Bank Health and Corporate Liquidity Provision

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Abstract

I provide evidence of a bank lending channel operating through the market for corporate liquidity, namely, corporate lines of credit. I argue that troubled banks face additional liquidity risk from lines of credit stemming from draw-downs by corporations for precautionary purposes. I use the differential exposure of banks to the collapse of the asset-backed commercial paper market – beginning August 2007 – as a source of cross-bank variation in financial condition and assess the impact on liquidity provision via syndicated lines of credit. I find that, following the initial shock, banks with greater exposure reduced issuance of credit lines both relative to other banks and relative to term loan issuance. Either a contraction in credit supply from exposed banks or a shift in credit demand across banks could explain this effect. I conduct my analysis at the loan-level and find evidence in favor of a credit supply effect. I find that exposed banks reduced the probability of syndicate participation, but only in credit lines and not in term loans. Conditional on roll over, troubled banks also issued credit lines on worse terms, especially on lines with long effective duration and issued to bank-dependent borrowers. My results suggest that the synergy between deposit-taking and lending-by-commitment can break down when bank solvency comes into question.

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I Introduction

Motivation

Banks perform an important liquidity provision function to non-financial corporations. In the theoretical literature, synergies between deposit-taking and lending give banks a comparative advantage in providing liquidity to firms, in the form of revolving lines of credit. Kashyap et al. (2002) argue that so long as depositor withdrawals and credit line draw-downs are imperfectly correlated, banks should pair these two activities. They argue that by pairing deposit-taking and lending by commitment, banks will economize on costs associated with holding a buffer – to hedge unforseen withdrawals and draw-downs – of liquid securities (e.g., cash) on their balance sheets. By economizing on such costs, banks will have a "natural" advantage insofar as they will be able to offer credit lines on more favorable terms than non-deposit taking financial institutions.

The empirical literature confirms that banks – as opposed to non-bank financial institutions – intermediate the bulk of liquidity risk associated with credit lines and even more so during times of market-wide stress (Gatev and Strahan, 2006, 2009). In particular, when market liquidity dries up and commercial paper spreads widen, banks experience deposit inflows – a "flight-to-safety" effect – leaving them better positioned to fund draw-downs from pre-committed lines.[1] In such times, corporations are insured against costly liquidations that may have occurred in the absence of such bank-provided liquidity. Much less is known about the ability of banks to provide liquidity when they are directly exposed to large losses associated with an aggregate shock.

In this paper, I investigate whether banks continue to perform their liquidity provision function when they are directly exposed to large losses associated with an aggregate shock. I study how this interacts with banks' credit provision function (i.e., term lending) and the traditional "bank lending channel" (Bernanke and Gertler, 1995). To this end, I use banks' differential exposure to the collapse of the asset-backed commercial paper (ABCP) market and assess the impact on corporate liquidity provision via U.S. syndicated lines of credit, relative to term lending. I investigate how impaired banks adjust the terms of their credit line contracts, which firms have their liquidity rationed, and whether strong firm-bank relationships are an effective mechanism for mitigating any adverse effects.

At the heart of this study is the question of why troubled banks' liquidity provision

[1] Pennacchi (2006) documents that before FDIC insurance came into effect, commercial banks did not have a comparative advantage over non-bank financial institutions in providing liquidity to corporations.

function might become impaired over and above banks' credit provision function. This effect is not obvious ex-ante: liquidity-constrained banks might prefer to make contingent commitments in the future rather than grant loans today. On the other hand, lending by commitment might become unattractive for the following reasons.

First, quite simply, credit lines are traditionally retained by banks and not sold in secondary loan markets to other institutions (Gatev and Strahan, 2009). If the capacity of the banking system to absorb liquidity risk is curbed following a large financial shock and these loans cannot be sold, then banks might prefer not to originate credit lines.

Second, investors doubting bank solvency and the presence of (explicit or implicit) government guarantees might instead divert funds into ultra-safe assets (e.g., Treasuries). In this case, when market liquidity dries up, impaired banks will have can no longer take for granted future deposit inflows that would offset concurrent draw-downs. Moreover, theses bank might expect difficulties in funding draw-downs ex-post by raising short-term financing at reasonable cost. This funding shock would limit banks' comparative advantage in providing credit lines.

Third, *credit line holders might also respond to shocks to bank health*. For instance – analogous to how creditors withdraw funds from banks they believe are, or might become, insolvent – corporate credit line holders might also fear losing access to bank credit. In this case, credit line holders may be prone to "run" on undrawn commitments for *precautionary purposes*; that is, draw down on their credit line without satisfying some present liquidity need. Recent empirical evidence suggests bank runs (correlated draw-downs) by non-financial corporate credit line holders may be important. For example, Ivashina and Scharfstein (2010) provide evidence that during the Fall of 2008 credit line holders drew on their lines for precautionary purposes, holding the drawn funds as cash on their balance sheets.[2]

On the second and third points, banks exposed to losses may simultaneously experience deposit outflows and credit line draw downs, and even more so as the bank edges closer to insolvency. Anticipating such an outcome, banks may *actively manage* their liabilities (or off-balance sheet commitments) *ex ante*; for example, by increasing rates on deposits (Acharya and Mora, 2011) or curtailing credit line issuance and exposure to other risky commitments (as I examine in this paper).

[2] A striking example comes from a press release from Fairpoint Communications Inc. on September 15th 2008: *"The Company believes that these actions* [fully drawing down on its $200 million revolving credit facility] *were necessary to preserve its access to capital due to Lehman Brothers' level of participation in the Company's debt facilities and the uncertainty surrounding both that firm and the financial markets in general."*

The discussion so far highlights an important twist on the traditional bank lending channel view of how banks transmit financial shocks to the real economy. This literature posits that credit market imperfections both at the firm and bank level might lead to a reduction in lending when banks experience funding shortfalls or liquidity shocks. The important distinction between credit line commitments and conventional term lending is the liquidity risk inherent in lending via commitment. In normal times credit line issuance is limited by expected borrower draw-downs; however, when the bank faces a greater likelihood of distress, an additional source of liquidity risk may materialize in the form of runs on credit lines for precautionary purposes. In contrast, with term lending banks are only exposed to the credit risk associated with the borrower. This observation suggests that banks experiencing distress may transmit shocks to the real economy primarily via lines of credit and corporate liquidity management; that is, via their liquidity provision function as opposed to their credit provision function.

Empirical Results

Empirically establishing a relationship between bank health and credit line provision is challenging for three main reasons. First, financial shocks are usually aggregate in nature and they tend to affect all banks at once, either via banks' direct exposure to the shock or indirect exposure to the shock via interbank linkages. It is therefore difficult to isolate banks' relative exposure to the shock and therefore construct a useful measure of bank health at the bank-level. Second, the banks' exposure to the shock will be determined by their asset or liability structure, but this structure is an endogenous choice and might reflect underlying agency problems, investment opportunities, or preference for risk-taking. Third, the same underlying shock that affects bank health may also affect the balance sheet of firms and thus either their perceived riskiness or demand for credit. In this paper, I attempt to address all of these difficulties by focusing on the fall-out from the asset-backed commercial paper (ABCP) market starting in August 2007 and its impact on the provision of syndicated lines of credit to U.S. publicly traded firms.[3]

The collapse of the ABCP market during the summer of 2007 constitutes an ideal setting to examine the impact of a bank funding shock on the market for corporate liquidity. First,

[3]There are several other papers that study the impact of financial shocks on the real economy using an experimental design (e.g., Chava and Purnanandam, 2011; Khwaja and Mian, 2008; Paravisini, 2008; Peek and Rosengren, 1997; Schnabl, 2011). There are also papers that investigate bank-level lending behavior during the recent financial crisis (e.g., Cornett et al., 2011; Ivashina and Scharfstein, 2010). The goal of this paper is to understand how financial shocks are transmitted to the market for liquidity insurance.

the shock was unexpected and originated outside of the corporate sector.[4] Second, the shock was large in magnitude. At the peak of the market (summer 2007) there was $1.3tn of outstanding ABCP, which halved in value by the end of 2008 (see Figure 1). Third, banks had differential exposure to the shock via guarantees written to the special purpose vehicles (conduits) that issued the ABCP.[5] For example, Citigroup had over 100% of its equity capital exposed to guarantees, whereas Wells Fargo had 0% exposed. When uncertainty arose regarding the value of underlying collateral, investors (notably, money market mutual funds) refused to roll over maturing paper (or substantially revised upward the return required for doing so) and sponsoring institutions were required to take assets back on their balance sheets or repurchase maturing paper at par value.[6] I am able to directly measure cross-sectional variation in the exposure of banks to this market using a unique dataset that covers the universe of conduits rated by Moody's.

Further, in order to separate a bank-driven effect from concurrent shocks to borrower risk or investment opportunities, I conduct my analysis at the loan-level using data from the U.S. syndicated loan market.[7] I exploit two institutional features of this market – illustrated in Figure 2 – to identify the causal effect of bank health on lending outcomes: repeated borrowing and the many-banks-to-one-borrower nature of syndicated lending.

I first study the decision of banks to quit participation in a syndicate rolling over (refinancing) an existing loan (i.e., the extensive margin). I observe dynamics of the lending syndicate and focus on variation in the bank exit decision between members of a given syndicate rolling over a particular loan to a particular borrower, using a difference-in-differences approach with syndicate fixed effects. In doing so, I hope to control for all borrower characteristics (loan demand and risk) that could confound inference.

[4] Note that financial and corporate commercial paper did not run into difficulties until after the bankruptcy of Lehman Brothers, i.e., post September 2008.

[5] In order to cheaply fund assets held in the conduits, banks required money market mutual funds to access this market. This was only possible if the short-term paper issued by conduits held at least the second highest credit rating (under Rule 2a-7 of the Investment Company Act of 1940). This was achieved by guarantees written by a sponsoring financial institution to repurchase maturing paper at par value.

[6] Acharya et al. (2009) show that 97% of the maturing asset-backed commercial paper was repaid in full and thus most losses associated with falling conduit asset values stayed within the financial sector. Consequently, banks with greater exposure to this market faced (off-balance sheet) a severe maturity mismatch and a greater risk of a run on liabilities. See He et al. (2010) for further discussion of the balance sheet adjustments that took place during the recent episode. See also Krishnamurthy et al. (2011) for a discussion of the importance of non-Agency ABS/MBS collateral in determining the contraction in short-term financing (i.e., repurchase agreements and ABCP).

[7] Aside from the size and importance of this market (e.g., Sufi, 2007), an advantage of focusing on this market is being able to control for a number of bank and firm factors (measures of investment opportunities, credit risk, etc.) that are known to drive much of the variation in loan contract terms.

On this extensive margin, I find that, after the collapse of the ABCP market, relatively more-exposed banks experience a greater propensity to exit a given syndicate which is rolling over a credit line: a one standard deviation increase in bank exposure led to a 14.8% increase in the probability of exit. I do not find any differential effect among banks for term loan exit. Looking across syndicates rolling over loans, I find that exposed banks are more likely to exit syndicates rolling over credit lines – which expose them to future liquidity risk – than term loans. This finding appears to be consistent with exposed banks actively managing the liquidity risk associated with corporate credit lines.

When I analyze the types of borrowers experiencing exit with exposed banks, two findings emerge. First, consistent with banks managing their liquidity risk exposure, I find that exposed banks are more likely to exit syndicates. Second, I find that high quality borrowers (investment grade) are more likely to exit relationships with exposed banks. I only find such effects among credit lines. Borrowing the term from Khwaja and Mian (2008), I interpret the second finding as a "strategic withdrawal" by high quality firms from exposed banks. This is also consistent with a bank-driven effect, as concerns that funding-constrained banks might become insolvent or unable to meet credit line commitments in the future motivates the borrowers' decision.

In addition, I find that syndicates experiencing exit during the post-event period write credit line contracts smaller in size and with higher spreads, except in the case of investment grade firms. These firms do not experience any meaningful deterioration in contract terms. Taking these findings together suggests that high quality borrowers no longer wished to secure their liquidity insurance from impaired banks, who may be unable to fulfil future commitments. Moreover, these findings highlight a potential interaction between the decision-making of impaired banks and actions on the part of firms, in a general equilibrium setting.[8,9] The net effect of these interactions might be that exposed banks experienced a deterioration in their credit line borrower quality.

Next, I examine how the contract terms (i.e., pricing, maturity, facility size) vary as a

[8]Note that I am unable to distinguish between firms switching away from exposed banks, or other syndicate members refusing to co-syndicate with exposed banks. The latter conjecture would be consistent with healthy banks not wanting to be "on the hook" for co-syndicators' undrawn commitments in case they default. However, it is not obvious why healthy banks would be unwilling to co-syndicate credit lines for investment grade borrowers, especially since these borrowers typically have a lower expected draw down rate.

[9]Mian and Santos (2011), using data from the Shared National Credit program at the Federal Reserve Board, documents active management of rollover risk by investment grade firms by timing *when* they refinance loans over the credit cycle. My findings complement theirs by suggesting that investment grade firms also actively manage *with whom* they refinance *credit lines*. Recall that with term lending there is no counterparty risk as funds are disbursed to the firm at time of origination.

function of bank exposure for firms that receive credit (i.e, the intensive margin). To this end, my second empirical strategy limits the analysis to credit lines extended to firms that borrowed both before and after the collapse of the asset-backed commercial paper market *from the same bank*. By focusing on such *within-relationship* changes in contract terms, I mitigate concerns regarding sample selection; in particular, biased estimates due to banks endogenously adjusting the composition of their borrowers (e.g., rationing weaker credits or risk-shifting).[10]

On this intensive margin, I find a strong average effect of bank exposure on contract terms – the all-in drawn spread and maturity – on lines of credit issued after the collapse of the ABCP market. This effect is large in magnitude and statistically significant at the 1% level: a one standard deviation increase in bank exposure led to a 28 basis point increase in the all-in drawn spread (22.4% of sample average) and a 4.74 month decrease in maturity (11.3% of the sample average).[11] Consistent with a traditional bank lending channel, there is also a statistically significant increase in the all-in drawn spread on term loans among exposed banks. However, the economic effect is 37.5% of the estimated effect on credit lines. This suggests that exposed banks pass on the increased cost of capital associated with the funding shock more so with credit line pricing.

