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Abstract

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Abstract

I analyze the effects of bank characteristics and macroeconomic shocks on interest rate risk-management behavior of commercial banks. My findings are consistent with hedging theories based on cost of financial distress and costly external financing. As compared to the derivative users, the derivative non-user banks adopt conservative asset-liability management policies in tighter monetary policy regimes. Finally, I show that the derivative non-user bank's lending volume decline significantly with the contraction in the money-supply. Derivative users, on the other hand, remain immune to the monetary policy shocks. My findings suggest that a potential benefit of derivatives usage is to minimize the effect of external shocks on a firm's operating policies.

Financial intermediation often exposes banks to interest rate risks by creating mismatches in the maturity structure and re-pricing terms of their assets and liabilities.[1] Banks use various tools, including the use of interest rate derivatives, to manage these risks.[2] In the presence of costly bank failures, Diamond's (1984) model implies that banks should hedge all market risks in which they don't have any special monitoring advantages. His model also implies that interest rate risk-management should improve the intermediation efficiency of banks by allowing them to take more credit risk. Smith and Stulz (1985) show that the hedging of interest rate risk can increase firm value by lowering the expected transactions cost of bankruptcy. Froot, Scharfstein and Stein (1993) endogenize the cost of financial distress and argue that firms should hedge in order to avoid the cost of external financing in low internal cash-flow states. Other motivations for managing risks include managerial risk aversion, information asymmetry between the insiders and outsiders of the firm, increased debt capacity and the convexity of taxes (see Stulz (1984), Smith and Stulz (1985), DeMarzo and Duffie (1991) and Leland (1998) among others).

This paper investigates two central questions: (a) "What motivates a bank to hedge?" and (b) "Does hedging improve a bank's intermediation capabilities?" I analyze the determinants of a bank's interest rate risk-management decisions both by means of on-balance sheet techniques (i.e., by matching the GAP in the maturity and re-pricing terms of their assets and liabilities) and off-balance sheet instruments (i.e., by using interest rate derivatives).[3] Although the role of maturity GAP and derivatives activities on a financial institution's stock returns has been studied well in the literature (e.g., Flannery and James (1984b) and Schrand (1997)), the goal of this paper is to understand how various bank characteristics, macroeconomic shocks and managerial incentives influence these decisions in commercial banks.

I use a panel data of about 8,000 banks to investigate these issues in this paper. My sample is particularly well suited for analyzing the theories of interest rate risk management. First, banks face a high degree of interest rate risks, and therefore these decisions have a first-order impact on their performance. Second, banks are highly leveraged and face significant direct and indirect costs of bankruptcy. James (1991) shows that the direct losses of bank failures

[1] Flannery and James (1984b) provide evidence on the economic importance of these mismatches by analyzing the relation between the interest rate sensitivity of common stock returns and maturity composition of the bank's assets and liabilities.
[2] See the case study of Banc One Corporation by Esty, Tufano and Headley (1994) for a clinical study of the risk-management practices at banks.
[3] All analyses of hedging theories in this paper are based on derivatives used for 'hedging purposes' only.

such as administrative and legal expenses are about 10% of the total assets. Third, due to stringent reporting requirements for the banking sector, I get much detailed information on bank's derivatives usage and hedging policies (including non-derivatives based hedging) as compared to non-financial firms. In addition, due to regular monitoring by regulators such as the FDIC, the data quality is expected to be much better. Finally, this sample provides a unique setting to analyze the effect of exogenous macroeconomic shocks on hedging decisions since these shocks affect the entire banking system considerably.

A large body of research investigates the determinants of the hedging activities of a firm.[4] My study differs from the existing literature on several dimensions and makes two key contributions to the literature. First, the panel data allows me to investigate the effects of macroeconomic shocks such as the tightness of money-supply and volatility of interest rates on the risk-management incentives of banks. To the best of my knowledge, these issues have not been analyzed in the literature so far. Further, I investigate if hedging activities make a bank's lending policies less sensitive to the stance of monetary policies.[5] I separately analyze the effects of fed funds rate changes on the lending behavior of derivatives user and non-user banks and provide evidence in support of a relatively unexplored incentive of using risk-management tools – it allows firms to insulate their operating policies from the external shocks. This finding also provides supporting evidence to the existence of credit channel of the transmission of monetary policy (Kashyap and Stein (1995, 2000)).

Second, unlike most of the previous studies that take the use of derivatives as a proxy for financial risk-management, I consider both the derivatives-hedging and non-derivatives hedging (i.e., maturity GAP decision) decisions simultaneously. Petersen and Thiagarajan (2000) show that firms with different derivatives position can still have very similar hedging strategy after considering their non-derivatives positions. I analyze the simultaneous choice of these alternative

[4]See Nance, Smith and Smithson (1993), Dolde (1993), Mian (1996), Tufano (1996), Geczy, Minton and Schrand (1997), Graham and Smith (1999), Haushalter (2000), Knoff, Nam and Thornton (2002), Graham and Rogers (2002) and Purnanandam (2004) among others for evidence on non-financial firms. For studies related to financial firms see Booth, Smith and Stolz (1984), Schrand and Unal (1998) and Carter and Sinkey (1998). See Gorton and Rosen (1995) for an analysis of the effect of interest rate swaps on the systemic risk in banks. Jorion (2005) explores the relation between trading risk and systemic risk in the banking sector. Gatev, Schuermann and Strahan (2004) study the management of liquidity risk in banks and conclude that the lending-deposit synergy is an important mechanism through which banks manage such risks. Cebenoyan and Strahan (2002) study the role of credit risk management on capital structure, lending and risk profiles of banks.

[5] Brewer, Minton and Moser (2000) analyze the effect of interest rate derivatives on the lending activities of commercial banks. In this paper, on the other hand, I investigate the sensitivity of lending volume to the monetary policy shocks across derivative users and non-users.

means of hedging. This captures the entire range of risk-management practices and allows me to investigate whether these methods act as complements or substitutes.

My paper also makes a methodological contribution by estimating a direct measure of financial distress cost to test the risk-management theories. Unlike previous studies that use leverage and interest coverage ratios as proxies for financial distress, I use the historical bank failure data to model a bank's failure likelihood and risk-management decisions as two endogenous variables in the empirical analysis and use a two-stage estimation framework to assess the impact of distress cost on hedging incentives of the banks.[6]

Using the detailed information on banks' derivatives and non-derivatives based hedging activities during 1997-2003 period, I find that the economies of scale play an important role in the derivatives usage.[7] Larger banks are the predominant users of derivatives. As predicted by the theories of Diamond (1984) and Smith and Stulz (1985), I find that the financial distress cost positively affects the banks' hedging decisions. Banks facing higher likelihood of financial distress manage their interest rate risks more - both by maintaining lower maturity GAPs and by engaging in higher derivatives activities. Consistent with the predictions of Froot et al. (1993), I find that the high growth banks and banks with less liquid assets engage in higher hedging activities. My findings are broadly consistent with the view that derivative instruments act as substitutes for the on-balance sheet hedging; however, this particular result is sensitive to the econometric specification used for the analysis.

Next I explore the relation between hedging activities and the stance of monetary policy. My analysis shows that in a tight money-supply regime, banks significantly lower their maturity GAPs. Thus, when liquidity is more valuable banks tend to avoid interest rate risks at the balance sheet level. However, this effect is concentrated in the derivative non-user banks only. While the derivative non-users respond very aggressively to the macroeconomic shocks, the derivative users seem immune to them. Firm-level variables affect the maturity GAP decisions of both groups in similar ways. This finding suggests that by using derivatives, banks are able to 'insulate' their maturity GAP policy from the external shocks.

[6] First I take the failure likelihood as a proxy for the cost of financial distress, which assumes that losses in the event of default are the same across the sample banks. Subsequently, I repeat my analysis by modeling the 'loss given default' and 'risk-management' decisions as endogenous. My results remain similar for these alternative specifications of financial distress proxies.

[7] In line with the earlier empirical work in the banking literature, I analyze 'very small' and other banks (banks with less or more than $100 million in assets) separately. I also analyze these groups together, and the key results remain qualitatively similar as discussed later in the paper.

To further explore the relation between banks' operating policies and derivatives usage, I analyze the effect of changes in the Fed funds rate (a widely used proxy for the stance of the monetary policy) on the lending volume of users and non-user banks separately. The lending channel view of monetary policy suggest that the monetary policy affects the economy though its impact on the supply of loans (in addition to the demand considerations) by the banking sector. Supporting the lending channel view, Kashyap and Stein (1995, 2000) show that large banks with liquid balance sheets are less affected by the Fed policy shocks. When the Fed tightens the money-supply, banks' ability to raise *reservable* forms of liabilities (such as insured deposits) is compromised which leads to a decline in the supply of loans by them. However, banks that can easily raise *non-reservable* sources of funds (such as large denomination uninsured CDs) can undo the Fed policy shocks by raising liabilities through these sources and meeting the lending demands of their clients.

Derivatives instruments can allow banks to raise funds in tighter money-supply regimes through several channels. First, contracts such as forward rate agreement and various forms of futures contract can have a direct impact on a bank's ability to raise resources in tighter monetary regimes as these contracts are designed precisely to protect against such undesired swings in the liquidity conditions in the market. Second, one of the biggest impediment in raising uninsured liabilities is the traditional principal-agent problems faced by the banks since they act as agents of their depositors. Diamond's (1984) model of delegated monitoring implies that diversification of loan portfolios as well as risk-management activities within a bank can minimize these agency problems. An implication of this argument is that the hedger banks should face lower agency problems as compared to the non-hedgers and therefore should be able to raise uninsured deposits more easily. Finally, hedging instruments greatly improves a bank's liquidity. For example Bank One (see Esty et al. (1994)) uses swaps as a proxy for some of its 'conventional' fixed rate investments. Instead of investing in medium or long-term U.S. treasury obligations, at times it simply enters into a medium or long-term receive-fixed swap and puts its money into short-term floating-rate cash equivalents. This synthetic fixed-rate investment considerably improves the liquidity position of the bank as compared to investing in long-date securities. When faced with liquidity constraints, the hedger banks can relatively easily cut their levels of liquid assets to meet the loan demand as compare to the non-hedger banks, which in turn can make their lending less sensitive to the monetary policy shocks.

To test these implications, I utilize data on the derivatives usage by banks from 1985 to 2003.[8] My results show that the lending volume of derivative user banks are not sensitive to the Fed rate shocks. Derivative non-user banks, on the other hand, significantly cut their lending volume when the Fed tightens the monetary policy. Since derivative users tend to be large banks, I estimate these models for various size groups to control for the well-known size effect. My result remains robust when I limit my analysis to the very large banks (top 25%, 10%, 5%, and 3% of banks). The key result here is that even the very large derivative non-user banks (in the top 3-10% of the size distribution) significantly cut their lending volume when fed funds rates are higher as compared to the similar-size derivative user banks. My results, therefore, suggest that derivative usage is a possible method by which large banks are able to shield themselves from the Fed policy shocks as shown in Kashyap and Stein (1995, 2000).

My findings suggest that the derivatives usage allows banks to make only minor (or no) adjustments to their operating policies (such as making loans and adjusting their asset-liability management policies) in the event of macroeconomic shocks. Making adjustments to the operating policies can be costly if banks must offer different terms to their relationship borrowers or depositors to achieve such adjustments. By allowing a bank to maintain its core business under changing macroeconomic environment, derivatives can add value to the shareholders. This evidence can potentially reconcile the findings of Allayannis and Weston (2001), who find a significant effect of derivatives on firm valuation, and Guay and Kothari (2002), who find that derivative instruments can generate only a modest level of cash-flows in the bad states of the world. My findings suggest that apart from their direct cash-flow impact, derivative contracts can

[8] To test the monetary policy implications, I need a reasonably long series of data on the derivatives usage which can allow me to better capture the changing stance of monetary policy. The reporting requirements pertaining to the derivatives usage and maturity GAP of the banks improved considerably from 1997. However, a coarser but longer data series on derivatives usage is available starting from 1985. Since I use derivatives information only as a classification variable for the monetary policy regressions (i.e., whether the bank used derivatives for end-user purposes or not), for these regressions I use the longer data series starting from 1985. For 1985-1994 period, I do not have sufficient information to conclude if a particular derivative instrument was used by the bank as an end-user or as a dealer. However, this does not pose a problem for my analysis since I use derivatives as a classification variable only. This happens because, predominantly only about 25 largest banks (based on size) act as dealers in the derivatives market and all of these banks use significant amount of derivatives for end-user purposes also. The remaining user banks use derivatives for the end-user purposes only and therefore the set of 'derivative *end-user* banks' is almost identical to the set of 'derivative *user* banks' (see the Office of the Comptroller of Currency, OCC's bulletin on derivatives in the banking sector at http://www.occ.treas.gov/deriv/deriv.htm for details). To test the hedging theories, on the other hand, I only use 1997-2003 data since for this time period I have precise information on the amounts of these instruments across end-usage and dealing purposes. I discuss the data related issues in more detail later in the paper.

be useful to firms by facilitating them to have a smooth operating policy when faced with external shocks. This result is consistent with the theoretical model of Froot et al. (1993).

