LIQUIDITY RISK AND SYNDICATE STRUCTURE

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Abstract

We produce a comprehensive decomposition of syndicated loan risk into credit, market and liquidity risk and test how these shape loan syndicate structure. Banks dominate relative to non-bank investors in loan syndicates that expose lenders to liquidity risk. This dominance is most pronounced when borrowers have high levels of credit or market risk. We then tie banks' comparative advantage to their access to transactions deposits by comparing investments across banks. The results suggest that risk-management considerations matter most for participants relative to lead arrangers. Links from transactions deposits to liquidity exposure, for instance, are about 50% larger at participants than at lead arrangers.

I. Introduction

Over the past 20 years the syndicated lending market has grown rapidly, with originations in 2006 surpassing $1.6 trillion (Loan Pricing Corporation). This market offers large firms access to long-term debt finance as well as liquidity support in the form of lines of credit and loan commitments. Many large firms use these lines both to reduce their need for cash and to support their commercial paper programs (Sufi, 2007; Gatev and Strahan, 2006). While financial institutions such as investment banks, insurance companies and hedge funds play an important role in funding syndicated loans, commercial banks maintain an advantage over competitors in products that expose lenders to systematic liquidity risk.[1] We show that this advantage shapes the structure of loan syndicates. Banks dominate in lending on lines of credit to all kinds of firms, but their dominance is especially pronounced in issuing large lines to risky borrowers. In contrast, bank dominance is much less pronounced in term lending that is fully funded at origination and thus brings no liquidity risk at all. We produce a comprehensive decomposition of syndicated loan risk into credit, market and liquidity risk and test how these factors shape loan syndicate structure. Existing studies have shown that structure varies with borrower attributes related to credit risk and transparency, but ours is the first to demonstrate how liquidity risk management shapes syndicate structure.[2]

Why do banks dominate in the market for credit lines?[3] Kashyap, Rajan and Stein (2002) explain the combination of transactions deposits and credit lines with a risk-management motive. In their model, as long as liquidity demands from depositors and borrowers are not too correlated, the bank reduces its costly buffer stock of cash by serving both customers.[4] Thus, their model yields a synergy because combining transactions deposits with unused loan commitments allows banks to diversify away liquidity shocks. Gatev and Strahan (2006) extend this idea, showing that banks are endowed with a unique hedge for the *systematic* risk that occurs when many large borrowers simultaneously increase their demand for bank credit during episodes of reduced market liquidity: offsetting inflows into government-protected transactions deposits. Banks' structure allows them to sell excess liquidity to firms at precisely those times when they need cash because markets are tight. Thus, deposits afford banks a comparative advantage in offering liquidity insurance relative to other financial intermediaries.

Based on these models, we argue that banks' advantage in syndicated lending ought to show up most strongly in their role as passive participants investing in lines of credit. Risk management considerations – such as the advantage of transactions deposits – matter more for passive participants compared to lead arrangers. In general, participants provide funds but otherwise rely on the lead lenders for negotiation and pricing of loans and, to a certain degree, in cases of covenant violations or default. Lead lenders therefore must account not only for risk management concerns associated with loan funding, but also with their ability to understand the borrower and to monitor over the life of the loan. Thus, for a lead lender liquidity-risk management is likely to be of second-order importance.

Table 1 illustrates our main finding in a simple way. Using the *Dealscan* data on syndicated loans, we present the average share of lenders that are banks for term loans and lines of credit, and then break these difference out based borrower type (investment grade v. speculative grade-rated v. unrated) and based on the role of the lender (lead v. participant). Across all cells, banks dominate in lines of credit relative to term loans. Their relative dominance is most pronounced, however, for high-risk borrowers; and, their dominance is also most pronounced as participants. For example, among speculative-grade rated firms, the bank share is 18 percentage points greater for lines of credit than for term loans. This difference becomes even more pronounced – 22 percentage points – when we focus only passive participants, where the liquidity risk management considerations are paramount. Non-bank lenders, lacking the systematic liquidity risk-hedging externality of transaction deposits, avoid credit lines.

Another way of making our main point: non-bank investors have successfully competed with banks in term lending to high-risk borrowers, where they have close to one-half of the market. In contrast, they have much less impact on lending to those same borrowers in the market for lines of credit because of the liquidity risk. To see the evolution of the market, Figure 1 plots the market share of non-bank investors in syndicated lending over time. During the early 1990s, banks dominated lending across both borrower types (investment grade v. speculative grade) and loan types (term loans v. lines of credit). Over the subsequent 15 years, however, non-bank investors' share grew sharply, but that growth was concentrated among high-risk borrowers, consistent with the idea that these investors look to take on credit risk. Despite this dramatic market entry, we see much less penetration in lending on lines of credit, where bank dominance remains throughout the sample. In fact, the difference in market share between lines and term loans grew over time, reflecting the success of non-bank investors in funding term loans to high-risk borrowers. The non-bank share in term lending to risky borrowers increased by 28 percentage points comparing the 1990-95 period with 2000-05, but only by 18 percentage points for lines of credit. In the context of a comprehensive decomposition of syndicated loan risk exposure, these simple findings illustrate our main proposition about risk-sharing where non-bank investors bear (and sometimes sell or securitize) credit risk, while banks bear the liquidity risk exposure.

The main results validate these simple comparisons with regressions of banks' share of syndicates in a large sample of loans. Our explanatory variables include facility type (lines v. term loans), borrower type (investment grade, speculative grade or unrated; high or low-beta industry), size (log of the tranche size), industry beta and the interaction of these characteristics with a line of credit indicator. Consistent with Table 1, banks dominate in lines of credit to all borrowers, regardless of credit or market risk, and their dominance strengthens with loan size. In contrast, non-bank investors gravitate toward high-risk term lending, both along the credit and market dimensions. These effects can *not be explained* by borrower, lender, loan, or deal characteristics, which we remove with fixed effects. We also find much stronger effects of all of the risk variables on banks' share as participants compared to their share as leads.

Following the main results, we then extend the bank specialization hypothesis by comparing investment decisions *across banks*. We test how transactions deposits affect bank originations in lines of credit relative to their total originations. Our approach has three advantages over existing studies. First, we measure banks' *ex ante* liquidity exposure in new lending. The existing evidence relies on the stock of off-balance sheet commitments relative to on-balance sheet loans from all past lending. These data (from *Call Reports*) do not allow researchers to separate *ex ante* exposure (i.e. supply) from *ex-post* realizations of liquidity demands because when borrowers draw funds, those funds move onto the lender's balance sheet. In contrast, our dependent variable measures the maximum potential future exposure from lines of credit relative to a bank's total exposure from all new lending (i.e. lines of credit plus term loans). This new *ex ante* measure reveals qualitatively different results. For example, the dollar-weighted share of new loans with liquidity exposure ranges up to 76% for the average bank in a given year, as opposed to 26% as reported in prior studies. Second, we observe borrower characteristics, which we can control for in our main tests, and which we can also use to test how bank allocation across other dimensions (e.g. borrower size and risk) varies with access to transactions deposits. Third, we separate our measure into exposures faced by lead banks v. participants. This helps us distinguish between relationship management and liquidity-risk management motives.

We find that bank investments in credit lines, as a fraction of total lending, increase with transactions deposits.[5] Thus, not only do banks dominate non-banks in issuing credit lines, we find that banks with more transactions deposits supply more credit lines than banks funded with other sources of debt. And, like the bank v. non-bank comparison, we also find that banks funded more with transactions deposits seem to specialize in liquidity risk bearing relative to credit or market risk. We show, for example, that banks with high levels of transactions deposits lend to firms with lower credit risk (based on the credit rating and the loan yield) and to firms in industries with lower betas. So, the comparisons across banks mirror those between banks and non-banks. Transactions deposits give banks a comparative advantage relative to non-banks, and the same advantage helps explain loan specialization across banks.

II. Background

What is the nature of the deposit-lending synergy that allows banks to provide liquidity to both borrowers and depositors? Kashyap et al. (2002) explain the combination of transactions deposits and loan commitments with a risk-management motive. While holding cash raises costs for both agency and tax reasons (Myers and Rajan, 1998), Kashyap et al. present a model where as long as liquidity demands from depositors and borrowers are not highly correlated, an intermediary will reduce its costly cash buffer by serving both customers. Thus, the KRS model yields a diversification synergy between transactions deposits and unused loan commitments. KRS report empirical evidence of a positive correlation across banks between unused loan commitments and transactions deposits. However, they do not test the key implication of their model that by exposing themselves to asset-side and liability-side liquidity risks simultaneously, banks can benefit from a diversification synergy.