Next, among credit lines, I find considerable heterogeneity in the average effect. I explore two sets of hypotheses in the cross-section, both of which play out in the data.

First, the deterioration in contract terms is concentrated among the riskiest commitments. By risky commitments, I am referring specifically to credit lines with the longest effective duration (e.g., long maturity, "covenant-lite" loans), and thus less bank control over the rollover decision, and lines extended to bank-dependent borrowers (without a public debt rating or speculative grade firms, for example). The latter borrowers rely on banks for access to liquidity and thus are more likely to draw down should there be doubts about their relationship bank's health.

Second, strong banking relationships help to mitigate the deterioration in credit line contract terms. While my analysis is within-relationship, following Bharath et al. (2011), I classify syndicates according to the intensity of relationship (current syndicate features a

[10] As a robustness check and to further reduce concerns regarding sample selection, I also estimate the supply-side effect by restricting attention to within-syndicate variation in loan contract terms. The results are robust to this modification.

[11] In a contemporaneous study, Bord and Santos (2011) considers the impact of bank liquidity risk on the all-in *undrawn* spread on credit lines. My study complements theirs by contrasting credit line and term lending, considering the extensive and intensive margins of lending, and offering a different empirical strategy.

repeat lead arranger, for example). I find that firms with strong bank relationships do not experience a deterioration in contract terms from exposed banks in the post-event period. This evidence is consistent with the hypothesis that stressed banks value existing banking relationships (e.g., Bharath et al., 2007) when faced with funding risk.

What are the implications of these findings? First, Amihud et al. (2007) provide evidence that firms with access to bank-financing have lower cash holdings and save less cash out of cash flows (a lower "cash-flow sensitivity of cash", as in Almeida et al. (2004)). My findings suggest that the willingness of banks to provide liquidity is not unconditional and depends on their financial condition.[12] Second, with regards to financial stability, the shift in borrower composition for impaired banks suggests that their economic as well as regulatory capital ratio will take a hit when draw-downs by a poorer quality customer base show up as on-balance sheet assets. This result, in particular, contributes to our understanding of how the bank lending channel interacts with *borrower decision-making* and has implications for banks' financial condition, some of which I discuss later in the paper.

The rest of the paper is organized as follows. Section II discusses the data. Section III presents the empirical design and results. Section IV presents numerous robustness checks. Section V concludes.

II Data and Institutional Background

A Asset-Backed Commercial Paper Conduits

Asset-backed commercial paper conduits are special purpose vehicles set up, typically by large commercial banks, for the purpose of purchasing and holding financial assets. These structures pool both securitized and unsecuritized assets acquired from a number of sellers. Most conduit assets were considered high quality before the crisis, AAA-rated asset-backed securities for example, although the asset base of some conduits consisted entirely of unrated assets originated by the conduit issuer.

The conduits issue short-term debt – ABCP – to finance the purchase of medium- to long-term maturity assets. Most ABCP issued has maturity of one to four days and the average maturity of outstanding liabilities is roughly one month (Covitz et al., 2009), meaning conduits frequently roll over their maturing liabilities. Should a conduit's asset value decline or if demand for ABCP dries up, conduits face the risk that maturing paper cannot be

[12] My findings complement recent empirical evidence that credit line commitments provided by banks are contingent on borrower (Sufi, 2009) and bank (Huang, 2010) financial condition.

refinanced. To mitigate this risk, conduit liabilities are guaranteed by financial institutions. Guarantees often amount to providing a line or letter of credit requiring the purchase of some fraction of maturing paper at par, as a function of the conduit's asset value. Guarantees may be provided by the institution setting up the conduit – often the case with conduits set up by commercial banks – or by some third party. By attaching such guarantees to conduits, issuers are often able to achieve A-1 ratings from credit ratings agencies and access investors, such as money market mutual funds, that are legally restricted to hold only the safest assets.

The strongest form of guarantee ("full credit") in use requires that paper is repaid at maturity, independent of the conduit's asset value. A "full liquidity" guarantee only requires repayment if the conduit's assets are *not* in default. Credit guarantees are considered to cover the credit risk of the underlying assets. Thus, a sponsor providing a full credit guarantee receives the same regulatory capital charge as if the assets were on balance sheet. Liquidity guarantees, on the other hand, only offer recourse to the sponsor's balance sheet if the conduit assets are not in default. Banking regulation treats such guarantees as only covering the *liquidity risk* of conduit assets, since assets cannot be in default when the guarantee is exercised. As such, under Basel I (II), commercial banks are levied a 0% (20%) capital charge for conduit assets covered by full liquidity guarantees.

To give an example of a particular conduit, as of January 1st 2007, Grampian Funding was the largest conduit rated by Moody's. The conduit had $37.9 billion of ABCP outstanding. It was set up by the British bank HBOS, rated AAA, and fully invested in U.S. assets with a 36% allocation to residential mortgages. HBOS provided a full liquidity guarantee for maturing paper, which was put to use on August 22nd 2007.[13]

In July 2007, asset-backed commercial paper was the largest money market instrument in the United States with $1.3 trillion outstanding. Following concerns regarding asset value beginning in August 2007, money market funds withdrew from the market and the value of outstanding paper collapsed to $833 billion in December 2007. During this turmoil, commercial banks providing guarantees to their own asset-backed commercial paper conduits provided liquidity support to conduits and redeemed maturing commercial paper at par. Thus, after the initial shock materialized, off-balance sheet conduit assets/liabilities became *de facto on-balance sheet*. Banks with greater exposure had a severe maturity mismatch and faced a greater risk of runs on their liabilities by creditors and, as argued previously, by a potentially large number of corporate credit line holders.

[13]See Acharya et al. (2009) for summary statistics regarding ABCP conduits.

B Sample Selection

Unfortunately, no comprehensive and widely available U.S. loan level data exist. The two popular alternatives are to use central bank credit register data from non-U.S. countries (for example, on Pakistani data, see Khwaja and Mian, 2008) or to use data from the U.S. syndicated loan market, most commonly the DealScan database of commercial loans.[14]

Loan syndication involves a ("lead") bank initiating a loan with a borrower and selling a share of the loan to other ("participant") financial institutions. In the case of a syndicated credit line, the outcome of the loan syndication process will be a collection of lenders with a commitment to extend credit to a borrower, up to a pre-specified limit on a revolving basis, for the duration of the loan.[15] Lenders in this market include non-bank financial intermediaries, such as Collateralized Loan Obligations (CLOs) or hedge funds. I will focus on regulated commercial banks operating in the U.S. market to control for the financial condition of lenders throughout my analysis.[16]

A common criticism of DealScan is that it covers only large loans to large, established borrowers. For instance, the average firm in my sample is 27 years old, has quarterly sales of \$2.5bn, and receives a \$700m line of credit. On the other hand, the quality of loan data at origination is excellent and coverage of this segment of the commercial loan market is comprehensive (e.g., Sufi, 2007). For the sample period I consider, DealScan contains all of the major credit lines issued to publicly traded U.S. firms.[17] A second criticism regarding comparing term loans to lines of credit is that most bank loans are issued via credit lines. This is not the case for my sample: as of 2007Q2 (annualized) gross issuance of term loans and credit lines stood at \$506bn and \$465bn, respectively. Evidently, syndicated term lending is a large market, both in absolute terms and relative to the market for credit lines.

I link the loan level data in DealScan to other sources containing borrower and lender

[14]The advantage of credit register data is that loan coverage is comprehensive, i.e., all outstanding loans are reported in the data set. From a practical perspective, a disadvantage of such data is that borrower and loan contract information are often not recorded at a satisfactory level of detail. Also, naturally, there is the issue of external validity when studying lending behavior in one country, since cross-border banking regulations and institutional quirks vary a great deal. This is exacerbated when analyzing developing countries, which is often where credit register data come from.

[15]Importantly, and often ignored in the literature, the syndicate structure for a given loan contract is not fixed: loan participants can and often do sell fractions of their loan allocations in an active secondary market. Due to data limitations and consistent with the literature, I will assume that the loan syndicate remains fixed post-origination.

[16]In any case, commercial banks dominate credit line issuance in the U.S. syndicated loan market. My sample of commercial banks issue greater than 90% of U.S. credit lines in 2007.

[17]Note that if any bank-driven effect is concentrated among small publicly traded or privately-held firms then my analysis will not be fruitful, i.e., my sample selection will bias against finding a supply-side effect.

accounts. In this paper, I link DealScan to four other data sources: Compustat, Call Reports, BankScope, and proprietary data on ABCP conduits provided by the Depository Trust and Clearing Corporation (DTCC) and Moody's Investor Services.[18] Compustat contains quarterly accounting information on publicly traded U.S. companies. Call Report data contains quarterly balance sheet information for all banks falling under the jurisdiction of the Office of Thrift or the Comptroller of Currency (OCC), which includes domestic branches of foreign banks. BankScope also provides additional data for foreign banks.

The data on ABCP conduits comes from the universe of 938 conduits rated by Moody's from January 2001 until December 2009. Moody's publishes a ratings report and an annual report each subsequent year. These ratings reports include information on conduit sponsor and credit guarantees, as well as other items. This data is linked to a proprietary data set from the DTCC, which contains all (777,758) primary market transactions conducted in the U.S. between January 2007 and February 2008. The DTCC data is used to calculate the value of outstanding asset-backed commercial paper. As of January 1st 2007, for each active conduit, the sponsor is identified using the Moody's data and assigned the value of outstanding paper.[19] Following Acharya et al. (2009), conduit exposure is measured as the ratio of outstanding ABCP to equity capital as of January 1st 2007 for the 58 largest global banks' sponsoring conduits. These banks to (bank holding company level) balance sheet data from BankScope.

It is worth noting that this measure of conduit exposure constitutes a lower bound on the amount of equity capital held by commercial banks that was exposed to asset-backed commercial paper. In almost all cases, a commercial bank setting up a conduit will also provide a liquidity guarantee (or enhancement). However, conduits sponsored by non-banks may well have liquidity lines coming from commercial banks. Moreover, commercial banks could have had further (indirect) exposure via credit lines extended to borrowers that set up conduits. For example, Countrywide Financial, a U.S. mortgage provider, set up conduits and secured guarantees for these conduits from commercial banks. In addition to these conduit guarantees, Countrywide also secured several lines of credit in the syndicated loan market without any (clearly) stated corporate purpose that could potentially be drawn upon should trouble arise with rolling over conduit liabilities. Unfortunately, this measure does not include these credit lines, as data on such facilities is not readily available. Finally, my

[18]The DTCC and Moody's data comes from Acharya et al. (2009). I thank them for making this available for this study.

[19]In this study, I focus exclusively on commercial banks. Commercial bank sponsored conduits constitute roughly three quarters of the dollar value of the market (as of January 1st 2007)

measure does not include exposure to conduits that were not rated by Moody's.

For the loan-level analysis, I employ a complementary measure of bank exposure computed (using Call Report data) as the fraction of on-balance sheet mortgage- and asset-backed securities (henceforth MBS and ABS, respectively). Following Cornett et al. (2011), I compute this variable as the sum of available-for-sale and held-to-maturity asset-backed and mortgage-backed securities. This second measure increases in the post-event window, as documented and discussed in He et al. (2010). Greater on-balance sheet holdings of these assets in the post-event window is consistent with conduit assets coming back onto banks' balance sheets and motivates use of this alternative measure. The downside of this measure is that I am unable to separate out Agency from non-Agency ABS/MBS, where the latter collateral has been shown to be at the heart of the run on short-term financing during the resent episode (Krishnamurthy et al., 2011).

For each facility in DealScan during my sample window (2003:Q1–2009:Q4), I link the borrowers to Compustat via the GVKEY identifier to obtain borrower information.[20] Then, for each lender in DealScan I hand-match lender names to Call Report data using lender name, dates of operation, and location. I also hand-match these lender names to Bankscope using lender name.[21] The end product of this matching procedure are two samples, which henceforth I will refer to as the "Call Report Sample" and the "Conduit Sample". The Conduit Sample is used in tests at the bank level and all other tests are conducted using the Call Report sample.

The unit of observation in each sample is a loan-firm-bank triple. Since loans are *syndicated*, each loan will appear multiple times in the sample if the syndicate has more than one participant (e.g., 2007 Revolver–Microsoft–Citi and 2007 Revolver–Microsoft–BoA). This feature of the data will allow me to exploit the *dynamics* of the loan syndicate to identify a bank effect in lending volumes, since lenders in the syndicate have some control over their loan exposure. However, when estimating a bank effect in all other contract terms this feature of the data might be of limited use, as each loan participant agrees to the same terms – for example, all participants agree to the same set of loan covenants.[22] A crucial feature of borrowing in the syndicated loan market is borrowing takes place repeatedly. For credit

[20]Thanks to Sudheer Chava and Michael Roberts for providing this link (see Chava and Roberts, 2008).

[21]Thanks to Sascha Steffen (see Cai et al., 2011) and Malcolm Wardlaw (see Wardlaw, 2010) for advice on matching lender names.

