFA is a dummy set to one after Dodd-Frank Act is issued and zero otherwise. Size is calculated as the logarithm of total asset. Exposure to housing price change is a weighted average of the returns on the state-specific Fannie Mae real estate index where the weights are the fraction of bank deposits in the various states. HHI is a weighted average of the Herfindahl-Hirschman index where the weights are the fraction of bank deposits in the various states. Special capital is a dummy set to one if the bank uses any of the government bailout special capital programs. Acquisition is a dummy set to one if the bank acquires other banks in that quarter. Standard errors are heteroskedasticity-consistent

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| 　 | (1) | (2) | (3) | (4) | (5) | (6) |
|  | △CoVaR | MES | Bank beta | △CoVaR | MES | Bank beta |
| IR Derivatives OTC | -0.0003 | 0.0001 | 0.0034 | -0.0001 | 0.0002 | 0.0074 |
| IR Derivatives exchange | -0.0141 | -0.0130 | 0.2062\*\* | -0.0225\*\* | -0.0210\* | 0.2804\*\* |
| Credit Derivatives OTC  | -0.0683 | -0.1299\* | 0.7001 | -0.1801\*\*\* | -0.1932\*\*\* | 0.9645\* |
| Loan to depository institutions | 0.1206 | 0.1111 | 0.7647 | 0.1066 | 0.0857 | 0.5596 |
| Balance due from depository institutions | 0.6788\* | -1.3582\*\*\* | 2.9534 | 0.7714\*\* | -1.3156\*\*\* | 1.9640 |
| Post DFA dummy |  |  |  | 0.0117\*\*\* | -0.0039\*\* | -0.4286\*\*\* |
| IR Derivatives OTC \* PostDFA |  |  |  | -0.0005 | -0.0003 | 0.0128\* |
| IR Derivatives exchange \* PostDFA |  |  |  | 0.0091 | 0.0082 | -0.1748\* |
| Credit Derivatives OTC \* PostDFA |  |  |  | 0.4436\*\*\* | 0.2790\*\* | -1.1274 |
| Size | -0.0004 | -0.0063\*\* | 0.2223\*\*\* | -0.0005 | -0.0063\*\* | 0.2204\*\*\* |
| Tier 1 ratio | -0.0290 | -0.0635 | 1.6993\*\*\* | -0.0300 | -0.0642 | 1.7100\*\*\* |
| Loan Loss Provision | -0.0022\*\*\* | -0.0050\*\* | 0.0082 | -0.0021\*\*\* | -0.0049\*\* | 0.0093 |
| Book to market ratio | -0.0002 | 0.0013 | -0.0325\*\*\* | -0.0002 | 0.0012 | -0.0330\*\*\* |
| Return on average assets | -0.0141 | -0.0009 | 0.2711 | -0.0134 | -0.0001 | 0.2808 |
| Short-term borrowing | -0.0861\*\*\* | -0.0789\*\* | -0.0757 | -0.0864\*\*\* | -0.0782\*\* | -0.0375 |
| Stock price volatility in 6m | -0.1457\*\*\* | -0.4993\*\*\* | 9.7403\*\*\* | -0.1386\*\*\* | -0.4935\*\*\* | 9.7227\*\*\* |
| Acquisition | 0.0008 | 0.0000 | -0.0463\*\*\* | 0.0009 | 0.0001 | -0.0462\*\*\* |
| Special capital users dummy | -0.0008 | -0.0005 | -0.0019 | -0.0007 | -0.0004 | -0.0016 |
| Exposure to housing price change | 0.0064 | 0.0693\* | -0.0926 | 0.0057 | 0.0688\* | -0.1006 |
| HHI index | 0.0017 | 0.0051 | 0.0037 | 0.0012 | 0.0047 | 0.0019 |
| Intercept | -0.0291 | 0.0239 | -1.1583\*\* | -0.0253 | 0.0275 | -1.1344\*\* |
| Adj.R-squared | 0.627 | 0.640 | 0.401 | 0.630 | 0.640 | 0.402 |
| N | 3414 | 3414 | 3414 | 3414 | 3414 | 3414 |