The main findings of this paper remain robust to alternative definitions of maturity GAP, control for the maturity structure of derivative instruments and various alternative econometric techniques. The plan for the rest of the paper is as follows. In section 1, I discuss the research design and explain the key hypotheses. Section 2 provides the data description and construction of hedging variables. In Section 3, I provide the main empirical findings for the determinants of hedging policies. Section 4 provides empirical findings for the effect of the Fed policy shocks on the lending volume of the derivative user and non-user banks. Section 5 provides some robustness results, and Section 6 concludes the paper.

1. Research Design

Diamond (1984) develops a theory of financial intermediation in which banks have monitoring advantages as compared to small depositors. But they also suffer from incentive problems due to the delegated monitoring on behalf of their depositors. He shows that diversification within a bank lowers the cost of delegated monitoring and generates net benefits of intermediation services. An implication of his model is that banks should not assume any risks that are not diversifiable unless they have special advantages in monitoring them. Thus in his model, banks find it optimal to hedge all interest rate risk either by using derivatives contract or by matching the maturity of assets and liabilities. The incentive to hedge interest rate risk increases with the cost of bank failure since assuming these risks increases the likelihood of bank failure without providing any incentive benefits to the banks as delegated monitors. Another implication of his model is that the financial intermediation capabilities of banks should increase with the extent of risk-management activities. In a more general context, Smith and Stulz (1985) show that hedging can increase firm value by reducing the variability of the firm's cash-flows, which in turn lowers the expected cost of bankruptcies (see also Mayers and Smith (1982)). Another benefit of hedging comes by way of increased debt-capacity of the firm as argued by Stulz (1996) and Leland (1998).[9]

[9] If banks receive subsidized deposit insurance from the FDIC, it may lead to a moral hazard problem (see Buser, Chen and Kane (1981)) by providing excessive risk-taking incentives to the owners of the banks. However, regulatory (such as FDIC inspection) and market discipline can help minimize this problem to a large extent. Since banks also raise funds from other sources, the extent of risk-seeking behavior would be further limited.

Froot et al. (1993) develop a model in which they endogenize the distress costs. In their model, external funds are costlier than the firm's internally generated cash. If a firm experiences negative shock to its cash flow, it would be forced to raise funds from an external market (and thus incur the deadweight costs) to meet its investment needs. Firms may have to forego positive NPV projects in some bad states (low internal cash-flow) of the world. Hedging strategies add value to the firm by removing these inefficiencies.

1.1 Empirical Model and Variable Selection

In line with the theoretical models, I hypothesize that the risk-management incentive of a bank is an increasing function of its expected financial distress costs. A firm should hedge more if it has higher expected costs of bankruptcies i.e., higher credit risks and associated cost of failure. At the same time a firm's likelihood of default (and therefore expected cost of bankruptcy) will come down if it hedges more. I model both the bank's hedging decision and its failure probability as endogenous variables in the model. Using a two-stage estimation technique I estimate the following model using each bank-quarter as a separate observation:

$$P(D=1) = f(X_1, H)$$
$$H = g(X_2, D)$$

D is a binary variable that equals one if bank fails and zero otherwise. H refers to the hedging decision both by means of 'derivatives' and 'maturity GAP management'. X_1 and X_2 are the other variables that affect a bank's default likelihood and hedging decisions respectively. These variables are chosen based on the existing theoretical models and empirical findings and are discussed below.

There is a large literature in finance and accounting studying the corporate bankruptcies (see Altman (1968), Ohlson (1998), Shumway (2001) and Chava and Jarrow (2004)). In line with these studies and the popular CAMEL rating of regulators such as the FDIC, I model the bank's failure probability as a function of its size (log of total assets), deposits (total deposits / total assets), non-deposit liabilities scaled by the total assets, profitability (net income / total assets), asset-mix (percentage of loans and leases in the total assets of the bank) and non-

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Purnanandam (2004) analyzes the issue of 'hedging' vs. 'risk-shifting' incentives for non-financial firms and shows that such risk-shifting incentives dominate the risk-management incentives of only those firms that are very close to financial distress.

performing asset (NPA/ total assets).[10] Duffie, Jarrow, Purnanandam and Yang (2002) use a similar model to estimate the failure probability of banks for estimating the market pricing of FDIC deposit insurance premium.

For the risk-management decisions, I use the bank's size as a control for the economies of scale in derivatives usage (see Dolde (1993)). In line with Froot et al. (1993), I include the average quarterly growth rate of a bank (measured as percentage growth in assets over the past four quarters) as a proxy for its need to access external capital markets. Froot et al. predict that high-growth banks should have higher hedging motivations to avoid the cost of external funding. I also include the level of liquid assets as a control variable since liquid assets can act as a substitute for the hedging activities. To capture the effect of insured deposit financing, I include a bank's deposit ratio in the hedging model. Banks that rely more on deposit financing may have less incentive to hedge due to the insurance provided by FDIC. Alternatively, these banks have perhaps limited access to external capital markets and thus face more binding capital constraints as compared to the other banks. Thus, this effect should induce them to hedge more in line with the predictions of Froot et al.

Finally, for a subset of banks that are covered on the COMPUSTAT executive compensation database, I control for the managerial incentives by computing the 'Delta' and 'Vega' of the top five managers of the bank. While 'Delta' captures the sensitivity of managerial wealth to stock prices, 'Vega' measures its sensitivity with respect to the stock return volatility. These measures are computed using the method suggested by Core and Guay (1999). In line with the predictions of Stulz (1984), risk-management incentives should be positively related to 'Delta', but negatively related to 'Vega' of managerial shares and options holdings.

In addition to the firm level variables described above, I use four macroeconomic variables in the hedging model. First, I control for the level of interest rate (measured by annualized yield on three-month treasury rates during the quarter) in the economy as a proxy for the tightness of money-supply.[11] The cost of cash-shortfall is higher in such a scenario, and

[10] I also experiment with additional and alternative variables such as the asset-liability ratios, percentage of real estate-backed loans in the total assets, provision for bad loans as a percentage of total assets, percentage of interest income in total income of the bank, capital ratios and deposit-equity ratio. The results don't change qualitatively.

[11] Bernanke and Blinder (1992) show that the Federal funds rate captures the stance of the monetary policy well. This is the prevalent measure of monetary policy used in the empirical work. I use the market based yield on three-month T-Bills as a proxy for the monetary policy. The correlation between three-month T-Bills rate and Fed Funds

therefore the hedging strategy may add value under such regime. I include the volatility of interest rates (measured as the standard deviation of three-month T-Bill yield during the quarter) as the second macroeconomic variable. Higher interest rate volatility increases the variance of a firm's cash-flows and thus induces higher risk-management incentives, all else remaining equal. Next I control for the term-spread and credit-spread variables in the model. Term spread is defined as the yield difference between 10- and one-year treasuries. Credit-spread measures the yield difference between the BAA and AAA corporate debt. Although the existing theoretical models of risk-management do not have direct predictions relating term spread and credit spread to hedging incentives, I control for these macroeconomic factors to gain insights into the roles played by economy-wide credit quality (proxied by credit-spread), cost-differential between long-term and short-term funds and future expectation about the macroeconomic growth (both proxied by term spread) on the hedging incentives of banks.

In the first stage of estimation, I use a discrete time hazard rate model with bank failure as the event and all exogenous variables as explanatory variables. Shumway (2001) shows that the discrete-time hazard rate can be modeled as a logit model with each bank quarter as separate observation. This estimation technique results in unbiased estimates of the default probabilities and it makes full use of the historical information. (See Shumway (2001) for a detailed discussion of this approach.)

I use the estimated probability of default (called PD) from the first stage estimation as an instrument for financial distress costs in the second stage risk-management equation. There are two ways in which a bank can manage its interest rate risks: (a) by matching the maturity and re-pricing terms of its assets and liabilities and (b) by engaging in derivatives transactions. First I consider these two methods of hedging as independent decisions and analyze the determinants of these choices separately. Next I treat them as simultaneous choices and model them together. My econometric analysis uses both a Fama-MacBeth-type cross-sectional analysis and a panel regression with fixed effect for every bank.

rate is over 98% during the period 1997-2003. In an alternative specification, I also used the Fed funds rate as a proxy for the stance of monetary policy and my results remain qualitatively similar.

1.2 Econometric and Methodological Issues

Before explaining the data and presenting my results, it is important to address two key issues related to the above methodological approach. First, an obvious concern with such a two-stage instrumental variable estimation is the issue of proper instrumentation in the first stage of the model. It is important to obtain economically sound and statistically valid instruments (i.e., properly identified system with satisfactory order and rank conditions) for making meaningful inferences in a two-stage regression model. In my model, I use the 'Non-Performing Assets' of the commercial banks as the identifying instrument in the first stage regression. This is based on the assumption that a bank's NPA is correlated with its risk-management activities only via its effect on the distress likelihood. It is hard to argue that *independent* of distress related factors, banks with high NPA have higher or lower incentive to hedge. Thus NPA is an economically motivated instrument used to identify the first stage equation.

Further I perform various econometric tests to ensure the statistical suitability of the instrument. As shown in detail in section 3, in the first stage regression the coefficient on the instrument (i.e., NPA) is positive and significant with a p-value of 0.01, which ensures that the rank condition is satisfied. The pseudo R-squared of the first stage regression is also reasonably high. These tests provide evidence in support of the econometric validity of my instrument. Even with a valid instrument, Bound, Jaeger and Baker (1995) and Staiger and Stock (1997) show that a weak instrument can aggravate the effect of simultaneity bias, rather than solving it. In particular, the IV estimates may be inconsistent and even biased for finite sample sizes. To estimate the strength of the instrument, Bound et al. suggest reporting the partial R^2 and the F-statistics from the first stage regression. High levels of partial correlation and joint significance of the instruments in the first stage regression ensures that the instrument is strong. My instrument does a reasonable job on all these dimensions as explained later in section 3. Finally, as a robustness I estimate all my models with the lagged values of default likelihood and obtain similar results.

The other issue about my analysis relates to the sample period. I use data on bank failure from 1980-2003 to estimate the distress likelihood for period 1997-2003. The key goal behind estimating the first stage regression is to obtain a meaningful and objective projection of bank characteristics on the likelihood of experiencing low cash-flow states. To that end, historical bankruptcies provide an attractive setting. Since bankruptcies are rare events, studies involving corporate bankruptcies have often looked at data over a long time-period (see Altman (1968), Ohlson (1998) and Shumway (2001)). My study takes a similar approach. However, the final test of this methodology rests with the predictive power of the model during the period of interest (1997-2003). Though bank failures have become rare in the late 1990s and early 2000s, there has been a considerable differences in the credit-quality of commercial banks in this period. For example, Duffie et al. (2002) report that the 1-year credit default swap rates (CDS) ranged from 43 to 350 basis points for a small sample of 11 banks as of September 2002. My goal is to simply capture the cross-sectional differences in credit-quality across banks in this time-period. As shown later in the analysis, the first stage instrument provides a reasonable characterization of the credit-quality of sample banks during the period of interest. In particular, the model implied distress likelihood is able to both predict the bank failures and explain the cross-sectional variation in the CDS rates during this period. Finally as a robustness test, I limit the bank failures during 1990s and obtain qualitatively similar results.

2. Data and Construction of Hedging Variables

2.1. Data Sources

There are two main sources of data in this study - (a) Call Report data obtained from the Federal Reserve Bank that contains quarterly accounting information for every insured commercial banks in the U.S. and (b) historical bank failure data from FDIC. These data sources are supplemented with COMPUSTAT executive compensation database and macroeconomic data obtained from the Federal Reserve Bank. FDIC's bank failure data covers all 'bank failures' and 'open bank assistances (OBA)' during the period 1980-2003.[12]

For the estimation of hazard rate model, I include all insured commercial banks with non-missing observations on total assets, total loans and equity at the end of the each quarter during 1980-2003 in my sample. In line with the earlier literature (see Campello (2002)), I exclude bank-quarter observations with more than 50% growth in assets. This filter removes observations for those quarters in which banks are involved in significant merger activities. I also require information on all covariates (i.e., X_1 and X_2 in the default and hedging model) to be available for

[12] In the case of a bank-failure FDIC steps in and closes the operations of the bank, whereas in OBAs banks are allowed to continue to operate with some re-structuring or help from FDIC. OBAs have become very uncommon in the recent years. During the sample period OBAs accounted for 6% of total bank distress events.

a bank-quarter observation to be included in the sample. This leaves me with a sample of 853,469 bank-quarter observations and 1,443 bank-failures over 1980-2003 that are used to fit the hazard rate model. Since the relevant items to compute both 'maturity GAP' and 'derivatives used for hedging purposes' are only available from the third quarter of 1997, the second stage hedging models are estimated using 25 quarters of observations from 1997Q3 to 2003Q3.

