Financial derivatives and bank risk: Evidence from eighteen developed markets

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Abstract

We examine the relationship between equity risk and the use of financial derivatives with a sample of 555 banks from eighteen developed markets from 2006 to 2015. Our main findings suggest that banks' use of financial derivatives increased their risk. This increase in risk can be driven by banks' use of derivatives for speculative purposes, by suboptimal hedging to obtain hedge accounting status, or from accounting mismatches that generate volatility in earnings. We also show that this relationship is nonlinear. Too-Big-To-Fail banks and those that employ a traditional retail banking business model are subject to lower idiosyncratic risk. We address endogeneity concerns using instrumental variables capturing the use of derivatives with portfolio ranking. Overall, our study contributes to understanding the impact of derivatives use on bank risk and the risk consequences of a bank's business model choice.

Keywords: *Derivative Accounting; Fair Value; Financial Derivatives; Risk Management.*

1. INTRODUCTION

This study examines the impact of the use of financial derivatives on bank realized risk. The derivatives market has grown substantially over the past fifteen years, with the total notional amount of outstanding over-the-counter (OTC) derivatives having reached US$493 trillion by the end of 2015—an increase of more than 424% over the year 2000 (Figure 1). Banks are the major player in the OTC market and have held a significant portion of these derivatives, acting as intermediaries in the interactions between nonbank participants, carrying out interbank trading as part of day-to-day business, and clearing positions created by making markets for their clients. The largest banks also provide OTC derivatives to both nonfinancial firms and other banks. In day-to-day business, these banks may take advantage of their market-making roles to see the flows of OTC derivatives trading and carry out proprietary trading accordingly. In fact, anecdotal evidence suggests that some, if not all, banks use financial derivatives to bet on future changes in the prices of underlying securities.[1] In the aftermath of the global financial crisis, regulators have expressed concerns about derivative exposures in banks' balance sheets.[2]

Derivatives are used by firms to hedge cash flow and earnings from unfavorable fluctuations in risk exposures, such as interest rates, foreign currency exchange rates, and commodity prices (Bartram et al., 2009). Prior literature generally supports that banks use derivatives to manage risk by complementing traditional lending activity (Brewer et al., 2001), to smooth earnings (Barton, 2001), or to manage equity risk directly and indirectly (Abdel-Khalik & Chen, 2015). Studies that focus on the impact of derivative accounting standards on firm risk management identify that: (a) fair value reporting of derivatives makes their use more transparent and encourages prudent risk management (Melumad et al., 1999) and, (b) although speculative activities have been reduced (Zhang, 2009), sound hedging strategies have also been compromised (Lins et al., 2011). By reducing speculative activities, we expect a decrease

[1] For example, the trader known as the "London Whale" within JP Morgan Chase gambled heavily on an obscure corner of the credit default swap (CDS) market and lost $6.2 billion (Financial Conduct Authority, 2013). Banks have also been fined for manipulating benchmark rates—including LIBOR, FOREX, and Isdafix, which determine the payout of derivatives—to benefit their own trading positions (Financial Conduct Authority, 2016).

[2] The Basel Committee (2010, 2011) pointed out that one of the main reasons the financial crisis became so severe was that the banking sector of many countries had built up excessive on- and off-balance sheet leverage.

in risk; however, given that sound hedging strategies are also compromised, the expectation is an increase in risk. Given this, whether the use of derivatives leads to more or less risk is unclear.

We study the impact of the use of derivatives on bank risk by regressing the extent of derivatives usage (measured in fair value) on bank-level risk measures (i.e., total risk, systematic risk, and idiosyncratic risk). We find an overall positive relationship between the use of derivatives and bank risk. A potential explanation for this finding is that low informativeness of derivative accounting curtails the decision usefulness of financial reporting. The different incentives for using derivatives, the complex nature of derivative accounting (FASB, 2008), banks' inability in applying accounting rules for derivatives correctly or consistently (Kawaller, 2004), and dispersed earnings forecasts due to analysts' misinterpretation of the effect of derivatives (Chang et al., 2016) have collectively posed substantial challenges for investors in evaluating the risk inherent in derivative securities.

We also show that the relationship between derivatives and bank risk is nonlinear. In particular, we show that in Too-Big-To-Fail (TBTF) banks and retail-oriented banks the use of derivatives lowers the level of idiosyncratic risk. Finally, we address potential endogeneity problems using instrumental variables capturing the use of derivatives with portfolio ranking and confirm that our results come from a causal relationship between banks' use of derivatives and realized risk.

Our study contributes to the literature in the following ways. First, our study complements prior literature, which is largely based on nonfinancial firms, on the effect of derivative accounting on firm risk management (Singh, 2004; Richie et al., 2006; Zhang, 2009; Glaum & Klöcker, 2011; Lins et al., 2011). Given banks' extensive participation in derivative activities for trading and risk management purposes, our focus on the banking industry provides some additional interesting insights into this issue. Second, this study contributes to the literature on the risk consequences of a bank's business model choice. Prior literature documents a number of benefits associated with a retail-oriented banking model.[3] We add to this body of research by investigating the effect of the business model choice on the association between the use of

[3] For instance, Altunbas et al. (2011) find that a strong deposit ratio and greater income diversification improve bank resilience. Ayadi et al. (2013) document that retail-oriented banks are less likely to default. Demirgüç-Kunt and Huizinga (2010) suggest that banking strategies that rely predominantly on attracting non-deposit funding or generating noninterest income are very risky. Mergaerts and Vander Vennet (2016) show that a strong reliance on retail banking activities is associated with higher profitability and stability.

derivatives and bank risk, and showing that retail-oriented banks are subject to lower risk than are investment-oriented banks. Third, our study is based on a sample of 555 banks listed in eighteen developed markets over the period 2006–2015, which compares favourably to prior studies (e.g., Choi & Elyasiani, 1997; Hirtle, 1997; Carter & Sinkey,1998; Li & Marinč, 2014; Mayordomo et al., 2014). We believe that this constitutes an important empirical contribution to the banking literature, as the results generated and conclusions drawn are likely to be more representative than are those that are derived from a smaller sample. In addition, the use of more recent data provides information about the current state of the banking sector.

The remainder of the paper proceeds as follows: In Section 2 we review the literature and develop the research hypotheses. Section 3 identifies the data sources, describes the sample selection process, defines the variables, and establishes the empirical methods. Section 4 reports the main results and robustness tests, and Section 5 concludes.

2. LITERATURE AND HYPOTHESES DEVELOPMENT

2.1. Derivative Accounting and Risk Management

A firm can hold derivatives to offset the inherent business risk (perfect hedge), to partially offset the inherent business risk (partial hedge), or to increase risk. Irrespective of the usage purpose, accounting rules for financial instruments follow a "mixed-attribute" model under which derivatives are reported as either assets or liabilities on the balance sheet at fair value, with unrealized gains/losses due to changes in fair value reported on the income statement (FASB, 1998). IAS 39 (*Financial Instruments: Recognition and Measurement*)[4] and SFAS 133 (*Accounting for Derivatives Instruments and Hedging Activities*) prescribed rules under which hedge accounting may be applied. Hedge accounting modifies the normal basis for recognizing gains/losses on a hedged item or hedging instrument. This treatment enables gains/losses on hedging instruments to be recognized in earnings in the same period as offsetting losses/gains on hedged items (Ramirez, 2015). This means income effects from both components of the hedge relationship (i.e., the hedging instrument and hedged item) affect earnings in a common

[4] While it was the regulation in place during the period under study, IAS 39 has been replaced by IFRS 9 since 1 January 2018. Key changes have been made to the following areas: classification and measurement of financial assets, classification and measurement of financial liabilities, impairment, and hedge accounting. See "*IFRS 9: Financial Instruments – High Level Summary*" (Deloitte, 2016) for a detailed discussion.

accounting period, thus minimizing income volatility (Kawaller, 2004). Unrealized gains/losses that result from transactions not qualifying for hedge accounting or that result from hedge infectiveness are recognized in earnings as they occur. Effective hedging can thus mitigate both earnings and cash flow volatility (Zhang, 2009).

However, IAS 39 and SFAS 133 had the potential to increase the volatility of both earnings and return on shareholders' equity (Lins et al., 2011). The extent to which volatility is affected depends on whether the derivatives position pass the effectiveness test to qualify for hedge accounting. To qualify for hedge accounting status, firms have to show that the derivative is designated to offset an underlying economic exposure, and that the hedge is highly effective (i.e., the exposure and the value of the hedging instrument are highly correlated). A hedge is deemed effective if the ratio of the change in derivative value to that of the hedged item falls within a range of 80%–125% over the life of the hedge (the 80/125 rule). This specific criterion leaves some scope for ineffectiveness. As Kalotay and Abreo (2001:94) observe, "an unintended and unfortunate consequence of the 80/125 rule is that during periods of market stability virtually any hedge is likely to fail, even though the resulting price movements are insignificant from a business perspective."

Let's assume, for example, that a bank hedges $100 million loans with an interest rate swap (IRS). A $10,000 change in the value of the loans and a $5,000 opposite change in the value of the swap would result in the ratio 0.5, which violates the 80/125 rule and leads to an "ineffective hedge." The bank is thus left with two basic choices: (1) obtaining hedge accounting status by increasing the use of the swap to at least $8,000 or (2) forgoing an economically effective hedging strategy rather than obtaining hedge accounting status (Lins et al., 2011), thus reflecting the impact of interest rate changes in reported earnings. Although the first choice allows the bank to obtain hedge accounting status, the bank is forced to take on additional risk as it uses more derivatives than it truly needs. The bank effectively pursues suboptimal hedging that is less efficient and prudent. The second choice would inflate the volatility of the bank's earnings.

In addition, the ratio 0.5 in the previous example is likely to be even lower if a bank holds a significant amount of non-term deposits that are fairly insensitive to changes in interest rate and thus serve as a type of hedge against the effect of interest rates changes on loans (Flannery

& James, 1984). When interest rates increase, the fair value of fixed-rate loans held by the bank will decrease. However, this loss will be offset by a rise in the fair value of the deposits due to the increasing benefits of low- or no-cost financing in an increasing interest rate environment. The bank will appear more volatile than it truly is if the hedge offered by deposits is not recognized but the fair value of loans is acknowledged (Blankespoor et al., 2013).