Gatev and Strahan (2006) suggest a stronger hypothesis, supported by findings that the correlation is not only low but is often *negative*. They show that a hedging externality can be attributed to transaction deposits because flows into these accounts offset the systematic liquidity risk exposure associated with origination of loan commitments and lines of credit. Gatev and Strahan (2006) extend KRS by considering the possibility that liquidity production could expose banks to systematic liquidity risk. A bank with many open credit lines may face a problem if systematic increases in liquidity demand occur periodically.[6] Gatev and Strahan (2006) show that funding to banks increases when market liquidity declines, meaning that liquidity demands become negatively correlated in tight markets. There are several reasons why banks enjoy funding inflows when liquidity dries up. First, the banking system has explicit guarantees of its liabilities.[7] Second, banks have access to emergency liquidity support from the central bank. Third, large banks such as Continental Illinois have been supported in the face of financial distress (O'Hara and Shaw, 1990). Thus, funding inflows occur because banks are rationally viewed as a safe haven for funds. Consistent with this notion, Pennacchi (2006) finds that during the years before the introduction of federal deposit insurance, bank funding supply did *not* increase when spreads tightened.

Gatev, Schuermann and Strahan (2006) find evidence that supports the notion that inflows into transaction deposits increase the capacity of banks to bear systematic liquidity risk. They show that lower stock return volatility for banks with high levels of both unused commitments and transactions deposits. The results suggest that bank risk, measured by stock return volatility, increases with unused loan commitments, reflecting asset-side liquidity risk exposure. This increase, however, is mitigated by transactions deposits. In fact, risk *does not* increase with loan commitments for banks with high levels of transactions deposits. Gatev et al. also show that these results are stronger during the 1998 'flight to quality'.

The ability of banks to absorb liquidity shocks is especially important during market crises. In a case study, Gatev, Schuermann and Strahan (2005) focus on the behavior of deposit flows *across banks* during the 1998 crisis. During the three-months leading up to the crisis, bank stock prices where buffeted by news of the Russian default, followed by the demise of LTCM in late September, and finally by the drying up of the commercial paper market in the first weeks of October.[8] To understand how banks weathered the 1998 storm, Gatev et al. (2005) explore the cross-sectional patterns in deposit flows. They found that first, investors moved funds from markets into banks; second, banks with higher levels of transactions deposits before the crisis had the largest flows of new money during the crisis; and third, that *all* of the flows of new money were concentrated in bank demand deposits. This evidence indicates that banks structured to bear increased demands for liquidity from borrowers (i.e. banks with transactions deposits) could meet those demands easily (because money flowed into those accounts). Thus, while government safety nets can explain why banks generally receive funding during crises, the evidence from Gatev et al. as well as Kashyap et al. suggests that the structure of banks also is important.

Before the introduction of government safety nets, transactions deposits tended to expose banks to liquidity risk when consumers removed deposits en-masse, either to increase consumption or because they had lost confidence in the banking system. This bank-run problem has traditionally been viewed as the primary source of liquidity risk and creates a public policy rationale for FDIC insurance as well as reserve requirements for demand deposits (Diamond and Dybvig, 1983). Today, in crisis investors run to banks, not away from them (at least they do in the U.S.). And, banks funded with transactions accounts receive the inflow. Thus, rather than open banks to liquidity risk, transactions deposits today help banks hedge that risk, which now stems more from the lending side.

III. Research Design

We report two sets of results. The first set uses loan-level data to test whether loan type determines banks' share within loan syndicates relative to other investors. The second set uses bank-level data to test how banks' investments across loan types vary with transactions deposits.

To test whether liquidity risk exposure explains bank involvement in the loan syndicates, we use *Dealscan* from 1991 to 2005 to build a facility-level dataset. We estimate regressions with the following general structure:

$$\begin{aligned} \textit{Fraction of bank lenders}_{i,j,t} = {} & \beta_1\, \textit{Credit Line}_{i,j,t} + \beta_2\, \textit{Investment grade}_{i,t} \qquad (1) \\ & + \beta_3\, \textit{Speculative}_{i,t} + \beta_4 \textit{Tranche Size}_{i,j,t} + \beta_5\, \textit{Credit Line}_{i,j,t} * \textit{Investment grade}_{i,t} \\ & + \beta_6\, \textit{Credit Line}_{i,j,t} * \textit{Speculative}_{i,t} + \beta_7\, \textit{Credit Line}_{i,j,t} * \textit{Tranche Size}_{i,j,t} \\ & + \beta_8\, \textit{Credit Line}_{i,j,t} * \textit{Industry Beta}_i + \varepsilon_{i,j,t}\ , \end{aligned}$$

where *i* is an index specific to the deal, and hence also specific to the borrower; *j* is an index specific to the facility within each deal; and *t* is an index for years. Equation (1) has some aspects of a panel regression, and we use fixed effects techniques to sweep out many potentially confounding variables. *Dealscan* contains facility-level data, with more than one facility per deal on average (mean facilities per deal = 1.4). In many cases, a deal will be composed of a term loan and a line of credit. Moreover, the same borrower may have many deals at different times. Given this structure, we can include annual time dummies to sweep out market trends. We can also include borrower fixed effects to sweep out the direct effects of borrower characteristics or other unobservable aspects of relationships between the borrower and potential lenders. Thus, our main focus will be on the effects of liquidity exposure (i.e. lines v. term loans), and how liquidity exposure interacts with the other risk characteristics (market and credit).

We estimate the model with three versions of the dependent variable. In the first, we compute *Fraction of bank lenders* = the number of banks in the syndicate / total number of lenders.[9] We then compute this ratio using first just lead arrangers in the numerator and denominator, and second using just participants. The explanatory variables of interest are indicators for *credit lines*, *investment-grade rated borrowers, speculative grade borrowers*, *tranche size* = logarithm of the tranche amount (normalized by the log of all loans for that year), and *industry beta* = the median beta for *Compustat* firms in the same 2-digit SIC as the borrower.[10] We use industry rather than firm betas because fewer than half of the firms in *Dealscan* have public equity. We also interact these borrower and industry characteristics with the *credit line* indicator. (Since it has no time variation, the direct effect of industry beta is absorbed by the borrower fixed effects.)

We first estimate simple models, and then we add the interaction effects. We also include an indicator for credit lines used to back commercial paper in the more complicated models. In the simple models, if liquidity risk management gives banks a comparative advantage, then $\beta_1 > 0$. In models with the interactions, if that advantage is more pronounced when the systematic liquidity risk exposure is greater, then $\beta_7 > 0$; if that advantage is stronger when credit risk is greater, then $\beta_5 < 0$ (because investment grade rated firms are safer on average than the unrated firms, which are the omitted category), and $\beta_6 > 0$ (because the speculative grade firms are riskier on average than the omitted category); and, if that advantage is stronger when market risk is greater, then $\beta_8 > 0$.

Beyond the firm effects, we also control for lead arranger fixed effects in all models, and we include loan purpose fixed effects in the simple models. (The commercial paper back-up line effect is not identified with loan-purpose fixed effects so we omit them.) Finally, because the market for lead arrangers is highly concentrated, and because lead arrangers directly shape the structure of the syndicate, we also cluster the error in equation (1) at the level of the lead arranger. This is a very conservative way to build standard errors because there are only 61 lead arrangers in the dataset.

In our second set of tests, we construct data at the level of the bank-year, rather than at the loan level. In these regressions, we test whether transactions deposits provide a hedge for liquidity risk exposure, as follows:

$$\begin{aligned} &\textit{Incremental liquidity exposure}_{i,t} = \alpha_t + \beta_1\, \textit{Transactions Deposit/Total Deposits}_{i,t-1} + \\ &\beta_2\, \textit{Prior liquidity exposure}_{i,t-1} + \textit{Other controls}_{i,t-1} + \varepsilon_{i,t}\,, \qquad (2) \end{aligned}$$

where i is an index for banks; t is an index for years; and α_t equals a year-specific intercept. We include the annual time dummies to sweep out trends such as the gradual decline over time in bank deposits. We follow KRS in using the ratio of transactions deposits to total deposits as our measure of the potential hedge afforded by combining liquidity exposure on both sides of the bank balance sheet. Based on the notion that transaction deposits hedge liquidity risk exposure, we expect that $\beta_1 > 0$. On the other hand, prior commitments could be negatively correlated with incremental liquidity risk exposure (reflecting a bank's hesitance to become too exposed to liquidity), or positively correlated with incremental liquidity exposure (reflecting a bank's market specialization), so we have no prior on the sign of β_2.