[22]Note, however, that the contract terms are set in such a way that syndicate participation is *individually rational* for all participants. Therefore one might expect that, in order to incentivize participation by exposed banks, syndicates featuring exposed banks might command higher spreads. This is exactly what I find in the data.

lines in particular, there is a high proportion of *refinanced* loans in the database: in my sample, 74% of the credit lines refinance an existing contract.[23] This feature of the data is particularly useful, as when the refinancing takes place the syndicate structure will often remain intact but the participants' relative exposures will shift, or certain participants will exit the syndicate altogether.

C Summary Statistics

Table 1 summarizes the Call Report sample, reporting average characteristics of loans, borrowers, and banks. The banks in this sample are those for which Call Report data is available, i.e., U.S. commercial banks and U.S. offices of foreign banks. The sample covers 11,237 lines of credit issued to 2,806 non-financial, non-real estate firms during the period 2003–2009 by 165 unique banks.[24] All variables used are precisely defined in Table A.1.

I have partitioned the sample according to whether loans were given before (2003Q1–2007Q3) or during (2007Q4–2009Q4) the collapse of the asset-backed commercial paper market.[25] A total of 9,612 of these credit lines were issued in the pre-event window by 165 banks and the remainder in the post-even window by 95 banks. Credit line contract terms deteriorated after August 2007: The average all-in drawn spread increased by roughly 80 basis points, maturity decreased by 5 months, and the line was more likely to be secured. This deterioration in credit line contract terms is consistent with either an increase in banks' opportunity cost of capital *or* borrower risk. However, as evidenced by the second panel of Panel A of the Table, the average risk profile of the pool of borrowers receiving loans *improves* post-event. In particular, borrowers receiving credit after August 2007 are older, larger, have more tangible assets, and appear more capable of servicing their debt obligations. The increased presence of large borrowers post-event is consistent with the observed increase in average credit line size. In light of the dramatic decrease in syndicated credit line issuance in the U.S., shown in Figure 1, this suggests that credit was rationed among private and small publicly traded firms.

[23]This represents a lower bound, as approximately 30% of my sample does not report whether the line refinanced an existing contract.

[24]I exclude all loans issued to borrowers with financial or real estate SIC codes.

[25]Following Cornett et al. (2011), I include the post-TARP period in my event window and interpret my results net of this government intervention when I conduct analysis at the loan level. Note that the majority of my loan-level results are identical when I restrict to one year post-event window (see Section IV). However, the sample size is dramatically reduced when I use my preferred identification strategy, leading to a loss of statistical significance for some of the intensive margin results. Analysis at the bank level always uses a pre/post one-year event window.

The third panel of Panel A of Table 1 presents summary statistics for the commercial banks of the Call Report sample. The average bank in the pre-crisis period had approximately \$400bn in assets, which increased to \$700bn during the crisis. This suggests that smaller banks were exiting the market, although, to some extent, this could be a reflection of consolidation in the banking industry during the 2003–2009 period. We can see how the condition of banks changed during the financial crisis. Measures of bank performance deteriorated rather dramatically during this period: for banks that continued to issue credit lines during the crisis, return on assets decreased by 50% and loan losses increased by 100%.

Panel B of Table 1 presents the summary statistics for the Conduit sample. This sample contains 58 of the largest global commercial banks that were involved in securitization via asset-backed commercial paper conduits.

Relative to loans extended pre-August 2007, and in contrast to the Call Report sample, facility size and fraction of secured lines do not appear to change noticeably post-event. Turning to borrower characteristics, the Conduit sample appears to be comprised of younger, smaller, and fewer investment grade firms that appear to be less levered and have fewer tangible assets. The difference between the Conduit and Call Report samples is the presence of international banks lending in the U.S. syndicated loan market. The summary loan and borrower characteristics suggest that the international banks operating in this market tended to lend to worse credits.

Conduit Exposure, the key bank variable in this sample, is computed as the ratio of a bank's own-conduit outstanding asset-backed commercial paper to equity capital. The sample average is approximately 76% and the standard deviation (unreported) is 139%, indicating that there is considerable cross-sectional variation in bank exposure and some banks have more than one hundred percent of their equity exposed to conduit assets.

Are Repeated Borrowers in the Syndicated Loan Market Different?

My empirical strategy exploits repeated borrowing in the syndicated loan market. This raises concerns that regarding sample selection: Are repeated borrowers representative of borrowers in syndicated loan market? The short answer to this question is: No. Unsurprisingly, as evidenced by Panel A of Table A.2, repeated borrowers are more established in the market.

In terms of borrower characteristics, repeated borrowers are older, larger, have more tangible assets, and are more likely to be investment grade. Repeated borrowers command better terms on credit line contracts, in terms of the all-in drawn spread, maturity, facility size, and collateral requirements. They also borrow from larger syndicates, on average. These findings are broadly consistent with recent empirical evidence on relationship borrowing in the syndicated loan market, see Bharath et al. (2011).

Does this difference matter for my purposes? How will this affect any conclusions I draw? As discussed previously, by studying the syndicated loan market I am already focusing on the largest segment of U.S. corporate borrowers. Evidently, repeated borrowers are a more established subset of these borrowers. It seems natural that these borrowers were *least likely* to bear the brunt of any credit supply contraction following the collapse of the ABCP market, since they had greater access to alternative sources of capital. Thus, any bank-driven effect I uncover is likely to be an *underestimate* of the true average credit supply effect, since less established (small publicly-traded or private) firms are more likely to experience syndicate exit or receive worse contract terms.

Are Banks with ABCP Exposure Different?

Banks with ABCP exposure are not a random subsample: Exposure to ABCP is a bank choice variable. It is therefore important to identify factors that vary systematically with bank exposure and loan outcomes. This motivates use of the bank and firm control variables in the regression specifications used throughout the analysis.

Panel B of Table A.2 tests whether exposed banks were systematically different along observable dimensions in the pre-event period.[26] Banks are sorted into terciles depending on their average pre-event exposure – "high" ("low") exposure banks fall into the top (bottom) tercile of the distribution post-event. I then compare average loan, borrower, and bank characteristics for these two types of banks.[27]

The top panel tests if loan outcomes differ systematically for banks with greater exposure. Similarly, the middle panel tests whether firms borrowing from these banks differ. Taking these two sets of results together, we observe that firms borrowing from more exposed banks are smaller (as measured by sales) and thus likely to receive a smaller credit line facility. The bottom panel indicates that banks with greater exposure closely resemble other banks with regards to profitability (return on assets), risk (non-performing loan ratio) and their equity ratio. While the difference is not statistically significant, it is clear that exposed banks were

[26] Asset-backed commercial conduits represent a form of securitization. Recent evidence, e.g., on Spain (Jimenez et al., 2010), suggests that banks undertaking securitization activities were systematically different and even lent to riskier borrowers on the margin.

[27] A similar way to test this would be to regress various loan, borrower, and bank characteristics on bank conduit exposure and see which, if any, of the coefficients are statistically significant. I have performed this test (unreported) and the results are similar; that is, high conduit exposure is concentrated among banks that tend to extend smaller credit facilities to smaller, less levered borrowers.

larger in size.

The similarity of exposed/unexposed banks, in terms of their own characteristics, and their customer base and loan outcomes, alleviates concerns that any contraction in credit (or deterioration in contract terms) might be driven by reduced credit demand from the type of firms borrowing from exposed banks. Of course, there remains the concern that firm-bank matching might occur along some unobservable dimension or that borrowers from exposed banks might become *unobservably* riskier *during* the post-event period. Another concern – common to empirical analyses of credit register data involving multiple loans to the same firm – is that there is a contraction in loan demand along certain loan types that are provided by exposed banks. Looking within-syndicate/relationship goes a long way to relieve such concerns, as I am able to fix the loan type and borrower directly.

III Empirical Results

A Bank Lending Following the Collapse of the ABCP Market

I investigate how banks with greater exposure to the collapse of the asset-backed commercial paper market adjusted their lending policy after August 2007, relative to other banks, using the following specification:

$$\Delta \text{Bank Credit}_{b,t} = \alpha + \beta \text{Conduit Exposure}_b + \gamma' \Delta X_{b,t} + \epsilon_{b,t} \tag{1}$$

where β is the coefficient of interest.

Bank Credit$_{b,t}$ is (log gross) credit issuance in period t by bank b.[28] Bank credit is aggregated for the pre- and post-event windows, which correspond to the 365 days before and after August 9th 2007. I denote these two windows t and $t-1$, respectively.[29] Credit is aggregated from individual deals from the syndicated loan market and includes all term loans and lines of credit. Conduit Exposure$_b$ is bank b's exposure to ABCP as a fraction of equity capital, measured as (log) bank-sponsored asset-backed commercial paper outstanding

[28] I stress *gross* issuance here, as the majority of loans in DealScan refinance existing loans. This could present significant problems for any study attempting to model the flow of *new* credit into the syndicated loan market. For example, net issuance is zero if a syndicate refinances over an existing contract with, say, exactly the same terms one day after issuance. I actually exploit this feature of the market as part of my identification strategy. For related discussion, see Roberts (2010).

[29] Note I could alternatively estimate (1), or any other of my specifications, using bank-(firm-)quarter fixed effects. However, I prefer time-average the bank controls one year before and after the event date. Doing so generates conservative standard errors (Bertrand et al., 2004; Stock and Watson, 2008).

relative to bank equity capital, on January 1st 2007. The "Δ" refers to time-differencing (post minus pre) by bank, which is equivalent to estimating my model with bank fixed-effects.[30] Thus β is estimated by examining the cross-sectional correlation between conduit exposure and within-bank credit growth.

$X_{b,t}$ is a vector of bank observables known to determine lending policy, consisting of the following (expected sign in parentheses): Assets$_{b,t}$ (−), Return on Assets$_{b,t}$ (−), Core Deposits$_{b,t}$ (−), Subordinated Debt$_{b,t}$ (−), Equity$_{b,t}$ (−), and Loan Losses$_{b,t}$ (+). Larger banks tend to be better diversified and viewed as less risky by investors, so I expect them to be able to pass on their lower cost of funds to their borrowers. I expect more profitable banks, as measured by return on assets, to have a lower cost of funds. The reverse would be true for banks experiencing losses, measured by net loan charge-offs. Finally, I expect banks with stable sources of funding – deposits and equity capital – to be able to lend on more favorable terms.

Table 2 presents the results estimating this regression. First, note that average credit issuance decreased by 30% following the collapse of the ABCP market. In the cross-section of banks there is a negative correlation between the contraction in loan issuance and conduit exposure. Once the sample of loans are partitioned, we see that the effect is concentrated in revolving lines of credit for which the relationship is negative and statistically significant. These results are economically significant: moving from Wells Fargo (0% conduit exposure) to Citibank (100%) leads to a 14% reduction in credit line issuance, over and above the aggregate effect. Similar hold in a specification weighted by bank assets and when bank controls are included (unreported).

These results indicate that after the collapse of the ABCP market, banks with greater conduit exposure reduced total lending relative to other banks. In addition, banks with greater exposure reduced credit line issuance relative to term loans. This finding suggests that the funding shock had a direct impact on the willingness of exposed banks to take on further liquidity risk by funding new credit line commitments.

The disadvantage of estimating (1) is the absence of controls for any borrower factors ("credit demand") that could drive changes in bank lending policy. For example, banks with greater conduit exposure could systematically differ from other banks by choosing to lend to firms whose investment opportunities and need for credit diminish at the onset of the crisis.[31] To mitigate concerns that liquidity demand effects contaminate my findings,

[30]Papers employing a similar approach, i.e., using variation across banks, include Kashyap and Stein (2000) and Ashcraft (2005).

[31]Note the importance of the qualification "at the onset of the crisis." Assuming time-invariant unobservable factors are adequately controlled for, any omitted variable that biases β *must* be time-varying in

I take several steps. First, as already noted, I include bank fixed effects. This forces the comparison of changes in lending policy to be within-bank, controlling for any time-invariant unobservable bank characteristics. This will be useful if characteristics of each bank's pool of borrowers (or any other unobservable bank characteristic) do not change over time. Second, to improve the validity of the bank fixed effects, I have restricted the panel data set to a two year window around the August 9th 2007 event date. Focusing on this narrow window gives me confidence that bank effects are indeed fixed. Third, I demonstrate that during the pre-crisis period, borrower characteristics and loan contract terms do not differ across banks with differential conduit exposure. Finally, I conduct my analysis at the loan-level, which allows me to control for shifts in borrower characteristics directly.

B Syndicate Participation Decision: Extensive Margin

Exposed Banks Exit Credit Lines

Does bank exposure to the funding shock induce them to stop lending to firms altogether? In particular, are exposed banks more likely to exit a lending syndicate rolling over a loan after the event date? Next, does exposed banks' propensity to exit vary *with loan type*, i.e., credit lines versus term loans?

I test the first question directly by comparing the syndicate exit rate during the post-event window as a function of bank exposure. For each syndicate-bank pair (8,069 pairs across 1,393 syndicates), I create a variable called *Exit* that is equal to one if the bank has exited the loan syndicate rolling over a loan during the post-event period.[32]

I limit the analysis to borrowers that successfully roll over credit during the post-event window, which mitigates concerns regarding credit demand. I then use a *syndicate* fixed effects approach, whereby I compare the propensity for a particular bank to exit a particular syndicate as a function of their exposure to the funding shock. By including syndicate fixed effects, I control for changes in borrower investment opportunities and risk (credit demand) at the *loan* level. Notice that this permits tighter identification than controlling for changes in credit demand at the firm-level using firm fixed effects. The firm-fixed effects methodology assumes that the credit demand shock applies uniformly across lenders for the estimator to

nature *and* correlated with bank exposure in the cross-section.