Due to the changing reporting requirements, some of the call report items are not comparable across reporting quarters. I follow Kashyap and Stein (2000) and Campello (2002) to form consistent time-series from these items. For the variables that are not covered in these studies (such as the maturity GAP and derivatives), I form consistent time series by analyzing the call report forms. A detailed description of the various call report data items that are used to form the consistent time series of these variables is provided in the Appendix.

2.2. Construction of Hedging Variables

Hedging by means of derivatives: I obtain the data on derivatives from the Schedule RC-L of the quarterly Call Reports and support it by sources such as 10-K filings. Commercial banks began to separately report their usage of derivatives for trading and non-trading purposes starting from the first quarter of 1995. Banks engage in derivative contracts both as intermediaries and as end-users. As an intermediary, the role of derivatives is for business purposes and not for hedging. In the Call Report, banks report contracts used in the course of dealing and other trading businesses as 'contract held for trading purposes'.[13] The derivative instruments used for hedging purposes are reported as 'contract held for non-trading' purposes. I take the notional amount of derivatives reported under the non-trading purposes and scale it by the total assets of the bank at the end of each quarter. I take the log of this ratio to construct the derivatives-hedging measure.

Empirical studies involving firm's use of derivative instruments almost always face the challenge of properly separating firm's hedging activities from speculation. My dataset provides a much richer identification of hedging activities since banks are required to clearly state their hedging deals under the 'contract held for non-trading purposes'. More importantly, regulators such as the FDIC and the Fed monitor these banks on a regular basis to ensure that they adhere to the prescribed norms while reporting such activities. Therefore unlike non-financial firms, it is

[13] Any derivative instrument bought as a hedge for these trading assets is also treated under 'contracts held for trading purposes'.

relatively unlikely that banks would 'misclassify' their speculative activities as hedging deals and face the consequences of regulator reprimand. Finally, majority of derivative user banks use derivatives for hedging purposes only and report that clearly to their shareholders and to the regulators (also see the OCC's quarterly bulletin on derivatives). Only about 25 banks are active traders in this market and have significant position in their derivatives trading account. One could argue that these banks may also be involved in speculative activities. These activities need to be reported under trading contracts in the call report and thus my hedging variable excludes them from the analysis. Though unlikely, my variable would be contaminated if these banks actively 'cheat' in their reporting and report speculative derivative trades as hedging activities. As a robustness, from my sample I exclude top 1% of the banks that are predominant dealers (and therefore perhaps the speculators) in the derivative markets and my results remain similar.

Hedging by means of non-derivative techniques: Following Flannery and James (1984 a, b), I construct a 12-month maturity GAP measure that captures the net imbalances in the effective maturity (i.e., adjusted for re-pricing terms) of asset and liabilities of a bank over a one-year period. My measure is similar to the SHORT measure used by Flannery and James and is defined as the absolute value of (asset that mature or re-price within a year minus liabilities that mature or re-price within a year) scaled by the total assets of the bank. The exact construction of this variable is provided in the Appendix. Lower maturity mismatch corresponds to higher risk-management activities.

Since demand deposits do not have any stated maturity, there are two approaches to incorporate them into the GAP variable. One view, consistent with the findings of Flannery and James, is to consider them as core deposits and therefore treat them as long-term liabilities.[14] I adopt this convention in the base case analysis. An alternative view is that demand deposits are subject to withdrawal at any time and therefore a part of it must be considered as short-term liability. In one of the robustness tests, I consider 50% of the demand deposits as short-term liability and re-estimate my models. The key findings remain qualitatively unchanged for the alternative definition of GAP.

[14] A similar view is presented in the case study of Banc One by Esty et al. (1994).

2.3. Descriptive Statistics

Table 1 provides summary statistics of the interest rate derivatives used for risk-management purposes by the commercial banks from 1997-2003. Out of more than 8,000 commercial banks, on average only 385 banks use interest rate derivatives for hedging purposes. As of the end of fourth quarter of 2003, the gross notional amount of interest rate derivatives amounted to about $2.4 trillion. As seen from this table, interest rate derivatives are the most widely used tool of risk management by the banks, representing about 90% of the total derivatives (including foreign currency, equity and commodity) used for the hedging purposes. The table also presents the total amount of derivatives used for risk-management purposes as reported by the OCC. The aggregate amount of derivative, used for hedging purposes, captured by my sample banks is very close to the numbers reported by the OCC. In the last column of Table 1, I provide the number of hedger banks that use derivatives for trading purposes also in a given quarter. On average out of 385 banks that use derivatives for hedging purposes, only 59 banks engage in trading activities as well. Majority of derivative users engage in well-defined hedging programs only. In unreported analysis, I find that the trader banks are very large banks (see also Gorton and Rosen (1995)) and all my results remain robust to the exclusion of these banks from the sample. Further there are only about 5 banks per quarter (unreported in the tables) that trade in derivatives, but do not engage in interest rate hedging. These banks are classified as non-hedgers.

In table 2, I provide the distribution of derivative users and bank failures across various size categories. I find that about 85% of the derivative hedgers belong to the top quintile of size distribution. There are practically no users of derivatives in the bottom 40% of the banks. As shown in Panel B, historically more banks have failed in the smaller size categories. The smallest size category accounts for about 33% of bank failures as compared to about 15% for the biggest banks. A large number of smaller banks fail, but only a very few of them engage in derivatives-hedging activities. This analysis points to a possibility of economies of scale in derivatives usage. Perhaps smaller banks do not have the necessary skill to use derivatives (see Dolde (1993)) or perhaps they manage their maturity GAP more conservatively and avoid the usage of derivatives in the first place. I analyze these possibilities in a multivariate setting later in the paper.

Table 3 provides the operating characteristics of the users and non-users of interest rate derivatives based on a sample of 213,874 bank-quarter observations for the period 1997-2003. There are 9,648 observations for the users of interest rate derivatives and the remaining for the non-users. The user banks are significantly bigger than the non-users. As expected, both users and non-users rely on deposit financing as their main source of funding; however, non-users have a higher percentage of deposit financing than users. To the extent that bigger banks have easier access to other sources of financing, it is not surprising that users, who are typically bigger banks, have relatively lower reliance on deposit financing. The derivative users keep a relatively lower amount of liquid assets as compared to the non-users. Consistent with the findings of Schrand and Unal (1998) and Brewer, Minton and Moser (2000), I find that the derivative users make more 'Commercial and Industrial Loans' than the non-users. Finally, users maintain higher maturity GAP (i.e., engage in lower on-balance sheet hedging) than the non-users.

3. Empirical Results

3.1. First-Stage Estimation of the Distress Likelihood

The parameter estimates from the first-stage distress likelihood model, estimated using a logistic regression, are provided in Table 4. I provide estimation results from three models: first by pooling all banks into one group and then by separating 'very small' and other banks (called 'medium and large' bank sub-sample in the rest of the paper) into two different groups depending on whether their asset value in 2003 dollar terms is below or above $100 million. In line with the prior empirical literature, I conduct my analysis separately for these two groups of banks. The pooled model uses 853,469 bank-quarter observations with 1,443 failures from 1980-2003. The 'very small' bank sub-sample is estimated using 513,836 bank-quarter observations and 1,064 failures, whereas the 'medium and large' bank sample is estimated using 339,633 bank-quarter observations and 379 failures.[15]

The parameter estimates are qualitatively similar across the two groups of banks. I find that the distress probability is negatively correlated with the size - smaller banks are more likely to experience distress than the bigger banks. Banks with higher deposits as well as non-deposit liabilities are more likely to experience financial distress. As expected, banks with higher non-

[15] As robustness, I also consider an alternative specification that fits the distress model using failure data up to 1997 only. Results from this model remain qualitatively similar to the case presented in the paper.

performing assets (NPA) are more likely to experience distress. Higher liquidity, larger percentage of loans in total assets and higher growth in total assets are negatively correlated with the distress likelihood. Bank failure is positively correlated with the level of interest rates and term-spread. Perhaps a little surprisingly, few banks fail in a more volatile interest rate regime. The model has robust goodness of fit properties as reflected by the high values of 'percent concordant' and 'Gamma' statistics. These statistics measure the power of the model to predict the dependent variable based on the values of the independent variables. Since I use the model implied default likelihood as the key explanatory variable in my empirical analysis, it is important that the default model captures the cross-sectional and time-series variations in the banks' expected distress costs well.

I conduct out-of sample tests to assess the predictive power of my model. The results are presented in Table 5. A good model of distress prediction should possess two properties: (a) In a cross-section of banks it should be able to discriminate between good and bad banks, and (b) In a time series, it should be able to separate periods of high distress from those of moderate and low distress. My model does a reasonable job on both dimensions. Starting from 1990, I estimate the model parameters with strictly ex-ante data and then compare the model predicted failure probability against the actual failures in the next year. For example, for year 1992 I take all bank failures till the end of year 1991 and estimate the model. With these parameter estimates and the accounting data from the last quarter of the 1991, I obtain the predicted default likelihood for all surviving banks. I sort the surviving banks into deciles based on the predicted default likelihood and provide a distribution of banks that actually failed during the year (i.e., during 1992 in this example) across these deciles. For this table, I only provide results based on 'all bank' model since other models produce similar results.

About 90% of the banks that fail during the year belong to the top decile of failure probability as of the beginning of the year. This is an encouraging result since it tells us that the model is able to differentiate between banks that are likely to experience distress from those that are not. In Table 5, I also report the model estimated annual failure rates of all banks in the sample and the banks that eventually failed during the year. As expected, the median failure likelihood is much higher for the banks that eventually failed than the median for the entire sample. The average annual predicted failure rate for the entire sample of banks over 1990-2003 works out to about 0.12% as against about 7.5% for the failed banks. The failure probability of the aggregate sample corresponds to the historical failure rate of a BBB+ rating of Standard & Poors and Baa2 of Moody's. The model predicts higher default likelihood (about 0.27% per annum) for the early nineties and a much lower likelihood for the later years. This is consistent with the actual failures and overall health of banking industry over this time-period.

As mentioned in section 1, I run various econometric tests to establish the validity of my first stage specification. In the first stage regression the coefficient on the instrument (NPA) is positive and significant at p-value 0.01 for all three models. Thus the rank condition of the IV regression is satisfied (see Wooldridge (2001)). Further, the pseudo R-squared is reasonably high for all three models – 45.67% for the 'all bank' sample, 50.36% for the 'very small' banks and 39.91% for the 'medium and large' banks. These tests provide evidence in support of the econometric validity of the instrument. Further, to estimate the strength of the NPA instrument, I compute the partial pseudo R-squared as suggested by Bound et al. (1995). The partial R-squared for the three models are reasonably high at: 2.69% for the 'all bank' sample, 2.21% for the 'very small' banks and 2.57% for the 'medium and large' banks. This indicates that not only my instruments are statistically valid, they are strong as well.

Finally, for a few banks with 1-year CDS data available, I compare the model implied annual default probability to the CDS rates as of September, 2002. The CDS and default probabilities, in increasing order of CDS spread, are as follows: Bank One NA (1-year CDS spread=49bp/ model implied-probability=0.07%); PNC Bank (74bp/ 0.11%); United Planters Corp (83bp/ 0.21%); Provident Bank (90bp/ 0.02%); Hudson United Corp (250bp/ 7.93%). Though it's based on a few cases of CDS-spreads, the results provide supporting evidence to the claim that the model implied probability of default captures the market's assessment of credit-risk fairly well during the period of analysis. Except for the case of Provident Bank, the two measures rank banks' credit-risk identically.

3.2. Cross-Sectional Regression Results

My first analysis uses a Fama-MacBeth approach to estimate the effect of firm level characteristics on maturity-GAP and derivatives-hedging decisions. In Panel A of table 6, I present the results for maturity-GAP decision for three models: 'all banks', 'very small' banks and 'medium and large' banks. For every quarterly observation, first I estimate a cross-sectional OLS regression with maturity GAP as dependent variable and then report the time-series means of the parameter estimates and their corresponding p-values. The p-values are computed using Newey-West heteroskedasticity- and autocorrelation-consistent errors. I use the log of predicted default likelihood (PD), obtained from the first stage regression, as independent variable in the entire paper.

I find a negative and significant coefficient on the probability of default variable (PD) for all three models. Firms with higher default likelihood maintain lower mismatch in their assets and liabilities i.e., they hedge their interest rate risk more. Moreover, this relationship is stronger for the 'very small' banks group. For a given increase in default likelihood, these banks are likely to reduce their maturity GAP by 50% more than the medium and large banks. For all three models, the parameter estimates are stable across quarters. On a quarterly basis, the coefficient on PD variable is negative and significant (at 1%) for 24 of 25 quarters for the 'medium and large' banks sub-sample and 22 of 25 quarters for the 'very small' banks sub-sample. For the 'medium and large' banks, I find that derivative-hedgers maintain a higher maturity GAP suggesting that these two methods of hedging act as substitutes. Since the 'very small' banks sub-sample has a very few derivative users, in the subsequent analysis I focus exclusively on the 'medium and large' banks. My main results remain qualitatively similar for the 'all banks' analysis.