The dependent variable in (2) equals the relative importance of liquidity to a bank's total new lending during the year, where: *Incremental Liquidity Exposure*$_{i,t}$ = (New commitments on lines of credit$_{i,t}$) / (new commitments on lines$_{i,t}$ + new commitments on term loans$_{i,t}$). To build this variable, we sum the total commitment amounts for all loans made by a given bank in a given year. The variable should be interpreted as the relative importance of a bank's investment in liquidity risk during a given year. We also test how average borrower characteristics (mean sales size, the fraction of borrowers who are rated, the fraction of rated borrowers who are speculative grade, and the average industry beta) and the markup of the loan spread over LIBOR vary with lender characteristics. For control variables, we include the following bank characteristics (from the fourth quarter of the year before banks' new loans were originated, labeled *t-1*): *Prior liquidity Exposure* = Existing un-drawn commitments / (loans + commitments); *Deposits* = Total deposits / assets; *Bank size* = Log of assets; *Capital ratio* = Book value of equity / assets; *Balance-sheet liquidity* = (Cash + securities) / assets. Each of these comes from the Call Report at the end of the previous year.

Data

We build our measures of banks' share of loan syndicates and bank liquidity exposure from Loan Pricing Corporation's *Dealscan.* These data offer the most complete record of bank lending to large businesses currently available. *Dealscan* provides data on the identity of the borrower; whether or not the borrower has a credit rating (as well as borrower sales and industry); the name, type (bank v. non-bank) and role of each lender (lead v. participant); the percentage of each loan funded by each lender; the loan amount and type (lines of credit versus term loans); and price and non-price terms (collateral & maturity).[11] We use data for 1991 to 2005. This sample period reflects several data limitations. First, prior to 1991, *Dealscan* coverage was relatively poor. Second, there are no data from *Call Reports* on unused commitments prior to 1991, which we use in our second set of tests.

In our first set of regressions (recall equation 1 above), we build the share of banks in the syndicate for each loan facility in *Dealscan*. We then decompose this share into banks' share of lead arrangers, and banks' share of participants. In classifying lenders, we rely on *Dealscan's* lender role variable. We define any lender that plays an active role as a 'lead'. The *Dealscan* variable takes on many different values for lenders that are 'active'. For example, 18% of the observations are coded as 'admin agent'; 7.5% are coded as 'co-agent'; 6.5% as 'documentation agent', and so on. In about 46% of the observations, a lender is coded as a 'participant'. We define a lender as playing some kind of active role if *Dealscan* does not code the bank as 'participant'. For lender type, we define the following types as banks: 'US bank'; 'African bank'; 'Asia-Pacific bank'; 'East. European / Russian Bank'; 'Foreign bank'; 'Middle Eastern Bank'; and 'Western European Bank'. The vast majority of the observations are either US banks or Western European banks. For loan type, we code the following three types as facilities as lines of credit: “Revolver/Line < 1 Yr.”, “Revolver/Line >= 1 Yr.,” and “364-Day Facility.” There are some facilities that are neither liquidity nor standard term loans such as standby letters of credit. Our results are robust to dropping these loans.

For our final dataset, we keep all loans with at least one lead arranger and one participant. In our simplest specifications, this filter yields a dataset with more than 42,000 loans made over the 1991 to 2005 period. When we add controls for other loan terms, the sample falls to about 40,000 loans. However, as noted earlier, we cluster by the small number of lead arrangers in all of the models, so the large sample size does not lead to unreasonably small standard errors.

For the analysis at the level of the bank-year (equation 2), we compute the total amount of new lending made by each bank lender by summing across the dollar amount committed by that lender during each year from 1991 to 2005. We then split the commitments into amounts with liquidity risk (lines of credit) and amounts without liquidity risk (other loans). For bank characteristics, we merge the *Dealscan* annual aggregate data to the *Call Reports* from the end of year previous year.[12] *Call Reports* contain data on bank size (assets), unused existing loan commitments, liability structure, capital, and balance-sheet liquidity, all of which we use in our main tests. After combining the two datasets we are left with an unbalanced panel spanning 1991 to 2005, with bank-year as the unit of observation. The final sample includes about 120 (mostly large) banks per year, or between 1,400 and 1,700 bank-year observations overall (depending on the set of controls included in the model).

IV. Results

Syndicate Structure: Banks dominate in lending with liquidity risk

As we describe in the introduction, Table 1 highlights the overwhelming importance of banks in syndicated loans, particularly those with liquidity exposure. We now report rigorous tests of our main hypothesis with a series of fixed effects models, where the dependent variable is the overall fraction of lenders that are banks. Table 2 reports summary statistics for the explanatory variables in the model. About 58% of the facilities are lines of credit, and about one third of borrowers are rated borrowers. For the other loan terms, the average facility size is $187 million, the average all-in spread is about 220 basis points over LIBOR, 38% of the loans are secured, and the average maturity is 49 months. There are 1,658 lenders across the sample of loans; 772 of these lenders are banks and the others are non-bank institutions. Non-banks include finance companies, insurance companies, investment banks and others.

Table 3 reports six models. There are two specifications for the explanatory variables times three specifications for the dependent variables: banks' share for all lenders banks, banks' share for participants only (numerator and denominator), and their share for leads only. The simple specification highlights the direct effect of the key variables of interest - credit risk and liquidity risk indicators. The second specification interacts the credit line indicator with firm characteristics. All specifications include time, borrower, and lead-lender fixed effects. The simple ones also include loan-purpose fixed effects.[13]

The results show that banks' comparative advantage lies in bearing liquidity risk, and that this advantage is stronger where liquidity risk is more systematic and where credit and market risk are relatively high. Looking first at the simple models (columns 1, 3 and 5), the coefficient on the lines of credit indicator equals 0.068 overall, rising from 0.015 for lead lenders to 0.088 for participants, meaning that banks hold a 1.5 percentage point to 8.8 percentage point greater share than non-bank investors in lines of credit (relative to term loans). Banks specialize in liquidity risk. Conversely, non-bank investors specialize in credit risk; for participants, the coefficient on the speculative grade indicator equals -0.036, meaning that the non-bank share is 3.6 percentage points higher when borrowers are very high risk compared to the omitted group (unrated borrowers). The non-bank share for investment grade borrowers is 3.2 percentage points lower than their share for unrated borrowers.

The model with interactions (columns 2, 4 and 6) shows that banks' liquidity advantage strengthens among large lines and among lines to otherwise riskier borrowers. The interaction between the credit line indicator and the log of the tranche amount is positive and statistically significant for participants. Loan size is weakly negatively related to banks' share for term loans (the direct effect), but strongly positively related to bank share for lines of credit (summing the direct effect with the interaction). The interaction between the credit line indicator and the credit ratings indicators suggest that banks dominate in making loans with liquidity risk across the board – their share in lines does not vary much with credit risk. That is, the sum of the direct effect of the speculative grade and investment grade indicators with the interaction term is close to zero and not statistically significant. In contrast, credit risk is highly correlated with banks' share in term lending. Said a slightly different way, institutional investors specialize in holding credit risk, but their willingness to take that risk does not carry over into loans that also expose them to liquidity risk.

The same can be seen with the effect of the market beta for the borrower's industry. Here, the direct effect is not identified, but the interaction term enters with a positive and significant coefficient (overall and for participants). In unreported models in which we split the sample into lines v. term loans, we find a negative association between the borrower's beta and banks' share for both loan types, but a much smaller effect of beta for lines than for the term loans (consistent with the positive interaction in Table 3). Thus, the impact of market risk is attenuated in lines of credit. Non-bank investors seem to specialize in bearing both credit and market risk in term lending, but this overall willingness to bear risk *does not* carry over into the lines of credit where bank dominance is overwhelming.