### Table 4 The Effects of Derivative Use and DFA on individual Risk

The dependent variables in the regressions are change in conditional Z-score, distance to default, 95% value at risk and 6-month volatility stock price. All regressions include unreported time fixed effects and firm fixed effects. PostDFA is a dummy set to one after Dodd-Frank Act is issued and zero otherwise. Size is calculated as the logarithm of total asset. Exposure to housing price change is a weighted average of the returns on the state-specific Fannie Mae real estate index where the weights are the fraction of bank deposits in the various states. HHI is a weighted average of the Herfindahl-Hirschman index where the weights are the fraction of bank deposits in the various states. Special capital is a dummy set to one if the bank uses any of the government bailout special capital programs. Acquisition is a dummy set to one if the bank acquires other banks in that quarter. Liquid is calculated as cash and cash equivalent scaled by total assets. Beta is the market beta calculated using 1 year of daily stock price. Standard errors are heteroskedasticity-consistent.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| 　 | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| 　 | Z-score | Distance to Default | Value at Risk | Volatility | Z-score | Distance to Default | Value at Risk | Volatility |
| IR Derivatives trading | -0.0488 | -0.0212 | 0.0001 | -0.0003\*\* | -0.0540 | -0.0251 | 0.0004 | -0.0004\*\*\* |
| IR Derivatives hedging | -0.6304 | -0.6689\*\*\* | -0.0126 | 0.0005 | -0.5952 | -0.5073\*\* | -0.0186\*\* | 0.0041\* |
| Net credit derivatives | -16.6273\* | -2.5398 | -0.1225 | 0.0947\*\* | -12.9801 | -7.8335\*\*\* | -0.2791 | 0.1670\*\*\* |
| Post DFA dummy |  |  |  |  | -6.2930\*\*\* | -2.8216\*\*\* | 0.0068\* | 0.0186\*\*\* |
| IR Derivatives trading \* PostDFA |  |  |  |  | 0.0053 | -0.0386\*\*\* | -0.0002 | 0.0001 |
| IR Derivatives hedging \* PostDFA |  |  |  |  | -0.2024 | 0.1847 | 0.0243\*\* | -0.0139\*\*\* |
| Net Credit Derivatives \* PostDFA |  |  |  |  | -12.8680 | 12.5521\*\* | 0.5182\*\*\* | -0.2379\*\*\* |
| Size | 0.5222 | 0.5726\*\*\* | -0.0050 | -0.0029 | 0.5265 | 0.5775\*\*\* | -0.0053 | -0.0027 |
| Tier 1 ratio | -11.9096 | 8.2909\*\*\* | 0.0106 | -0.1227\*\*\* | -11.8795 | 8.2511\*\*\* | 0.0073 | -0.1197\*\*\* |
| Loan Loss Provision | -0.0805 | -0.1152\*\* | -0.0047\*\* | 0.0052\*\*\* | -0.0843 | -0.1210\*\* | -0.0041\*\* | 0.0049\*\*\* |
| Book to market ratio | 0.0149 | -0.1051\*\* | -0.0026\*\*\* | 0.0054\*\*\* | 0.0157 | -0.1013\*\* | -0.0027\*\*\* | 0.0054\*\*\* |
| Return on average assets |  |  | 0.0362 | -0.0285\* |  |  | 0.0406 | -0.0307\*\* |
| Short-term borrowing | 10.0717\*\* | -2.4137\*\* | -0.0590\*\* | 0.0256\*\* | 10.0487\*\* | -2.6994\*\* | -0.0520\* | 0.0210\*\* |
| Stock price volatility in 6ms | -6.7872 | -17.2819\*\*\* | -0.4159\*\*\* |  | -7.0170 | -17.3024\*\*\* | -0.3978\*\*\* |  |
| Acquisition | -0.2811 | 0.0199 | -0.0009 | -0.0006 | -0.2814 | 0.0211 | -0.0010 | -0.0005 |
| Special capital users dummy | 0.0027 | -0.0264 | -0.0002 | 0.0012\*\* | -0.0012 | -0.0316 | 0.0001 | 0.0010\*\* |
| Exposure to housing price change | -7.8388 | -1.0887 | 0.1619\*\*\* | -0.0162 | -7.8099 | -1.0972 | 0.1591\*\*\* | -0.0146 |
| HHI index | 0.3301 | -0.0868 | 0.0062\* | -0.0003 | 0.3394 | -0.0558 | 0.0055 | 0.0001 |
| Intercept | 2.5650 | 0.3353 | -0.0683 | 0.0477\*\* | 2.4690 | 0.0919 | -0.0607 | 0.0428\*\* |
| Adj.R-squared | 0.388 | 0.685 | 0.750 | 0.840 | 0.387 | 0.685 | 0.751 | 0.842 |
| N | 3724 | 3724 | 3724 | 3724 | 3724 | 3724 | 3724 | 3724 |