[32]Pinning down the *dynamics* of loan syndicates is no easy task. While DealScan provides information on which new loan issues are refinanced, no information is provided on *which previous loan is being refinanced.* This information is essential to establish which syndicate members have exited the syndicate. To establish this link, I use a web crawler to download and parse thousands of loan "tear sheets" from the Loan Pricing Corporation's LoanConnector website. I thank Bill Robinson at Thomson Reuters for making this possible.

be unbiased. Here, I am looking at a particular loan, so there is no concern that any observed exit is correlated with *loan type*.

I also control for the same bank-level observables as in specification 1. I can then test whether an exposed bank is more likely to exit the *same syndicate* as less exposed, where the syndicate is renewing a loan to the same firm during the post-event window. To this end, I estimate the following specification:

$$\text{Exit}_{s,b,t} = \alpha_s + \beta \text{Exposure}_{b,t} + \gamma' X_{b,t} + \epsilon_{s,b,t} \quad (2)$$

where β is the coefficient of interest and the s subscript refers to the syndicate of interest.[33]

Table 3 presents the results. The first column shows that banks with greater exposure to the collapse of the asset-backed commercial paper market were more likely to exit syndicates rolling over loans. This finding is highly statistically significant and economically meaningful. In particular, a one standard deviation increase in *Exposure* leads to a 13.3% increase in the probability of syndicate exit (the mean exit rate for loans was 33.7% during the post-event period).

Next, I break out the sample into term loans and lines of credit and re-estimate equation 2 on each sample. I examine whether term loans or credit lines are more likely to experience syndicate exit when rolled over during after the funding shock. The middle two columns of Table 3 present the results. I find that bank exposure is not a statistically significant determinant of syndicate exit for term loans, whereas it is for lines of credit. Moreover, the economic effect – the probability of exit – is over twice as large in the case of lines of credit.

The final column investigates whether the difference in the exit-exposure relationship across loan types is statistically significant. To this end, I estimate specification (2) without syndicate fixed effects, but including a full set of firm controls and a *Credit Line* $\times$ *Exposure* interaction term. The full set of firm controls are listed in Table 1. Ideally, I would include a firm fixed-effect and compare, for the same firm, whether a given bank is more likely to exit rollover on a term loan versus a credit line during the post-event window. Unfortunately, there is not enough of this kind of variation in the data, i.e., too few firms roll over *both* a term loan and credit line post-shock.

The estimated results show that credit lines are less likely to experience exit than term loans on-average and that there is a significant difference in exit rates in response to the

[33] Linear probability models, while easy to estimate, might yield estimates that imply probabilities greater than one (or negative). I also estimate non-linear (probit and logit) models including syndicate fixed effects. The implications of these models (unreported) are similar, so, for the remainder of the paper when the dependent variable is binary, I report estimates from linear probability models.

funding shock between term loans and lines of credit.

High Quality Borrowers Exit Relationships with Exposed Banks

Does exposed banks' propensity to exit credit line syndicates depend on borrower quality? And, conditional on exit, what happens to the contract terms of the rolled over lines?

In order to address the first question, I use DealScan's "Investment Grade" classification: I create a variable called *Investment Grade* that is equal to one if DealScan classifies the market segment of the loan as such, and equal to zero otherwise.[34] I adopt the same regression specification as in the last section (no syndicate fixed effects, *Investment Grade* interaction term) and test whether the exit rate on syndicates rolling over lines of credit during the post-event window is higher for exposed banks.

Panel A of Table 4 present the results. For comparison, the first column replicates the result from Panel A using OLS and including full set of firm and bank controls, pooling both term loans and credit lines.[35] The second column breaks out the exit rate by borrower type. As expected, on average, exposed banks are more likely to exit syndicates rolling over loans during the post-event window. In addition, the *Investment Grade* main effect suggests that high quality borrowers are less likely to experience exit on average. Interestingly, as evidenced by the positive and statistically significant coefficient on the *Investment Grade* $\times$ *Exposure* interaction term, I find that exposed banks are *more likely* to experience exit with investment grade borrowers than observably similar banks.

I interpret this finding as "strategic withdrawal" (see Khwaja and Mian, 2008) on the part of high quality borrowers from exposed banks. This finding consistent with the bank lending channel and is a matter of interpretation. That is, provided the choice to exit the relationship is a function of the banks exposure to the funding shock – and exogenous to firms' credit demand – this is a supply-side effect. Why would high quality firms choose to exit relationships with exposed banks? From the perspective of the borrower, as a stake holder in the health of their syndicate, such switching behavior makes sense as exposed banks may be less likely to satisfy *future* draw down requests on committed lines of credit. This may be due to a greater risk of insolvency or lenders offering less flexibility following covenant violations. On the other hand, with term loans funds are disbursed upfront and therefore – with the exception of funds being recalled following a covenant violation – it seems less likely that borrowers would care about the health of their lender.

[34] Results are similar if I classify firms as investment grade whenever S&P's long-term debt rating is better than BBB-.

[35] For the same reasons discussed previously, I will not be employing any fixed effects in this analysis.

The next two columns investigate whether or not this is the case. In particular, if this strategic withdrawal effect is stronger among credit lines relative to term loans. The estimated coefficients for credit lines mirror those for the average effect in terms of statistical and economic significance: exit with exposed banks is pronounced for investment grade firms. In contrast, with term loans, none of the estimated coefficients are statistically significant and, in terms of direction, the coefficient on the *Investment Grade* $\times$ *Exposure* interaction term has the opposite sign.

An alternative hypothesis is that other syndicate members refuse to co-syndicate lines of credit with exposed banks. Co-syndicating a credit line with a bank facing insolvency is costly as it increases the expected draw down rate on solvent syndicate members' obligations. However, it seems unlikely that this is happening in my sample because I observe exposed banks exiting syndicates with investment grade borrowers. Such high quality borrowers will have a lower expected draw down rate relative to poor quality borrowers (Mian and Santos, 2011). Thus, co-syndicating credit lines with exposed banks to low quality credits is a riskier prospect and I would expect to see exit occurring on those lines. This is the opposite of what I find in the data, which suggests that the action is on the part of the borrower, i.e., the choice to purchase their liquidity insurance from safer banks.

I next test to see whether syndicates experiencing exit adjust the terms of lending. At this point, I focus exclusively on credit lines and test to see how the credit line commitment size, all-in drawn spread, and maturity adjust for syndicates experiencing exit versus syndicates that do not experience exit during the post-event window. I am particularly interested in whether investment grade borrowers incur any cost when experiencing exit on credit lines, relative to non-investment grade borrowers. To this end, I estimate the following model at the syndicate level:

$$\begin{aligned} y_{s,t} = \alpha + \beta_1 \text{Exit}_{s,t} + \beta_2 \text{Investment Grade}_{f,t} + \beta_3 \text{Investment Grade}_{f,t} \times \text{Exit}_{s,t} \\ + \gamma' X_{f,b,t} + \epsilon_{s,t} \end{aligned} \tag{3}$$

where $y_{s,t}$ is a loan contract term (log facility size, all-in drawn spread, or maturity) for syndicate s in period t (pre- or post-event), $X_{f,b,t}$ is a vector of firm-bank controls measured at time of roll over, and *Exit* is equal to one if the syndicate experiences exit during the post-event window.

These results are presented in Panel B of Table 4. First, note that, on average, investment grade borrowers generally take out bigger commitments on better terms. Second, syndicates experiencing exit face a deterioration in contract terms. Finally, investment grade firms experiencing exit when they roll over credit lines did not experience a deterioration in contract terms. This evidence is consistent with high quality borrowers *costlessly* switching away from relationships with banks that are exposed to the funding shock.

My extensive margin results complement recent findings by Mian and Santos (2011). These authors document active management of rollover risk by investment grade firms by timing *when* they refinance loans over the credit cycle. In particular, they find higher incidence of investment grade firms refinancing loans during the borrower-friendly interest rate environment of 2003–2005. My findings suggest that investment grade firms also actively manage *with whom* they refinance *credit lines*.

C Contract Terms Conditional on Rollover: Intensive Margin

So far I have focused on the extensive margin of bank lending. I find strong evidence suggesting that banks with a greater exposure to the funding shock associated with the collapse of the asset-backed commercial paper market are more likely to exit syndicates rolling over lines of credit. I find that investment grade borrowers are more likely to exit relationships with exposed banks and they are able to do so without any cost.

In what follows, I consider the intensive margin of bank lending via syndicated credit lines. The aim is to investigate whether there is a bank lending channel operating for firms that *continue to receive credit lines from exposed banks*.

I address three distinct questions. First, on average, do exposed banks offer worse contract terms (spread, size, maturity) when rolling over credit line contracts after the shock to the asset-backed commercial paper market? Second, does any deterioration in contract terms depend on features of the loan or borrower? I focus on longer-term commitments and bank-dependent borrowers, in particular. Third, do strong firm-bank relationships mitigate any deterioration in contract terms?

Empirical Methodology

In this section I will describe the empirical methodology I will be using to analyze the intensive margin of bank lending.

The basic approach is to estimate a linear model of the same form as (1), but now including a vector of borrower controls (X_f) and firm-bank fixed-effects ($\alpha_{f,b}$):

$$\begin{aligned} y_{l,f,b,t} = {} & \alpha_{f,b} + \beta_1 \text{Post}_t + \beta_2 \text{Exposure}_{b,t} + \beta_3 \text{Post}_t \times \text{Exposure}_{b,t} \\ & + \gamma X_{f,b,t} + \epsilon_{l,f,b,t} \end{aligned} \tag{4}$$

$y_{l,f,b,t}$ now corresponds to some loan characteristic (spread, log size, maturity) attached to specific loan l, issued to firm f, by bank b in period t (pre- or post-event). A unit of observation is now a firm-bank-loan triple.[36,37] $X_{f,b,t}$ is a vector of firm and bank controls measured in the most recent quarter prior to loan origination.

Controlling for observable bank and borrower characteristics will go a long way to explain variation in credit line contract terms.[38] The firm controls in $X_{f,b,t}$, that are used and their respective expected signs are as follows: $\text{Age}_{f,t}$ (–), $\text{Sales}_{f,t}$ (–), $\text{Leverage}_{f,t}$ (+), $\text{Profit Margin}_{f,t}$ (–), $\text{Interest Coverage}_{f,t}$ (–), $\text{Net Working Capital}_{f,t}$ (–), $\text{Tangibles}_{f,t}$ (–), $\text{Market to Book}_{f,t}$ (–), and $\text{Investment Grade}_{f,t}$ (–). I expect older, larger firms to be perceived as more established, better diversified, and thus less risky overall. Moreover, such firms are less likely to suffer from adverse selection problems due to information asymmetry and are more likely to have established banking relationships, so I expect they are able to command more favorable contract terms. Levered, unprofitable firms are less likely to be able to service their debt, so are perceived as default risks by lenders. Similarly, once in default, firms with less working capital and intangible assets should lose more value, thus making them less desirable credits ex ante. These firms are likely to receive stricter contracts. Firms with growth options, as measured by their market-to-book ratio, should be more desirable credits, all else equal. Finally, investment grade firms are viewed as having lower default risk, so should receive better contract terms on average.

It is important to control for unobservables that might be driving changes in lending policy and matching between firms and banks. First, I continue to be concerned about a credit demand shock that is somehow correlated with the bank exposure in the cross-section. The inability to control for such a shock is unsatisfactory and motivates my use of the panel data estimation techniques; in particular employing firm-bank fixed effects.

Including firm-bank fixed effects in equation (4) allows me to identify β_3 from within-*relationship* variation in credit line contract terms. The firm-bank fixed effect removes the

[36]For this model, as discussed in Section II, I will be using the fraction of assets allocated to ABS and MBS as a proxy for *Exposure* to the collapse of the asset-backed commercial paper market.

[37]My empirical strategy is broadly consistent with others using DealScan (e.g., Hubbard et al., 2002; Lin and Paravisini, 2010; Murfin, 2010; Santos and Winton, 2008; Santos, 2011; Wardlaw, 2010).

[38]This is evidenced by the high R^2 in baseline OLS regressions of this form, excluding fixed effects.

cross-sectional mean of the characteristics that influence the firm-bank match (selection on unobservables). The impact of bank exposure on loan contract terms is identified from *between-bank* variation at each point in time. From a practical standpoint, the sample will contain only credit lines issued to firms that receive at least two lines from the same bank: the firm and bank relationship are held fixed for purposes of estimating β_3. Firms in the sample that *switch* banks will be excluded, since unobservables driving the decision to switch might also drive the change in contract terms.

Note that I have not included loan controls in the regression specification. Loan contract terms are jointly-determined by firm and bank characteristics, and macroeconomic conditions. My maintained assumption is that the inclusion of firm and bank controls, as well as firm-bank fixed effects, is sufficient to overcome any omitted variable bias.[39]

Finally, I estimate all models with heteroscedasticity-robust standard errors, clustered by firm and bank (Petersen, 2009).[40] This approach allows for correlations in the un-modeled component of the loan outcome ($\epsilon_{l,f,b,t}$) for different years in the same firm and also across firms for loans issued by the same bank. This is important as the funding shock occurs at the bank level and thus changes in loan contract terms from the same bank may be correlated. Moreover, since an individual firm may receive multiple loans in either the pre- or post-event window, changes in contract terms from different banks (syndicates) to the same firm might be correlated.