Table 3 also shows that the effects of risk on loan syndicate structure matters much more in explaining participant behavior compared to the behavior of lead arrangers. The direct effect of the lines of credit indicator is more than two times larger in the participant equations, and interactions effects are also quantitatively much larger as well (columns 3&4 v. 5&6). The link between liquidity risk exposure and bank dominance becomes even more evident in the detailed specification including the size of the liquidity risk exposures. For participant lenders, the coefficient on the interaction between the credit line indicator and the size of the tranche is statistically and economically significant at 0.56. In contrast, that interaction is not significant for the lead lenders. Thus, syndicate structure for participation – where funding and the associated credit and liquidity risks are all that matter – is driven by the comparative advantage of banks to manage liquidity exposure.[14] The identity of lead arrangers, in contrast, varies much less across loan or borrower types, suggesting that risk management concerns are less important relative to relationship considerations between borrowers and their lenders.

The distribution of loan exposures across lender types reflects a risk-sharing arrangement where banks bear the liquidity risk and non-banks shoulder the credit and market risks. These latter risks can more easily be securitized and dispersed further among investors. This allocation also helps explain activity in loan secondary markets, where Drucker and Puri (2007) find that only 34% of loans traded are lines of credit, while over 70% of the loans in their comparison group of non-traded loans are lines of credit. Much of the demand to purchase these loans comes from *non-bank* financial institutions, which explains the low level of volume for lines of credit.

Robustness Tests

Table 4 shows that the results in Table 3 are robust to re-scaling the dependent variable in a logit specification (*ln [p] / (ln [1-p]*). This transformation expands the potential range of the dependent variable while maintaining the same ordering. Since sometimes the raw shares lie at the extremes, we transform the data by adding 0.01 to cases where banks' share equals zero, and subtracting 0.01 in cases where banks' share equals one. The table confirms that as passive participants, banks dominate all of the loan syndicates with liquidity risk, while non-bank investors tend to have a large investment in term loans to high-risk borrowers. Generally the fit and statistical power of the variables are similar in comparing Tables 3 and 4, although we find evidence that tranche size is positively related to bank share for lines of credit in Table 4.

We have also estimated the specifications with interaction effects that include deal-level fixed effects rather than borrower fixed effects (unreported). In these models, only the interaction terms are identified because the deal fixed effects absorb any characteristic of the borrower (or the relationship between the borrower and the lead arrangers) that is constant across all tranches within a deal. So, for example, the direct effect of credit rating can not be measured.

In these models, however, the interaction terms are very close to those reported in Table 3. For example, the coefficient on the interaction between lines and investment grade borrowers equals -0.046 (t=5.76) with deal effects, compared to -0.071 (t=6.55) with borrower effects; the coefficient on the speculative grade * lines interaction equals 0.073 (t=7.59) with deal effects compared to 0.079 (t=7.48) with borrower effects; and the interaction between tranche size and lines equals 0.431 (t=8.10) with deal effects compared to 0.560 (t=7.28) with borrower effects.

Bank specialization stems from access to transaction deposits

To link bank dominance in lending on lines of credit to their access to transactions deposits, we now test how bank portfolio allocation decisions vary with the structure of their liabilities. In these models the data varies by bank-year rather than by loan. We are interested in whether banks funded more with transactions deposits exhibit a comparative advantage in bearing liquidity risk relative to credit risk.

Table 5 reports summary statistics for the bank-year level data. This analysis is similar to Kashyap et al. (2002), but we use *Dealscan* as our source for the dependent variable, rather than relying on unused loan commitments from *Call Reports*. The table illustrates the advantage of using *Dealscan*. The share of loans with liquidity exposure for a bank equals the dollar-weighted average across all loans originated during the year by that bank; the amount invested in a loan equals the bank's share times the commitment amount. Since the share is sometimes missing, we also build a measure allocating a bank's investment assuming each lender funds $1/N_j$ of each loan, where N_j equals the number of lenders in syndicate *j*. Liquidity exposure ranges from 65% to 76% for the average bank in a given year. In contrast, KRS report a median value of just 26% for large banks from Call Report; this figure is close to the 30% mean we report for existing exposure (undrawn commitments / (undrawn commitments + loans)). Part of this difference between existing commitments and new liquidity exposure occurs because the *Call Report* data include draw-down realizations; once a borrower draws funds from a line, those funds move from the off-balance sheet accounts onto the lender's balance sheet. Thus, the old variable contains substantial measurement error. The liquidity exposure ratio could be low, for example, either because the bank chose not to supply much liquidity, or because the bank experienced an unusually high realization of liquidity demand.

Table 5 also reports summary statistics for the lead share for each bank-year. This variable is constructed in a similar way to our measure of liquidity exposure, where for each bank we sum its total lending in which it acts as the lead lender, relative to its total new lending during the year. The two measures range from 0.29 to 0.37, although some of our banks are almost always lead lenders while others are almost always participants. For example, in 2001 *Dealscan* reports that First Merit bank participated in 10 loans, but only as a participant. In contrast, *Dealscan* records that Citibank acted as a lead bank in 95% of its total 2001 lending (almost 1,000 loans).

Table 6 reports the main bank-level results tying their specialization in liquidity risk bearing to transactions deposits. We estimate the dependent variables using the information on each bank's actual lending shares within the syndicate (the first measure reported in Table 5). Loans for which the share is missing are not included. Each regression includes unreported time effects, and we cluster the residual at the bank level in computing standard errors. To establish the main result, moving from the left to right columns we report a series of models in which we introduce an increasing number of control variables. As the table shows, the effect of transactions deposits on the liquidity exposure variable is stable across these six specifications. The coefficient on transactions deposits equals 0.44 in the simplest model, which includes only annual time indicators, falls to 0.37 when we add the log of bank assets, and then remains at that level as we add past commitments, total deposits to assets, capital to assets, and the balance sheet liquidity ratio. The fit of the model improves with these additional variables, but the basic finding does not. In all six models the key coefficient is statistically significant at better than one percent. Moreover, the effect of transactions deposits is economically large. A standard deviation increase in this variable comes with an increase in lending that exposes the bank to liquidity risk of about 4.3 percentage points (0.36 * 0.12 = 0.043). This effect is similar in magnitude to the effect of a standard deviation increase in the log of bank assets ($\sigma = 1.48$), where a standard deviation increase comes with an increase in liquidity exposure of about 4.4 percentage points (1.48 * 0.03 = 0.044).

Tables 6 also shows that large banks are more active suppliers of liquidity facilities than smaller banks, which may in part reflect the greater demand for liquidity from large borrowers that are more likely to be served by large banks. In addition, large banks may be better able to manage systematic liquidity risk than smaller banks. For example, large banks typically have better access to overnight liquidity in the Federal Funds market than smaller banks. Also, we find a negative correlation between the capital ratio and the relative importance of liquidity. This negative relationship could in part reflect the impact of the Basel I capital treatment for un-drawn commitments (zero for loans with maturity less than one year), and because the expected loss on lines of credit is lower than expected losses on term loans.

If banks with high levels of transactions deposits have a comparative advantage in bearing liquidity risk, we would expect to see this advantage shape not only the type of product offered but also the kinds of borrowers served. So, we regress average characteristics of banks' portfolios across five additional dimensions beyond liquidity against transactions deposits and the other lender characteristics. The five dimensions are: average borrower size (log of sales), the share of loans to rated firms, the share of the rated borrowers who are speculative grade, the average loan-spread markup over LIBOR, and the average beta of the borrowers' industry. We include the same bank controls as well as time effects in all of these models. As shown in Table 7, banks with liquidity hedging capacity - high transactions deposits - tilt their lending toward larger firms, toward rated firms, and toward observably safer firms. The transactions deposits ratio is significant across all five portfolio allocation variables. Banks with high levels of transactions deposits are less exposed to both credit risk and market risk. They lend to larger, rated borrowers; among those with a rating, they lend to firms less likely to be poorly rated; and, they lend more to firms in low-beta industries. The advantage that we saw in comparing banks with non-banks – banks taking the liquidity risk and non-banks specializing in credit and market risk – also emerges in our comparisons *across* banks. Transactions deposits thus seem to play the key role in understanding the comparative advantage banks have in bearing liquidity risk.