An accounting mismatch may also be present when banks use credit default swaps (CDS) to hedge the credit risk arising from loans and loan commitments. Such a mismatch arises mainly because loans and loan commitments are normally not accounted for at fair value through profit or loss. The simplest accounting treatment would designate the credit risk as a risk component in a hedging relationship. However, as noted by the International Accounting Standards Board, it is difficult to isolate the credit risk as a separate risk to meet the eligibility criteria for risk components. The accounting mismatch would, in turn, create volatility in profit or loss (EY, 2014).

To summarize, there are at least three potential channels through which banks increase their risks when using and reporting derivatives. First, banks can use derivatives for a speculative purpose rather than for hedging risks. Second, when banks use derivatives to manage risks (hedge) they can pursue suboptimal hedging to obtain hedge accounting status. Third, an accounting mismatch may arise from the difficulty in isolating the credit risk as a separate risk when banks use CDS to hedge the credit risk arising from loans and loan commitments, generating profit or loss volatility.

Based on this discussion, we posit:

Hypothesis 1. Banks that ex-ante hold a higher level of derivatives experience more risk ex-post than do banks that ex-ante hold a lower level of derivatives.

2.2. Financial Derivatives and Bank Risk

There are two primary sources of revenue for banks that participate in derivatives markets: one that comes from using derivatives as speculative vehicles, and the other that is generated when banks act as OTC dealers and charge fees to institutions that are placing derivative positions (Brewer et al., 2001). The former is considered one of the main motivations for using financial derivatives, a view that is well established in the literature. Instefjord (2005) identifies two effects of credit derivatives innovation on the banking sector: they enhance risk sharing but also make additional acquisition of risk more attractive. A frequently asked question in this line of literature concerns whether firms use derivatives to hedge or to speculate. Most of these studies are based on nonfinancial firms. Chernenko and Faulkender (2011) consider hedging and speculation as the two sides of derivatives use, while Hentschel and Kothari (2001) provide detailed definitions that distinguish one from the other: "risk management that reduces [stock] return volatility is frequently termed hedging, and risk management that increases [stock] return volatility is called speculation." According to O'Conner et al. (2011), hedging takes place when companies protect themselves against unexpected changes in rates that affect the returns they obtain from their underlying business, while speculation is associated with firms' profit-seeking behavior by trading against a mispriced market. The two sets of definitions are similar, as both state that speculation takes place when the motive for using derivatives is associated with additional risk taking driven by profit seeking, not with hedging risk. The key assumption in these studies is that the motive behind the decision to use derivatives is to hedge risk rather than to speculate, but there are other reasons for using derivatives that may or may not reduce risk: reducing the expected cost of financial distress (Smith & Stulz, 1985), avoiding costly external financing by improving the match between internal cash flow and financing needs (Froot et al., 1993), reducing the volatility of executive compensation (DeMarzo & Duffie, 1995), and speculating on movements in interest rates and earnings management (Bodnar et al., 1998; Faulkender, 2005; Geczy et al., 2007), among other reasons.

With regard to the relationship between the use of derivatives and their impact on firm risk, Guay (1999) examines the impact of derivatives on firm risk among new users of derivatives and finds evidence that firm risk declines following the initial use of derivatives. Hentschel and Kothari (2001) study 425 large US corporations and find that, although many firms manage exposure with large positions in derivatives, their use does not necessarily reduce firm risk below that of firms that do not use them. Based on a sample of Australian firms, Nguyen and Faff (2010) show a nonlinear relationship between the use of derivatives and firm risk, finding that moderate users of derivatives reduce firm risk, while extensive users increase it. Based on a large sample of nonfinancial firms from forty-seven countries, Bartram et al.'s (2011) findings suggest that the use of financial derivatives reduces both total risk and systematic risk and that derivative use was associated with significantly higher firm value, higher abnormal returns, and larger profits during the economic downturn in 2001-2002, when firms were hedging downside risk.

In the context of the banking industry, Hirtle (1997) argues that derivatives have played a significant role in shaping US bank holding companies' (BHCs) exposure to interest rate risk and that the positive association between the use of derivatives and exposure to interest rate risk is particularly strong for smaller banks, end-user banks, and BHCs that act as dealers. Choi and Elyasiani (1997) also establish a link between derivatives transactions and a bank's overall risk exposure, which indicates that derivatives can be a source of increased solvency exposure. Venkatachalam (1996) contends that the average bank during the 1993-1994 period reduced its risk exposure by using derivatives, although more than half of the banks in Venkatachalam's study appeared to use derivatives to assume additional risk rather than to reduce it. Minton et al. (2009) examine the extent to which US BHCs with assets in excess of US$1 billion used credit derivatives to hedge in the decade from 1995 to 2005, primarily for the purpose of dealer activities rather than for hedging credit exposure from loans.

We predict that the relationship between banks' use of derivatives ex-ante and realized idiosyncratic risk is nonlinear. Moderate use and aggressive use would lead to two opposite consequences: risk reduction and excessive risk taking, respectively. Therefore, we posit:

Hypothesis 2. The relationship between banks' use of derivatives ex-ante and realized idiosyncratic risk is nonlinear: moderate use reduces risk, while aggressive use results in excessive risk taking.

2.3. Bank Financial Characteristics

Some studies focus on the financial characteristics of banks that use (and do not use) financial derivatives. Carter and Sinkey (1998) find that a large community bank's decision to use interest-rate derivatives is positively associated with its size. They also find a positive relationship between the use of IRS and capital position, which they interpret as the effect of regulatory and/or market discipline on banks' obedience to capital adequacy requirements.

However, Sinkey and Carter's (2000) later study of US commercial banks' use of derivatives reveals no evidence of an association between banks' capital positions and derivatives activities. They also find that banks that use derivatives have riskier capital structures, larger maturity mismatches between assets and liabilities, lower net interest margins, and more loan charge-offs than those that do not use derivatives. The positive relationship between bank size and the use of derivatives is often interpreted as a cost-related motive for using derivatives or economies of scale–that is, that larger banks are more likely to make the investment in intellectual capital and control systems that is necessary to participate in derivatives activities (Carter & Sinkey, 1998; Sinkey & Carter, 2000). TBTF banks[5] are perceived to have a higher propensity to assume excessive risk in order to profit in the short term, because they rely on an implicit government backstop. The existence of TBTF banks has often been criticized as one of the main factors in the distortion in banks' risk-taking incentives (Boyd et al., 2009). The financial system is a system of promises, and derivatives allow TBTF banks to shift those promises around to arbitrage differences in risk weightings, regulatory differences, and taxes between sectors and jurisdictions. In the case of credit spreads, where TBTF banks are concerned, risk tends to be underpriced, resulting in lower credit spreads than would apply to separate derivative trading entities that do not have access to retail/commercial bank capital and official and unofficial guarantees and support (Blundell-Wignall & Atkinson, 2011). Based on this discussion, we anticipate that the ex-post risk for TBTF banks is lower than that of non-TBTF banks that also use derivatives, so we formulate the following hypothesis:

Hypothesis 3. TBTF banks' use of derivatives leads to a lower level of idiosyncratic risk than does non-TBTF banks' use of derivatives.

The modern theory of financial intermediation explains how derivative contracting and lending can be complementary activities in banking. Diamond's (1984) model shows that banks have monitoring advantages over small depositors, as banks can reduce their exposure to

[5] TBTF banks refer to the global systemically important banks (G-SIBs) identified by the Financial Stability Board (in consultation with Basel Committee on Banking Supervision and national authorities). G-SIBs are subject to higher capital buffer requirements, total loss-absorbing capacity requirements, resolvability requirements, and higher supervisory expectations (Financial Stability Board, 2016).

systematic risk by using derivatives to resolve mismatches in their assets' and liabilities' sensitivities to interest rates. Thus, interest-rate derivative activity can complement lending activity, but derivatives can also replace lending activities. A bank may alter its business model and move away from traditional lines of business in order to improve its financial performance. Brewer et al. (2000) document an increasing trend in FDIC-insured commercial banks' use of derivatives, a trend that is accompanied by a downward trend in traditional lending activity, suggesting a substitution role for derivatives. Clark et al. (2007:40) observe, "At the bank level, the principal attraction of retail banking seems to be the relief that its revenues are stable and thus can offset volatility in the nonretail businesses. At the aggregate level, […] interest in retail banking fluctuates in rather predictable ways with the performance of nonretail banking and financial market activities."

Banks disclose relatively uniform and detailed information about their loan portfolios, such as loan charge-offs and nonperforming loans, which facilitates control of the intrinsic value of loans (Nissim, 2003). Retail-oriented banks are also better able to convert additional credit risk into a higher net interest margin, implying that retail banks can screen and monitor loans more effectively (Mergaerts & Vander Vennet, 2016). On the other hand, retail deposits represent a relatively stable source of long-term funding for banks. This is primarily because deposits are insured by the government in almost all developed economies[6] and their withdrawals, in most cases, are motivated by individual depositors' liquidity needs and thus predictable at the aggregate level (Huang & Ratnovski, 2011). The "sluggishness" of retail deposits also stems from the high switching costs associated with transaction services (e.g., information costs to discover a bank with more favorable rates; costs of learning different rates and conditions on the new deposits) that retail deposits receive from banks (Sharpe, 1997; Kim et al., 2003). Because non-term deposits (e.g., demand and savings deposits) are considerably insensitive to changes in interest rates, they also serve as a type of hedge against the impact of changes in the interest rate on loans (Flannery & James, 1984).

Based on this discussion, we formulate the following hypothesis:

[6] The only exception is New Zealand. See Demirgüç-Kunt et al. (2014) for a complete list of countries with explicit deposit insurance schemes as of the end of 2013.

Hypothesis 4. The use of derivatives by banks that employ a traditional retail banking business model leads to a lower level of idiosyncratic risk than it does for banks that employ a nonretail banking business model.