In panel B of Table 6, I provide Fama-MacBeth regression results for the derivatives activities of 'medium and large' banks sample. In Panel B.1, I provide results for the yes-no decision of hedging by derivatives. Every quarter, I fit a logistic regression with decision to use derivatives for risk-management or not as dependent variable. The table reports the time-series means and Newey-West adjusted p-values of the cross-sectional estimates. Panel B.2 provides results for the extent of derivatives (measured by the log of notional amount of derivatives used for hedging scaled by total assets) used by the user banks.[16] Results from both these analyses (yes-no decision of derivative usage and the extent of hedging) indicate that banks with higher distress likelihood engage in higher hedging activities. I discuss the economic significance of these results later in the paper.

Consistent with prior empirical work, larger banks are more likely to engage in derivatives transactions. Banks with higher deposits use fewer derivatives. One possible

[16] The extent of derivatives model is estimated using observations on derivative users only. This is a selected sample and, therefore, my results may be biased due to sample selectivity. To ensure my results are not driven by these considerations, I re-estimate this model with a Heckman selection bias model and obtain qualitatively similar results.

explanation of this finding is the presence of subsidized FDIC insurance on the bank deposits, which creates a disincentive to manage risk. Consistent with Froot et al. (1993), high-growth banks and banks with lower liquid assets engage in higher derivatives-hedging activities.

Overall, my results indicate there is a greater inclination to manage the interest-rate risks (both by using derivatives and managing maturity GAP) when banks are faced with higher likelihood of financial distress. Smaller banks achieve this mainly by adopting a conservative maturity GAP policy, while larger banks make use of derivatives as well. The impact of firm growth and liquid assets on derivatives-hedging is significant and in the same direction as predicted by the hedging theories. However their impact on maturity GAP is not conclusive. Finally, maturity GAP decision and derivatives-hedging decisions act as substitutes for one another.

3.3. Simultaneous Choice of Maturity GAP and Derivatives

The results presented so far assume that banks make their maturity GAP and derivatives decisions separately, which may not be true.[17] Therefore, I model them as simultaneous choices using an instrumental variable approach. I instrument the derivatives-hedging decision by a bank's 'derivatives skill'. If a bank uses foreign currency, equity or commodity derivatives for trading or non-trading purposes, then I assign a value of one to the 'derivative skill' instrument, zero otherwise. The choice of this instrument is motivated by the fact that a bank with derivatives position in other markets has all the necessary skills to engage in interest rate risk management using derivative instruments. The maturity GAP variable is instrumented with its own lag. The choice of lagged variable as an instrument is motivated by the assumption that frequent adjustments to maturity GAP is costly. Every quarter I fit a simultaneous equation model with maturity GAP and derivatives decision as endogenous variables. For the maturity GAP model, in the first stage regression I use the yes-no decision to use derivatives as dependent variable and fit a logistic model to obtain the predicted likelihood of derivatives usages. The predicted derivatives usage likelihood is used as an explanatory variable in the second stage estimation with maturity GAP as dependent variable. Similarly, for the derivatives model, in the

[17] In their case study of Banc One Corporation, Esty, Tufano and Headley (1994) state, '….in carrying out this mandate (mandate of interest rate risk-management) Banc One used investments (in securities) and derivatives as substitutes for one another.'

first stage estimation I fit an OLS model with maturity GAP as dependent variable and use the predicted value of GAP in the second stage estimation.

Table 7 provides the Fama-MacBeth coefficient estimates and p-values of these models. Most of the results of this model are qualitatively similar to the results of the earlier model without simultaneous estimation. Maturity GAP management and derivatives usage remain substitutes for one another. The key difference between the two models is the effect of growth variable on maturity GAP decision. In the simultaneous equation estimation, I find that high-growth banks manage their risks more, both by means of maintaining lower GAP and by using more derivatives. The effect of distress likelihood on hedging activities remains positive and significant as in the earlier model. As expected, there is positive and significant relation between 'derivative skill' dummy and the usage of interest rate derivatives for hedging. Other findings are similar to the earlier model.

3.4. Panel Data Estimation

I now estimate a panel regression with macroeconomic variables added to the model. To conserve space, I only provide results for the simultaneous estimation of maturity GAP and derivatives hedging decisions. I estimate a bank fixed-effect model in simultaneous equation framework with 'lag GAP' and 'derivative skill' dummy as instruments as described earlier. For the maturity GAP model, in the first-stage regression I estimate a pooled logistic regression with derivative usage (yes-no decision) as dependent variable and 'derivative skill' as the instrument. The predicted likelihood of derivatives usage is used as an independent variable in the second stage regression. For the 'extent of derivatives' model, in the first stage I estimate an OLS model with the maturity GAP as dependent variable and the lagged GAP as an instrument. The predicted maturity GAP values are then used in the second-stage estimation as an explanatory variable.[18]

The results are provided in Table 8. Panel A provides the second-stage estimation result for maturity GAP decision, while Panel B provides results for the extent of derivatives used by the user banks.[19] The firm level variables produce similar results in the panel regression as in the

[18] To ensure my results are not driven by sample-selectivity of derivative user banks, I re-estimate this model with a Heckman selection bias correction and obtain qualitatively similar results.

[19] Since there are very few banks that initiate or terminate derivatives hedging decision during the sample period, I am unable to fit an economically meaningful panel data model for the yes-no decision of hedging.

Fama-MacBeth regression both in terms of the estimate value and their statistical significance. The probability of failure has a positive impact on hedging decisions. In economic terms, one percentage point increase in the log distress likelihood leads to about 0.74% decrease in the bank's maturity GAP and about 9.9% increase in the extent of derivatives used by the banks. The only noticeable difference between the two models is the relation between predicted derivatives usage and maturity GAP. For the panel data specification, I find a negative coefficient on the predicted derivatives usage variable indicating that derivative hedging and maturity GAP act as complements and not substitutes as established earlier. Apart from this result, all other models analyzed in the paper indicate that these two methods of hedging act as substitutes to one another. Thus results for 'whether derivatives act as substitutes or complements' remain model dependent. While most of the models point in the direction of 'substitution effect', once I use the panel data and control for bank-specific fixed effects these two methods of hedging seem to act as complements to each other.

The panel data estimation allows me to relate the hedging activities to macroeconomic shocks. I find that the levels of interest rates and term-spread positively influence the risk-management decisions via maturity GAP. A one percentage point increase in interest rates leads to about a 0.38 percentage point decrease in the bank's maturity GAP. Higher levels of interest rate correspond to a tighter monetary policy regime (see Bernanke and Blinder (1992)), and our results show that during such periods banks engage in higher risk-management activities via the on-balance sheet methods of hedging. Consistent with the costly external financing as well as distress cost-based theories, I find negative and significant coefficients on the interest rate volatility and credit-spread variable. When volatility is high, all else remaining equal, the likelihood of experiencing an adverse interest rate scenario increases – banks cut their maturity GAP in such regimes to protect against these scenarios. Similarly, when economy-wide credit quality is bad, there is a higher likelihood of experiencing default on the loans made by the banks and therefore the possibility of distress by the bank itself – banks reduce asset-liability mismatches in such regimes to protect against such risks.

In Panel regressions, I also control for the term-spread prevailing during the quarter. The term-spread variable captures two economic forces in the model: (a) it changes the profitability of maturity mismatch strategy by changing the relative costs of long- and short-term assets and liabilities, and (b) it controls for the expectation of future economic conditions (see Estrella and

Mishkin (1998) for example). Although there is no ex-ante prediction about the relation between term-spread and hedging incentives, my empirical findings indicate that when the term-spread widens banks reduce their maturity GAP, which is indicative of higher on-balance sheet hedging incentives in a higher term-spread economy. To uncover the exact mechanics that drive this relation, one would need to carefully analyze the individual elements of banks' balance sheets (such as whether term deposits increase or decrease with term-spread). Since this is not the main focus of the current paper, these analyses have been left for the future research.

Although the level of interest rates influences the on-balance sheet hedging decisions in a positive and significant manner, its impact on derivatives-hedging decision is just the opposite. In Panel B of Table 8, I provide regression results for the extent of derivatives used by the sample of derivative user banks. After controlling for bank-specific effects, I find that in tighter monetary regimes these banks decrease their derivative hedging positions. There are two possible explanations for this result: (a) these banks close some of their derivatives-hedging positions in higher interest rate scenario to generate cash out of the derivative instruments (for example, to meet the loan demands), which produces a negative contemporaneous correlation between interest rates and derivative hedging, or (b) these banks are taking a view in the interest rate markets. (See Stulz (1996) for a discussion on a firm's incentive to incorporate market-views in their hedging program.) It's important to re-emphasize that the dependent variable in all regressions in this paper are derivatives used for hedging purposes only. Thus a negative correlation between derivatives-holding and interest rates is only suggestive of a decrease in hedging position and not of any speculative behavior

3.5. Users vs. Non-users of Derivatives

To further explore the relation between macro-economic forces and risk-management activities, I analyze the maturity GAP decisions of the users and non-users of derivatives separately to shed light on the on-balance sheet hedging decisions of these two groups. Since for this analysis I already partition my sample into two groups based on derivatives usage, I do not use the likelihood of derivatives usage as an explanatory variable.[20] I simply regress the maturity GAP on firm-level and macro-economic variables in an OLS framework and report the results in Table 9. The firm-level variables provide qualitatively similar results; therefore I focus on the macro

[20] Estimating a simultaneous equation model, as in Table 8, provides qualitatively similar results.

variables. The negative effect of interest rates on maturity GAP is concentrated in the sample of derivative non-user banks only. Though the derivative user banks do decrease their maturity GAP when interest rates go up, statistically it is an insignificant relation.

These results suggest that the derivative users are able to maintain their asset-liability mix in the event of macro-shocks, whereas non-users make significant adjustments. In other words, the derivative non-users make significant changes to their operating policies to respond to the macroeconomic shocks. These changes can be achieved by offering different terms to their borrowers and depositors or making changes in other investment policies. Derivative instruments allow banks to maintain a stable operating policy, which presumably leads to a less volatile income stream. My results show that derivatives can smooth earnings not only by means of providing financial hedges, but also by allowing a more stable operating policy. Reduction in cash-flow and earning volatility can be desirable as evidenced by the findings of Minton and Schrand (1999) and Allayannis and Weston (2003). In the next section, I address this issue more directly by investigating the relation between lending volume and the Fed funds rate across derivative user and non-user banks.

4. Derivative Usage and the Lending Behavior of Banks

The results of the previous section indicate there is a considerable heterogeneity in the derivative user and non-user banks' responses to monetary shocks with respect to their maturity GAP activities. Unlike the non-users, the derivative user banks are able to maintain their mix of assets and liabilities in the wake of changing stance of monetary policy. Motivated by these findings and the theoretical model of Diamond (1984) I ask the following question: "Does the use of derivatives allow banks to make their lending activities less sensitive to the monetary polices?" An affirmative answer to this question would be evidence that derivative usage provides a direct advantage to the banks by insulating their core business decisions from the monetary policy shocks.

4.1 Existing Evidence on the Impact of Monetary Policy on a Bank's Lending Volume

There is a large literature studying the role of the Fed policy changes on the lending behavior of banks. Using similar data as in the current paper, Kashyap and Stein (2000) show that the impact of monetary policy on lending behavior is stronger for banks with less liquid balance sheets.

Further their findings are largely driven by the small banks, i.e., banks in the bottom 95% of the size distribution. They find that the smaller liquidity-constrained banks' lending activities respond strongly to the contraction or expansion in the various measures of monetary policy indicators. On the other hand, large banks' lending policy is less sensitive to the monetary policy shocks. These findings, taken together with the fact that large banks have better access to *non-reservable* sources of funding, provide evidence in support of the lending channel view of the transmission of monetary policy.

The lending channel view of the transmission of monetary policy suggests the monetary policy affects the economy through its impact on the supply of loans by the banking sector. This effect is in addition to the demand of loans by the borrowers. Under the lending channel view a contraction in reserves from the monetary system affects banks' ability to raise funds which in turn leads to shrinkage in the overall supply of loans to the bank dependent borrowers. This results in a fall in output. The crucial assumptions underlying this view of transmission policy are (a) there are some firms that cannot find a perfect substitute for bank loans, and (b) banks cannot raise uninsured funds (*non-reservable* funds) to make up for a Fed-induced shortfall in money-supply. (See Bernanke and Blinder (1992), Kashyap, Stein and Wilcox (1993), Stein (1998) and Kashyap and Stein (2002) among others for further theoretical discussions and empirical findings on these issues).