As shown earlier, banks' share in loan syndicates varies with liquidity risk of the loan *only* for participations; we find no consistent effects of liquidity risk on banks' share among lead arrangers. This suggests that the portfolio allocation decisions of participant banks ought to reflect their access to transactions deposits much more than banks that act mainly as lead arrangers. So, we next consider separately each bank's exposure to liquidity risk, depending on whether the bank acts mainly as a lead lender (i.e. the bank has above-median share of loans as a lead) or not (i.e the bank has below-median share of loans as a lead). Our identifying assumption is that participant banks rely on the lead lender for negotiation and pricing of loans, and they also rely to a large though not perfect degree on the lead in cases of covenant violations or default. Thus, the pure risk management advantage of transactions deposits ought to matter more for banks that act mainly as passive participants, while the lead bank has to take account not only of diversification but also its ability to understand the borrower and monitor over the life of the loan. Lead banks as monitors of the borrower face a moral hazard problem relative to participants. This problem is solved in part through incentives (e.g. lead banks keep some 'skin' in the game by holding the largest piece of syndicated loans, and they do so more when borrowers are opaque) and in part through reputation. Thus, given a large transaction deposit base, systematic liquidity-risk management is likely to be second order in importance for lead banks.

In Table 8, we re-estimate our model of liquidity exposure after splitting the sample based on the lead-bank share. We split at the median of the actual lead-bank share.[15] We find a significant effect of hedging-capacity on loan portfolio decisions for passive investor banks. For the participants, the coefficient on transactions deposits equals 0.43, more than twice as large as the effect for banks that specialize in *leading* loan syndicates. This result confirms our central argument that transactions deposits are critical for systematic liquidity risk management, which in this case is the primary risk management objective of syndicate participant banks. Moreover, the larger effects that we observe across participant banks mirrors the larger effects of loan type in explaining the allocation of holdings between banks and non-banks within syndicates.

In another set of (unreported) tests, we have also decomposed our initial dependent variable into two parts, one reflecting the total commitments made on lines where a given bank acts as the lead lender, and the other reflecting total commitments on lines where the bank acts only as a passive participant.[16] In this approach, there are two liquidity measures for each bank. We use the same denominator as before (total exposure), so the sum of these two variables equals the original measure of liquidity exposure from the prior tables. This decomposition allows us to separate the relationship management motive (attributed to the lead bank) from the pure liquidity risk management motive (which we assume drives the portfolio decisions of participant banks) without splitting the sample. In other words, we are testing whether banks manage their own liquidity exposure differently depending on whether or not they act as lead on a given loan. These results are similar to the approach where we split the sample based on a bank's overall emphasis on lead lending. That is, we find that the effect of transactions deposits is about 50% larger for banks' liquidity exposures as participants compared to their exposures as leads.

Robustness Tests

We have conducted several (unreported) robustness tests on the statistical procedure that we have used to estimate the models in Table 6. First, we have tested whether the results vary with the way we construct our measure of liquidity exposure, the dependent variable. We have checked *four* proxies to construct new commitments for bank *i* in year *t:*

$$\begin{aligned}
&(1)\ \text{New commitments}_{i,t} = \Sigma_j\ \text{Commitment}_{i,j,t}\text{*share}_{i,j,t} && (j \text{ indexes new loans})\\
&(2)\ \text{New commitments}_{i,t} = \Sigma_j\ \text{Commitment}_{i,j,t}\text{*maturity}_{i,j,t}\text{*share}_{i,j,t}\\
&(3)\ \text{New commitments}_{i,t} = \Sigma_j\ \text{Commitment}_{i,j,t}\text{*}(1/\text{N}_{i,j,t})\\
&(4)\ \text{New commitments}_{i,t} = \Sigma_j\ \text{Commitment}_{i,j,t}\text{*maturity*}(1/\text{N}_{i,j,t}) && (3)
\end{aligned}$$

As noted, the numerator of our liquidity measure includes commitments on just lines of credit, whereas the denominator includes commitments for all types of new loans. The first measure was used in Table 6, based on the *Dealscan* data on each bank's actual share of funding at origination ($share_{i,j,t}$). This variable, however, is missing for a large number of observations (more than 50%), so we construct a second measure in which each bank's share is assumed to equal 1/number of participants ($N_{i,j,t}$). The other two measures weight the commitment amounts by the maturity of the loan. Banks with more transactions deposits expose themselves to more liquidity risk in subsequent lending relative to other banks across all four measures. Coefficient magnitudes are larger when we use all loans to build the dependent variable. This difference makes sense because the specification implicitly give more weight to participant banks relative to lead banks (lead-bank share averages around 30%, compared to about 10% for participants), and the relationships that we estimate are stronger for participant banks. Magnitudes are not affected by whether or not we weight commitments by maturity. This similarity may reflect the distinction between contractual maturity (observable) and de facto maturity (unobservable).[17]

Second, we have estimated a weighted least-squares procedure, where weights depend on the number of loans originated by a bank during the year. The logic of this weighting scheme is that there may be less error in the dependent variable, and hence less variance in the residual, for banks making more loans. This weighting approach, however, essentially means giving more weight to large banks. These results are qualitatively consistent for the transactions deposit coefficient and remain statistically significant (t-statistics > 3), although the coefficient magnitudes decrease. The effect of bank size in the weighted regression falls and loses statistical significance.

Third, we have added a bank-specific component to the error term and compute both the 'within' and 'between' estimator. Here we again find similar results. Relative to the pooled

OLS model in Table 6, column 1 (transaction deposit coefficient = 0.36), the between estimator equals 0.49 (t-statistic = 3.12) and the within estimator equals 0.26 (t-statistic = 2.04). The 'between' estimator essentially builds off a single cross-section, based on the time-series averaged data for each bank. As an alternative, we have estimated year-by-year cross sectional regression and find that the positive effect of transactions deposits is consistent over time.

Fourth, we have estimated the main results in Table 6 controlling for the set of borrower characteristics in Table 7. In these models, we include the average borrower size, the share rated, the average loan interest rate, as well as a set of 2-digit SIC loan-share variables. These results are similar to those reported in Table 6, although the effect of transactions deposits falls from 0.36 to 0.26 (T=2.94). Thus, even controlling for borrower type we still see that banks with high levels of transactions deposits bear more liquidity risk than banks funded less with transactions deposits.

V. Conclusions

The structure of loan syndicates typically involves banks, whose unique capacity to hedge systematic liquidity risk allows them to fund credit lines with little competition from outside the banking system. In contrast, non-bank lenders, who do not enjoy the liquidity risk-hedging externality of transaction deposits, avoid syndicated credit lines but shoulder much of the credit and market risk exposure than can be securitized and dispersed further among investors (e.g. term lending). Banks bear the systematic liquidity risk exposure because their access to funds expands elastically in response to declines in market liquidity. This competitive advantage stems largely from the government safety nets protecting the banking system.

Within the banking system, those banks with more transactions deposits in turn have a comparative advantage in supplying lines of credit over other banks. The advantage stems from two sources. First, by combining transactions deposits and loan commitments, a bank can hedge out the idiosyncratic demands for liquidity from depositors and borrowers. Second, investors tend to move money into transaction deposits during periods of market turmoil. These funding inflows provide a generic hedge for unexpected liquidity shortages during market-wide shocks, and they help banks supply credit when markets would not do so.

Our results show that banks' funding advantage shows up most notably in lines of credit among passive participant lenders. Lead banks are responsible for information production and monitoring the relationship with the borrower over time; hence, their specific liquidity position is less important in driving their portfolio decisions. Our results support the idea that syndicate structure is explained in part by credit and liquidity risk management. Banks participation in syndicates is driven by their competitive advantage in hedging systematic liquidity risk that stems from a key synergy linking deposits to lending.

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Endnotes

[1] Nandy and Pei (2007) and Ivashina and Sun (2007) study the role of institutional investors in the syndicated lending market. Nandy and Pei focus on the fact that many institutional investors participate in high risk and high yield loans. Ivashina and Sun offer evidence that such lending in some cases gives investors access to private information.

[2] For example, Dennis & Mullineaux (2000), Lee & Mullineaux (2004), Jones, Lang and Nigro (2005) and Sufi (2007) all report evidence that the share of the lead bank and the concentration of the syndicate reflect borrower opacity and the resulting moral hazard problem. Ivashina (2007) uses risk management concerns (industry-level diversification) as an instrument that shifts a lead bank's willingness to fund a fraction of a loan and finds that prices reflect the lead bank's incentive to monitor effectively. Her study suggests that lead banks trade off risk management concerns against their need to preserve monitoring incentives.