### Table 5 The Effects of Derivative Use and DFA on individual Risk

The dependent variables in the regressions are change in conditional Z-score, distance to default, 95% value at risk and 6-month volatility stock price. All regressions include unreported time fixed effects and firm fixed effects. PostDFA is a dummy set to one after Dodd-Frank Act is issued and zero otherwise. Size is calculated as the logarithm of total asset. Exposure to housing price change is a weighted average of the returns on the state-specific Fannie Mae real estate index where the weights are the fraction of bank deposits in the various states. HHI is a weighted average of the Herfindahl-Hirschman index where the weights are the fraction of bank deposits in the various states. Special capital is a dummy set to one if the bank uses any of the government bailout special capital programs. Acquisition is a dummy set to one if the bank acquires other banks in that quarter. Liquid is calculated as cash and cash equivalent scaled by total assets. Beta is the market beta calculated using 1 year of daily stock price. Standard errors are heteroskedasticity-consistent.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| 　 | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| 　 | Z-score | Distance to Default | Value at Risk | Volatility | Z-score | Distance to Default | Value at Risk | Volatility |
| IRD traded OTC  | -0.0079 | -0.0124 | 0.0007 | -0.0003\*\* | -0.0435 | -0.0144 | 0.0008 | -0.0004\*\*\* |
| IRD traded on exchange | -0.4727 | -1.1655\*\*\* | -0.0297\*\*\* | 0.0009 | -1.0977 | -0.8481\*\*\* | -0.0457\*\*\* | 0.0064 |
| Credit Derivatives net OTC  | -20.2441\*\* | -2.7659 | -0.1422 | 0.0946\*\* | -13.8295 | -8.5115\*\*\* | -0.2331\* | 0.1384\*\*\* |
| Post DFA dummy |  |  |  |  | -6.3133\*\*\* | -2.8115\*\*\* | 0.0077\*\* | 0.0182\*\*\* |
| IRD OTC \* PostDFA |  |  |  |  | -0.0647 | -0.0289\* | -0.0007\*\* | 0.0001 |
| IRD exchange \* PostDFA |  |  |  |  | 1.2884 | -0.1308 | 0.0180\*\*\* | -0.0049 |
| Credit OTC \* PostDFA |  |  |  |  | -19.4349 | 15.0831\*\* | 0.4704\*\*\* | -0.2136\*\*\* |
| Size | 0.5235 | 0.5638\*\*\* | -0.0053 | -0.0029 | 0.5327 | 0.5706\*\*\* | -0.0056 | -0.0027 |
| Tier 1 ratio | -11.9331 | 8.2922\*\*\* | 0.0096 | -0.1228\*\*\* | -11.9240 | 8.2667\*\*\* | 0.0087 | -0.1220\*\*\* |
| Loan Loss Provision | -0.0837 | -0.1130\*\* | -0.0046\*\* | 0.0052\*\*\* | -0.0857 | -0.1210\*\* | -0.0044\*\* | 0.0051\*\*\* |
| Book to market ratio | 0.0169 | -0.1047\*\* | -0.0026\*\*\* | 0.0054\*\*\* | 0.0174 | -0.1010\*\* | -0.0027\*\*\* | 0.0054\*\*\* |
| Return on average assets |  |  | 0.0362 | -0.0285\* |  |  | 0.0388 | -0.0295\* |
| Short-term borrowing | 10.0210\*\* | -2.5908\*\* | -0.0621\*\* | 0.0257\*\* | 9.9983\*\* | -2.8607\*\* | -0.0612\*\* | 0.0251\*\* |
| Stock price volatility in 6m  | -6.8618 | -17.4519\*\*\* | -0.4209\*\*\* |  | -6.8462 | -17.4969\*\*\* | -0.4110\*\*\* |  |
| Acquisition | -0.2739 | 0.0335 | -0.0006 | -0.0006\* | -0.2760 | 0.0326 | -0.0005 | -0.0007\* |
| Special capital users dummy | 0.0009 | -0.0308 | -0.0003 | 0.0012\*\* | 0.0002 | -0.0350 | -0.0001 | 0.0011\*\* |
| Exposure to housing price change | -7.8641 | -1.1291 | 0.1607\*\*\* | -0.0162 | -7.8187 | -1.1217 | 0.1597\*\*\* | -0.0156 |
| HHI index | 0.3353 | -0.0750 | 0.0064\* | -0.0003 | 0.3330 | -0.0495 | 0.0054 | 0.0001 |
| Intercept | 2.4791 | 0.3280 | -0.0661 | 0.0474\*\* | 2.4481 | 0.1001 | -0.0571 | 0.0432\*\* |