3. DATA AND EMPIRICAL DESIGN

3.1. Data and Sample Selection

To investigate the effects of derivatives use on bank risk, we collected data from Bankscope on the derivatives held at the end of each fiscal year during our sampling period (2006-2015) and other accounting data for banks from eighteen countries, and daily stock price data from Compustat from January 2006 to December 2015. We also retrieved stock indices for the financial sector from Thomson Reuter Datastream to calculate market return in each of the eighteen countries.

Specifically, we employed the following risk measures:

- Total risk (TR): The variance in daily stock returns in the fiscal year that derivatives were reported.
- Systematic risk (SR): The product of the variance between the financial services sector's daily market return and bank i's market beta (β_m) squared. β_m is obtained from a market model as follows:

$$R_{it} = \beta_0 + \beta_m R_{mt} + \varepsilon_{it}$$

R_{it}: Daily stock return of bank i

R_{mt}: Daily return on the financial sector

ε_{it}: Error term

- Idiosyncratic risk (IR): Variance in the residuals ε_{it} from the market model above.

After matching the two datasets and dropping observations with missing data, we obtained a final sample of 555 banks and 3,313 bank-year observations. Tables 1 and 2 report the sample composition by country and by year, respectively. Although a substantial part of our sample comprises US banks, the number of non-US banks facilitates a balance between US and non-US banks (i.e., 56.6 percent versus 43.4 percent).

Insert Tables 1 and 2 about here

3.2. Empirical Design

To determine the impact of the use of derivatives on bank risk, we estimate the following five models:

$$
\begin{aligned}
TR_{i,t} = {} & \alpha_0 + \alpha_1 DETA_{i,t-1} + \alpha_2 SIZE_{i,t-1} + \alpha_3 MTB_{i,t-1} + \alpha_4 NEA_{i,t-1} + \alpha_5 NPL_{i,t-1} + \alpha_6 LIQUID_{i,t-1} \\
& + \alpha_7 TIER1_{i,t-1} + \alpha_8 NETCO_{i,t-1} + \alpha_9 NIM_{i,t-1} + \alpha_{10} INCO_{i,t-1} + \alpha_{11} CIR_{i,t-1} \\
& + \alpha_{12} ROAA_{i,t-1} + \alpha_{13} GLG_{i,t-1} + \alpha_{14} DEPOSIT_{i,t-1} + \alpha_{15} DIV_{i,t-1} + FE + \varepsilon_{i,t-1}
\end{aligned} \tag{1}
$$

$$
\begin{aligned}
SR_{i,t} = {} & \beta_0 + \beta_1 DETA_{i,t-1} + \beta_2 SIZE_{i,t-1} + \beta_3 MTB_{i,t-1} + \beta_4 NEA_{i,t-1} + \beta_5 NPL_{i,t-1} + \beta_6 LIQUID_{i,t-1} \\
& + \beta_7 TIER1_{i,t-1} + \beta_8 NETCO_{i,t-1} + \beta_9 NIM_{i,t-1} + \beta_{10} INCO_{i,t-1} + \beta_{11} CIR_{i,t-1} \\
& + \beta_{12} ROAA_{i,t-1} + \beta_{13} GLG_{i,t-1} + \beta_{14} DEPOSIT_{i,t-1} + \beta_{15} DIV_{i,t-1} + FE + \varepsilon_{i,t-1}
\end{aligned} \tag{2}
$$

$$
\begin{aligned}
IR_{i,t} = {} & \gamma_0 + \gamma_1 DETA_{i,t-1} + \gamma_2 SIZE_{i,t-1} + \gamma_3 MTB_{i,t-1} + \gamma_4 NEA_{i,t-1} + \gamma_5 NPL_{i,t-1} + \gamma_6 LIQUID_{i,t-1} \\
& + \gamma_7 TIER1_{i,t-1} + \gamma_8 NETCO_{i,t-1} + \gamma_9 NIM_{i,t-1} + \gamma_{10} INCO_{i,t-1} + \gamma_{11} CIR_{i,t-1} \\
& + \gamma_{12} ROAA_{i,t-1} + \gamma_{13} GLG_{i,t-1} + \gamma_{14} DEPOSIT_{i,t-1} + \gamma_{15} DIV_{i,t-1} + FE + \varepsilon_{i,t-1}
\end{aligned} \tag{3}
$$

$$
\begin{aligned}
IR_{i,t} = {} & \theta_0 + \theta_1 PR_{i,t-1} + \theta_2 PR^2_{i,t-1} + \theta_3 SIZE_{i,t-1} + \theta_4 MTB_{i,t-1} + \theta_5 NEA_{i,t-1} + \theta_6 NPL_{i,t-1} + \theta_7 LIQUID_{i,t-1} \\
& + \theta_8 TIER1_{i,t-1} + \theta_9 NETCO_{i,t-1} + \theta_{10} NIM_{i,t-1} + \theta_{11} INCO_{i,t-1} + \theta_{12} CIR_{i,t-1} \\
& + \theta_{13} ROAA_{i,t-1} + \theta_{14} GLG_{i,t-1} + \theta_{15} DEPOSIT_{i,t-1} + \theta_{16} DIV_{i,t-1} + FE + \varepsilon_{i,t-1}
\end{aligned} \tag{4}
$$

$$
\begin{aligned}
IR_{i,t} = {} & \lambda_0 + \sum_{j=1}^{10} \lambda_j \, PORT_{i,j} + \lambda_{11} SIZE_{i,t-1} + \lambda_{12} MTB_{i,t-1} + \lambda_{13} NEA_{i,t-1} + \lambda_{14} NPL_{i,t-1} + \lambda_{15} LIQUID_{i,t-1} \\
& + \lambda_{16} TIER1_{i,t-1} + \lambda_{17} NETCO_{i,t-1} + \lambda_{18} NIM_{i,t-1} + \lambda_{19} INCO_{i,t-1} + \lambda_{20} CIR_{i,t-1} \\
& + \lambda_{21} ROAA_{i,t-1} + \lambda_{22} GLG_{i,t-1} + \lambda_{23} DEPOSIT_{i,t-1} + \lambda_{24} DIV_{i,t-1} + \varepsilon_{i,t-1}
\end{aligned} \tag{5}
$$

Models 1, 2, and 3 are baseline models for our empirical analyses. Model 1 evaluates the impact of the extent of derivative use on banks' TR, while Models 2 and 3 test the impact on SR and IR. In all three models, ex-post bank risk is modeled as a function of ex-ante derivatives use and other bank characteristics. DETA, which measures the extent of derivatives use, is the total fair value of a bank's derivatives scaled by total assets. Nguyen and Faff (2010) document that it is not the use of derivatives but its extent that affects firm risk. The use of the total fair value of derivatives enables the total exposures to the derivatives' counterparties to be accounted for, along with the counterparty risk (Venkatachalam, 1996). The coefficients of interest are α_1, β_1, and γ_1. We expect that banks that used more derivatives ex-ante are subject to higher level of realized risk. Models 4 and 5 test for a nonlinear relationship between bank risk and derivatives use. In estimating Model 4, we segment the sample at each decile of DETA to create a portfolio ranking (PR). PR equals 0 for nonusers of derivatives and ranges from 1 to

10 according to the PR by decile. Model 5 uses portfolio dummy variables to examine the marginal effect of derivatives use on bank risk. We divide our sample into eleven portfolios and include them in the same regression. Portfolio 0 is the baseline portfolio that contains banks that do not use derivatives, and portfolios 1−10 are generated by partitioning the banks in the sample according to their extent of derivatives use (DETA) at each decile, such that Portfolio 1 contains the lowest level of nonzero derivatives use in our sample and Portfolio 10 the highest. Thus, Model 5 is a fixed-effects model that benchmarks each portfolio's bank risk against the baseline portfolio's risk after taking the control variables into account. Thus, a negative coefficient on the portfolio dummy implies risk reduction, while a positive coefficient indicates an increase in the risk level over that of the baseline portfolio. The coefficient of interest is λ_j, and $PORT_j$ is banks' extent of derivatives use in each of the eleven portfolios. Therefore, a negative λ_j indicates a risk-reducing effect of derivatives use in comparison to the baseline portfolio, while a positive λ_j suggests a risk-inducing effect.

We include a number of control variables that are relevant to explaining bank risk: We calculate SIZE by taking the natural logarithm of total assets, as extant studies suggest that larger firms are more likely to engage in risk-reducing behavior (Nance et al., 1993; Geczy et al., 1997). Larger size also implies greater systemic importance, so the contribution to system-wide risk increases more than proportionately with relative size (Tarashev et al., 2010; Mayordomo et al., 2014). Market-to-book ratio (MTB) is a proxy for bank charter value[7], which plays a disciplinary role. Demsetz et al. (1997) find a negative relationship between charter value and bank-risk taking, while Galloway et al. (1997) document that banks with low charter value take significantly more risk. Nonearning assets (NEA) are computed by dividing nonearning assets by total assets. Under both US GAAP and IFRS, items included in the category of nonearning assets, such as goodwill and other intangibles that have been determined to have indefinite lives, are subject to an impairment test at least once per annum. In practice, the impairment test may not necessarily capture the value of the impaired assets, as the quantification of impairment loss often relies on a discount rate that does not reflect current market assessments or the appropriate risk. Therefore, we expect a positive relationship

[7] The charter value can be derived from factors related to entry into the industry and/or access to protected markets.

between NEA and TR. Nonperforming loans (NPL) are calculated by scaling nonperforming loans by total assets. Banks with higher NPL are more likely to be financially distressed (Purnanandam, 2007), so we expect a positive relationship between NPL and TR. LIQUID, which measures liquidity, is calculated by scaling the sum of liquid assets, cash and due from banks, and other securities by total assets. Since more liquid banks are less likely to be financially distressed (Purnanandam, 2007), we expect a negative association between LIQUID and IR. Tier 1 capital ratio (TIER1) measures a bank's capital position. Since banks with stronger capital positions are less likely to face financial distress (Minton et al., 2009), we expect a negative relationship between TIER1 and IR. NETCO, a proxy for exposure to credit risk, is calculated by dividing net loan charge-offs by total assets. We anticipate a positive association between NETCO and IR. Net interest margin (NIM) is calculated by dividing net interest income by total assets. INCO (interest coverage) is calculated as earnings before interest and taxes (EBIT) divided by total interest expense to provide a prederivative measure of exposure to interest rate risk. Cost-to-income ratio (CIR) is calculated by dividing operating expenses by the sum of net interest revenue and other operating income. We include this variable to control for differences in technical efficiency across banks (Boyd et al., 2006). Return on average assets (ROAA) is a profit measure. It is calculated by scaling net income by yearly averaged total assets. GLG refers to yearly growth rate of gross loans, while DEPOSIT is calculated by dividing total deposits by total assets. DIV is a dummy that takes the value of 1 if the bank paid dividends during the fiscal year, and zero otherwise. If a bank paid a dividend, it is less likely to be capital-constrained, as it could cut its dividends to strengthen its capital position. All variables in the final sample are winsorized at 1% in both tails to account for extreme observations. We also include fixed effects (FE) in our analysis to account for country- and year-specific effects.