Average Effects

Table 5 presents the result of the within-relationship estimation strategy in equation (4). These results address the question: How did exposed banks adjust contract terms on credit lines they rolled over post-shock relative to other banks?

Panel A provides an expanded analysis of how credit line pricing changed. All columns are estimated with firm-bank fixed effects, and include firm and bank controls. Column (1) shows that a firm receiving a credit line from the same bank both before and after the collapse of the ABCP market paid an additional 62 basis points in the post-event period. Column (2) indicates that exposed banks passed on a higher cost of liquidity insurance to their corporate borrowers in the period following the shock to the asset-backed commercial paper market. This is evident from the positive and statistically significant coefficient on the

[39]Alternatively, I could estimate the loan contract term equations as simultaneously, acknowledging the fact that these terms are jointly-determined. This would lead to an efficiency gain. For an example of this approach, see Dennis et al. (2000).

[40]Thanks to Mitchell A. Petersen for making routines for calculating double-clustered available online.

interaction term. This effect is also economically large: a one standard deviation increase in bank exposure led to a 28 basis point increase in the all-in drawn spread (22.4% of the sample average).

The final column of Panel A re-estimates the firm-bank fixed effects specification on the sample of term loans. Consistent with a traditional bank lending channel, I find that exposed banks pass on a higher cost of borrowing on term loans relative to those banks with less exposure to the funding shock. The economic effect is approximately 37.5% of the estimated effect on credit lines.

Panel B repeats this analysis for (log) commitment size and maturity. The average effect is consistent with exposed banks passing on the shock to their corporate borrowers. The credit line maturity on rolled over lines contracts decreases, as does the facility size, for exposed banks in the post-event window. The average effect is highly significant for maturity (at the 1% level) and not statistically significant for facility size.[41] In terms of economic magnitude, a one standard deviation increase in bank exposure leads to a 4.74 month reduction in credit line maturity (11.3% of the sample average).

Since firm-bank fixed effects are included in the regression, the coefficient estimates are identified from contract changes for a set of (relationship) borrowers that receive credit lines from the same bank both before and after the shock. It is perhaps not surprising that facility size does not change on average. After all, this is the subset of borrowers that are not rationed credit lines by exposed banks post-shock, so they may continue to receive their credit line but on worse terms (i.e., price and maturity).

In what follows, I will explore the considerable heterogeneity in the treatment effect, which is consistent with exposed banks actively managing the liquidity risk associated with lines of credit.

Syndicate Structure: Lead Arrangers versus Participants

The average effect estimated does not yet exploit any information regarding the syndicate structure. I investigate whether the position (lead versus participant role) of the exposed bank within the loan syndicate has any impact on the intensive-margin deterioration in contract terms.

Incorporating such information reassures me that I am identifying a bank-driven effect when estimating the intensive margin model of equation (4). Note that lead arrangers should

[41]Note that the number of observations for facility size decreases here as I require there to be complete information regarding bank exposure within the lending syndicate.

have more influence over the terms of a rolled over loan. At a minimum, the lead arranger will price the contract so as to ensure that their own participation is rational.[42] Thus, if exposed banks face an increased cost of capital I would expect to observe them increasing loan rates more so when they are in a lead arranger role. An exposed bank in a participant role will have less bargaining power and so, when rolling over a loan with an observably similar borrower, will have less influence over a rate hike.

How does this approach alleviate concerns about credit demand shocks? One might be concerned that exposed banks are lending to firms that become (unobservably) riskier post-event. A key feature of my empirical strategy is that I fix bank-borrower match ex ante. Therefore, by also including information about the exposed bank's role in the syndicate, one would have to be concerned about a demand shock that is correlated with both bank exposure *and* the syndicate structure. In particular, that exposed banks lend to firms that become riskier ex post *and do so in a lead arranger role.*[43]

Panel C of Table 5 incorporates information on syndicate structure and continues to focus on credit lines. I estimate the intensive margin model on the full sample, for lead arrangers only, and for participants only. These results show that the difference-in-differences estimate is close to twice as large among banks in the lead arranger role. This evidence is consistent with exposed banks leveraging their position as lead arranger to pass on the costs associated with the funding shock to their corporate borrowers. Note, however, that exposed banks only roll over credit lines in a participant role provided the spread increases, which suggests that they are still able to influence the price of the contract. This finding is consistent with lead arrangers increasing the price of the contract to ensure that participation is individually rational for *all* participants, including exposed banks.

Risky Loan Types and Bank-Dependent Borrowers

Fearing "runs" by creditors and indeed corporate credit line holders, did exposed banks actively manage the liquidity risk associated with committed lines of credit?

To provide further supportive evidence, I look at the cross-section of rolled over credit

[42]For themselves and as many syndicate participants as required to fund the loan.

[43]Of course, one can construct examples where this behavior makes sense. For example, securitization activities might relax funding constraints (e.g., Loutskina, 2011) and lead these banks to originate more loans to weaker credits. These credits might run into trouble ex post and hence the observed increase in interest rates on rolled over loans. While plausible, this is not what happens in my sample, as discussed in Section II. My goal is not to rule out such alternative stories – this is impossible – but instead present a collective body of results consistent with a bank-driven effect on the intensive margin. Analyzing the role of syndicate structure is one more piece of evidence in this regard.

lines and test to see whether exposed banks pass on the deterioration in credit line contract terms to the "riskiest commitments". I consider two classes of risky credit line commitment: first, lines that are held by firms that are more likely to run should the bad state materialize; second, lines that banks have less control over the roll over decision, i.e., those lines with the longest effective duration.

I classify firms without access to alternative sources of financing (e.g., commercial paper) as "bank-dependent" (e.g., Chava and Purnanandam, 2011). These firms are more reliant on bank-provided liquidity and it would be more costly for them to substitute to other sources of cash (e.g., retained earnings) should their relationship bank fail. Consequently, these borrowers will be more likely to draw down on their lines of credit independently of actual liquidity needs. I hypothesize that exposed banks internalize this additional source of risk and pass on worse contract terms to these borrowers.

First, I consider two types of bank-dependent borrowers: those without access to commercial paper markets and those considered speculative grade.[44] Following Murfin (2010), a borrower is classified as having access to commercial paper markets if they have S&P short-term debt rating of A-2 or better. I estimate the within-relationship specification, equation (4), separately on bank-dependent and non-bank dependent subsamples based on these two definitions and compare the magnitude and statistical significance of the *Post* $\times$ *Exposure* interaction term.[45]

Panel A of Table 6 reports the results of this first test. I find that bank-dependent borrowers suffer a deterioration in credit line contract terms that is more severe than the average effect. Focusing first on unrated borrowers, I observe that those that successfully roll over their credit lines post-shock with exposed banks do so on worse terms: first, relative to rated firms borrowing from the same bank; second, relative to unrated firms borrowing from less exposed banks. This pattern also holds for facility size.

Interestingly, I find that exposed banks uniformly reduce the maturity of credit lines rolled over with both unrated and rated borrowers. We know that ABCP conduits exhibited a severe maturity mismatch: long-term conduit assets (ABS, MBS, etc.) were funded with short-term commercial paper (i.e., ABCP). Exposed banks therefore faced the prospect of bringing this maturity mismatch back on their balance sheet. It is therefore not surprising

[44]See Jimenez et al. (2008) for recent empirical evidence on draw down rates of across the credit spectrum.

[45]I also estimate (4) pooling both subsamples and interacting the entire model with a "bank-dependent" indicator variable. I assess the statistical significance of the triple interaction term to formally test if there is a difference in the *Post* $\times$ *Exposure* between groups. In this case, and for every other groups comparison I analyze, I find the difference in coefficients is significant at (at least) the 10% level in all cases.

that exposed banks adjusted the maturity of their credit line commitments accordingly, relative to unexposed banks that did not face the same problem.

When I consider speculative grade borrowers as being bank-dependent a similar pattern emerges. Note that the finding on investment grade firms complements those from the extensive margin analysis: investment grade firms that roll over credit lines with exposed banks – those that do not switch away – accept a worse all-in drawn spread. Moreover, speculative grade firms that continue to borrow from exposed banks experience an even worse deterioration in credit line pricing. Collectively, these findings are inconsistent with any risk-shifting argument on the part of exposed banks.

In the next set of tests, I consider how the average effect varies across different loan types. Credit lines with a longer (effective) duration offer banks less control over the roll over decision. Credit lines with longer effective duration pose a greater risk for exposed banks, as they allow for the possibility of draw-downs for a longer period of time. I hypothesize that more exposed banks will limit their exposure to these commitments (reducing maturity and size) and increasing the cost to borrowers (increasing spread).

Panel B of Table 6 reports the results. I classify credit lines according to whether they are short- or long-term according to maturity: long-term lines have maturity exceeding one year. As hypothesized, exposed banks increase the price and decrease the maturity of long duration credit lines, relative to long duration credit lines rolled over by otherwise similar banks. The magnitudes exceed the average effect by more than 50%, suggesting that this is a particularly risky form of commitment from the perspective of exposed banks. I find a marginally statistically significant, but not economically significant effect along the facility size margin.

The cross-sectional results in this section are consistent with the hypothesis that troubled banks actively managed liquidity risk associated with credit lines by offering worse terms on the riskiest commitments that they rolled over.

Strong Relationships Mitigate Effects

Do strong banking relationships mitigate the deterioration in terms on rolled over lines?

It is unclear ex ante which way this will go. On the one hand, borrowers with strong banking relationships may be "locked-in" to their relationship bank and have fewer outside options. This lock-in may be a consequence of their relationship bank having an "information monopoly" (e.g., Santos and Winton, 2008). When the exposed bank runs into trouble, they will be better positioned to exploit this monopoly and pass on worse contract terms to these borrowers. On the other hand, stressed banks may continue to value the future sale of products and services to relationship borrowers (e.g., Bharath et al., 2007) and thus choose not to leverage their informational advantage.

Table 7 explores this empirical question. While my empirical specification is already "within-relationship" (already uses repeated loans), I am able to further classify each firm-bank link according to whether or not it has a strong bank relationship by comparing the features of the current and previous syndicate. I do so by following Bharath et al. (2011), classifying a link as strong if the firm received a loan from the same lender in the previous year, and the current syndicate (i.e., rolling over the credit line) features: (1) a repeat lead arranger; and (2) the previous lead arranger is present in the current syndicate. Column (3) classifies the link as strong if the previous loan was issued within the last year, i.e., the presence of a previous lead arranger is not considered.[46] Given I am already using repeated loans in the benchmark model, the estimated credit supply effects in Table 7 are identified from joint restrictions on the timing of lending (previous loan issued last year) and the syndicate structure (presence of repeated lead arrangers).

According to any of the three classifications we see the same pattern: exposed banks pushed costs associated with the funding shock onto non-relationship borrowers. Relationship borrowers experienced a statistically significant increase in the price of bank-provided liquidity, but this effect is smaller than the average treatment effect. Evidently, strong firm-bank relationships were not enough to fully offset the effects of the funding shock. On the other hand, non-relationship borrowers experienced an effect approximately 22% larger than the average effect.

IV Robustness

Post-Event Window

The results at the loan-level are conducted using a two year post event window. My empirical strategy relies on observing loans given to the *same borrower* by the *same bank* both before and after the event date and therefore there is a trade-off when selecting the size of the post-event window. In particular, a short post-event window (e.g., six months) will limit the number of admissible observations in the analysis. On the other hand, a long post-event

[46]These three measures have pairwise correlation equal to roughly 70%. This is evident when comparing the number of observations across Columns (1) to (3). While these measures are correlated I believe there value in considering them individually as there could be interesting effects associated with, for example, the identity of the lead arranger switching.

window (e.g., three years) will include other events and therefore make it difficult for me to attribute any bank-driven effect I uncover to one particular event.

As a robustness check, I limit the length of the post-event window to one year. This now means that the post-event window runs from August 2007 through August 2008 and excludes the period following the collapse of Lehman Brothers. I then repeat the analysis in Tables 3 and 5. Panel A of Table 8 reports the results for the extensive margin and Panel B for the intensive margin.

For both the intensive and extensive margins, the estimated coefficients have the same direction and statistical significance as compared to the estimates for two year post event window. In terms of magnitudes, the estimated coefficients become attenuated but are still large and economically significant.

On the extensive margin, I continue to find that exposed banks have a greater propensity to exit syndicates and that this effect is strongest for credit lines. The estimated coefficient in the final column of Panel A is roughly the same size as the equivalent coefficient in Table 3.[47] I thus find a similar of exposure on the relative propensity to exit credit lines versus term loans with the restricted post-event window.

On the intensive margin – for loans that are rolled over – I find that the magnitude of the estimated difference-in-differences coefficient reduces to one-third of its size when I restrict the post-event window. The estimated effect for term loans experiences a greater decline and is now statistically indistinguishable from zero.

Taken together, these results suggest that there was still a bank lending channel in effect during the pre-Lehman period. I continue to find that the estimated effect is stronger for credit lines, suggesting that banks transmitted the funding shock via corporate lines of credit.

Placebo Crises: Pre-Existing Trend?

To further test the validity of my empirical strategy, I run a series of placebo (or falsification) regressions. This test involves bringing the "event date" forward one year, i.e., to August 9th 2006, and repeating the same set of tests. If the results of my analysis are driven by some time-invariant characteristic of the data – for example, exposed banks always extend credit lines to riskier borrowers – then we would expect to see this trend existing in the period prior to the shock.

Panel A of Table 5 contains an example of such analysis and demonstrates that there is no

[47]The 95% confidence interval contains the estimated coefficient from the specification with a two year window, i.e., 0.815.

pre-existing trend in the data for the result on credit line pricing. In particular, the coefficient on the *Post* $\times$ *Exposure* interaction flips sign and becomes statistically insignificant. This indicates that banks that were going to experience a negative funding shock in the future offered comparable terms to other banks rolling over credit lines.