[3] Early literature attempts to understand how banks' role in liquidity production leads to fragility. Diamond and Dybvig (1983) argue that by pooling their funds in an intermediary, agents can insure against idiosyncratic liquidity shocks while still investing most of their wealth in high-return but illiquid projects. This structure leads to the potential for a self-fulfilling bank run and sets up a policy rationale for deposit insurance. More recent theoretical and empirical studies focus on liquidity risk from the asset side. For example, Berger and Bouwman (2006) document the importance of banks in liquidity production on both sides of bank balance sheets, and show that this role has grown sharply over time. There is also a growing literature showing the liquidity-risk management or liquidity shocks to banks affect loan supply. See Paravisini (2004), Kwaja and Mian (2005), Loutskina (2005) and Loutskina and Strahan (2006).

[4] Holding cash raises costs for both agency and tax reasons (Myers and Rajan, 1998).

[5] The result holds under four measures of exposure (the dependent variable) and under various statistical models and specifications (e.g. GLS v. OLS; within v. between regressions; with or without controls for bank and borrower characteristics).

[6] For example, during the first weeks of October 1998, following the coordinated restructuring of the hedge fund Long Term Capital Management, spreads between safe Treasury securities and risky commercial paper rose dramatically. Many large firms were consequently unable to roll over their commercial paper as it came due, leading to a sharp reduction in the amount of commercial paper outstanding and a corresponding increase in take-downs on pre-existing lines of credit (Saidenberg and Strahan, 1999). As a result of this market pullback, banks faced a spike in demand for cash as many of their largest customers drew funds from pre-existing backup lines of credit.

[7] Deposit insurance limits have recently been expanded for the first time sine 1980. In addition, some small banks have begun to avoid binding limits on deposit insurance by splitting very large deposits across multiple institutions. For a broad discussion for deposit insurance and policy ramifications, see Kroszner and Strahan (2005).

[8] For policy discussion on LTCM, see Edwards (1999). For a discussion of bank exposure to the hedge fund, see Kho, Dong and Stulz (2002) and Furfine (2002).

[9] Note that this is equivalent to assuming equal dollar shares for each bank. The results are qualitatively similar if we use actual dollar weighted shares, but these are not available for 60% of the data (see below). Moreover, the correlation between the dollar weighted and equal-weighted bank shares is around 0.99, for both lead and participant banks, so we use the full sample and report equal-weighted bank shares.

[10] For each company we first estimate their beta using a time-series regression of monthly stock returns against the value-weighted return on all NYSE/AMEX/Nasdaq stocks during the 1990 to 2005 period. The beta for the median of these across all firms operating in the same 2-digit SIC is then matched to each *Dealscan* borrower based on the 2-digit SIC.

[11] *Dealscan* also contains some information on covenants in text fields.

[12] *Call Report* data are available at the website of the Federal Reserve Bank of Chicago (http://www.chicagofed.org/economic_research_and_data/).

[13] Since many loans have more than one lead lender, we include a fixed effect for the lead holding the largest share of the loan. If the share is missing, we select one of the lead arrangers randomly to define the fixed effect. Note that the results do not change if we drop the lead arranger fixed effects.

[14] The weaker results for lead arrangers are *not* merely because non-banks fail to participate as lead arrangers. Loan Pricing Corporation ranks lead arrangers annually in League Tables. In fact, non-bank leads are quite important. Goldman Sachs and Lehman Bros. ranked in the Top 10 based on dollar volume in 2005, while GE Capital ranked in the top 10 based on number of deals (http://www.loanpricing.com/analytics/league_table_us.htm#2005). Merrill Lynch and Morgan Stanley also have significant market share as lead arrangers.

[15]As a robustness test not reported here, we also split at the median of the predicted lead-bank share. This second split depends only on a bank's characteristics in the prior year. Also, this second split is not based on bank size. The results are similar to the ones reported in the paper.

[16] This last test is not reported here but is available from the authors.

[17] Contractual maturity for 22% of the lines of credit equals 364 days exactly, presumably to avoid a capital requirement on the un-drawn funds under the Basel I Capital Accord. Capital requirements for un-drawn loan commitments under one year equal zero. For off-balance sheet loan commitments above one year, however, banks are required to hold capital reflecting the credit quality of the counterparty (crudely measured). This regulatory loophole will be closed under the revision to the Capital Accord ("Basel II") . Banks routinely roll over these "364-day facilities" each year, however, so the de facto maturity may be much longer than what we can observe.

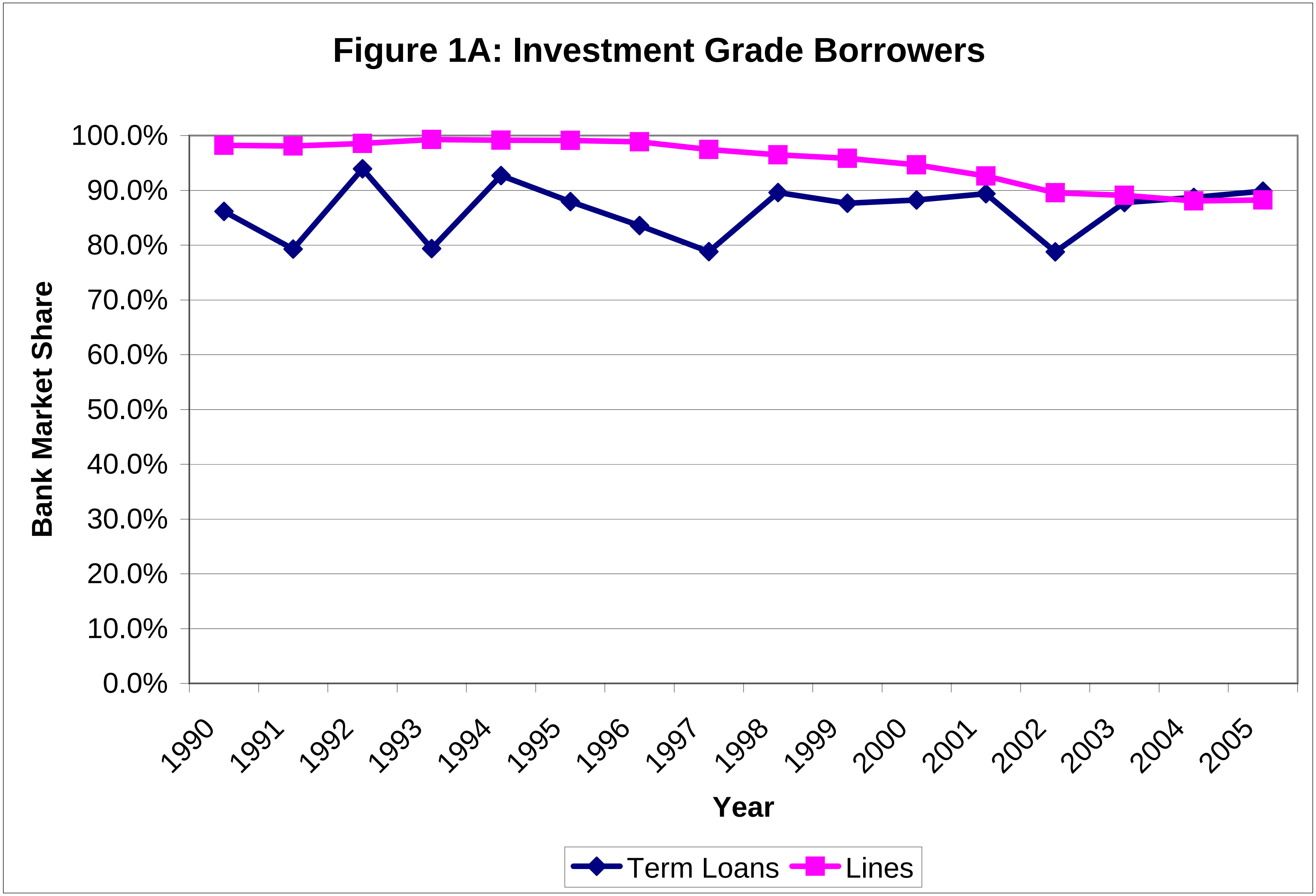
Figure 1A: Investment Grade Borrowers
Bank Market Share
100.0%
90.0%
80.0%
70.0%
60.0%
50.0%
40.0%
30.0%
20.0%
10.0%
0.0%
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
Year
Term Loans
Lines