4. RESULTS

4.1. Descriptive Statistics

Table 3 provides summary statistics of the variables used in the empirical analysis. Of the 555 banks in eighteen countries in our sample, 387 banks are derivatives users. The average total assets of all banks in our sample is US$150 billion, but the total assets of banks that use derivatives are US$215 billion. Banks that use derivatives tend to be larger primarily because large banks are usually more willing to invest in the training required to use derivatives, as the fixed costs associated with training can be spread among the opportunities offered by using a large number of derivatives (Brewer et al., 2001). Our sample includes G14 banks–the fourteen most active derivative dealer banks–the average total assets of which are US$1.92 trillion during the sample period. The mean interest coverage ratio of our sample is 2.97, suggesting that these banks can easily make the interest payments on outstanding debt with their EBIT. The mean Tier 1 regulatory capital ratio is 13.08 percent, suggesting that the banks in our sample are overall well capitalized. For ease of presentation, TR, SR and IR are multiplied by 100.

Table 4 reports the correlation for each of the variables. Univariate analysis shows a significant and negative correlation between TR and SIZE, TR and LIQUID, and TR and TIER1, as well as a significant and positive correlation between TR and NEA, TR and NPL, and TR and NETCO, providing preliminary support for our anticipated relationship between TR and these three control variables. The significant correlation between SIZE and DETA is consistent with the view that economies of scale and/or scope are present in banks' derivatives activities: the barriers to entry are high and include high setup costs for large global businesses and the need for sophisticated trading platforms with rapid execution times in the derivatives business (Blundell-Wignall & Atkinson, 2011). The significant and negative association between DETA and TIER1 provides preliminary support for the view that banks with less capital have greater incentive to manage capital by using derivatives. This finding contrasts Carter and Sinkey's (1998) finding of a positive relationship between the amount of capital and the use of derivatives and Sinkey and Carter's (2000) finding of no relationship. The significant and negative relationship between DETA and DEPOSIT indicates that banks that employ a business model that relies more on deposit taking are less engaged in derivatives activities.

Insert Tables 3 and 4 about here

4.2. Baseline Model Regression Results

Our baseline models (Models 1, 2, and 3) estimate whether the use of derivatives causes banks to undertake higher levels of risk. Hypothesis 1 pertains to a positive relationship between the use of derivatives ex-ante and ex-post bank risk. We test this hypothesis 1 by running the OLS estimation of bank risks (i.e., TR, SR, IR) at time t as a function of the level of derivatives at time t-1, controlling for other variables. We cluster standard errors at the bank- and year-level to account for within-bank and within-year correlation of the error terms, so standard errors computed are robust to heteroskedasticity, autocorrelation, and a correlated panel. The results, reported in Table 5, support Hypothesis 1: The coefficient of DETA is positive and statistically significant (columns 1 and 3); that is, bank risk is an increasing function of the extent of derivatives use, the extent of derivatives use is associated with an increase in banks' idiosyncratic risk, and there is no evidence for a link between derivative use and systematic risk. This last point is consistent with the conventional view that idiosyncratic risk is more relevant than systematic risk is in explaining the variation in an individual stock's risk over time. We also find that larger banks are better at mitigating risk (TR and IR), while they pose greater systematic risk (SR). Banks with higher charter value take less risk, confirming the disciplinary role of charter value in bank risk taking. Banks with more NEA are subject to higher TR and IR, indicating the substantial risk associated with evaluating and managing nonearning assets. LIQUID has a negative correlation with TR, but it is not statistically significant in the baseline results. The results for other control variables, such as NPL, TIER1, NETCO and DIV, are significant and consistent with our predictions. We also perform additional tests that decompose DETA at Levels I, II, and III[8], obtaining overall consistent results, as reported in Table 6. While all three of these measures are significantly and positively associated with IR, Level III derivatives result in the highest IR, a finding that is in line with the difficulties and uncertainty associated with fair value measurement of unobservable inputs at Level III. In unreported tests, we use derivatives with positive fair value and negative fair value separately and obtain results

[8] Level I inputs are quoted prices in active markets for identical assets or liabilities that the entity can access on the measurement date [IFRS 13:76]. Level II inputs are inputs other than the quoted market prices included in Level I that are observable for the asset or liability, either directly or indirectly [IFRS 13:81]. Level III inputs are unobservable inputs for the asset or liability [IFRS 13:86].

that are consistent with estimations that use the total fair value of derivatives to estimate baseline models.

Insert Tables 5 and 6 about here

4.3. A Nonlinear Relationship

We estimate Models 4 and 5 to test Hypothesis 2, which proposes that the relationship between banks' idiosyncratic risk and the use of derivatives ex-ante is nonlinear. We use OLS regression with robust standard errors computed as described in Section 4.2. The results, shown in Table 7, support Hypothesis 2. The coefficient of PR is negative and statistically significant, while the coefficient of PR^2 is positive and significant, so moderate use of derivatives reduced banks' idiosyncratic risk while aggressive use of derivatives led to excessive risk compared to that of nonusers. This finding of nonlinearity is consistent with Nguyen and Faff's (2010) finding. However, the story changes in regard to the banking industry. As our results show, a substantial number of banks assume additional risk by using derivatives, while other banks reduce risk. We believe that this difference is driven primarily by the differences between banks' and nonfinancial firms' business models. To ascertain the marginal impact of derivatives use on bank risk, we estimate Model 5, which employs portfolio dummy variables, as described in Section 3.2. Table 8 reports the relationship between the extent of derivatives use and the three risk measures, which relationship is in line with the results of Model 4. While the results in columns 1 and 3 are similar, we focus on the results in column 3 for purposes of brevity. Overall, in comparison to the baseline portfolio (Portfolio 0), banks in Portfolios 3, 4, 6, and 7 reduced their risk, banks in Portfolios 1, 9, and 10 increased their risk, and the risk level of Portfolios 2, 5, and 8 does not differ statistically significantly. IR appears to be a decreasing function of the extent of derivatives use up to the level of average derivatives held by banks in Portfolio 4 (0.2 percent), so the optimal level of derivatives held in the current sample is 0.2 percent, a level at which IR is minimized. Bank risk starts to increase when a bank's use of derivatives exceeds 3 percent, corresponding with the upper bound of banks' level of derivatives use in Portfolio 7. In Portfolios 8, 9, and 10—large banks with average total assets of US$0.17 trillion, US$0.55 trillion, and US$1.22 trillion, respectively—there is a tendency for the increase in bank risk to be an increasing function of the level of derivatives use. Together with the significant and negative coefficient of SIZE, this result reaffirms that larger banks have more expertise in risk management than smaller banks do. Banks in Portfolio 1 do not appear to be effective in achieving risk reduction through derivatives use, so the extent of derivatives use in Portfolio 1 can be seen as a threshold for using derivatives for the purpose of reducing risk. Moreover, the average size of the banks in Portfolio 1 is the lowest among the ten portfolios, which suggests that scale is an important barrier to entry into derivatives activities. It is also possible that the banks in Portfolio 1 are new derivatives users that do not have a well-developed system with which to hedge and apply hedge accounting effectively. However, banks in the four risk-reducing portfolios are smaller than those in risk-inducing portfolios, which, in conjunction with the greater reduction in risk achieved in these portfolios, provides support for the conventional view that smaller banks benefit the most from hedging with derivatives since the costs of bankruptcy are greater for these firms (Warner, 1977).

Insert Tables 7 and 8 about here

4.4. Too-Big-To-Fail Banks

The test for Hypothesis 3 examines the moderating effect of a bank's TBTF status in the association between a bank's use of derivatives and ex-post idiosyncratic risk. We estimate Models 1, 2, and 3 with an additional dummy variable, TBTF, and its interaction with DETA ($TBTF \times DETA$). TBTF equals 1 if a bank is identified as a globally systemically important bank in the Basel Committee's G-SIB assessment, and 0 otherwise. All other control variables are the same as defined in Section 3.2. The results, shown in Table 9, support Hypothesis 3. The coefficient on DETA remains positive and statistically significant, and the coefficient on the interaction term is negative and significant, which means that *ceteris paribus*, TBTF banks are subject to lower idiosyncratic risk than non-TBTF banks are.

Insert Table 9 about here

4.5. Bank Business Model

Similar to the test for Hypothesis 3, we test Hypothesis 4 based on the estimations of Models 1, 2, and 3, with an additional dummy variable, traditional retail banking (TRB) and its interaction with DETA ($TRB \times DETA$). TRB takes a value of 1 if a bank's deposits and loans exceed the sample's median[9], and 0 otherwise. Banks whose TRB equals 1 focus more on traditional banking activities and less on derivatives markets. All other control variables are the same as defined in Section 3.2. Table 10 reports the results for this estimation, which support Hypothesis 4. The coefficient on DETA is positive and statistically significant, while the interaction term is negative and significant, suggesting that banks that employ a traditional retail banking business model that focuses on deposit taking and loan making are subject to lower idiosyncratic risk than are banks that operate an investment banking business model.