I also conduct this test for maturity and facility size and find there is no evidence of a pre-existing trend in the data and, if anything, exposed banks tend to offer more favorable terms when rolling over credit lines.[48]

Intensive Margin Within-Syndicate Estimator

One residual concern with (4) is that the firm-bank relationship might be subject to *time-varying* unobservable shocks that might determine the nature of credit extended to the firm, even within-relationship. For example, firms borrowing from banks with illiquid asset bases might have become unobservably riskier during the crisis. In a broader sense, variation in the distribution of firms across banks that correlates with changes in borrower risk at the time of the funding shock may bias the estimation of a credit supply shock. The final specification that I shall consider accounts for this possibility by focusing on firms that were issued multiple credit lines both before and during the crisis. Following Khwaja and Mian (2008), the empirical model is specified as follows:

$$\Delta y_{l,f,b,t} = \alpha_f + \beta \text{Exposure}_{b,t} + \gamma' \Delta X_{b,t} + \epsilon_{l,f,b,t} \tag{5}$$

where $\Delta y_{l,f,b,t}$ is the change in loan contract term before and after the event date and α_f is a firm fixed effect. In order to estimate this equation, I focus exclusively on firms that have multiple relationship lenders; in particular, firms must receive a credit line from at least two of the same banks both pre- and post-event. By taking a time difference (denoted Δ) and forcing the comparison to be within-firm, β is now identified from between-bank variation in loan contract terms offered to the *same* firm. Including the firm fixed effect in the time-differenced specification removes *all* time-varying firm effects that might contaminate my estimate of β. The idea is to control for firm-specific changes in credit demand by contrasting differences in lending across firm-bank relationships within-firm rather than across firms, as in equation (4).

The results of this analysis (unreported) are consistent with the previous findings (see

[48] These are unreported, for brevity. Also note that the number of observations falls in Panel A of Table 5, as I did not extend the link between DealScan and Call Report data into 2002, which is the year prior to the beginning of my sample.

Table 5).

Cyclical Loan Types

A residual concern is comparability across types of credit lines, since not all lines are used for the same purpose. I am particularly concerned that my results are driven by a withdrawal of cyclical loan types, such as loans issued for corporate restructuring purposes (e.g., mergers and acquisitions or leveraged buy outs). It may well be the case that banks that tend to engage in securitization activities also tend to finance cyclical loan types. If this were so, then the results so far might not be a general statement about lines of credit, but rather a *subset* of lines being withdrawn from the market.

This criticism applies to my analysis of the extensive margin. This analysis is within-syndicate, so even if exit only occurs on cyclical loan types, I am satisfied that I am identifying a bank-driven effect.

The bigger concern is with identifying the intensive margin, i.e., when estimating equation (4). This specification is *not* within-syndicate, so when I compare across firm-bank-loan pairs I may actually be comparing a change in contract terms on an acquisition credit line (arguably, a cyclical loan type) with a line used for working capital purposes. The latter loan is used for traditional corporate liquidity management and is more in the spirit of this paper. If, as discussed above, the cyclical loan type tends to be issued by banks undertaking securitization activities *and* demand for cyclical loans decline (or they become riskier) in the post-event window then I might be identifying a demand-driven effect.

I have taken two steps to directly address the latter concern. First, I have excluded cyclical loan types throughout my analysis of the intensive margin of bank lending.[49] Second, I reproduce Panel B of Table 5 using only credit lines used for working capital purposes (29.8% of sample) and obtain almost identical results. These results are shown in Panel C of Table 8.

TED Spread Interaction

As a final robustness check, I adopt a continuous measure of the "intensity" of the crisis by replacing *Post* with the *TED Spread* in equation (4). The TED Spread (3-month LIBOR rate minus 3-month Treasury rate) is a measure of perceived credit risk in the general economy

[49]These include credit lines classified by DealScan as: acquisition line, debt repayment, dividend recapitalization, IPO related financing, LBO, and so on.

and, in particular, the counterparty risk associated with interbank lending.[50] I have argued that the probability of runs by corporate credit line holders depends on the health of their relationship bank. If so, then liquidity risk associated with credit lines should increase with the TED spread, and more so for unhealthy banks.

Panel B of Table 8 explores this hypothesis by looking at changes in credit line pricing as a function of bank exposure and the TED spread. *TED Spread* is measured as the quarterly average of daily differences between the 3-month LIBOR and the 3-month T-bill rate and matched to the timing of bank balance sheet data. The evidence presented is consistent with the above discussion. I find that when the TED spread is high, banks tend to increase the spread on newly issued credit lines, and even more so for banks exposed to the collapse of the asset-backed commercial paper market. This result is statistically significant once I estimate the model with firm-bank fixed effects.

In a final step, I check the robustness of this finding by lagging the entire TED spread series one year (2007Q4 TED spread now assigned to 2006Q4) and re-estimating the model. As can be seen from the final column of the Table, the estimated coefficient on the *Post* $\times$ *TED Spread* interaction term is now negative and statistically insignificant. This suggests that the timing of the variation in the TED spread and how it interacts with bank exposure is an important determinant of credit line pricing.

V Concluding Remarks

The aim of this study was to understand how the funding shock associated with the collapse of the asset-backed commercial paper market was transmitted to the market for corporate liquidity. I focused on participation of commercial banks providing committed lines of credit in the U.S. syndicated loan market. This study suggests that synergy between deposit-taking and lending via loan commitment might break down when banks are heavily exposed to losses associated with an aggregate shock.[51]

[50]After August 2007 the TED spread increased from 50bps to around 150bps and eventually spiked to above 400bps around the time of Lehman Brothers' failure. See Cornett et al. (2011) for a similar approach and a discussion of the TED Spread during the 2007-09 period.

[51]The link from financial market frictions to corporate liquidity continues to be relevant in the context of the Eurozone sovereign debt crisis. For example, from the Wall Street Journal on September 15th 2011: *"Potash Corp.* [a Canada-based producer of fertilizer, industrial and animal feed products] *is looking for lenders to increase their commitments after embattled French bank Societe Generale pulled out of a lending syndicate for the refinancing of a $2.5 billion revolving credit line, according to people familiar with the situation. The move, believed to be in reaction to SocGen's difficulty obtaining access to U.S. dollars, suggests that the French bank is reducing its dollar-denominated business in reaction to its recent troubles."*

I find evidence consistent with banks actively managing the liquidity risk associated with credit lines following the initial shock to the asset-backed commercial paper market. In particular, banks with greater exposure to the shock are less likely to participate in syndicates rolling over credit lines. When they are willing to participate they do so on less favorable terms, especially on credit lines that pose greater liquidity risk. Only the highest quality borrowers are able to costlessly switch out of relationships with impaired lenders, which suggests there are distributional consequences of such funding shocks. These distributional consequences apply are relevant for *both* firms and banks. In the first instance, low quality borrowers locked-in to exposed banks receive the brunt of the bank funding shock in terms of worse contract terms. Second, exposed banks experience a deterioration in the composition of their customer base. Therefore, when these commitments are drawn and show up on-balance sheet, exposed banks' capital adequacy ratio might take a further hit.

I find that strong banking relationships are a means by which firms can limit the deterioration in contract terms, although these borrowers are not able to avoid an increase in pricing entirely. This suggests that there are fixed costs associated with switching out of relationships and forming new ones, which might be an important friction in lending and borrowing markets, especially for small and opaque borrowers.

There are several questions I have not addressed in the present study that are worthy of further investigation.

First, and most importantly, I did not consider the impact of the withdrawal of bank-provided liquidity on financial and real outcomes for corporations. In particular, I did not explore the implications for liquidity (e.g., cash) management and investment decisions for firms borrowing from impaired banks.

Second, I did not consider the impact of the funding shock on lending via loan commitment to *private firms*. My within-syndicate approach for the extensive margin, exploits repeated lending and syndicate dynamics to identify a bank-driven effect, without requiring any firm-level accounting information. Such an approach could, in principle, permit an analysis of whether exposed banks were more likely to ration liquidity to private firms, than publicly traded firms.

Third, I did not consider the role of loan covenants at all. Despite the period of "covenant-lite" lending in the run up to August 2007, banks may still exercise control over outstanding credit line commitments. Covenant violations enable banks to renegotiate outstanding commitments and limit exposure to liquidity risk. Whether impaired banks were willing to waive covenant violations and disburse pre-committed funds or not is still an open question.

Finally, recent work by Acharya and Mora (2011) suggests that banks with weak balance sheets (including those that subsequently fail) actively seek to attract deposits by increasing rates. Further investigation of how banks manage liquidity risk associated with loan commitments *as they approach failure* would be very interesting.

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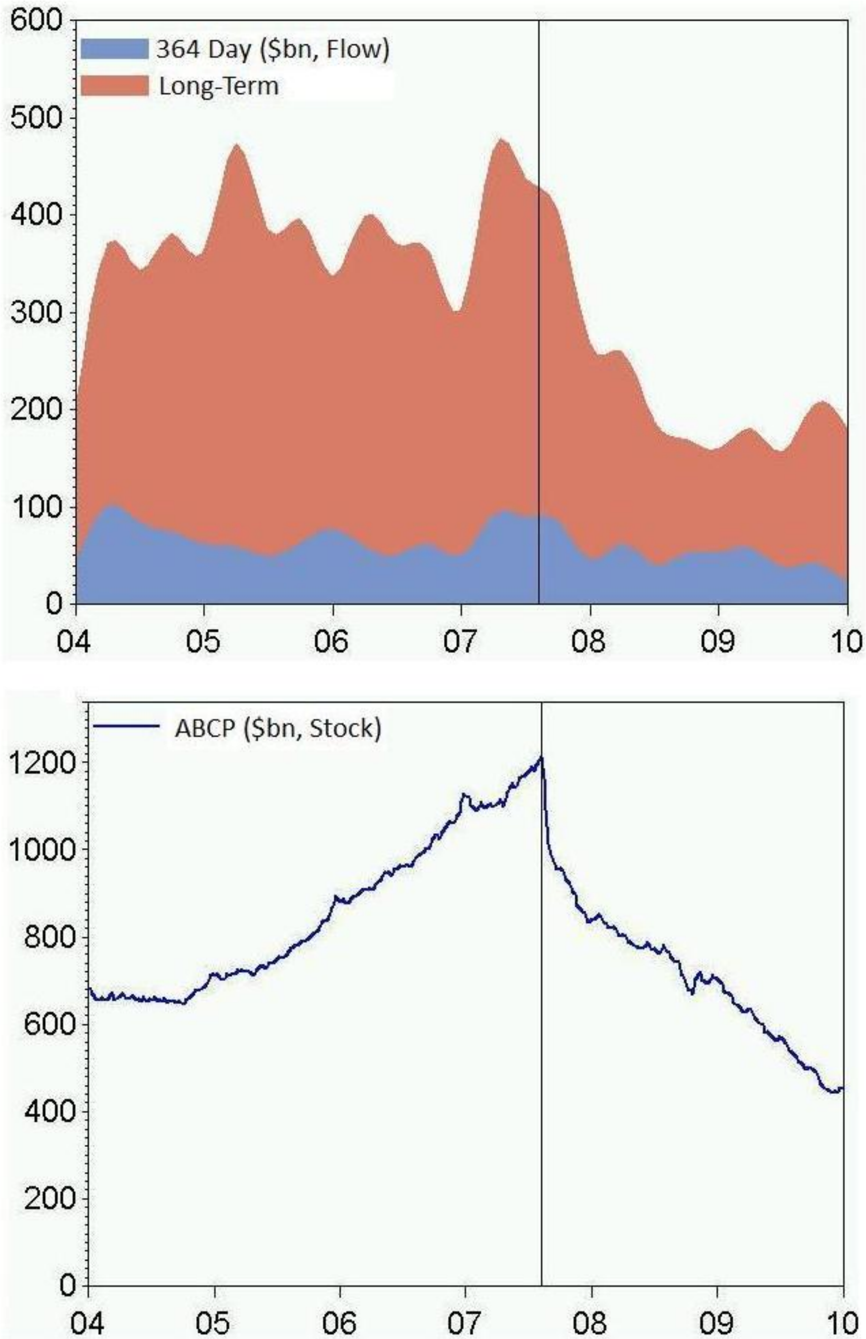

Figure 1: U.S. Syndicated Credit Line Issuance and ABCP Market 2004–10
This figure (top panel) shows the gross issuance ($ billion) of U.S. syndicated lines of credit at a quarterly frequency for the period 2004-2010. Issuance broken down by maturity into long-term (red, maturity greater than 12 months) and short-term (blue, maturity less than 12 months) lines of credit. All data comes from DealScan. Loans to real estate and financial firms are excluded (primary SIC code in 1520–1600 or 6000–7000). The bottom panel shows the total amount ($ billion) of asset-backed commercial paper (ABCP) outstanding in the U.S. market from January 2004 through January 2010. Data comes from the Federal Reserve Board website. The vertical line in both figures corresponds to the date August 9th 2007.