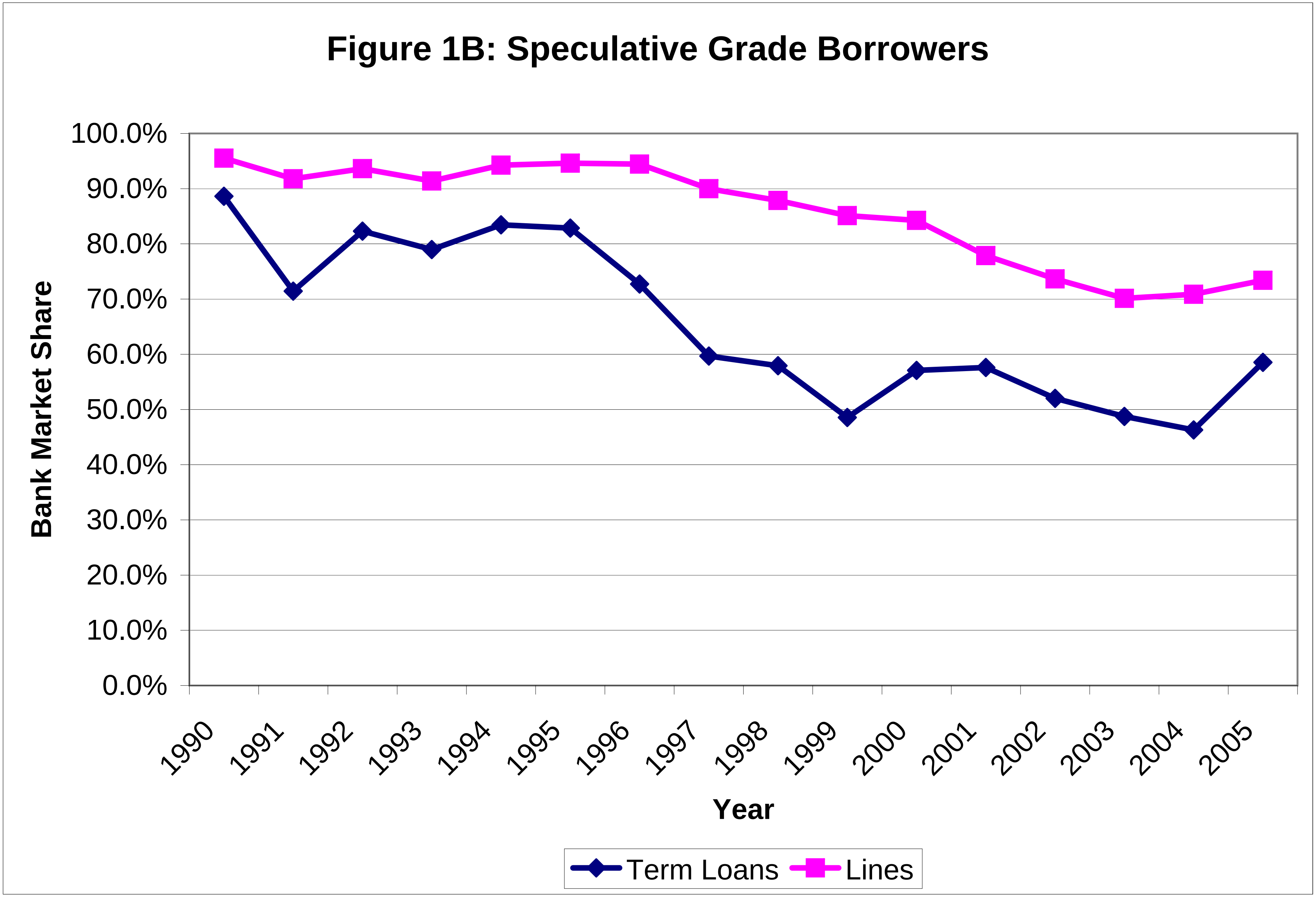
Figure 1B: Speculative Grade Borrowers
Bank Market Share
100.0%
90.0%
80.0%
70.0%
60.0%
50.0%
40.0%
30.0%
20.0%
10.0%
0.0%
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
Year
Term Loans
Lines

Table 1: Bank Market Share in Loan Syndicates

	Percentage of Bank Lenders to Total Lenders		
	Lines of Credit	Term Loans	Difference
Bank share of total lenders			
Rated Borrowers			
Investment Grade	93.0%	79.0%	14.0%
Speculative Grade	76.0%	59.0%	17.0%
Unrated Borrowers	88.0%	79.0%	9.0%
Bank share as lead arrangers			
Rated Borrowers			
Investment Grade	94.0%	88.0%	6.0%
Speculative Grade	79.0%	73.0%	6.0%
Unrated Borrowers	90.0%	84.0%	6.0%
Bank share as participant lenders			
Rated Borrowers			
Investment Grade	92.0%	76.0%	16.0%
Speculative Grade	74.0%	54.0%	20.0%
Unrated Borrowers	87.0%	76.0%	11.0%

Table 2: Characteristics of Syndicated Loan Facility-Level Data

	Mean	Standard Deviation	Mean Weighted by Loan Size
Share rated	30.3%	-	63.2%
Share that are lines of credit	58.5%	-	73.2%
Share that are lines to rated borrowers	39.1%	-	48.0%
Facility Size ($s millions)	187	487	-
All in Spread (basis point spread over LIBOR)	223	142	124
Share that are secured	38.0%	-	21.5%
Maturity (months)	49	161	43

Table 3: Share of Syndicated Loans Financed by Banks

This table reports regressions of the number of banks as a share of total lenders for syndicated loans. Explanatory variables include indicators for rated borrowers, lines of credit and their interaction, along with borrower and loan control variables. Observations vary at the loan level, rather than at the bank level, but standard errors are clustered by lead arranger (there are 61 clusters).

	Bank lenders / total lenders		Bank participants / participants		Bank leads / total leads	
Indicator for lines of credit	0.068	-0.251	0.088	-0.321	0.015	-0.001
	(0.90)	(7.41)	(9.72)	(6.88)	(4.08)	(0.02)
Indicator for investment grade borrowers	0.028	0.075	0.032	0.093	0.015	0.023
	(5.00)	(6.70)	(4.20)	(6.68)	(3.06)	(2.25)
Indicator for speculative-grade borrowers	-0.035	-0.070	-0.036	-0.085	-0.023	-0.024
	(7.65)	(9.73)	(5.99)	(9.65)	(4.01)	(3.69)
Indicator for lines backing commercial paper issues	-	0.001	-	0.001	-	-0.001
	-	(0.26)	-	(0.36)	-	(0.22)
Line of credit * investment grade	-	-0.054	-	-0.071	-	-0.009
	-	(6.07)	-	(6.55)	-	(1.04)
Line of credit * speculative-grade	-	0.057	-	0.079	-	-0.001
	-	(6.13)	-	(7.48)	-	(0.18)
Log of tranche amount	-	-0.173	-	-0.148	-	0.077
	-	(3.09)	-	(2.04)	-	(1.97)
Lines of credit * Log of tranche amount	-	0.444	-	0.56	-	0.03
	-	(7.61)	-	(7.28)	-	(0.63)
Lines of credit * Industry Beta	-	0.017	-	0.030	-	-0.001
	-	(2.62)	-	(3.55)	-	(0.20)
Time fixed effects?	y	y	y	y	y	y
Borrower fixed effects?	y	y	y	y	y	y
Lead-lender fixed effects?	y	y	y	y	y	y
Loan purpose fixed effects?	y	n	y	n	y	n
Observations	42,318	40,565	42,318	40,565	42,318	40,565
R-squared (within borrower)	0.1810	0.1850	0.1055	0.1108	0.2634	0.2591

Absolute value of t-statistics in parentheses.

Table 4: Logit of Share of Syndicated Loans Financed by Banks

This table reports regressions of the number of banks as a share of total lenders for syndicated loans. Explanatory variables include indicators for rated borrowers, lines of credit and their interaction, along with borrower and loan control variables. Observations vary at the loan level, rather than at the bank level, but standard errors are clustered by lead arranger (there are 61 clusters).