Insert Table 10 about here

4.6. Robustness Tests

4.6.1. Endogeneity

The main empirical challenge that is critical to our study's design is a potential endogeneity problem induced by the reverse causality between the use of derivatives and bank risk; that is, a bank's risk level might affect its decision to use derivatives. Consequently, a simple regression of bank risk on derivatives use would likely to generate a biased coefficient on DETA. This methodological concern is aggravated by the difficulties in finding an ideal exogenous instrument that is correlated with DETA but uncorrelated with the error term in our baseline model specification. To control for the potentially endogenous use of derivatives in estimating the relationship between derivatives use and bank risk, we perform instrumental variables (IV) regression analyses, which are equivalent to two-stage least squares regression. Considering the nonlinear relationship between bank risk and derivatives use as discussed in Section 4.3, we use PR by decile and its quadratic form, PR^2, as the instruments[10] in the two-

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[9] Both loans and deposits are scaled by bank total assets. The sample medians are 0.820 and 0.649 for deposits-to-total-assets and loans-to-total-assets, respectively.

[10] We also perform Durbin-Wu-Hausman (Durbin, 1954; Wu, 1973; Hausman, 1978) test to compare the IV and OLS estimates. We reject the null hypothesis that both the IV and the OLS estimates are consistent at the 5% level, suggesting that OLS estimates are biased and that IV should be considered.

stage least squares regression. Identification of the IV model requires a strong correlation between the instruments and DETA. We perform the Kleibergen-Papp Rank LM test to determine whether the equation is identified such that it indicates whether the excluded instruments are correlated with the endogenous predictor, DETA. We reject the null hypothesis for this underidentification test, so the two instruments are relevant and the model is identified. We also perform a weak instrument test as proposed by Stock and Yogo (2005); if the F-statistic from the first-stage regression exceeds the critical value (using 10% bias), the instrument is deemed to be valid. The critical value is 19.93, which is less than the F-statistic, so we conclude that the instruments are not weak. In addition, the Hansen (1982) J test for overidentifying restrictions indicates that the null hypothesis of valid instruments is not rejected. (The p-values for the J-statistic of Models 1 and 3 are 0.687 and 0.147, respectively.) Overall, the results from these additional tests, reported in Table 11, are consistent with the results of the baseline model estimation, so we conclude that the potential endogeneity problem does not bias our results.

Insert Table 11 about here

The potential feedback effects between some facets of banking activity and the size and intensity of derivatives use also deserve a comment. For example, the use of derivatives may reduce banks' incentive to monitor their loan portfolios (Morrison, 2005). We share this concern with studies in this line of research (e.g., Mayordomo et al., 2014) and acknowledge that the use of derivatives can affect some bank activity, so tests of reverse causality among control variables are necessary to address this issue. However, neither our sample size nor frequency (yearly) is ideal for tests of reverse causality among explanatory variables, which is unlikely to generate results of high statistical power. We are also confined by the nontrivial identification of suitable instruments for each of these explanatory variables. Notwithstanding that this potential feedback is still a controversial problem, we refrain from performing these tests while acknowledging that the feedback effects between bank characteristics that are rooted in various aspects of banking activity should be monitored and addressed in future research, when the nature of the sample allows it to be.

4.6.2. Individual Effects of Different Types of Derivatives

We acknowledge that the impact on bank risk of the type of derivatives (e.g., interest rate derivatives, credit derivatives, foreign exchange derivatives, commodity derivatives, and equity derivatives) may differ, so tests of individual effect of these derivatives may be important. However, we refrain from performing these tests for three reasons. First, this type of data is readily available only for US banks, while for non-US banks considerable effort is required to either hand-collect the data or to combine multiple databases that are not compatible in the format of reporting. Second, we attempted to perform these tests based on a subsample consisting of available data on US banks[11] and found that the pairwise correlation between each of these five types of derivatives ranges from 73.4 percent to 96.8 percent, which makes disentangling the effect by type of derivatives difficult. Third, previous studies document a negative impact of interest rate derivatives on bank equity risk (Carter & Sinkey, 1998) and a positive impact of credit derivatives on bank equity risk (Minton et al., 2009). Future studies may look into the individual effects of different types of derivatives through more comprehensive and formal empirical tests, which should also be contingent upon data availability across countries.

4.6.3. Exclusions

We perform additional analyses to check on the robustness of baseline models' estimations. We first base our estimation on the sample that contains only banks that used derivatives during our sample period (2,001 observations) and obtain similar results (Table 12), although the effect of DETA on TR is not significant in this case. The main implication of these results is that banks that hold higher levels of derivatives assume additional risk, and this effect is still present in the sample that comprises only user banks. We also base our estimation for Models 4 and 5 on this user-only sample and obtain consistent results. Then we exclude the G14 banks—as, in addition to derivatives trading, they also undertake market-making and underwriting activities—and obtain results similar to baseline model results. We also exclude the financial crisis period (2007–2009) to rule out the excessive volatility in stock returns the crisis caused, which reduces the number of observations to 2,617 but leads to consistent results.

[11] Combining the accounting data from Bankscope, stock data from CRSP, and data on holdings of the five types of derivatives obtained from the Federal Reserve Bank, we obtain a sample of 293 US banks (1,875 observations).

Insert Table 12 about here

4.6.4. Out-of-sample Model Prediction

If a bank's use of derivatives increases its idiosyncratic risk, then a predictive model based on all of the control variables except DETA used in Model 3 should under-predict the idiosyncratic risk of banks that use derivatives. We divide the sample according to banks' participation in derivatives and estimate predicted idiosyncratic risk for two subsamples. The user sample comprises banks that used derivatives in the sample period (2,456 observations), and the nonuser sample comprises banks that did not use derivatives in the sample period (1,509 observations). We estimate Model 6 for the nonuser sample.

$$\begin{aligned} IR_{i,t} = \delta_0 &+ \delta_1 SIZE_{i,t-1} + \delta_2 MTB_{i,t-1} + \delta_3 NEA_{i,t-1} + \delta_4 NPL_{i,t-1} + \delta_5 LIQUID_{i,t-1} + \delta_6 TIER1_{i,t-1} \\ &+ \delta_7 NETCO_{i,t-1} + \delta_8 NIM_{i,t-1} + \delta_9 INCO_{i,t-1} + \delta_{10} CIR_{i,t-1} + \delta_{11} ROAA_{i,t-1} + \delta_{12} GLG_{i,t-1} \\ &+ \delta_{13} DEPOSIT_{i,t-1} + \delta_{14} DIV_{i,t-1} + FE + \varepsilon \end{aligned} \tag{6}$$

The coefficients estimated from the nonuser sample are applied to the sample of user variables to calibrate predicted IR for banks in the user sample. The average predicted IR for the user sample is 0.031, and the average actual IR is 0.035. A paired comparison test for the difference between these averages gives a t-statistic of -4.198, which indicates a statistically significant underprediction of IR by the baseline model (Model 3) without considering the role played by DETA.

5. CONCLUSION

We provide evidence on the relationship between the use of derivatives and bank risk. We find an overall positive relationship between banks' ex-ante use of derivatives and ex-post risk, suggesting that banks generally increase risk by using derivatives. In particular, we find that this relationship is nonlinear: moderate use of financial derivatives reduces risk, whereas aggressive use increases it. We also document that TBTF banks' use of derivatives lowers the level of idiosyncratic risk more than it does for non-TBTF banks and, for banks that operate a traditional retail banking business model, the use of derivatives lowers the level of idiosyncratic risk. Overall, our study contributes to understanding the impact of derivatives use on bank risk, and the risk consequences of a bank's business model choice.

This study has some limitations that are shared with previous studies mainly pertaining to data availability. First, the use of archival data (e.g., Singh, 2004; Richie et al., 2006; Zhang 2009) does not allow direct observation or measurement of firms' hedging behavior (Glaum & Klöcker, 2011; Lins et al., 2011). Second, because the use of derivatives is bonded with the financial reporting of derivatives, it is difficult to determine whether the effects on banks' risk are driven by the use or reporting of derivatives. Third, this study shows only the effect of derivative use on bank risk but not the potential return generated. Ultimately, banks are in the business of taking risk—without risk, they cannot generate required returns for shareholders. An interesting topic for future research can be whether the risk arising from using derivatives is "efficient" such that it increases bank performance enough to justify the risk taking.

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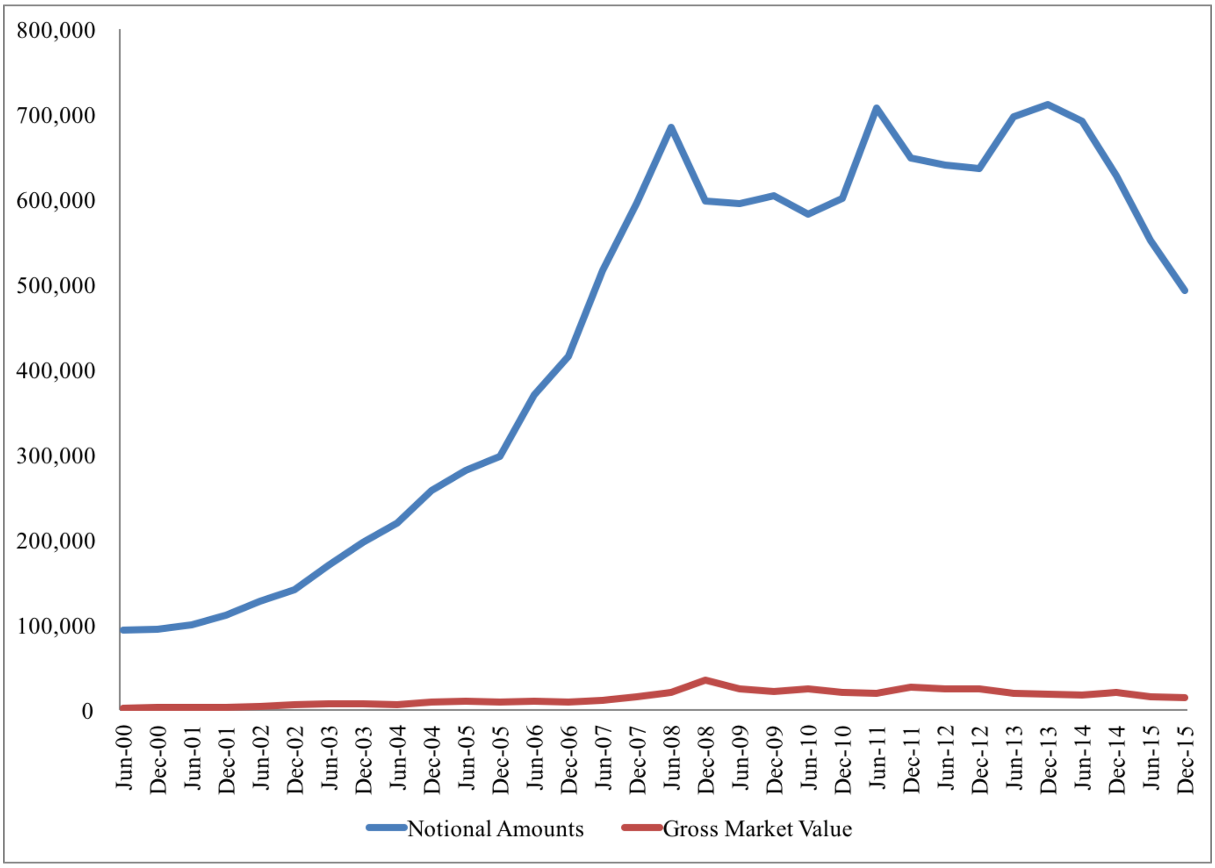
Figure 1. Global OTC Derivatives 2000-2015 (USD billion)