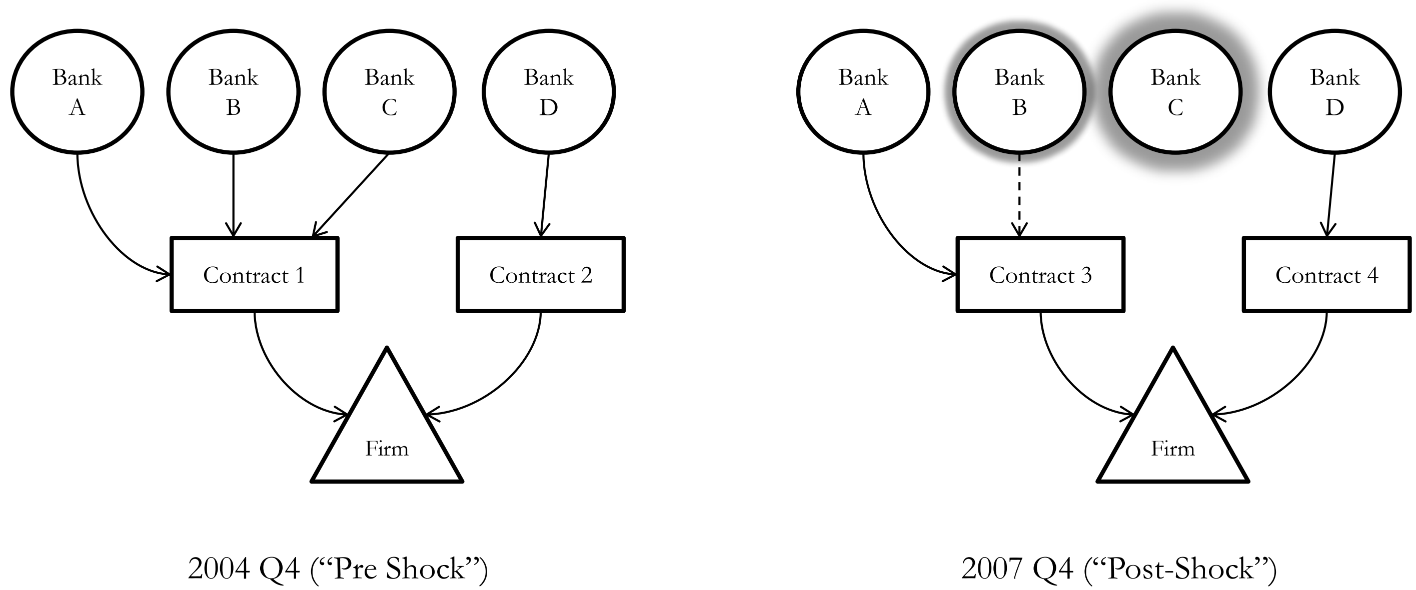

Figure 2: Identification and the U.S. Syndicated Loan Market
This figure provides a schematic of how a firm borrows in the syndicated loan market. Circles denote banks, rectangles loan contracts, arrows link banks to loan contracts and contracts to the firm (denoted by a triangle) and represent the flow of credit. The broken arrow corresponds to a weak flow of credit. Shading around banks corresponds to bank financial condition: a bigger halo corresponds to a more exposed bank. My identification strategy exploits two features of syndicated lending in the U.S.: repeated borrowing over time and many banks lending to one firm at a given point in time.

Table 1
Summary Statistics

Panel A: Call Report Sample				
	Pre Event	Post Event	Difference	[t-statistic]
Credit Line				
All-In Drawn Spread	118.314	203.883	85.569***	[51.75]
Facility Amount	7.034	8.478	1.444***	[8.123]
Maturity	43.260	38.468	-4.793***	[-15.82]
Secured	0.501	0.628	0.128***	[14.17]
Syndicate Size	13.844	12.649	-1.195***	[10.17]
Borrower				
Age	27.637	28.521	0.884***	[3.05]
Sales	2505.976	2961.892	272.622***	[4.88]
Leverage	0.306	0.299	-0.007**	[-2.30]
Market to Book	1.707	1.582	-0.125***	[-9.03]
Interest Coverage	25.907	33.435	7.528*	[1.69]
Net Working Capital	3.844	4.211	0.367***	[6.43]
Tangibles	0.491	0.511	0.020***	[5.33]
Investment Grade	0.490	0.324	-0.165***	[23.16]
Bank				
Assets	389.232	735.680	346.448***	[48.75]
Return on Assets	0.007	0.004	-0.003***	[-34.98]
Deposits	0.637	0.652	0.015***	[7.50]
Core Deposits	0.280	0.258	-0.023***	[10.35]
Subordinated Debt	0.022	0.021	-0.001**	[-2.39]
Equity	0.089	0.091	0.002***	[2.78]
Loan Losses	0.002	0.004	0.002***	[43.96]
Exposure	0.115	0.112	-0.003**	[2.39]
Observations				
Loans	9,612	1,625		
Firms	2,750	1,069		
Banks	165	95		
Loan-Firm-Bank Triples	41,642	5,465		

Panel B: Conduit Sample				
	Pre Event	Post Event	Difference	[t-statistic]
Credit Line				
All-In Drawn Spread	173.639	217.101	43.462***	[12.76]
Facility Amount	3.273	2.997	0.277	[1.42]
Maturity	53.399	45.598	-7.801***	[-15.29]
Secured	0.777	0.782	-0.005	[0.32]
Borrower				
Age	23.686	22.010	-1.676*	[-1.74]
Sales	1413.549	808.986	-604.563***	[-2.65]
Leverage	0.285	0.215	-0.070***	[-5.54]
Market to Book	1.899	1.959	-0.061	[-1.47]
Tangibles	0.442	0.406	-0.036**	[-2.53]
Investment Grade	0.375	0.339	-0.036	[-1.44]
Bank				
Assets	741.485			
Deposits	0.488			
Subordinated Debt	0.016			
Equity	0.088			
Conduit Exposure	0.755			
Observations				
Loans	4,260	1,819		
Firms	1,555	484		
Banks	58			
Loan-Firm-Bank Triples	17,407	6,933		

Timing: *Pre Event*: Period from 2003Q1 until 2007Q3; *Post Event*: From 2007Q4 until 2009Q4. Credit line characteristics (at-origination): *All-In-Drawn Spread*: Spread over base rate (LIBOR) in basis points; *Facility Amount*: Line size in hundreds of millions of dollars; *Maturity*: Line maturity in months; *Secured*: One if the line is secured. Borrower characteristics: *Age*: In years; *Sales*: Measured in millions of dollars; *Leverage*: Book value of debt divided by total assets; *Market to Book*: Market over book value of equity; *Interest Coverage*: Ratio of operating income before depreciation to interest expense; *Net Working Capital*: Ratio of current assets minus liabilities to total debt; *Tangibles*: Ratio of plants, property and equipment plus inventory to assets; *Investment Grade*: One if the loan is classified as investment grade in DealScan. Bank characteristics: *Assets*: Total assets in billions of dollars; *Return on Assets*: Net income over assets; *Deposits*: Total deposits divided by assets; *Core Deposits*: Deposits under $100k plus transactions deposits as a fraction of total assets; *Subordinated Debt*: Normalized by assets; *Equity*: Equity capital divided by assets; *Loan Losses*: Charge-offs net of recoveries divided by assets; *Exposure*: MBS and ABS (available for sale plus held-to-maturity) over assets; *Conduit Exposure*: Asset-backed commercial paper outstanding for sponsored conduits to equity capital (as of January 1st 2007). An observation is at the loan-borrower-bank level. Values in the *Pre Event* and *Post Event* columns are simple averages across observations. The difference-in-means test is simple (equal/pooled variance). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 2
Bank-Level Credit Growth and Conduit Exposure

	Δ Bank Credit					
	All	Term Loans	Credit Lines	All	Term Loans	Credit Lines
Conduit Exposure	-0.069	-0.026	-0.139***	-0.080**	-0.061	-0.127***
	(0.035)	(0.069)	(0.037)	(0.039)	(0.044)	(0.043)
Constant	-0.301***	-0.324**	-0.305***	-0.325***	-0.377***	-0.268***
	(0.077)	(0.126)	(0.068)	(0.054)	(0.075)	(0.051)
Method	OLS	OLS	OLS	WLS	WLS	WLS
N	58	58	58	58	58	58
R^2	0.043	0.003	0.163	0.078	0.026	0.144

This table shows bank-level regressions relating the 2006/07 (Jul ‘06 to Jul ‘07) to 2007/08 (Aug ‘07 to Aug ‘08) change in log gross credit issuance against bank exposure to the asset-backed commercial paper freeze commencing August 9th 2007. These regressions correspond to specification (1). Bank *Conduit Exposure* is measured as the fraction of bank equity exposed to asset-backed commercial paper conduits (measured as of December 2006). *Bank Credit* is the sum of all revolving lines of credit and/or term loans issued by a given bank in the U.S. syndicated loan market. Loan data comes from DealScan linked to bank data from Moody’s, the DTCC, and BankScope. Loans to real estate and financial firms are excluded (primary SIC code in 1520–1600 or 6000–7000). *WLS* means that the regression is weighted by total bank assets as of December 2006. All specifications report heteroscedasticity-robust standard errors in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3
Syndicate Exit: Term Loans vs. Credit Lines

	Exit			
	All	Term Loans	Credit Lines	All
Exposure	0.730***	0.350	0.815***	-0.014
	(0.19)	(0.49)	(0.21)	(0.38)
Credit Line				-0.152***
				(0.05)
Credit Line × Exposure				0.785**
				(0.38)
Firm Controls	No	No	No	Yes
Bank Controls	Yes	Yes	Yes	Yes
Syndicate FE	Yes	Yes	Yes	No
N	5,298	1,019	4,279	3,943
R^2	0.44	0.50	0.43	0.33

This table examines how lenders exited banking relationships for syndicated lines of credit during the period 2007Q4 to 2009Q4. I consider relationships that were formed in the syndicated loan market in the pre-event period 2003Q1 through 2007Q3. The sample is restricted to firms that were issued credit post event. *Exit* is a dummy variable equal to one if the bank is not present in any loan syndicate in the crisis period; *Exposure* is the fraction of bank assets in ABS or MBS. *Bank Controls* refer to the same control variables in Table 5, see Table 1 for definitions of these control variables. Loans to real estate and financial firms are excluded (primary SIC code in 1520–1600 or 6000–7000). Standard errors are reported in parentheses and are heteroscedasticity-consistent and clustered at the bank-level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4
Syndicate Exit: Investment Grade Borrowers

Panel A: Exit				
	All		Term Loans	Credit Lines
Exposure	0.691***	0.347	0.440	0.463*
	(0.20)	(0.24)	(0.63)	(0.24)
Investment Grade		-0.133***	0.016	-0.161***
		(0.04)	(0.09)	(0.04)
Investment Grade × Exposure		0.823***	-0.324	0.863***
		(0.28)	(0.74)	(0.30)
Firm Controls	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes
N	3,943	3,943	737	3,206
R^2	0.05	0.06	0.10	0.07

Panel B: Contract Terms			
	Amount	Spread	Maturity
Exit	-0.106*	61.646***	-1.434
	(0.06)	(8.92)	(1.49)
Investment Grade	0.149*	-114.773***	4.101**
	(0.08)	(12.07)	(2.09)
Investment Grade × Exit	0.154*	-55.132***	0.149
	(0.09)	(13.02)	(2.17)
Firm Controls	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes
N	778	721	771
R^2	0.83	0.62	0.73

This table examines how lenders exited banking relationships for syndicated lines of credit during the period 2007Q4 to 2009Q4. I consider relationships that were formed in the syndicated loan market in the pre-crisis period 2003Q1 through 2007Q3. The sample is restricted to firms that were issued loans post event. In Panel A, *Exit* is a dummy variable equal to one if the bank is not present in any loan syndicate in the crisis period; in Panel B, *Exit* is a dummy equal to one if the syndicate experiences exit post event; *Exposure* is the fraction of bank assets in ABS or MBS. *Bank Controls* refer to the same control variables in Table 5, see Table 1 for definitions of these control variables. Loans to real estate and financial firms are excluded (primary SIC code in 1520–1600 or 6000–7000). Standard errors are reported in parentheses and are heteroscedasticity-consistent and clustered at the bank- and firm-level in Panels A and B, respectively. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5
Intensive Margin: Average Effect on Credit Line Contract Terms

Panel A: Credit Line Pricing (All-In Drawn Spread)

	Credit Lines			Term
	(1)	(2)	Placebo	Loans
Post	62.379***	31.061***	-1.429	82.662***
	(3.22)	(4.40)	(3.40)	(10.23)
Exposure		11.960	6.874	-32.694***
		(15.73)	(11.78)	(10.49)
Post × Exposure		359.622***	-25.845	135.114**
		(44.51)	(21.97)	(57.80)
Age	-5.757	-6.378	-37.543***	-85.471***
	(10.03)	(9.98)	(11.67)	(17.76)
Sales	-23.009***	-22.627***	-9.151***	-48.471***
	(2.83)	(2.78)	(2.44)	(7.08)
Leverage	119.013***	117.69***	106.034***	144.728***
	(13.85)	(13.65)	(12.13)	(17.62)
Market to Book	-19.460***	-18.289***	-8.323***	-37.227***
	(2.13)	(2.09)	(1.55)	(4.47)
Profit Margin	-44.83***	-43.948***	-26.88***	-45.260***
	(7.76)	(7.58)	(7.29)	(7.02)
Interest Coverage	2.380	2.433*	-0.332	4.991
	(1.50)	(1.47)	(1.60)	(3.25)
Net Working Capital	-0.001	-0.001	-0.001*	0.050***
	(0.00)	(0.00)	(0.00)	(0.01)
Tangibles	46.022***	39.679**	28.375**	261.425***
	(16.62)	(16.25)	(14.35)	(39.98)
Investment Grade	-83.243***	-81.289***	-57.513***	-80.506***
	(2.85)	(2.78)	(2.38)	(8.96)
Assets	-10.767***	-12.230***	-25.81***	-0.113
	(4.17)	(4.15)	(3.73)	(0.52)
Core Deposits	98.902***	124.54***	23.585	19.209***
	(18.26)	(18.59)	(17.59)	(6.22)
Equity	43.279	94.709	-24.722	-11.84
	(63.53)	(66.37)	(52.57)	(21.64)
Return on Assets	-1172.052***	-1082.26***	-101.485	-658.086***
	(175.68)	(174.90)	(155.47)	(228.30)
Subordinated Debt	-334.206***	-437.24***	-191.24	10.861
	(164.32)	(164.08)	(133.60)	(53.99)
Firm-Bank FE	Yes	Yes	Yes	Yes
N	20,899	20,899	18,246	7,002
R^2	0.83	0.84	0.87	0.82