Derivative instruments can allow a bank to shield itself from the fed policy shocks through several means. First of all, instruments such as the forward rate agreements allow banks to lock in at a pre-determined rate of borrowings. This in turn means that when there is a tightening of liquidity supply in the market, derivative user banks can still raise resources to support their lending activities. Second, as Diamond (1984) shows, risk-management can minimize the agency cost faced by banks as delegated monitors on behalf of their depositors. Agency cost of delegation is one of the main frictions that prevents banks from raising uninsured or *non-reservable* sources of funds. Derivative instruments, by lowering these costs, can make a bank's access to these resources easier. Finally, many banks use derivative instruments to create liquidity in their balance-sheet investments as discussed earlier for the case study of Banc One corporation. Thus derivative instruments can allow banks to generate liquid cash relatively easily and therefore when the Fed tightens the money-supply, derivative user banks are in a better position to meet the loan demands (by drawing on their liquid assets) of their borrowers than the non-user banks.

4.2. Data and Research Design

To investigate the relation between derivatives usage and the bank's lending to money-supply sensitivity, I face an important challenge in terms of the data availability and the sample period. While testing the risk-management theories I focused on the 1997-2003 period since detailed information on the hedging activities of banks are available only for this period.[21] However, to assess the impact of monetary policy on the lending volume, a longer time-series of data is preferable. In figure 1, I plot the effective Federal Funds rate, the proxy for the stance of the monetary policy, for the period 1985-2003. As seen from this figure, in the 1997-2003 period there has been one significant contraction (during 2000) and one significant expansion (in post-2001 period when the Fed cut interest rates to historically low levels). In the earlier periods, on the other hand, there has been a considerable increase in both the frequency and the magnitude of expansions and contractions. Thus the longer time-series provides me with a much richer time-series variation in the explanatory variable and therefore an attractive setting to explore the relation between lending activities and money-supply.

One of the earliest reportings of bank's derivative usage started in 1985 when banks were required to report their swap holdings on a quarterly basis. Starting from the second quarter of 1985, banks were required to report their holdings of interest rate swaps (both trading and hedging) under the data item RCFD3450 of the call reports. I make use of this variable for the monetary policy estimation. Swaps are the most widely used (over 60%) form of derivative instruments by the banking sector and therefore capture a significant portion of their hedging activities. I classify banks into derivative user and non-user groups based on this variable for the period 1985-1994. For the subsequent periods, I use the data described earlier for the hedging theory test.

While this data does not precisely classify banks into derivatives-hedgers (i.e., end-user) and non-hedgers (i.e., dealers and/or speculators), it provides a much longer series and therefore allows me to draw meaningful inferences from the estimation. There are several reasons to

[21] Detailed information on derivatives usage is available from 1995 itself. But starting with 1997, I also get detailed information on the on-balance sheet risk-management techniques needed to compute the maturity GAP variable. Therefore, my analyses for tests of hedging theories are based on 1997-2003 data.

justify the use of this variable for my analysis. First of all, I only need a classification variable for the monetary policy regressions – i.e., I only need to classify firms into derivative users (for hedging purposes) and non-users and therefore the notional amount of derivatives is not relevant for this estimation. Thus, as long as derivative users are using at least a part of it for hedging purposes my analysis will have no bias. A bias in data is possible if there are banks that use swaps only for speculative or trading purposes. As shown earlier, during the 1997-2003 period, there are only about 5 banks per quarter (out of over 8000) that use derivatives solely for trading purposes. Assuming a similar pattern for the earlier years, the extent of misclassification is minimal. More importantly, there is no theoretical argument to justify a systematic link between speculation and lending-money-supply sensitivity. Therefore, if I classify some of the speculators into hedger category, it's only going to add noise to my estimation for the hedger group and thus bias me against finding a systematic pattern between hedging and lending-money supply sensitivity. The benefit of using the longer time-series is considerable as it captures various periods of monetary contraction and expansions depicted in figure 1. As a robustness, I estimate the models for the shorter time period of 1995-2003. My results for the shorter time-series remain qualitatively similar with lower statistical significance - presumably both due to smaller sample size and lower time-series variability in explanatory variable (the Fed funds rate).[22]

I conduct my empirical tests on the sample of 'medium and large' banks (i.e., banks with assets of more than $ 100 million) as well as various finer sub-categories of the large banks such as banks in top 25%,10%, 5% and 3% of size-distributions based on their 2003 asset value.[23] For each size-group, I divide banks into two groups based on their derivatives usage. Earlier studies find that small and large banks respond to the Fed policy shocks differently. Therefore by dividing banks into these size groups and then focusing on the derivative users and non-users separately allows me to better control for the size effects. Second, as shown earlier in the paper, the majority of derivative users are in the top decile of the size distribution. Therefore, I obtain

[22] I find that the number of banks that are classified as derivative-users during 1994-1995 period (i.e., the period when my data item changes) remain remarkably similar. For example, both in 1994Q4 and 1995Q1 there are about 450 hedgers with almost identical set of banks; 1994Q4 classification being based on earlier period, 1995Q1 on the later period. This gives additional confidence that our measure for the first half and the second half of the period are capturing similar set of banks.

[23] In various unreported analyses, I estimate this model with the sample of all banks and size-based cutoffs such as banks with assets of more than $200 mn, $300 mn and $500 mn only. All my results are similar for these alternative categories of banks.

comparable number of observations for users and non-users when I conduct my analysis with top 10%, 5% and 3% of banks. To estimate how derivative user and non-user banks respond to the Fed shocks, I follow the methodology of Kashyap and Stein (1995) and estimate the following time-series regression model:

$$\Delta \log(LOAN)_{jt} = \alpha_0 + \sum_{k=1}^{k=4} \alpha_k \Delta \log(LOAN)_{jt-k} + \sum_{k=1}^{k=8} \beta_k \Delta FED_{t-k} + \sum_{k=0}^{k=3} \gamma_k \Delta \log(NGDP)_{t-k} + \varepsilon_{jt}$$

In the above model, the log change in total loans and leases of group *'j'* of banks in quarter t is regressed on its own four lags, eight lags of the Fed funds rate changes and contemporaneous and three lags of log change in nominal GDP.[24] FED stands for the change in the effective annualized Federal funds rate over a given quarter. LOAN includes both loans and leases as described earlier. NGDP stands for the nominal GDP for the given quarter and controls for the level of economic opportunities. This variable controls for the changes in lending opportunities faced by the banks in the past one year. This regression is estimated with 69 quarterly observations from 1986Q2 to 2003Q3.[25] After estimating the above model, I test for the null hypothesis that the sum of coefficients on the Fed funds rate variable (i.e., $\sum_{k=1}^{k=8} \beta_k$) is equal to zero. A negative and significant coefficient on $\sum_{k=1}^{k=8} \beta_k$ indicates that when Fed fund rates increase (money-supply tightens), banks' lending volume decreases.

The dependent variable in the above equation is computed by summing the lending volume of all banks in group *'j'* in quarter 't' and from that (after log transformation) subtracting the corresponding number for quarter 't-1' (after log transformation). In such a methodology, I have to be careful to account for the potential bias that may arise due to the addition or deletion of banks (e.g., due to bank merger, failure or newly born entities) from my sample in a given quarter. To do so, I follow an approach similar to Kashyap and Stein (1995). In particular, to estimate the growth in lending volume for group *'j'* over say quarter 1997 Q1 to Q2, I require that a bank must be present in group *'j'* in both quarters. I ensure this by considering only those banks that have data available in both quarters. With all such banks, I classify them into user

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[24] In alternative specification, I control for four lags of GDP growth after dropping the contemporaneous GDP growth. Results remain similar. I prefer the model with the contemporaneous GDP growth as it controls for the current as well as most recent past of lending opportunities.

[25] Since I need the lag changes in loan growth, I start from 1986Q2 rather than 1985Q2 which is the first quarter with data available on the derivative usage.

group if they used derivatives in both quarters (1997Q1 and Q2 in the example). The rest of them are labeled are non-users. With this sample, I sum the lending volume of all banks in Q1 and Q2 for group *'j'* and compute the dependent variable by taking the log difference in summed lending volume of the respective group. For this analysis, in line with the earlier literature I exclude banks with less than 5% of lending assets and less than 1% of commercial and industrial lending assets as a percentage of their total assets. These filter removes outlier banks that have trivial amount of lending business to begin with and therefore unlikely to be affected by contractions or expansions in the money-supply.

Finally, to compare the differences in the user and non-user group. I estimate the above model with difference in the lending growth of the two groups (non-user minus user) in a given quarter as the dependent variable. As in the other cases, the difference in the lending growth of non-user and user banks is regressed on its own four lags, eight lags of Fed funds rate and contemporaneous and three lags of GDP growth in the following model:

$$\Delta\log(LOAN)_{0t} - \Delta\log(LOAN)_{1t} = \alpha_0 + \sum_{k=1}^{k=4} \alpha_k[\Delta\log(LOAN)_{0t-k} - \Delta\log(LOAN)_{1t-k}] + \sum_{k=1}^{k=8} \beta_k \Delta FED_{t-k} + \sum_{k=0}^{k=3} \gamma_k \Delta\log(NGDP)_{t-k} + \varepsilon_j$$

Further, I test for the null hypothesis that the sum of coefficients on the Fed funds rate variable (i.e., $\sum_{k=1}^{k=8} \beta_k$) is equal to zero. A negative and significant coefficient on $\sum_{k=1}^{k=8} \beta_k$ indicates that when Fed fund rates increase (money-supply tightens), non-user banks' lending volume decreases significantly more than that of user banks.

4.3. Results for the Monetary Policy Regressions

Table 10 provides the results of the above regression models. I report the summed coefficients ($\sum_{k=1}^{k=8} \beta_k$) for 'non-users' and 'users' for various size categories: (a) 'medium and large' banks, (b) banks that fall in top 25% of the size distribution, (c) banks in top 10% , (d) banks in top 5% and (e) banks in top 3% of the size distribution. Since most of the banks in top 2% are derivative users, I stop at the top 3% cutoff point. For the various percentile based cutoffs, the table also presents the asset value of the cutoff. For example, top 25% banks include all banks with asset base of \$150.35 million or higher. I report the p-values for the test of the null hypothesis that $\sum_{k=1}^{k=8} \beta_k = 0$. These p-values are corrected for the heteroskedasticity and autocorrelation of up to four lags using the Newey-West method. I also report the median number of banks in hedger and non-hedger group per quarter used in the estimation.

A consistent pattern emerges from these results. Non-users have negative summed coefficients on the 'FED' variable indicating that when the Fed tightens the money-supply, these banks cut their lending volume no matter what size group they belong to. Except for the banks in 'top 3%' category, this relation is statistically significant at 10% significance level or lower. This is an important finding – even banks in top 10% or 5% of the size distributions are significantly responding to the FED shocks when they don't use derivatives. Derivative user banks on the other hand do not cut their lending volume when the Fed tightens the money-supply. In fact the summed coefficient is positive and insignificant for all models of derivative users. The main interest in this analysis lies with the comparison of the two groups within a given size-category. Compared to the derivative-users, the non-user banks cut their lending significantly more when the Fed fund rates increases. This result is statistically significant at 0.08 or lower p-values for all models. For example, in the 'top 5%' category the summed coefficient for the derivative non-user minus user group is -1.48 and statistically significant at 5% significance level. Even within the 'top 3%' category, I find that non-users cut their lending volume significantly more than the users at a p-value of 0.06.

Taken together with the results of Kashyap and Stein (1995 and 2000), where they find that large banks are less sensitive to Fed policy shocks, my results indicate that within large banks it's the subset of derivative user banks that predominantly drive their results. To the extent that large banks face similar frictions in raising external capital and have comparable investment opportunities, my findings provide supporting evidence for the lending channel view of the transmission of monetary policy. Overall my results provide an interesting link between derivative usage and the impact of Fed policy shocks on the lending volume of banks.

5. Robustness and Additional Tests

5.1. Managerial Incentives of Hedging

Managerial incentives can have a significant impact on a firm's hedging decisions. Consistent with the model of Stulz (1984), in a sample of 48 gold mining firms Tufano (1996) finds that the hedging incentives increase with managerial shareholdings, but decrease with their option holdings. Schrand and Unal (1998) provide evidence that S&L's risk management activities after their conversion from mutual thrift to stock institution are related to their manager's compensation structure. Further studies (see, for example, Graham and Rogers (2002), Knopf, Nam and Thorton (2002) and Geczy, Minton and Schrand (2003)) also have investigated these issues by using sophisticated measures of managerial incentives such as the sensitivity of managers' wealth to stock prices changes (called the 'Delta') and stock return volatility (called the 'Vega') based on Black-Scholes-Merton model.