Source: BIS Derivatives Statistics

Table 1. Sample Composition by Country

Country	Frequency	Percentage
AUT	54	1.63
BEL	12	0.36
CAN	20	0.60
CHE	103	3.11
DEU	78	2.35
DNK	170	5.13
ESP	60	1.81
FIN	11	0.33
FRA	69	2.08
GBR	81	2.44
GRC	50	1.51
ITA	159	4.80
JPN	342	10.32
NLD	18	0.54
NOR	145	4.38
PRT	29	0.88
SWE	37	1.12
USA	1,875	56.60
Total	**3,313**	**100.00**

Table 2. Sample Composition by Year

Year	Frequency	Percentage
2006	171	5.16
2007	213	6.43
2008	221	6.67
2009	262	7.91
2010	286	8.63
2011	421	12.71
2012	452	13.64
2013	406	12.25
2014	436	13.16
2015	445	13.43
Total	**3,313**	**100.00**

Table 3. Descriptive Statistics

	Count	Mean	Standard Deviation	25th Percentile	Median	75th Percentile
TR*	3,313	0.064	0.079	0.021	0.033	0.070
SR*	3,313	0.020	0.036	0.001	0.007	0.020
IR*	3,313	0.043	0.063	0.012	0.021	0.043
DETA	3,313	0.035	0.094	0.000	0.001	0.015
SIZE	3,313	16.134	2.300	14.129	15.710	17.674
MTB	3,313	6.910	19.281	0.720	1.128	1.914
NEA	3,313	0.078	0.050	0.049	0.068	0.095
NPL	3,313	0.013	0.013	0.006	0.009	0.014
LIQUID	3,313	0.358	0.198	0.229	0.313	0.425
TIER1	3,313	0.131	0.044	0.105	0.125	0.148
NETCO	3,313	0.003	0.006	0.000	0.001	0.004
NIM	3,313	0.026	0.011	0.015	0.028	0.033
INCO	3,313	2.969	3.569	1.330	1.936	3.653
CIR	3,313	0.665	0.153	0.573	0.651	0.732
ROAA	3,313	0.006	0.010	0.003	0.007	0.010
GLG	3,313	0.071	0.158	-0.006	0.044	0.109
DEPOSIT	3,313	0.773	0.138	0.718	0.820	0.865
DIV	3,313	0.738	0.440	0.000	1.000	1.000

*For ease of presentation, TR, SR and IR are multiplied by 100.

Variable definitions are provided in Appendix 1.

Table 4. Correlation Between Variables

	TR	SR	IR	DETA	SIZE	MTB	NEA	NPL	LIQUID	TIER1	NETCO	NIM	INCO	CIR	ROAA	GLG	DEPOSIT
SR	0.610***	1															
IR	0.878***	0.156***	1														
DETA	0.047**	0.258***	-0.094***	1													
SIZE	-0.064***	0.388***	-0.310***	0.588***	1												
MTB	-0.103***	-0.010	-0.121***	-0.066***	0.212***	1											
NEA	0.092***	0.150***	0.025	0.093***	0.137***	0.081***	1										
NPL	0.340***	0.262***	0.269***	-0.053**	-0.015	-0.133***	0.102***	1									
LIQUID	-0.083***	0.042*	-0.127***	0.354***	0.319***	0.214***	0.353***	-0.124***	1								
TIER1	-0.164***	-0.120***	-0.133***	-0.043*	-0.192***	0.008	0.211***	-0.081***	0.342***	1							
NETCO	0.503***	0.182***	0.516***	-0.056**	-0.167***	-0.135***	0.163***	0.369***	-0.098***	0.000	1						
NIM	0.112***	-0.107***	0.201***	-0.368***	-0.607***	-0.357***	0.000	0.143***	-0.428***	0.047**	0.347***	1					
INCO	-0.306***	-0.164***	-0.282***	-0.112***	-0.008	0.167***	0.134***	-0.250***	0.199***	0.199***	-0.244***	0.003	1				
CIR	0.340***	0.025	0.409***	0.036*	-0.173***	-0.048**	0.091***	0.025	0.079***	-0.047**	0.187***	-0.006	-0.172***	1			
ROAA	-0.531***	-0.281***	-0.494***	-0.081***	-0.073***	-0.040*	0.049**	-0.367***	0.031	0.220***	-0.405***	0.156***	0.414***	-0.499***	1		
GLG	-0.207***	-0.086***	-0.208***	-0.007	-0.008	-0.027	0.025	-0.201***	-0.007	-0.021	-0.243***	0.049**	0.159***	-0.132***	0.267***	1	
DEPOSIT	0.018	-0.179***	0.127***	-0.510***	-0.484***	0.146***	-0.089***	-0.019	-0.265***	-0.050**	0.118***	0.395***	0.164***	0.111***	-0.032	-0.003	1
DIV	-0.229***	-0.065***	-0.249***	-0.037*	0.036*	0.103***	-0.023	-0.356***	-0.052**	-0.022	-0.178***	0.028	0.196***	-0.171***	0.231***	0.140***	0.112***

** p<0.05, ** p<0.01, *** p<0.001*

Variable definitions are provided in Appendix 1.

Table 5. Impact of Derivatives Use on Bank Risk – Baseline Results

	(1)	(2)	(3)
	$\boldsymbol{TR_t}$	$\boldsymbol{SR_t}$	$\boldsymbol{IR_t}$
$DETA_{t-1}$	0.030**	-0.002	0.034***
	[2.380]	[-0.254]	[4.318]
$SIZE_{t-1}$	-0.003***	0.008***	-0.011***
	[-2.999]	[17.495]	[-15.558]
MTB_{t-1}	-0.000*	0.000	-0.000**
	[-1.813]	[0.114]	[-2.374]
NEA_{t-1}	0.115***	0.044***	0.068***
	[5.120]	[3.949]	[3.981]
NPL_{t-1}	0.981***	0.367***	0.594***
	[5.318]	[3.589]	[4.640]
$LIQUID_{t-1}$	-0.001	0.001	-0.002
	[-0.181]	[0.349]	[-0.441]
$TIER1_{t-1}$	-0.114***	0.037***	-0.153***
	[-3.462]	[3.018]	[-5.193]
$NETCO_{t-1}$	1.182***	-0.327**	1.511***
	[3.315]	[-2.370]	[4.581]
NIM_{t-1}	-0.269	0.170*	-0.444***
	[-1.446]	[1.949]	[-2.651]
$INCO_{t-1}$	0.001***	0.000	0.001***
	[3.877]	[1.146]	[4.153]
CIR_{t-1}	0.016	-0.011*	0.028***
	[1.493]	[-1.781]	[3.046]
$ROAA_{t-1}$	-2.317***	-0.611***	-1.670***
	[-9.976]	[-3.976]	[-8.482]
GLG_{t-1}	-0.010*	0.000	-0.010**
	[-1.655]	[0.114]	[-2.462]
$DEPOSIT_{t-1}$	-0.024**	-0.001	-0.024***
	[-2.498]	[-0.246]	[-3.162]
DIV_{t-1}	-0.011***	-0.001	-0.010***
	[-5.009]	[-0.954]	[-5.044]
Constant	0.112***	-0.113***	0.233***
	[5.027]	[-10.064]	[12.207]
Country FE	YES	YES	YES
Year FE	YES	YES	YES
Observations	3,313	3,313	3,313
R-squared	0.573	0.523	0.517

*** *p<0.01*, ** *p<0.05*, * *p<0.1* [Robust t-statistics in brackets]

Variable definitions are provided in Appendix 1.