| Adj.R-squared | 0.387 | 0.685 | 0.750 | 0.840 | 0.387 | 0.685 | 0.751 | 0.841 |
| N | 3724 | 3724 | 3724 | 3724 | 3724 | 3724 | 3724 | 3724 |

### Table 6 The Effects of Derivative Use and DFA on Bank Performance

The dependent variables in the regressions are change in conditional Tobin’s Q, net interest margin ratio and return on assets. PostDFA is a dummy set to one after Dodd-Frank Act is issued and zero otherwise. All regressions include unreported time fixed effects and firm fixed effects. Size is calculated as the logarithm of total asset. Exposure to housing price change is a weighted average of the returns on the state-specific Fannie Mae real estate index where the weights are the fraction of bank deposits in the various states. HHI is a weighted average of the Herfindahl-Hirschman index where the weights are the fraction of bank deposits in the various states. Special capital is a dummy set to one if the bank uses any of the government bailout special capital programs. Acquisition is a dummy set to one if the bank acquires other banks in that quarter. Liquid is calculated as cash and cash equivalent scaled by total assets. Beta is the market beta calculated using 1 year of daily stock price. Standard errors are heteroskedasticity-consistent.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| 　 | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| 　 | Tobin's Q | Roa | Cost to Income | Market cap Return | Tobin's Q | Roa | Cost to Income | Market cap Return |
| Interest Rate Derivatives held for trading | 0.0024 | 0.0000 | -0.0017 | -0.0034 | 0.0020 | -0.0000 | 0.0004 | -0.0049 |
| Interest Rate Derivatives held for hedging | 0.0496\*\* | -0.0014 | 0.0106 | -0.1208\* | 0.0630\*\*\* | -0.0006 | -0.0440 | -0.1154\* |
| Net notional amount of credit derivatives | -0.2857 | 0.0208 | 0.3197 | 1.1701\* | -0.3164\*\* | 0.0056 | 0.4990 | 1.0768\* |
| Post DFA dummy |  |  |  |  | -0.0814\*\*\* | 0.0041\* | 0.0104 | 0.2753\*\*\* |
| IRD held for trading \* PostDFA |  |  |  |  | -0.0011\*\* | -0.0002\*\* | 0.0062\*\*\* | -0.0051\*\* |
| IRD held for hedging \* PostDFA |  |  |  |  | -0.0256 | 0.0017 | 0.0681 | 0.0903 |
| Net Credit Derivatives \* PostDFA |  |  |  |  | -0.0421 | 0.0108 | 0.3892 | -0.9338 |
| Size | 0.0160 | -0.0080\*\*\* | -0.0399\* | -0.2385\*\*\* | 0.0165 | -0.0080\*\*\* | -0.0424\* | -0.2376\*\*\* |
| Tier 1 ratio | 0.0742 | -0.0073 | -0.2080 | -4.1499 | 0.0769 | -0.0076 | -0.2166 | -4.1617 |
| Loan Loss Provision | -0.0167\*\*\* | -0.0077\*\*\* | -0.0067 | -0.0461 | -0.0176\*\*\* | -0.0077\*\*\* | -0.0027 | -0.0462 |
| Book to market ratio |  | -0.0033\*\*\* | 0.0215 |  |  | -0.0033\*\*\* | 0.0204 |  |
| Return on average assets | 0.1048\*\* |  | -0.7070 |  | 0.0952\* |  | -0.6673 |  |
| Short-term borrowing | 0.5360\*\*\* | 0.0138 | -0.3480 | 0.2807 | 0.5160\*\*\* | 0.0125 | -0.2678 | 0.2674 |
| Stock price volatility in 6 months | -0.6004\*\*\* | -0.1078\*\* | 2.0541\*\*\* | 3.9287\*\*\* | -0.6157\*\*\* | -0.1083\*\* | 2.1425\*\*\* | 3.9380\*\*\* |
| Acquisition | 0.0010 | -0.0003 | -0.0031 | -0.0015 | 0.0012 | -0.0003 | -0.0038 | -0.0023 |
| Special capital users dummy | 0.0040 | -0.0002 | -0.0143 | -0.0088 | 0.0035 | -0.0002 | -0.0120 | -0.0098 |
| Exposure to housing price change | -0.1041 | 0.0950\*\*\* | -0.8786\* | 1.0700 | -0.1009 | 0.0950\*\*\* | -0.8915\*\* | 1.0671 |