The data on managerial compensation is obtained from the COMPUSTAT executive compensation database. This database only covers the publicly traded commercial banks. Thus the study involving managerial incentives is limited to only a small subset of my sample. Further, the data contained in the executive compensation database pertains to the publicly traded bank holding companies, and not the individual banks I consider in the study. I use the compensation structure of these holding companies as a proxy for the managerial incentives of all banks within a given holding company.[26] Since the data on compensation is available only at annual intervals, I take the quarter corresponding to the fiscal year-end for the accounting variables from the Call Report. The resulting sample comprises 1,275 bank-year observations with 472 observations belonging to the derivative users.

Following Core and Guay (1999), I construct the 'delta' and 'vega' for the top five managers of each bank in the sample. The median 'delta' and 'vega' for the sample firms are \$195,000 and \$49,680. These measures are added to the firm and market-wide variables used in the earlier models. To save space I don't report the complete regression results for this model. The firm level results remain qualitatively similar to the earlier results (with lower p-values due to smaller sample size used in this study). However, I do not find a statistically significant relation between the risk-management activities and 'Delta' or 'Vega' measures for my sample

[26] In an alternative specification, I restrict my sample to only the largest bank within a holding company, and the results remain qualitatively similar.

of banks after controlling for bank fixed-effects. In the maturity GAP regression, I find a positive and insignificant coefficient on ‘Delta’ (estimate of 0.0091 with p-value of 0.20) and negative and insignificant coefficient on ‘Vega’ (estimate of -0.0063 with p-value of 0.25). For the extent of derivatives model the coefficient on ‘Delta’ (‘Vega’) is -0.0963 (-0.0048) with a p-value of 0.54 (0.97). I find a negative and significant coefficient on PD variable for the maturity GAP regression and a positive and marginally significant coefficient on the extent of derivative regression. Therefore, my main results remain robust to the control for managerial incentives of hedging.

5.2. Loss Given Default Model

I use the predicted value of default likelihood as a measure of expected financial distress costs. This assumes that the losses in the event of default are equal for all banks. To ensure that my results are not driven by this assumption, I consider an alternative model where I generate an instrument for the ‘expected loss in the event of default’ rather than ‘the probability of default’. To accomplish this task, in addition to the historical failure rates, I also need data on the losses incurred in each of these failures. Ideally, I need the information on deadweight losses, such as legal and administrative expenses, to estimate this model. Since exact estimates of these costs are not available, I use an alternative proxy which is based on the cost incurred by FDIC in resolving these failures. The data is obtained from the FDIC for all bank failures over my sample period (1980-2003). I estimate an OLS regression with cost to FDIC (scaled by the bank’s asset in a quarter prior to failure) as the dependent variable and all exogenous variables (as in the estimation of the distress likelihood model) as the independent variable. Results (unreported) from this regression show that the losses of failure are higher for smaller banks, high-growth banks, banks with higher level of non-deposit borrowings, higher non-performing assets, lower liquid assets and lower levels of loan asset. The losses are higher when overall credit quality in the economy is bad (i.e., higher credit-spread) and interest rates and term-spreads are lower. Using the estimates from the OLS model, I obtain the predicted value of ‘losses in the event of default’ for each bank-quarter observation and obtain the expected loss of default by the following formula:

Expected Loss of Default = Estimated Probability of Default (used in earlier analysis) x Estimated Loss in the event of default

I take the log of this variable as a proxy for financial distress costs and repeat my entire analysis using this new proxy. My results remain qualitatively similar. The parameter estimates and p-values on the distress cost variables (for the bank fixed-effect panel regression model) are provided in Table 11.[27] Consistent with the distress cost theory, I find a negative (positive) and significant relation between the expected loss of default and maturity GAP (derivatives usage).

5.3. Demand Deposits as Non-Core Deposits

Demand deposits have unstated maturity. The median level of demand deposits in my sample is 11% of total assets and thus it can have significant effect on the computation of maturity GAP. Flannery and James (1984a) find evidence in support of the view that demand deposits are treated as 'sticky', i.e., as long-term liabilities by the market. Esty et al. (1994) mention a similar view of demand deposits in their case study of Banc One. My analysis makes this assumption while computing the maturity GAP. However, as robustness I assume that 50% of the demand deposits are core deposits (and therefore long-term liabilities), while the rest can be withdrawn in the short term. With the new assumption, maturity GAP is computed again and I re-estimate the model with modified maturity GAP. My results remain robust. Table 11 provides the coefficients and p-values for the distress likelihood variable and confirms the findings of the earlier analysis. Other results are also similar to the base case presented in the paper.

5.4. Maturity-Adjusted Derivatives

Consistent with the prior literature, I use the notional amount of derivatives as a proxy for the derivatives-hedging activities of a bank. A bank using $100 million of derivatives with a one-year maturity is considered to have similar level of hedging activity as another bank with a five-year maturity contract of $100 million. This can be a reasonable assumption if the first bank in this example rolls over its hedge year after year. An alternative view is to adjust these instruments for their effective maturity and use the maturity-adjusted notional amount of derivatives as a proxy for the bank's derivative-hedging activities. Banks report the maturity of

[27] To save space, I only report these estimates in the paper. The other results are similar to the model discussed earlier in the paper. These results and the estimation of loss given default model are available from the author upon request.

their derivative positions into three crude groups: interest rate derivatives with maturity of one year or less (item RCFD 3809 of the call report), maturity of one to five years (RCFD 8766) and the rest (RCFD 8767). Though it is not possible to construct an exact measure of the maturity-weighted derivatives position from this information, it allows considerable refinement over the un-weighted measure. To construct this measure, I consider the average maturity of 0.5 years for derivatives maturing within a year and three years for derivatives maturing within 1-5 years. I assume that all derivative instruments with greater than five-year maturity have effectively similar effect on the firm's hedging policy and therefore I consider the maturity of five years for all such contracts. I multiply the notional amount of derivatives-hedging with average maturities to construct the maturity-weighted derivatives position of every bank and use this as a proxy for hedging activities. My results are robust to this adjustment as shown in table 11.

5.5. Other Robustness Tests

The results of the study remain robust to the exclusion of top 25 banks from the sample. These banks are active dealers in the derivatives market and account for over 99% of dealing activities. The remaining derivative users engage in derivative transactions for their hedging needs only. Finally, my results remain robust to a separate estimation of the model for banks with assets of more than $500 million.

6. Concluding Remarks

In this study, I analyze the determinants of interest rate hedging in commercial banks. Interest rate risk has a significant impact on the banking sector and it provides a useful setting to test the theories of risk management. Using a comprehensive measure of interest rate hedging that includes both on-balance sheet and off-balance sheet risk-management techniques, I find that the hedging activities of banks are consistent with theoretical models based on the cost of financial distress and costly external financing.

This study suggests that a potential benefit of derivative usage comes from its ability to allow a firm to maintain smooth operating policies in the event of external shocks. Unlike derivative non-user banks, the user banks make fewer (or no) adjustments to their on-balance sheet maturity GAPs and do not significantly cut their lending volume when the Fed tightens the money-supply. This means the user banks adjust their lending, borrowing and investing policies much less than the non-user banks. This provides an additional channel by which derivative instruments can provide smooth cash-flows to the firm. Apart from generating cash in the adverse states of the world, derivative instruments can smooth cash-flows through its interaction with the operating decisions also. This finding is consistent with the model of Froot et al. (1993) in which hedging allows firms to undertake optimal investment policies in the future. More research is needed to assess the impact of derivatives on the cash-flows and subsequently on the valuation of the banks.

My findings have policy implications for the role of risk-management in commercial banking. The fact that derivative user bank’s lending volume remains unaffected by the changes in the Fed funds rate suggests that the presence of derivative contracts can change the impact of monetary policies on the aggregate lending volume in the economy. The policymakers should consider the role of derivative instruments in setting monetary policies and evaluating their effects on the credit channels. Kashyap and Stein (1995, 2000) show that lending activities of large banks are less sensitive to the monetary policies than those of small banks. My findings suggest that derivative usage can be a potential mechanism through which large banks are able to achieve this. The role of derivatives on the transmission of monetary policy must be analyzed more thoroughly to further enrich our understanding of the frictions in the capital markets and their potential impact on the overall capital allocation in the economy.

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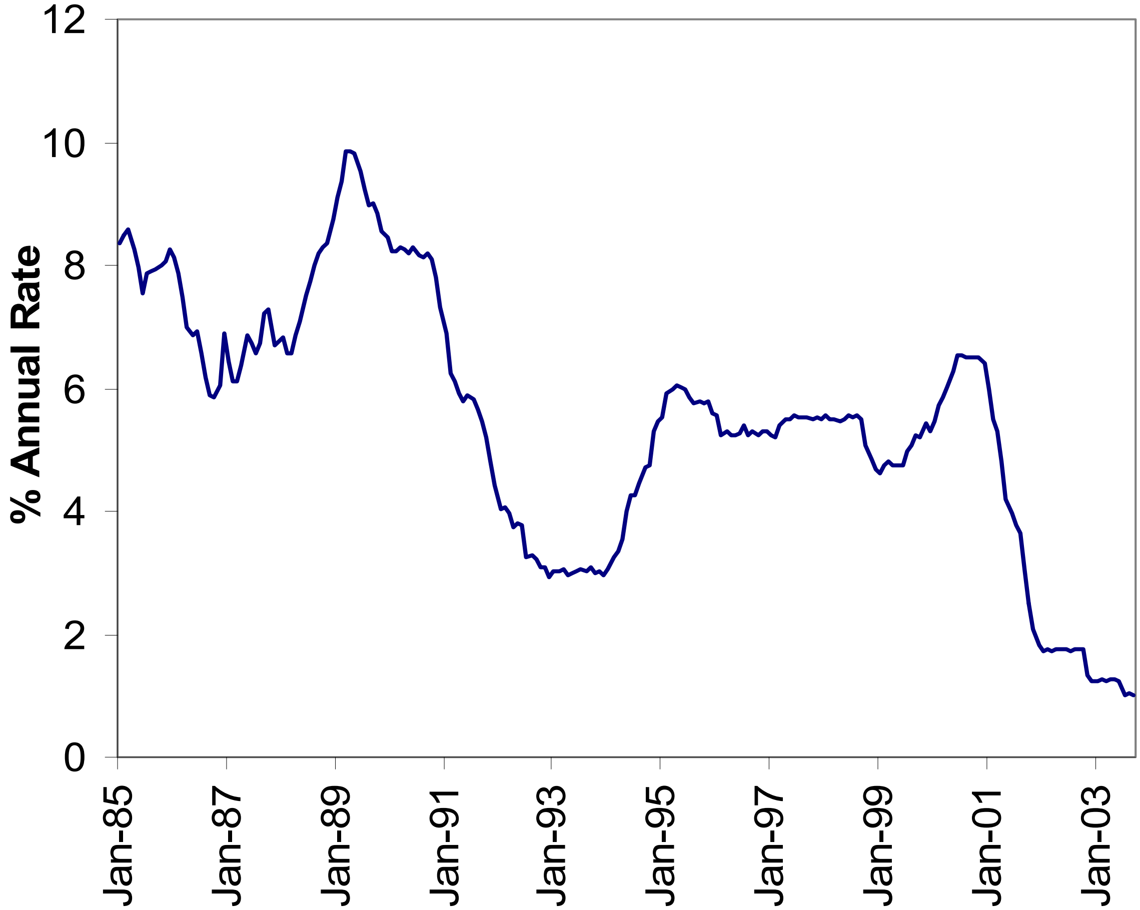
Figure 1
Effective Annualized Federal Funds Rate

This figure plots the annualized effective federal funds rate on a monthly basis from January, 1985 to September, 2003. Federal funds rate data has been obtained from the Board of Governor's release H.15.



Appendix: Construction of Variables from Call-Report Data

Total Assets: Total Assets is taken from item RCFD2170.

Total Loans: Total Loans and Leases (Gross) are reported under item RCFD1400.

Derivatives Hedging: Till the fourth quarter of year 2000, derivatives used for non-trading purposes were reported under two items: derivatives that have been marked to market and the others. For example, the interest rate derivatives used for non-trading purposes were reported under item number RCFD8725 for the portion that were marked to market and under RCFD8729 for the portion not marked to market. From the first quarter of 2001, the entire amount is being reported under RCFD8725. To form consistent time-series, I take the sum of RCFD8725 and RCFD8729 for the earlier period and RCFD8725 for the period starting from 2001Q1. Similarly for the currency, equity and commodity derivatives the consistent way to form the time series would be the following: RCFD8726+RCFD8730 (currency), RCFD8727+RCFD8731 (equity) and RCFD8728+RCFD8732 (commodity) for the earlier period and RCFD8726, RCFD8727 and RCFD8728 respectively for the period starting from 2001Q1.

Derivatives Used for Trading: I take the total notional values of derivatives used for trading by the banks reported under items RCFDA126 (interest rate), RCFDA127 (currency), RCFD8723 (equity) and RCFD8724 (commodity).