Table 6. Impact of Derivatives Use on Bank Risk – Level I, II & III

	(1)	(2)	(3)
	TR_t	SR_t	IR_t
$LEVELI_{t-1}$	0.000	-0.001***	0.001***
	[0.286]	[-7.044]	[2.829]
$LEVELII_{t-1}$	0.001	-0.005**	0.007*
	[0.283]	[-2.097]	[1.773]
$LEVELIII_{t-1}$	0.023***	0.003	0.019***
	[2.927]	[1.056]	[2.793]
$SIZE_{t-1}$	-0.002**	0.008***	-0.010***
	[-2.469]	[18.896]	[-15.584]
MTB_{t-1}	-0.000*	0.000	-0.000**
	[-1.885]	[0.221]	[-2.517]
NEA_{t-1}	0.111***	0.042***	0.066***
	[4.978]	[3.769]	[3.884]
NPL_{t-1}	0.943***	0.368***	0.555***
	[5.075]	[3.610]	[4.254]
$LIQUID_{t-1}$	0.001	0.003	-0.002
	[0.103]	[0.953]	[-0.444]
$TIER1_{t-1}$	-0.117***	0.037***	-0.156***
	[-3.549]	[3.011]	[-5.308]
$NETCO_{t-1}$	1.156***	-0.327**	1.485***
	[3.228]	[-2.363]	[4.492]
NIM_{t-1}	-0.302	0.156*	-0.464***
	[-1.629]	[1.782]	[-2.774]
$INCO_{t-1}$	0.001***	0.000	0.001***
	[3.897]	[0.967]	[4.211]
CIR_{t-1}	0.017	-0.011*	0.029***
	[1.632]	[-1.746]	[3.223]
$ROAA_{t-1}$	-2.340***	-0.609***	-1.696***
	[-10.065]	[-3.966]	[-8.557]
GLG_{t-1}	-0.010*	0.000	-0.011***
	[-1.752]	[0.141]	[-2.600]
$DEPOSIT_{t-1}$	-0.029***	-0.002	-0.029***
	[-3.039]	[-0.325]	[-3.805]
DIV_{t-1}	-0.011***	-0.001	-0.010***
	[-4.940]	[-0.895]	[-5.007]
Constant	0.110***	-0.115***	0.231***
	[4.927]	[-10.313]	[12.132]
Country FE	YES	YES	YES
Year FE	YES	YES	YES
Observations	3,313	3,313	3,313
R-squared	0.574	0.524	0.518

*** $p<0.01$, ** $p<0.05$, * $p<0.1$ [Robust t-statistics in brackets]

Variable definitions are provided in Appendix 1.

Table 7. Impact of Derivatives Use on Bank Risk – Portfolio Ranking Results

	(1)		(2)		(3)	
	$\boldsymbol{TR_t}$		$\boldsymbol{SR_t}$		$\boldsymbol{IR_t}$	
PR_{t-1}	0.0002	[0.443]	0.0009***	[3.964]	-0.0008**	[-2.310]
$PR^2{}_{t-1}$	0.0002*	[1.958]	-0.0002***	[-3.238]	0.0005***	[5.438]
$SIZE_{t-1}$	-0.0012	[-1.498]	0.0077***	[18.409]	-0.0094***	[-13.972]
MTB_{t-1}	-0.0004***	[-5.299]	-0.0001***	[-4.255]	-0.0002***	[-4.507]
NEA_{t-1}	0.1415***	[6.127]	0.0543***	[4.557]	0.0828***	[4.972]
NPL_{t-1}	0.7238***	[3.784]	0.4723***	0.0047***	0.2366**	[2.254]
$LIQUID_{t-1}$	-0.0138**	[-2.101]	-0.0033	[-0.968]	-0.0103**	[-2.047]
$TIER1_{t-1}$	-0.0719**	[-2.135]	0.0536***	[3.684]	-0.1297***	[-4.611]
$NETCO_{t-1}$	1.4889***	[4.166]	-0.3376**	[-1.962]	1.8172***	[5.864]
NIM_{t-1}	0.2962*	[1.888]	0.4921***	[5.637]	-0.2260*	[-1.774]
$INCO_{t-1}$	0.0015***	[3.890]	0.0003**	[2.074]	0.0011***	[4.036]
CIR_{t-1}	0.0265**	[2.336]	-0.0082	[-1.103]	0.0353***	[4.003]
$ROAA_{t-1}$	-2.4457***	[-8.939]	-0.7125***	[-3.504]	-1.6906***	[-8.538]
GLG_{t-1}	-0.0050	[-0.833]	0.0050	[1.494]	-0.0104**	[-2.508]
$DEPOSIT_{t-1}$	0.0086	[0.833]	0.0184***	[2.942]	-0.0120*	[-1.783]
DIV_{t-1}	-0.0079***	[-3.442]	-0.0008	[-0.671]	-0.0072***	[-3.662]
Constant	0.0347*	[1.706]	-0.1424***	[-13.029]	0.1860***	[11.720]
Country FE	YES		YES		YES	
Year FE	YES		YES		YES	
Observations	3,313		3,313		3,313	
R-squared	0.534		0.422		0.508	

*** $p<0.01$, ** $p<0.05$, * $p<0.1$ [Robust t-statistics in brackets]; Variable definitions are provided in Appendix 1.

Table 8. Impact of Derivatives Use on Bank Risk – Portfolio Analysis Results

	(1)		(2)		(3)	
	TR_t		SR_t		IR_t	
$PORT1_{t-1}$	0.025***	[3.909]	0.011***	[4.775]	0.013**	[2.501]
$PORT2_{t-1}$	0.007	[1.300]	0.008***	[3.532]	-0.001	[-0.234]
$PORT3_{t-1}$	-0.009*	[-1.861]	-0.001	[-0.466]	-0.008**	[-1.977]
$PORT4_{t-1}$	-0.009*	[-1.700]	0.002	[1.026]	-0.011***	[-2.914]
$PORT5_{t-1}$	0.005	[0.822]	0.006**	[2.249]	-0.002	[-0.585]
$PORT6_{t-1}$	-0.003	[-0.517]	0.004	[1.100]	-0.007**	[-2.449]
$PORT7_{t-1}$	0.000	[0.005]	0.005	[1.579]	-0.006*	[-1.816]
$PORT8_{t-1}$	0.011*	[1.721]	0.010**	[2.446]	0.001	[0.183]
$PORT9_{t-1}$	0.010*	[1.694]	0.004	[0.912]	0.007**	[2.215]
$PORT10_{t-1}$	0.015**	[2.349]	0.003	[0.685]	0.013***	[3.721]
$SIZE_{t-1}$	-0.003***	[-3.413]	0.007***	[14.202]	-0.011***	[-15.238]
MTB_{t-1}	-0.000	[-0.115]	-0.000	[-0.003]	-0.000	[-0.139]
NEA_{t-1}	0.184***	[5.901]	0.071***	[4.697]	0.107***	[5.351]
NPL_{t-1}	0.321	[1.601]	0.302**	[2.570]	0.016	[0.150]
$LIQUID_{t-1}$	-0.003	[-0.425]	0.000	[0.017]	-0.003	[-0.648]
$TIER1_{t-1}$	-0.330***	[-9.247]	-0.042***	[-2.905]	-0.284***	[-9.917]
$NETCO_{t-1}$	1.327***	[3.488]	-0.311*	[-1.712]	1.639***	[5.205]
NIM_{t-1}	0.815***	[3.987]	0.667***	[6.322]	0.099	[0.673]
$INCO_{t-1}$	-0.002***	[-3.809]	-0.001***	[-4.347]	-0.001***	[-2.847]
CIR_{t-1}	0.037***	[2.849]	-0.006	[-0.818]	0.044***	[4.587]
$ROAA_{t-1}$	-2.238***	[-7.350]	-0.604***	[-2.919]	-1.601***	[-7.674]
GLG_{t-1}	0.013	[1.618]	0.012***	[2.959]	0.000	[0.005]
$DEPOSIT_{t-1}$	-0.047***	[-3.849]	-0.002	[-0.296]	-0.045***	[-5.796]
DIV_{t-1}	-0.001	[-0.465]	0.001	[0.708]	-0.002	[-1.075]
Constant	0.144***	[5.893]	-0.106***	[-8.789]	0.257***	[14.209]
Observations	3,313		3,313		3,313	
R-squared	0.277		0.254		0.356	

*** *p<0.01,* ** *p<0.05,* * *p<0.1* [Robust t-statistics in brackets]; Variable definitions are provided in Appendix 1.

Table 9. Impact of Derivatives Use on Bank Risk – TBTF vs. Non-TBTF

	(1)		(2)		(3)	
	$\boldsymbol{TR_t}$		$\boldsymbol{SR_t}$		$\boldsymbol{IR_t}$	
$DETA_{t-1}$	0.033**	[2.167]	-0.007	[-0.562]	0.040***	[4.431]
$TBTF_{t-1}$	0.014*	[1.912]	0.000	[0.055]	0.014***	[2.633]
$TBTF_{t-1} \times DETA_{t-1}$	-0.027	[-1.028]	0.010	[0.492]	-0.038**	[-2.329]
$SIZE_{t-1}$	-0.003***	[-3.161]	0.008***	[17.156]	-0.011***	[-15.479]
MTB_{t-1}	-0.000*	[-1.793]	0.000	[0.114]	-0.000**	[-2.350]
NEA_{t-1}	0.116***	[5.175]	0.044***	[3.962]	0.069***	[4.056]
NPL_{t-1}	0.986***	[5.342]	0.370***	[3.603]	0.597***	[4.661]
$LIQUID_{t-1}$	-0.003	[-0.451]	0.001	[0.473]	-0.004	[-0.840]
$TIER1_{t-1}$	-0.111***	[-3.367]	0.036***	[2.998]	-0.150***	[-5.080]
$NETCO_{t-1}$	1.184***	[3.319]	-0.326**	[-2.359]	1.512***	[4.582]
NIM_{t-1}	-0.291	[-1.549]	0.167*	[1.902]	-0.464***	[-2.742]
$INCO_{t-1}$	0.001***	[3.980]	0.000	[1.075]	0.001***	[4.299]
CIR_{t-1}	0.016	[1.493]	-0.011*	[-1.779]	0.028***	[3.046]
$ROAA_{t-1}$	-2.315***	[-9.955]	-0.609***	[-3.949]	-1.671***	[-8.467]
GLG_{t-1}	-0.010	[-1.639]	0.001	[0.157]	-0.010**	[-2.474]
$DEPOSIT_{t-1}$	-0.024**	[-2.442]	-0.001	[-0.205]	-0.023***	[-3.106]
DIV_{t-1}	-0.011***	[-4.941]	-0.001	[-0.968]	-0.010***	[-4.966]
Constant	0.115***	[5.116]	-0.114***	[-10.072]	0.236***	[12.245]
$DETA_{t-1}$+$TBTF_{t-1} \times DETA_{t-1}$	0.005	[0.230]	0.004	[0.210]	0.002	[0.160]
Country FE	YES		YES		YES	
Year FE	YES		YES		YES	
Observations	3,313		3,313		3,313	
R-squared	0.574		0.523		0.517	