| HHI index | -0.0202\*\* | 0.0004 | 0.0237 | 0.0343 | -0.0184\* | 0.0006 | 0.0147 | 0.0393 |
| Intercept | 0.2764\*\* | 0.0809\*\*\* | 0.8010\*\*\* | 2.0780\*\*\* | 0.2597\* | 0.0792\*\*\* | 0.8806\*\*\* | 2.0400\*\*\* |
| Adj.R-squared | 0.475 | 0.189 | 0.046 | 0.136 | 0.477 | 0.188 | 0.047 | 0.136 |
| N | 3724 | 3724 | 3724 | 3724 | 3724 | 3724 | 3724 | 3724 |

### Table 7 The Effects of Derivative Use and DFA on Bank Performance

The dependent variables in the regressions are change in conditional Tobin’s Q, net interest margin ratio and return on assets. PostDFA is a dummy set to one after Dodd-Frank Act is issued and zero otherwise. All regressions include unreported time fixed effects and firm fixed effects. Size is calculated as the logarithm of total asset. Exposure to housing price change is a weighted average of the returns on the state-specific Fannie Mae real estate index where the weights are the fraction of bank deposits in the various states. HHI is a weighted average of the Herfindahl-Hirschman index where the weights are the fraction of bank deposits in the various states. Special capital is a dummy set to one if the bank uses any of the government bailout special capital programs. Acquisition is a dummy set to one if the bank acquires other banks in that quarter. Liquid is calculated as cash and cash equivalent scaled by total assets. Beta is the market beta calculated using 1 year of daily stock price. Standard errors are heteroskedasticity-consistent.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| 　 | (1) | (2) | (3) | (4) | (5) | (6) |
| 　 | Tobin's Q | Roa | Cost to Income | Tobin's Q | Roa | Cost to Income |
| IRD traded OTC  | 0.0017 | 0.0002 | -0.0026 | 0.0020 | 0.0001 | 0.0040 |
| IRD traded on exchange | 0.0591 | -0.0051\* | 0.0602 | 0.0988\*\* | -0.0040 | 0.0656 |
| Credit Derivatives net OTC  | -0.2396 | 0.0156 | 0.3226 | -0.3889\*\* | 0.0043 | 0.0899 |
| Post DFA dummy |  |  |  | -0.0819\*\*\* | 0.0042\* | 0.0144 |
| IRD OTC \* PostDFA |  |  |  | 0.0009 | -0.0002\* | 0.0146\*\*\* |
| IRD exchange \* PostDFA |  |  |  | -0.0457 | 0.0007 | -0.1468\*\*\* |
| Credit OTC \* PostDFA |  |  |  | 0.1225 | 0.0137 | 1.6326 |
| Size | 0.0162 | -0.0081\*\*\* | -0.0390\* | 0.0167 | -0.0080\*\*\* | -0.0426\* |
| Tier 1 ratio | 0.0725 | -0.0077 | -0.2043 | 0.0727 | -0.0077 | -0.2054 |
| Loan Loss Provision | -0.0168\*\*\* | -0.0077\*\*\* | -0.0069 | -0.0174\*\*\* | -0.0078\*\*\* | -0.0037 |
| Book to market ratio |  | -0.0033\*\*\* | 0.0216 |  | -0.0033\*\*\* | 0.0207 |
| Return on average assets | 0.1048\*\* |  | -0.7074 | 0.0974\* |  | -0.6759 |
| Short-term borrowing | 0.5477\*\*\* | 0.0135 | -0.3441 | 0.5381\*\*\* | 0.0122 | -0.2882 |
| Stock price volatility in 6m  | -0.5949\*\*\* | -0.1087\*\* | 2.0650\*\*\* | -0.6042\*\*\* | -0.1093\*\* | 2.0987\*\*\* |
| Acquisition | 0.0001 | -0.0003 | -0.0035 | -0.0001 | -0.0003 | -0.0026 |
| Special capital users dummy | 0.0042 | -0.0002 | -0.0141 | 0.0038 | -0.0002 | -0.0126 |
| Exposure to housing price change | -0.1020 | 0.0948\*\*\* | -0.8762\* | -0.1008 | 0.0949\*\*\* | -0.8904\*\* |
| HHI index | -0.0211\*\* | 0.0004 | 0.0238 | -0.0191\* | 0.0006 | 0.0170 |
| Intercept | 0.2820\*\* | 0.0816\*\*\* | 0.7912\*\*\* | 0.2638\* | 0.0800\*\*\* | 0.8615\*\*\* |
| Adj.R-squared | 0.473 | 0.189 | 0.046 | 0.476 | 0.188 | 0.048 |