Net Income: RIAD4340

Maturity Gap: I construct one-year maturity GAP as follows: (Loans and Leases due to mature and re-price within a year + Securities due to mature or re-price within a year + Fed Fund Sold + Customer's Liability to the Bank for Outstanding Acceptance) minus (Term Deposits due to mature or re-price within a year + Fed Funds Borrowed + Other Liabilities for Borrowed Funds + Bank's Liabilities on Customer's Outstanding Acceptance). I take the absolute value of this number and scale it by the total assets of the bank to compute the one-year maturity gap ratio. Since the third quarter of 1997, the construction of the GAP variable is relatively straightforward. Fixed rate loans and leases that mature within a year and floating rate loans that re-price within a year are constructed by summing RCONA570, RCONA571, RCONA564 and RCONA565. Debt securities that re-price (if floating) or mature (if fixed) within a year can be constructed by summing items RCONA549, RCONA550, RCONA555 and RCONA556. Term Deposits that matured or re-price within a year are obtained by summing RCONA579, RCONA580, RCONA584 and RCONA585. Fed Funds Sold and Borrowed come from RCFD1350 and RCFD2800 respectively. Other Liabilities for Borrowed money comes from RCFD2850. Customer's Liabilities to the Bank and Bank's Liabilities to the customers come from RCFD2155 and RCFD2920 respectively.

Non-Performing Assets (NPA): In line with Campello (2002), I use a measure of loan performance independent of the managerial discretion. I use loans over 90 days late (RCFD1407) plus loans not accruing (RCFD1403) scaled by total assets for this purpose.

Liquidity: I define the liquidity ratio as a sum of (Cash + Fed Funds Sold + Securities) scaled by the total assets of the bank outstanding at the end of the quarter. Cash is reported under RCFD0010. Fed Funds Sold comes from data item RCFD1360. To construct a consistent time series, I define securities as the sum of two items: Total Investment Securities (RCFD0390) and Assets Held in Trading Account (RCFD2146) for quarters till 1993Q4. From the first quarter of 1994, it is defined as the sum of two items: Securities Held to Maturity (RCFD1754) and Securities Available for Sale (RCFD1773).

Total Equity: RCFD3210.

Demand Deposits: RCON2210.

Total Deposits: RCON2200.

Total Liabilities: RCFD2950.

Table 1
Derivatives for Risk-Management Purposes
Summary Statistics

This table presents the descriptive statistics of the amount of interest rate and other derivatives used by commercial banks for risk-management purposes. The first two columns provide the total number of banks in the sample and the number of banks that used derivatives for risk management purposes as of the end of a calendar year. 'Outstanding – IR Derivatives' provides, in billions of dollars, the gross notional amount of outstanding derivatives contract used by the entire banking system for hedging purposes. "All derivatives" measures the gross notional value of interest rate, foreign exchange, equity and commodity derivatives used for the risk-management purposes. I also provide the gross notional value of derivatives used for risk-management purposes as reported in the quarterly bulletin of the Office of Comptroller of Currency (OCC). The last column reports the number of banks, out of banks using derivatives for hedging, that used derivatives for trading purposes as well.

Quarter	Number of Banks	Users of IR Derivatives for Risk-Management Purposes		Outstanding - IR Derivatives ($ Billion)	Outstanding - All Derivatives ($ Billion)	IR Derivatives as a % of Total Derivatives	Derivatives OCC report ($ Billion)	Number of Banks with Trading Position in IRD
		Number	% of Total					
1997Q4	9147	426	4.66%	1282.80	1509.31	84.99%	1500.00	62
1998Q4	8778	418	4.76%	1215.97	1411.04	86.18%	1400.00	61
1999Q4	8580	382	4.45%	1476.15	1580.44	93.40%	1600.00	65
2000Q4	8313	348	4.19%	1097.42	1211.78	90.56%	1200.00	54
2001Q4	8080	309	3.82%	1725.68	1774.63	97.24%	1800.00	54
2002Q4	7755	353	4.55%	2034.81	2094.40	97.15%	2100.00	57
2003Q3	7678	456	5.94%	2437.96	2494.65	97.73%	2500.00	58
Average	**8333**	**385**	**4.62%**	**1610.11**	**1725.18**	**92.47%**	**1728.57**	**59**

Table 2
Distribution of Derivatives End Users and Bank Failures Across Size Quintiles

At the end of the fourth quarter of each year, I divide all banks in the sample into five groups based on their Total Assets in 2003 dollar terms. In Panel A, I provide the distribution of interest rate derivative users (for hedging purposes) across five size groups. 1 corresponds to the smallest group banks, 5 the largest. Panel B provides the distribution of failed banks across size quintiles over different time periods.

Panel A: Distribution of Derivative End Users Across Quintiles

	Size Quintiles					
Quarter	**1**	**2**	**3**	**4**	**5**	**Total**
1997Q4	0	2	16	39	369	426
1998Q4	0	1	19	39	359	418
1999Q4	1	1	11	33	336	382
2000Q4	0	6	13	39	290	348
2001Q4	0	3	4	32	270	309
2002Q4	0	5	12	39	297	353
2003Q3	5	6	27	60	358	456
Average	**0.86**	**3.43**	**14.57**	**40.14**	**325.57**	**384.57**
%	**0.22%**	**0.89%**	**3.79%**	**10.44%**	**84.66%**	**100.00%**

Panel B: Distribution of Failed Banks Across Quintiles

	Size Quintiles					
Period	**1**	**2**	**3**	**4**	**5**	**Total**
1980-84	47	49	34	20	26	176
1985-89	328	196	160	116	148	948
1990-94	132	95	62	62	69	420
1995-03	17	7	9	6	6	45
Total	**524**	**347**	**265**	**204**	**249**	**1589**
%	**32.98%**	**21.84%**	**16.68%**	**12.84%**	**15.67%**	**100.00%**

Table 3
Operating Characteristics of Users vs. Non-Users of IR Derivatives

This table presents the descriptive statistics of users and non-users of interest rate derivatives (for hedging purposes) based on a sample of 213,874 bank-quarter observations from the third quarter of 1997 to the third quarter of 2003 (on average 8,368 observations per quarter). Out of this, there are 9,648 observations for the users of the interest rate derivatives. I provide the mean and median of the key operating characteristics of the two groups along with the p-values for the differences. The test for mean is based on a two-sample t-statistics computed under the assumption of independence. The test for median is based on the standard Wilcoxson-Mann-Whitney statistics. All numbers are from the quarterly Call Report data.

	Derivative Users		**Derivative Non-Users**		**Users minus Non-Users**		**p-value**	
	Mean	**Median**	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**
Size ($ millions)	11985.88	1168.83	185.58	75.57	11800.30	1093.26	0.01	0.01
Total Deposit (% of total assets)	71.88%	75.53%	84.05%	86.19%	-12.18%	-10.66%	0.01	0.01
Demand Deposit (% of total assets)	9.95%	9.27%	12.48%	11.24%	-2.53%	-1.97%	0.01	0.01
Liquid Assets (% of total assets)	30.64%	29.05%	35.86%	33.92%	-5.22%	-4.88%	0.01	0.01
Loans & Leases (% of total assets)	63.90%	65.83%	60.86%	62.74%	3.05%	3.09%	0.01	0.01
Net Income (% of total assets)	0.85%	0.70%	6.03%	0.63%	-5.18%	0.06%	0.83	0.01
NPA (% of total assets)	0.64%	0.47%	0.64%	0.37%	-0.01%	0.10%	0.77	0.01
C&I Loans (% of total assets)	13.84%	12.01%	10.17%	8.47%	3.67%	3.54%	0.01	0.01
Quarterly Growth Rate	2.98%	2.39%	2.54%	1.75%	0.43%	0.65%	0.01	0.01
Total Equity (% of total assets)	9.53%	8.25%	10.83%	9.52%	-1.30%	-1.27%	0.01	0.01
Maturity Gap (% of total assets)	17.58%	13.38%	13.56%	10.64%	4.02%	2.74%	0.01	0.01

Table 4
First Stage Estimation of Distress Likelihood

This table presents the results of Logit Regression model for the estimation of distress likelihood using accounting data from the quarterly Call Reports and historical bank failure. The dependent variable is a binary variable that equals one for the quarter of failure and zero otherwise. I use all bank failures and Open Bank Assistances (OBAs) during the period 1980-2003 for which relevant data items could be obtained from the Call Reports. The model has been estimated for three groups: (a) All Banks (b) Very Small Banks (i.e., banks with less than $100 million in assets in 2003 dollar terms) and (c) Medium and Large Banks (assets more than $100 million). The number of observations used in each analysis is provided at the bottom of the table. The explanatory variables are as follows: Size represents the log of Total Assets of the bank; NI measures Net Income; TD stands for total deposit; NDL stands for non-deposit liabilities; NPA for Non-Performing Assets; Loan for the gross amount of loans and leases; Liquid for cash and liquid assets. All these variables (except size) have been scaled by the total assets of the bank as of the end of the given quarter. Growth measures the average quarterly growth rate in total assets over the past four quarters. IR Level represents the average interest rate (three-months T-Bills) during the quarter; IR Volatility measures the standard deviation of daily interest rates within the quarter; Term-spread is the average yield difference between 10-year and one-year Treasury Bond in the quarter; Credit-spread measures the yield difference between a BAA and AAA corporate debt.

Variable	**All Banks**		**Very Small Banks**		**Medium & Large Banks**	
	Estimate	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**
Intercept	-28.7649	0.01	-28.7466	0.01	-28.3164	0.01
Size	-0.1355	0.01	-0.5629	0.01	0.0225	0.75
NI/TA	0.0005	0.78	0.0010	0.68	-7.8501	0.01
TD/TA	33.6763	0.01	38.1967	0.01	29.8816	0.01
NDL/TA	10.9762	0.01	6.8357	0.01	24.2766	0.01
NPA/TA	16.6648	0.01	15.0465	0.01	18.7071	0.01
Loan/TA	-8.6559	0.01	-8.2343	0.01	-8.5508	0.01
Liquid/TA	-10.4367	0.01	-11.5059	0.01	-6.7335	0.01
Growth Rate	-12.8686	0.01	-10.0274	0.01	-13.5333	0.01
IR Level	0.1932	0.01	0.2375	0.01	0.1087	0.04
IR Volatility	-0.4888	0.05	-0.9536	0.01	0.0573	0.90
Termspread	0.3047	0.01	0.3795	0.01	0.3196	0.01
Creditspread	-0.0623	0.69	-0.1414	0.45	-0.3276	0.25
# of Failures	1443		1064		379	
Total # of obs	853469		513836		339633	
% Concordant	90.20%		94.00%		87.50%	
Gamma Statistics	97.90%		98.20%		98.30%	

Table 5
Out-of-Sample Predictive Power of the Distress Model

This table provides the result of out-of-sample predictive power of the distress likelihood model. At the beginning of each year, I fit the distress logistic model using bank-quarter observations available till the end of the previous year. Based on these ex-ante parameter estimates and accounting data as of the latest Call Report of the previous year, the failure likelihood is estimated for all surviving banks at the beginning of the year. Banks are sorted into deciles based on fitted probability values. I report the percentage of banks that failed in the following year across various deciles of fitted values. 1 stands for the highest likelihood of failure and 10 for the lowest as per the fitted probability values. The table also reports the model predicted median failure rate (in terms of % probability of failure per year) for the aggregate sample of banks and the banks that failed during the year.

Year	Median Failure Rate (%) - All Banks	Median Failure Rate (%) - Failed Banks	Number of Failed Banks	Distribution of Failed Banks in Failure-Probability Deciles				
				1	2	3	4	5-10
1990	0.27	19.51	152	148	0	0	2	2
1991	0.21	12.97	103	99	0	1	1	2
1992	0.23	18.01	94	79	8	3	1	3
1993	0.23	15.25	39	37	0	0	0	2
1994	0.15	11.84	11	10	0	0	0	1
1995	0.11	13.39	6	5	0	0	0	1
1996	0.08	9.00	5	4	0	0	0	1
1997	0.08	0.08	1	0	0	0	0	1
1998	0.06	0.14	3	1	1	0	0	1
1999	0.03	1.83	7	5	0	0	0	2
2000	0.06	0.08	5	2	0	0	1	2
2001	0.04	0.07	3	1	0	1	0	1
2002	0.04	0.16	8	3	1	1	0	3
2003	0.03	2.62	2	1	0	0	0	1
Aggregate	**0.12**	**7.50**	**439**	**395**	**10**	**6**	**5**	**23**
% of total				**89.98%**	**2.28%**	**1.37%**	**1.14%**	**5.24%**

Table 6
Risk Management Decisions: Fama MacBeth Regression

This table provides the results of Fama MacBeth regressions. In Panel A, first I estimate a cross sectional regression every quarter with maturity GAP as dependent variable and the firm characteristics as independent variables. In this table I report the time-series mean of the parameter estimates and the corresponding p-values. The p-values are corrected for autocorrelation of four lags and heteroskedasticity using the methods suggested by Newey-West. PD stands for the log likelihood of default and is computed in the first-stage distress likelihood model. Size measures the log of total assets of the bank. TD/TA refers to total deposits as a ratio of total assets. Growth is computed as the average quarterly growth over last four quarters. Liquid measures the extent of liquid assets held by the bank scaled by its total assets. Derivatives Dummy equals 1 if the bank has used interest rate derivatives for hedging purposes, zero otherwise. I report results for three models: (a) 'All Banks' that uses all observations; (b) 'Very Small Banks' for banks with assets less than \$100 million and (c) 'Medium and Large Banks' for banks with assets greater than \$100 million. In Panel B.1, I report the results from the 'yes-no' decision of derivative-hedging for the sample of 'Medium and Large Banks'. A logistic regression is estimated every quarter using the Derivatives Dummy as the dependent variable, and the table presents the time-series mean and p-value of these cross-sectional estimates. In Panel B.2, I take the extent of derivatives (log of notional amount of derivatives scaled by total assets) used by the user banks as the dependent variable and estimate the model using an OLS approach.