*** *p<0.01,* ** *p<0.05,* * *p<0.1* [Robust t-statistics in brackets]; Variable definitions are provided in Appendix 1.

Table 10. Impact of Derivatives Use on Bank Risk – Traditional Retail Banking

	(1)		(2)		(3)	
	$\boldsymbol{TR_t}$		$\boldsymbol{SR_t}$		$\boldsymbol{IR_t}$	
$DETA_{t-1}$	0.028**	[2.195]	-0.001	[-0.075]	0.030***	[3.775]
TRB_{t-1}	0.003	[1.174]	-0.002**	[-1.973]	0.006**	[2.162]
$TRB_{t-1} \times DETA_{t-1}$	0.239	[0.629]	0.939***	[3.531]	-0.759***	[-2.733]
$SIZE_{t-1}$	-0.002***	[-2.857]	0.007***	[16.963]	-0.010***	[-14.693]
MTB_{t-1}	-0.000*	[-1.885]	0.000	[0.029]	-0.000**	[-2.412]
NEA_{t-1}	0.115***	[5.135]	0.045***	[4.076]	0.067***	[3.908]
NPL_{t-1}	0.974***	[5.271]	0.345***	[3.408]	0.611***	[4.750]
$LIQUID_{t-1}$	0.001	[0.188]	0.002	[0.475]	-0.000	[-0.067]
$TIER1_{t-1}$	-0.111***	[-3.315]	0.030**	[2.481]	-0.143***	[-4.749]
$NETCO_{t-1}$	1.174***	[3.282]	-0.313**	[-2.336]	1.488***	[4.536]
NIM_{t-1}	-0.277	[-1.494]	0.168**	[1.974]	-0.451***	[-2.708]
$INCO_{t-1}$	0.001***	[3.817]	0.000	[1.162]	0.001***	[4.025]
CIR_{t-1}	0.016	[1.512]	-0.011*	[-1.756]	0.028***	[3.050]
$ROAA_{t-1}$	-2.304***	[-9.850]	-0.581***	[-3.882]	-1.691***	[-8.711]
GLG_{t-1}	-0.010*	[-1.750]	0.000	[0.132]	-0.011***	[-2.608]
$DEPOSIT_{t-1}$	-0.028***	[-2.818]	-0.003	[-0.636]	-0.025***	[-3.312]
DIV_{t-1}	-0.011***	[-4.914]	-0.001	[-1.178]	-0.010***	[-4.841]
Constant	0.112***	[4.994]	-0.107***	[-9.541]	0.225***	[11.727]
$DETA_{t-1}$+$TRB_{t-1} \times DETA_{t-1}$	0.267	[0.700]	0.938***	[3.520]	-0.729***	[-2.620]
Country FE	YES		YES		YES	
Year FE	YES		YES		YES	
Observations	3,313		3,313		3,313	
R-squared	0.574		0.529		0.518	

*** *p<0.01,* ** *p<0.05,* * *p<0.1* [Robust t-statistics in brackets]; Variable definitions are provided in Appendix 1.

Table 11. Robustness – Endogeneity (IV Approach)

	(1)	(2)	(3)
	$\boldsymbol{TR_t}$	$\boldsymbol{SR_t}$	$\boldsymbol{IR_t}$
$DETA_{t-1}$	0.094***	0.027*	0.067***
	[3.850]	[1.877]	[3.856]
$SIZE_{t-1}$	-0.004***	0.007***	-0.011***
	[-4.223]	[16.118]	[-15.395]
MTB_{t-1}	-0.000**	0.000	-0.000***
	[-2.305]	[0.441]	[-3.352]
NEA_{t-1}	0.134***	0.044***	0.087***
	[5.893]	[3.969]	[5.155]
NPL_{t-1}	0.772***	0.417***	0.333**
	[3.825]	[3.906]	[2.297]
$LIQUID_{t-1}$	0.000***	-0.000***	0.001***
	[3.820]	[-3.008]	[5.212]
$TIER1_{t-1}$	-0.001	-0.002	0.002
	[-0.080]	[-0.694]	[0.332]
$NETCO_{t-1}$	-0.093***	0.034***	-0.129***
	[-3.239]	[2.886]	[-5.337]
NIM_{t-1}	1.189***	-0.306**	1.496***
	[3.553]	[-2.258]	[4.929]
$INCO_{t-1}$	-0.050	0.151*	-0.205
	[-0.276]	[1.716]	[-1.295]
CIR_{t-1}	0.001***	0.000*	0.001***
	[4.345]	[1.715]	[4.481]
$ROAA_{t-1}$	0.008	-0.012*	0.021**
	[0.742]	[-1.919]	[2.331]
GLG_{t-1}	-2.231***	-0.628***	-1.567***
	[-9.952]	[-4.123]	[-8.479]
$DEPOSIT_{t-1}$	-0.008	0.000	-0.008**
	[-1.403]	[0.016]	[-2.090]
DIV_{t-1}	-0.013	0.002	-0.016**
	[-1.281]	[0.387]	[-2.019]
Constant	0.112***	-0.102***	0.221***
	[5.035]	[-9.197]	[11.753]
Country FE	YES	YES	YES
Year FE	YES	YES	YES
Observations	3,313	3,313	3,313
R-squared	0.584	0.522	0.545
Hansen J statistic (p-value)	0.687	0.001	0.147

*** *p<0.01*, ** *p<0.05*, * *p<0.1* [Robust z-statistics in brackets]

Variable definitions are provided in Appendix 1.

Table 12. Robustness – User Banks Only

	(1)	(2)	(3)
	TR_t	SR_t	IR_t
$DETA_{t-1}$	0.021	-0.007	0.030***
	[1.600]	[-0.745]	[3.870]
$SIZE_{t-1}$	-0.000	0.008***	-0.008***
	[-0.381]	[14.255]	[-12.355]
MTB_{t-1}	-0.000	0.000	-0.000**
	[-0.770]	[1.397]	[-2.181]
NEA_{t-1}	0.078***	0.043***	0.030*
	[2.928]	[3.109]	[1.664]
NPL_{t-1}	1.194***	0.495***	0.672***
	[5.325]	[3.423]	[5.666]
$LIQUID_{t-1}$	-0.000	0.001	-0.001
	[-0.041]	[0.229]	[-0.256]
$TIER1_{t-1}$	-0.003	0.067***	-0.076***
	[-0.081]	[3.897]	[-3.016]
$NETCO_{t-1}$	0.634*	-0.596***	1.240***
	[1.647]	[-3.136]	[3.819]
NIM_{t-1}	-0.039	0.063	-0.095
	[-0.201]	[0.551]	[-0.655]
$INCO_{t-1}$	0.001*	0.000	0.001**
	[1.756]	[0.135]	[2.389]
CIR_{t-1}	0.004	-0.017**	0.023**
	[0.257]	[-1.979]	[1.990]
$ROAA_{t-1}$	-2.490***	-0.890***	-1.546***
	[-8.777]	[-4.376]	[-6.690]
GLG_{t-1}	-0.006	0.001	-0.007*
	[-0.910]	[0.189]	[-1.741]
$DEPOSIT_{t-1}$	-0.013	0.006	-0.020***
	[-1.159]	[0.882]	[-2.633]
DIV_{t-1}	-0.010***	-0.004***	-0.006***
	[-3.797]	[-2.886]	[-2.763]
Constant	0.058**	-0.117***	0.182***
	[2.274]	[-7.719]	[9.101]
Country FE	YES	YES	YES
Year FE	YES	YES	YES
Observations	2,001	2,001	2,001
R-squared	0.644	0.589	0.553

*** *p<0.01,* ** *p<0.05,* * *p<0.1* [Robust t-statistics in brackets]

Variable definitions are provided in Appendix 1.

Appendix 1. Variable Definitions

Variable	Definition
TR (Total risk)	The variance in daily stock returns in the fiscal year that derivatives were reported
SR (Systematic risk)	The product of the variance between the financial services sector's daily market return and individual bank's market beta squared
IR (Idiosyncratic risk)	Variance in the residuals ε_{it} obtained from the market model: $R_{it} = \beta_0 + \beta_m R_{mt} + \varepsilon_{it}$ R_{it}: Daily stock return of bank i R_{mt}: Daily return on the financial sector ε_{it}: Error term
DETA (Extent of derivatives use)	Total fair value of a bank's derivatives divided by total assets
LEVELI	The sum of the fair value of Level 1 trading assets and liabilities divided by total assets
LEVELII	The sum of the fair value of Level 2 trading assets and liabilities divided by total assets
LEVELIII	The sum of the fair value of Level 3 trading assets and liabilities divided by total assets
SIZE (Bank size)	Natural logarithm of total assets
MTB (Market-to-book)	Market value of common equity divided by book value of common equity
NEA (Nonearning assets)	Nonearning assets divided by total assets
NPL (Nonperforming loans)	Nonperforming loans divided by total assets
LIQUID (Liquidity)	The sum of liquid assets, cash and due from banks, and other securities divided by total assets
TIER1 (Tier 1 capital ratio)	Tier 1 regulatory capital divided by risk-weighted assets
NETCO (Net charge-offs)	Net loan charge-offs divided by total assets
NIM (Net interest margin)	Net interest income divided by total assets
INCO (Interest coverage)	EBIT (earnings before interest and taxes) divided by total interest expense
CIR (Cost-to-income ratio)	Operating expenses divided by the sum of net interest revenue and other operating income
ROAA (Return on average assets)	Net income divided by yearly averaged total assets
GLG (Gross loan growth)	The yearly growth rate of gross loans
DEPOSIT (Deposits)	Total deposits divided by total assets
DIV (Dividend dummy)	Dummy=1 if a bank paid dividend during the fiscal year, and 0 otherwise
TBTF (Too-Big-To-Fail)	Dummy=1 if a bank is identified as a global systemically important bank in the Basel Committee's G-SIB assessment
TRB (Traditional Retail Banking)	Dummy=1 if a bank's levels of deposits and loans exceed the median of the sample