| N | 3724 | 3724 | 3724 | 3724 | 3724 | 3724 |

|  |  |  |
| --- | --- | --- |
| Dependent Variables **Appendix** | Description | Relevant Literature |
| △CoVaR | The difference between the financial system’s Value at Risk (VaR) conditional on bank *i’*s being in distress and the financial system’s VaR in the median state of bank *i.* Bank *i’*s industry beta captures the sensitivity of its stock returns to the returns of the S&P Banks Selected Industry Index over a one-year period. | Gregor and Rouven(2016); Li and Marinč (2016); Mayordomo, Rodriguez-Moreno and Peña (2014); |
| MES | Marginal expected shortfall is defined as bank *i’*s mean return on days when the S&P Banks Selected Industry Index return reaches its lowest 5 percent level over a quarter period. | Li and Marinč (2016); Mayordomo, Rodriguez-Moreno and Peña (2014); Acharya, Pederseb, Philippon and Richardson (2017) |
| Banking industry beta | Sensitivity of stock daily return to the return of the S&P Banks Selected Industry Index based one-year time window | Nijskens and Wagner( 2010) |
| Z-score | Sum of the mean return on assets and the mean ratios of equity to assets, divided by the standard deviation of the return on assets | Mohsni and Otchere (2014); Keppo and Korte (2016); Bolhat, Bolton and Lu (2015) |
| Distance to Default | Calculated as the market value of assets minus the value of total debt, then scaled by the product of the market value of assets and annualized standard deviation in the market value of assets. | Eichler and Sobanski (2016); Jessen and Lando (2015) Hoque, Andriosopoulos and Douday (2015) |
| Value at Risk | The worst return that a bank expects to suffer at a confidence interval of 95% in a quarter.  | Li and Marinč (2016); Williams (2016)Adrian and Brunnermeier (2014);  |
| Stock price volatility in 6 months | Volatility of daily stock return in last 6 months | Trapp and [Weiß](https://www.sciencedirect.com/science/article/pii/S0378426616301145%22%20%5Cl%20%22%21) (2016); Dang and Helwege (2017)Chiang, Chung and Louis (2017);  |
| Tobin’s Q | The ratio of market value to book value of total assets | Chen, Li, Luo and Zhang (2017); Bhandari and Javakhadze (2017) Zeidan and Shapir (2017) |
| Cost to income ratio | Operating expense as a percent of operating income | Borio, Gambacorta, and Hofmann (2017);Almazari (2014); [Pelletier](https://www.sciencedirect.com/science/article/pii/S0378426617302844#!) (2018)Bitar, Pukthuanthong, and Walker (2017);  |
| Return on Asset | Net income as a percent of assets | Berger, Black, Bouwman and Dlugosz (2014); Beck, Chen, Lin and Song (2016); Dang and Helwege (2017) |

|  |  |  |
| --- | --- | --- |
| Independent Variables | Description | Relevant Literature |
| IR derivatives trading | The notional amount or par value of all off-balance-sheet interest rate derivative contracts held for trading purposes reported in Y9 call report, and then scaled by the bank’s total asset.  | Li and Marinč (2016); Li and Marinč (2014); Mayordomo, Rodriguez-Moreno and Peña (2014) |
| IR derivatives hedging | The notional value or par value of interest rate off-balance-sheet derivative contracts held for purposes other than trading reported in Y9 call report, and then scaled by the bank’s total asset | Li and Marinč (2016); Li and Marinč (2014); Mayordomo, Rodriguez-Moreno and Peña (2014) |