	Bank lenders / total lenders		Bank participants / participants		Bank leads / total leads	
Indicator for lines of credit	0.463	-1.310	0.714	-2.071	0.093	-1.392
	(8.14)	(4.72)	(9.51)	(4.80)	(4.16)	(3.83)
Indicator for investment grade borrowers	0.183	0.586	0.215	0.794	0.552	0.555
	(3.93)	(6.11)	(3.31)	(6.48)	(4.37)	(3.72)
Indicator for speculative-grade borrowers	-0.315	-0.524	-0.337	-0.711	0.117	0.172
	(5.96)	(7.12)	(6.32)	(9.17)	(1.48)	(2.05)
Indicator for lines backing commercial paper issues	-	-0.048	-	-0.028	-	0.025
	-	(1.19)	-	(0.67)	-	(0.35)
Line of credit * investment grade	-	-0.460	-	-0.668	-	0.001
	-	(5.27)	-	(6.72)	-	(0.01)
Line of credit * speculative-grade	-	0.331	-	0.601	-	-0.070
	-	(4.74)	-	(6.84)	-	(1.57)
Log of tranche amount	-	-2.183	-	-1.870	-	1.993
	-	(4.70)	-	(2.87)	-	(6.15)
Lines of credit * Log of tranche amount	-	2.480	-	3.70	-	2.32
	-	(5.11)	-	(5.26)	-	(4.31)
Lines of credit * Industry Beta	-	0.113	-	0.264	-	0.024
	-	(2.24)	-	(3.48)	-	(0.29)
Time fixed effects?	y	y	y	y	y	y
Borrower fixed effects?	y	y	y	y	y	y
Lead-lender fixed effects?	y	y	y	y	y	y
Loan purpose fixed effects?	y	n	y	n	y	n
Observations	42,318	40,565	42,318	40,565	42,318	40,565
R-squared (within borrower)	0.1904	0.1889	0.1033	0.1061	0.3103	0.3011

Absolute value of t-statistics in parentheses.

Table 5: Summary Statistics

This tables reports summary statistics for bank-year variables on loan allocations and lender characteristics. The sample includes roughly 120 banks per year (those that we could match by name from Dealscan to the Call Reports), over the 1991 to 2005 period.

	Mean	Standard Deviation
Share of Loans with Liquidity Exposure (Dollar-weighted share new loans in lines of credit)		
Loans with Lender Share	0.76	0.29
All Loans[1]	0.69	0.31
Maturity-Weighted Loans, with Lender Share	0.73	0.30
Maturity-Weighted, all Loans	0.65	0.31
Lead Share (Dollar-weighted share of new Loans where bank is lead)		
Loans with Lender Share	0.37	0.35
All Loans[1]	0.29	0.34
Maturity-Weighted Loans, with Lender Share	0.36	0.35
Maturity-Weighted, all Loans	0.28	0.34
Bank Assets (billions of dollars)	\$33	\$91
Undrawn Commitments / (Commitments+Loans)	0.30	0.14
Transactions Deposits / Deposits	0.25	0.12
Total Deposits / Assets	0.74	0.12
Capital / Assets	0.08	0.02
Marketable Securities / Assets	0.23	0.12

[1]For the sample including all loans, each bank in a syndicate is assumed to hold an equal share of each loan.

Table 6: Regression of Share of Loan Originations with Liquidity Risk on Lender Characteristics

This table reports a regression of the share of a bank's new loans that are lines of credit and thus expose the bank to future liquidity exposure, as a function of the prior year's characteristics. The unit of observation varies by bank-year. The sample includes about 120 banks per year, from 1991 to 2005. All regressions include year indicator variables.

	Dependent Variable = L/C Share, using loan shares					
Transactions Deposits / Deposits	0.44	0.37	0.37	0.37	0.36	0.36
	(4.38)**	(3.93)**	(3.77)**	(3.91)**	(3.94)**	(3.83)**
Log of Bank Assets	-	0.03	0.03	0.04	0.03	0.03
	-	(4.75)**	(4.01)**	(4.84)**	(4.72)**	(3.76)**
Undrawn Commitments / (Commitments+Loans)	-	-	0.02	0.02	0.03	0.02
	-	-	(0.32)	(0.38)	(0.55)	(0.34)
Total Deposits / Assets	-	-	-	0.24	0.20	0.16
	-	-	-	(2.44)*	(2.04)*	(1.72)
Capital / Assets	-	-	-	-	-1.67	-1.84
	-	-	-	-	(3.37)**	(3.75)**
Marketable Securities / Assets	-	-	-	-	-	-0.19
	-	-	-	-	-	(2.29)*
Observations	1,460	1,460	1,460	1,460	1,460	1,460
R-squared	0.07	0.09	0.09	0.1	0.11	0.12

Absolute value of t-statistics in parentheses; standard errors clustered by bank.

* significant at 5% level; ** significant at 1% level

[1]For the sample including all loans, each bank in a syndicate is assumed to hold an equal share of each loan.

Table 7: Regression of Average Borrower Characteristics and Loan Terms on Lender Characteristics

This table reports regressions of the average borrower characteristics and loan terms on lender characteristics. The regressions with loan terms include borrower characteristics as regressors, include a full set of 1-digit SIC variables indicating the share of loans to borrowers in each industry class. The unit of observation varies by bank-year. The sample includes about 120 banks per year, from 1991 to 2005. All regressions include year indicator variables.

	Log of Mean Borrower Sales	Share of Loans to Rated Borrowers	Share of Rated Loans that are Speculative Grade	Mean Drawn All-in Spread	Average Industry Beta
Transactions Deposits / Deposits	1.49	0.31	-0.34	-88.32	-0.17
	(2.31)*	(2.69)**	(2.12)*	(2.60)**	(2.06)*
Log of Bank Assets	0.472	0.043	-0.021	-15.938	-0.004
	(7.73)**	(4.38)**	(1.70)	(5.25)**	(0.67)
Undrawn Commitments / (Commitments+Loans)	1.19	0.09	-0.39	-79.77	0.10
	(1.93)	(0.92)	(2.77)	(1.96)	(1.11)
Total Deposits / Assets	-1.09	-0.07	-0.08	2.09	0.09
	(1.82)	(0.66)	(0.49)	(0.06)	(1.20)
Capital / Assets	0.84	0.76	0.18	-14.61	-0.11
	(0.32)	(1.49)	(0.26)	(0.09)	(0.40)
Marketable Securities / Assets	-0.09	-0.04	-0.44	-74.69	0.01
	(0.14)	(0.39)	(3.07)	(2.67)	(0.11)
Observations	1,665	1,797	1,305	1,721	1,772
R-squared	0.290	0.120	0.129	0.206	0.037

Absolute value of t-statistics in parentheses; standard errors clustered by bank.

* significant at 5% level; ** significant at 1% level

Table 8: Share of Loan Originations with Liquidity Risk on Lender Characteristics,

This table reports a regression of the share of a bank's new loans that are lines of credit and thus expose the bank to future liquidity exposure, as a function of the prior year's characteristics. The regressions include borrower characteristics as regressors, including a full set of 1-digit SIC variables indicating the share of loans to borrowers in each industry class. The unit of observation varies by bank-year. The sample includes about 120 banks per year, from 1991 to 2005. All regressions include year indicator variables.

	Lead Share Below Median	Lead Share Above Median
Transactions Deposits / Deposits	0.43	0.21
	(3.00)**	(1.84)
Log of Bank Assets	0.028	0.017
	(1.74)	(1.59)
Undrawn Commitments / (Commitments+Loans)	-0.03	0.00
	(0.30)	(0.04)
Total Deposits / Assets	0.29	0.21
	(1.78)	(2.17)*
Capital / Assets	-1.64	-1.23
	(2.22)*	(2.17)*
Marketable Securities / Assets	-0.19	-0.20
	(1.39)	(2.16)*
Log of Mean Borrower Sales	0.02	0.04
	(1.45)	(2.91)**
Share of Rated Borrowers	0.1180	-0.1570
	(2.08)*	(1.67)
Observations	633	784
R-squared	0.15	0.24

Absolute value of t-statistics in parentheses; standard errors clustered by bank.
* significant at 5% level; ** significant at 1% level