Panel A: Dependent Variable - 12-month Maturity Gap

	All Bank		Very Small Banks		Medium & Large Banks	
	Estimate	p-value	Estimate	p-value	Estimate	p-Value
Intercept	-0.2412	0.11	-0.2143	0.43	-0.0249	0.78
PD	-0.0218	0.01	-0.0232	0.02	-0.0154	0.01
Size	-0.0019	0.07	-0.0245	0.01	0.0083	0.01
TD/TA	0.3694	0.02	0.5961	0.08	-0.0047	0.94
Growth	-0.1330	0.05	-0.0741	0.45	-0.0121	0.79
Liquid	-0.0556	0.02	-0.0773	0.12	-0.0110	0.46
Derivatives Dummy	0.0263	0.01	-0.0138	0.16	0.0162	0.01

Panel B: Derivatives for risk-management purposes (Medium & Large Bank Sample)

	B.1: Yes-No Decision		B.2: Extent of Derivatives Usage	
Intercept	-13.2100	0.01	-2.8840	0.01
PD	0.1957	0.01	0.0558	0.04
Size	1.1175	0.01	0.0988	0.01
TD/TA	-3.3460	0.01	-1.7080	0.01
Growth	1.7004	0.21	1.9383	0.02
Liquid	-0.7042	0.01	-1.4350	0.01
Maturity Gap	0.6543	0.01	1.7394	0.01

Table 7
Simultaneous Choice of Maturity Gap and Derivatives Position

This table provides the results from Fama-MacBeth regressions for simultaneous estimation of on- and off-balance sheet risk management decisions of the banks. The maturity GAP decision and the decision to use derivatives or not are taken as endogenous variables. I instrument maturity GAP with its own lag and the derivatives usage decision by a bank's 'derivatives skill' and adopt a two-stage methodology to estimate the model. The estimation is carried every quarter from 1997Q4 to 2003Q3. This table provides the time-series mean and p-value for the cross-sectional parameter estimates. All estimations use Newey-West heteroskedasticity- and autocorrelation-consistent errors. Panel A provides the results for Maturity GAP decision. Panel B provides the estimation results for decision to use derivatives (for risk-management purposes) or not. Finally Panel C provides results on the extent of derivatives used by the derivative users. PD stands for the log likelihood of default and is computed in the first stage distress likelihood model. Size measures the log of total assets of the bank. TD/TA refers to total deposits as a ratio of total assets. Growth is computed as the average quarterly growth over last four quarters. Liquid measures the extent of liquid assets held by the bank scaled by its total assets. 'Skill' is a dummy variable that equals 1 if a bank uses other derivatives (foreign currency, commodity or equity) for trading or non-trading purposes. 'Derivatives-Est' is the estimated probability (from first stage regression) of derivatives usage by a bank. 'GAP-Est' is the estimated maturity GAP from the first-stage regression.

	Panel A: Maturity Gap Decision		**Panel B: Yes-No Decision to use Derivatives**		**Panel C: Extent of Derivatives for the User Sample**	
Variable	**Estimate**	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**
Intercept	-0.0287	0.11	-12.1300	0.01	-1.6630	0.01
PD	-0.0026	0.01	0.1882	0.01	0.0594	0.02
Size	0.0011	0.04	1.0353	0.01	0.0178	0.10
TD/TA	0.0203	0.15	-3.3480	0.01	-1.8100	0.01
Growth	-0.0274	0.06	1.8097	0.23	1.9670	0.02
Liquid/TA	0.0015	0.72	-0.9652	0.01	-1.7180	0.01
Lag GAP	0.9087	0.01				
Skill			1.1512	0.01	0.5233	0.01
Derivatives-Est	0.0050	0.03				
GAP-Est			0.4734	0.06	1.6680	0.01

Table 8
Fixed-Effect Panel Regressions

This table provides the result from a fixed-effect panel regression with simultaneous estimation of maturity GAP and derivatives usage decision. Panels A and B provide the result for maturity GAP and extent of derivative usage decisions respectively. Maturity GAP model is estimated using 88,397 observations over 1997Q4 to 2003Q3. Derivatives model is estimated using the sample of 8,439 derivative users over the same time period. I provide the parameter estimates and p-values from the second stage regression. PD stands for the log likelihood of default and is computed in the distress likelihood model. Size measures the log of total assets of the bank. TD/TA refers to total deposits as a ratio of total assets. Growth is computed as the average quarterly growth over the last four quarters. Liquid measures the extent of liquid assets held by the bank scaled by its total assets. 'Skill' is a dummy variable that equals 1 if a bank uses other derivatives (foreign currency, commodity or equity) for trading or non-trading purposes. 'Derivatives-Est' is the estimated probability (from first stage regression) of derivatives usage by a bank. 'GAP-Est' is the estimated maturity GAP from the first stage regression. IR Level refers to the average interest rate (three-month Treasury) during the quarter. IR Volatility measures the standard deviation of the same interest rate series during the quarter. Term-Spread is the yield difference between 10- and one-year Treasury. Credit Spread measures the yield difference between a BAA and a AAA corporate borrower.

	Panel A: Maturity GAP Decision		**Panel B: Extent of Derivatives Used**	
Variables	**Estimate**	**p-value**	**Estimate**	**p-value**
PD	-0.0074	0.01	0.0991	0.01
Size	0.0085	0.01	0.1101	0.01
TD/TA	0.1017	0.01	-0.4078	0.06
Growth	-0.0892	0.01	0.3698	0.27
Liquid/TA	0.0131	0.01	-1.0564	0.01
Lag GAP	0.7127	0.01		
Skill			0.0333	0.51
Derivatives-Est	-0.0212	0.01		
GAP-Est			0.3113	0.02
IR Level	-0.0038	0.01	-0.3074	0.01
IR Volatility	-0.0030	0.09	-0.1825	0.07
Term-spread	-0.0027	0.01	-0.3694	0.01
Credit-spread	-0.0084	0.01	-0.5086	0.01
R-squared	83.56%		78.21%	

Table 9
Maturity Gap Decision Across Derivative Users and Non-Users

This table provides the result from a fixed effect panel regression model for the maturity GAP decisions of two groups of banks: (a) users of derivatives (for risk-management purposes) and (b) non-users of derivatives. Every quarter I classify a bank as a user if it used derivatives for hedging in that quarter and as a non-user if it did not. Panel A (users) is estimated with 8,439 observations while Panel B uses 79,958 observations. I regress the Maturity GAP variable on the bank-specific and macroeconomic variables. PD stands for the log likelihood of default and is computed in the first stage distress likelihood model. Size measures the log of total assets of the bank. TD/TA refers to total deposits as a ratio of total assets. Growth is computed as the average quarterly growth over last four quarters. Liquid measures the extent of liquid assets held by the bank scaled by its total assets. IR Level refers to the average interest rate (three-month Treasury) during the quarter. IR Volatility measures the standard deviation of the same interest rate series during the quarter. Term-Spread is the yield difference between 10- and one-year Treasury. Credit Spread measures the yield difference between a BAA and a AAA corporate borrower. I provide the parameter estimates and p-value from the estimation in this table.

	Panel A: Derivative Users		**Panel B: Derivative Non-Users**	
Variables	**Estimate**	**p-value**	**Estimate**	**p-value**
PD	-0.0121	0.01	-0.0071	0.01
Size	0.0179	0.01	0.0039	0.01
TD/TA	0.1169	0.01	0.1038	0.01
Growth	-0.1612	0.01	-0.0776	0.01
Liquid/TA	0.0387	0.01	0.0063	0.01
Lag GAP	0.6838	0.01	0.7012	0.01
IR Level	-0.0005	0.79	-0.0042	0.01
IR Volatility	-0.0117	0.09	-0.0014	0.01
Term-spread	0.0006	0.80	-0.0029	0.01
Credit-spread	-0.0052	0.32	-0.0083	0.01
R-squared	89.08%		85.26%	

Table 10
Impact of Monetary Policy Shocks on Lending Volume of Derivative Users vs. Non-Users

I regress the change in a bank's log (total loans and leases) in quarter 't' on its own four lags and eight lags of changes in fed funds rates. I also control for the growth rate in GDP by adding four lags in changes in log (nominal GDP) in the current and three previous quarters. The following regression model is estimated:

$$\Delta \log(LOAN)_{jt} = \alpha_0 + \sum_{k=1}^{k=4} \alpha_k \Delta \log(LOAN)_{jt-k} + \sum_{k=1}^{k=8} \beta_k \Delta FED_{t-k} + \sum_{k=0}^{k=3} \gamma_k \Delta \log(NGDP)_{t-k} + \varepsilon_j$$

The model is estimated separately for the derivative non-users *(j=0)*, users *(j=1)* and the difference between non-users and users *(j=2)*. The coefficient on the eight lags of Fed funds rate change are summed and reported under the column $\sum_{k=1}^{k=8} \beta_k$ in the table below. I estimate these models for various size groups. Row labeled as 'medium and large banks' uses all banks with asset values of at least $100 million (in 2003 dollar terms) in a given quarter. In the next four rows, I restrict my analysis to 'top 25%' (based on total assets of the bank in 2003 dollar terms, the cutoff is given within the brackets), 'top 10%', 'top 5%' and 'top 3%' of the banks. For each estimation, I report the sum of coefficient on the fed funds variables, the p-values for the test that the sum is zero, adjusted R-squared of the regression and the median number of observations used per quarter in the derivative user and non-user category. All p-values are corrected for heteroskedasticity and autocorrelation of four lags using Newey-West adjustment.

	Derivative Users				**Derivative Non-Users**				**Non-Users Minus Users**	
Size Group	$\sum_{k=1}^{k=8} \beta_k$	**p-value**	**Adj-R^2**	**NOBS**	$\sum_{k=1}^{k=8} \beta_k$	**p-value**	**Adj-R^2**	**NOBS**	$\sum_{k=1}^{k=8} \beta_k$	**p-value**
Medium and Large Banks(> $100 mn)	0.4253	0.70	9.87%	349	-1.0269	0.08	48.43%	3539	-1.1565	0.08
Top 25% Banks (>$150.35 mn)	0.4259	0.70	9.89%	337	-0.9715	0.10	45.85%	2219	-1.2227	0.06
Top 10% Banks (>$356.47 mn)	0.4272	0.70	9.96%	282	-0.9384	0.10	37.31%	787	-1.3194	0.05
Top 5% Banks (>$741.09 mn)	0.4322	0.69	9.65%	235	-1.1000	0.05	30.85%	301	-1.4828	0.05
Top 3% Banks (>$1428.48 mn)	0.4910	0.66	8.94%	188	-0.9748	0.20	18.44%	138	-1.5366	0.06

Table 11
Robustness Table

This table provides three robustness results estimated on the sample of 'medium and large' banks. In the first model, instead of using the probability of default as an explanatory variable, I use the expected loss in the event of default as a proxy for financial distress cost. First I estimate a loss-given-default model based on actual losses experienced by FDIC in bank failures. Based on these estimates and the probability of failure, I construct an instrument for the expected loss of distress (=estimated probability of distress x estimated loss in the event of distress). In the second model, I consider 50% of demand deposits as non-core deposits, i.e., these deposits are treated as short-term liabilities for the purpose of computing maturity GAP. Finally in the third model, I compute a maturity weighted average of firm's derivatives position and use this measure as a proxy for the extent of hedging by means of derivatives. For each of these models, I provide the coefficient on default likelihood variable (expected loss variable for the first model) for a bank fixed effect regression model. In Panel A, the maturity GAP is the dependent variable, while in Panel B the log of the IR derivatives scaled by the total assets of the firm has been used as the dependent variable.

Models	**Panel A: Maturity GAP**	**Panel B: Extent of Derivatives**
Loss Given Default Model	-0.0105	0.1368
	(0.01)	(0.01)
50% of DD as *non-core*	-0.0052	0.0951
	(0.01)	(0.01)
Maturity-Adjusted Derivatives	---------	0.0874
		(0.01)