| Net credit derivatives (traded OTC) | The net notional amount is calculated as the notional amount of all credit derivatives for which the bank has obtained a guarantee against credit losses from other parties, minus the notional amount of all credit derivatives for which the bank has extended credit protection to others, then scaled by the bank’s total asset. According to SNL database, credit derivatives reported are all traded in OTC market. | Li and Marinč (2014); Hirtle (2009); Minton, Stulz and Williamson (2009) |
| IR derivatives traded OTC | Sum of the notional amount of interest rate forwards, interest rate swaps and the net long positions in OTC interest rate options  | - |
| IR derivatives traded on exchanges | Sum of the notional amount of interest rate futures and net long positions in exchange-traded interest rate options.  | - |
| Loan to depository institutions | Loans to all depository institutions as a percent of gross loans and leases | Mayordomo, Rodriguez-Moreno and Peña (2014) |
| Balance due from depository institutions | Balance due from depository institutions as a percent of gross loans and leases | Mayordomo, Rodriguez-Moreno and Peña (2014) |
| Loan loss provision | Loan loss provisions as a percent of net interest income | Dang and Helwege (2017); Li and Marinč (2014); Li and Marinč (2016) |
| Tier 1 ratio | Tier 1 capital as a percent of total risk-weighted assets | Berger, Black,Bouwman and Dlugosz (2014); Li and Marinč (2016); Dang and Helwege (2017) |
|  |  |  |
| Independent Variables | Description | Relevant Literature |
| PostDFA | Dummy equals to one after the DFA was singed into the federal law on July 21, 2010 | Cumming, Dai and Johan (2017);Keppo and Korte (2016);Sorokina and Thornton (2016) |
| Size | Logarithm of total asset  | Mayordomo, Rodriguez-Moreno and Peña (2014);Berger and Roman (2015); Li and Marinč (2017) |
| Special capital users dummy | Dummy equals to one if a bank disclosed to use the discount window borrowing or any of the four special capital programs namely troubled asset relief program (TARP), term securities lending facility, term auction facility and primary dealer credit facility. | Dang and Helwege (2017);Berger and Roman (2015);Berger, Black, Bouwman and Dlugosz (2014) |
| Exposure to housing price change | The average weighted housing return derived by using the proportion of deposits a bank has in each state.  | Dang and Helwege (2017) |
| HHI index | The average weighted Herfindahl-Hirschman Index derived by using the proportion of deposits a bank has in each state, | Berger and Roman (2015) |
| Book to market ratio | Book value of total equity as a percent of market capitalization | Dang and Helwege (2017); Bhandari and Javakhadze (2017);Weiß, Bostandzic and Neumann (2014) |
| Short-term borrowing | Borrowings with a maturity of one year or less as a percent of asset | Mayordomo, Rodriguez-Moreno and Peña (2014); |
| Acquisition | Dummy equals to one if a bank acquired another bank in that quarter | Dang and Helwege (2017); |
| Liquid | The sum of cash and cash equivalents as a percent of asset | Li and Marinč (2017); Li and Marinč (2014);Dang and Helwege (2017); |
| Beta  | Sensitivity of stock daily return to the return of the S&P 500 Index based on one-year time window | Li and Marinč (2017); Dang and Helwege (2017);Trapp and [Weiß](https://www.sciencedirect.com/science/article/pii/S0378426616301145#!) (2016); |

**Figure 1**

1. Data retrieved from Federal Reserve Bank of Chicago, https://www.chicagofed.org/applications/bhc\_data/bhcdata\_index.cfm [↑](#footnote-ref-1)
2. The five classes of derivatives are interest rate derivatives, foreign exchange derivatives, credit derivatives, equity derivatives and commodity derivatives. [↑](#footnote-ref-2)
3. Other studies have also examined the effects of the DFA on market principle (Balasubramnian and Cyree, 2014) and credit rating (Dimitrov, Palia and Tang, 2014) [↑](#footnote-ref-3)
4. The list of variables describing the current market situation includes: VIX, the index of implied volatility of the stock market tracked by the Chicago Board Options Exchanges; Liquidity Spread, which captures the difference between the three-month repo rate, and the three-month bill rate; Changes in Three-Month Treasury Bill Rate; Changes in the Slope of the Yield Curve, measured by the yield spread between the ten-year treasury rate and the three-month bill rate; Changes in the Credit Spread, measured by the credit spread between ten-year BAA-rated bonds and the ten-year treasury rate; Return of the S&P 500 Index and Real Estate Sector Return in Excess of the Market Return. [↑](#footnote-ref-4)
5. There were more than 18 banks that underwent stress test. We get the sample of 18 banks due to data unavailability for some stress tested banks. [↑](#footnote-ref-5)
6. Contracts held for trading purposes include those used in dealing and other trading activities accounted for at market value (or at lower of cost or market value) with gains and losses recognized in earnings. [↑](#footnote-ref-6)
7. Interest rate derivatives traded OTC includes interest rate forwards, swaps and the net long positions in OTC interest rate options while interest rate derivatives traded on exchange includes interest rate futures and net long positions in exchange interest rate options. According to SNL database, credit derivatives reported are all traded in OTC market. [↑](#footnote-ref-7)
8. Accordingly, interconnectedness measures the content to which a bank is connected with other institutions in such a way that its stress could easily be transmitted to other institutions. [↑](#footnote-ref-8)
9. In a robustness analysis, we employ *Non-performing loans* and *Leverage ratio* as in Mayordomo et al (2014). The key results are discussed in the robustness analysis section. [↑](#footnote-ref-9)
10. Date source: https://www.federalreserve.gov/regreform/discount-window.htm [↑](#footnote-ref-10)
11. In a robustness analysis, we categorise derivatives into two sub-groups: derivatives traded in the OTC market and derivatives traded in the Exchange. We examine the effects of these two sub-groups on bank’s contribution to systemic risk. The key results are discussed in the robustness analysis section. [↑](#footnote-ref-11)
12. Results of robustness test are available upon request. [↑](#footnote-ref-12)
13. In later regression, we apply the logarithm value of total asset, loan to depository institutions as a percent of total loans and balance due from depository institutions as a percent of total loans instead of their dollar values. [↑](#footnote-ref-13)