Panel B: All Contract Terms			
	Spread	Amount	Maturity
Post	31.061***	-0.099	-10.945***
	(4.40)	(0.08)	(1.03)
Exposure	11.960	-0.347	2.410
	(15.73)	(0.32)	(4.98)
Post × Exposure	359.622***	-0.770	-59.611***
	(44.51)	(0.59)	(8.08)
Firm Controls	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes
Firm-Bank FE	Yes	Yes	Yes
N	20,899	8,841	20,899
R^2	0.84	0.82	0.55

Panel C: Syndicate Structure			
	All-In Drawn Spread		
	All	Lead	Participant
Post	31.06***	28.68***	34.29***
	(4.40)	(8.49)	(5.39)
Exposure	11.96	-43.44	8.66
	(15.73)	(58.37)	(16.48)
Post × Exposure	359.62***	601.32***	295.62***
	(44.51)	(96.00)	(53.41)
Firm Controls	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes
Firm-Bank FE	Yes	Yes	Yes
N	20,899	5,568	15,331
R^2	0.84	0.84	0.85

This table reports coefficient estimates from regressions at the loan level relating contract terms on loans issued during 2003Q1 to 2009Q4 to lending bank's exposure. These regressions correspond to specification (4). Panels B and C consider revolving lines of credit only. Panel C partitions the sample according to whether the bank is awarded lead arranger credit in DealScan. *Post* is an indicator equal to one if the loan was issued during the period 2007Q4 through 2009Q4; *Exposure* is the fraction of bank assets in ABS or MBS, see Table 1 for definitions of the remaining variables. Loans to real estate and financial firms are excluded (primary SIC code in 1520–1600 or 6000–7000). All specifications include 2-digit SIC code dummies. Standard errors are reported in parentheses and clustered by firm and bank. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6
Cross-Section I: Risky Commitments

Panel A: Bank-Dependent Borrowers								
	CP Rated						Investment Grade	
	Spread		Amount		Maturity		Spread	
	Rated	Unrated	Rated	Unrated	Rated	Unrated	IG	Non-IG
Post	21.665***	34.326***	-0.222*	0.044	-19.788***	-7.179***	7.862***	52.618***
	(4.53)	(6.40)	(0.12)	(0.12)	(2.17)	(1.10)	(2.54)	(9.45)
Exposure	12.041	2.549	-0.484	-0.285	4.187	-2.311	25.978***	-59.157
	(12.99)	(26.64)	(0.43)	(0.49)	(8.36)	(5.76)	(8.99)	(48.57)
Post × Exposure	205.698***	415.456***	0.975	-1.635**	-52.344***	-56.374***	137.820***	422.597***
	(44.24)	(66.45)	(0.95)	(0.83)	(15.68)	(9.12)	(30.37)	(88.40)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	6,990	13,909	3,500	5,341	7,389	14,585	11,866	9,013
R^2	0.79	0.81	0.81	0.83	0.44	0.63	0.79	0.77

Panel B: Short- vs. Long-Term Credit Lines

	Spread		Amount		Maturity	
	Short	Long	Short	Long	Short	Long
Post	13.13	31.35***	-0.18	-0.04	0.22	-5.50***
	(15.74)	(4.97)	(0.29)	(0.11)	(0.30)	(0.71)
Exposure	18.09	3.05	-0.24	-0.41	-0.28	-4.18
	(21.49)	(23.96)	(0.78)	(0.42)	(0.79)	(4.03)
Post × Exposure	261.12**	416.71***	0.18	-1.35*	0.72	-47.84***
	(126.87)	(51.31)	(1.89)	(0.81)	(1.76)	(6.41)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4,473	16,426	2,115	6,726	4,833	17,141
R^2	0.84	0.84	0.89	0.87	0.66	0.66

This table reports coefficient estimates from regressions at the loan level relating the size and maturity of revolving lines of credit issued during 2003Q1 to 2009Q4 to lending bank exposure. These regressions correspond to specification (4). Each loan is assigned to a model according to whether DealScan classifies the borrower as investment grade or not. *Amount* is the logarithm of the loan size ($ hundreds of millions); *IG* denotes investment grade; *Post* is an indicator equal to one if the loan was issued during the period 2007Q4 through 2009Q4; *Exposure* is the fraction of bank assets in ABS or MBS. For "CP Rated," an observation is classified "Rated" if the borrower has concurrent short-term debt rating of A-2 or better from S&P. For Panel B, a loan is classified as "Long" if it has maturity greater than 12 months. *Firm Controls* and *Bank Controls* refer to the same control variables in Table 5, see Table 1 for definitions of these control variables. Loans to real estate and financial firms are excluded (primary SIC code in 1520–1600 or 6000–7000). All specifications include 2-digit SIC code dummies. Standard errors are reported in parentheses and are clustered by firm and bank. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7
Cross-Section II: Relationship Banking

	Strong Relationship?					
	(1)		(2)		(3)	
	No	Yes	No	Yes	No	Yes
Post	33.45***	32.20***	32.86***	33.29***	31.80***	30.10***
	(7.33)	(8.30)	(7.97)	(7.88)	(10.05)	(6.57)
Exposure	44.03	31.73	40.47	27.35	28.92	30.31
	(27.09)	(27.62)	(29.97)	(25.56)	(44.04)	(19.70)
Post × Exposure	427.97***	231.32***	443.76***	249.60***	443.57***	270.37***
	(69.35)	(82.79)	(75.76)	(79.58)	(101.78)	(69.07)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
N	12,599	8,300	11,609	9,290	9,034	11,865
R^2	0.87	0.82	0.87	0.90	0.88	0.88

This table reports coefficient estimates from regressions at the loan level relating the all-in drawn spread of revolving lines of credit issued during 2003Q1 to 2009Q4 to lending bank's exposure and lending relationship. These regressions correspond to specification (4). The sample is partitioned according to whether a loan-firm-bank triple is classified as having a strong banking relationship, where the observation is assigned "Yes" if: (1) the syndicate features the same lead lender from a loan issued to the same borrower in the previous year; (2) the syndicate features a lead lender from a loan issued to the same borrower in previous year (lender not necessarily lead this time); and, (3) the lender participated in a loan to the same borrower in the previous year. *Post* is an indicator equal to one if the loan was issued during the period 2007Q4 through 2009Q4; *Exposure* is the fraction of bank assets in ABS or MBS. *Firm Controls* and *Bank Controls* refer to the same control variables in Table 5, see Table 1 for definitions of these control variables. Loans to real estate and financial firms are excluded (primary SIC code in 1520–1600 or 6000–7000). All specifications include 2-digit SIC code dummies. Standard errors are reported in parentheses and are clustered by firm and bank. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8
Robustness Checks

Panel A: Post-Event Window (Extensive Margin)				
	Exit			
	All	Term Loans	Credit Lines	All
Exposure	0.493**	0.017	0.591**	-0.390
	(0.25)	(0.61)	(0.27)	(0.45)
Credit Line				-0.215***
				(0.05)
Credit Line × Exposure				0.822*
				(0.46)
Firm Controls	No	No	No	Yes
Bank Controls	Yes	Yes	Yes	Yes
Syndicate FE	Yes	Yes	Yes	No
N	3,283	627	2,656	2,453
R^2	0.43	0.45	0.42	0.39

Panel B: Post-Event Window (Intensive Margin)		
	All-In Drawn Spread	
	Credit Lines	Term Loans
Post	13.540***	57.791***
	(3.40)	(19.42)
Exposure	8.617	-110.213
	(12.46)	(67.56)
Post × Exposure	110.258***	28.089
	(33.69)	(177.26)
Firm Controls	Yes	Yes
Bank Controls	Yes	Yes
Firm-Bank FE	Yes	Yes
N	20,899	7,002
R^2	0.88	0.87

Panel C: Working Capital Credit Lines Only			
	Spread	Amount	Maturity
Post	25.527***	-0.351**	-8.798***
	(8.25)	(0.18)	(2.11)
Exposure	54.097	-0.657	-1.195
	(46.76)	(0.78)	(11.34)
Post × Exposure	345.515***	0.695	-55.892***
	(93.85)	(1.50)	(21.06)
Firm Controls	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes
Firm-Bank FE	Yes	Yes	Yes
N	6,238	6,238	6,238
R^2	0.91	0.89	0.75

Panel D: Crisis Intensity		
	All-In Drawn Spread	Placebo
TED Spread	32.23***	-34.863***
	(4.65)	(3.60)
Exposure	-13.86	-41.733**
	(16.72)	(18.10)
TED Spread × Exposure	131.07**	-8.256
	(56.30)	(25.15)
Firm Controls	Yes	Yes
Bank Controls	Yes	Yes
Firm-Bank FE	Yes	Yes
N	20,899	20,899
R^2	0.82	0.83

This table reports coefficient estimates from robustness checks described in Section IV. Panels A and B restrict the post-event window to end on August 9th 2008. Panel C restricts the sample to working capital revolving lines of credit, as defined by the "Primary Purpose" in DealScan. Panel D uses the TED Spread as a measure of the intensity of the crisis period. *All-In Drawn Spread* is the spread over base rate (LIBOR) in basis points; *TED Spread* is the quarterly average of daily differences between the 3-month LIBOR and 3-month U.S. T-Bill rate; *Exposure* is the fraction of bank assets in ABS or MBS. *Firm Controls* and *Bank Controls* refer to the same control variables in Table 5, defined in Table 1. Loans to real estate and financial firms are excluded (primary SIC code in 1520–1600 or 6000–7000). All specifications include 2-digit SIC code dummies. Standard errors (in parentheses) heteroscedasticity-robust and clustered by firm and bank. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

A Additional Tables and Figures

Table A.1
Variable Names and Construction

Variable	Source	Definition
Credit Line		
All-In Drawn Spread	DealScan	Currfacpricing/AllInDrawn
Amount	DealScan	Facility/FacilityAmt
Maturity	DealScan	Facility/Maturity
Secured	DealScan	Facility/Secured
Borrower		
Age	Compustat	Number of active years in Compustat
Sales	Compustat	saleq
Leverage	Compustat	(dlttq+dlcq)/atq
Market to Book	Compustat	(atq-ceqq+cshoq*prccq)/atq
Interest Coverage	Compustat	oibdpq/xintq
Net Working Capital	Compustat	(atq-lctq)/(dlttq+dlcq)
Tangibles	Compustat	(ppentq+invtq)/atq
Investment Grade	DealScan	Marketsegement/MarketSegment
Bank		
Assets	Call Reports	RCFD2170
	BankScope	DATA2025
Return on Assets	Call Reports	RIAD4340/RCFD2170
	BankScope	DATA2115/DATA2025
Deposits	Call Reports	RCFD2200/RCFD2170
	BankScope	DATA2030/DATA2025
Subordinated Debt	Call Reports	RCFD3200/RCFD2170
	BankScope	DATA2165/DATA2025
Equity	Call Reports	RCFD3210/RCFD2170
	BankScope	DATA2055/DATA2025
Core Deposits	Call Reports	(RCON2702+RCON2215)/RCFD2170
Loan Losses	Call Reports	(RIAD4635-RIAD4605)/RCFD2170
Exposure	Call Reports	(RCFD1754-RCFD1737-RCFD1742 -RCFD0211-RCFD1289-RCFD1294 -RCFD8496)+(RCFD1773-RCFD1737 -RCFDA511-RCFD1746-RCFD1741 -RCFD1287-RCFD1293-RCFD1298) /RCFD2170
Conduit Exposure	Moody's, DTCC, BankScope	Total ABCP outstanding divided by equity

This table defines the variables used throughout the paper.

Table A.2
Sample Selection

Panel A: Repeated Borrowers and Pre-Event Sample Characteristics				
	Non-Repeat	Repeat	Difference	[t-statistic]
Credit Line				
All-In Drawn Spread	125.278	108.425	-16.853***	[-16.47]
Facility Size	6.111	8.338	2.223***	[18.74]
Maturity	41.746	44.332	2.586***	[12.27]
Secured	0.316	0.285	-0.031***	[-6.69]
Syndicate Size	13.370	14.514	1.143***	[13.32]
Borrower				
Age	26.609	29.023	2.415***	[12.21]
Sales	1879.450	3350.150	1470.700***	[24.03]
Leverage	0.305	0.307	0.002	[0.93]
Market to Book	1.753	1.646	-0.107***	[-10.78]
Interest Coverage	25.964	25.670	-0.294	[-0.12]
Net Working Capital	3.897	3.660	-0.237	[-0.62]
Tangibles	0.477	0.510	0.034***	[13.23]
Investment Grade	0.464	0.526	0.063***	[12.64]
Observations				
Loans	6,288	4,949		
Firms	1,800	1,006		
Banks	95	165		
Loan-Firm-Bank Triples	26,208	20,899		

Panel B: Bank Exposure and Pre-Event Sample Characteristics	Low	High	Difference	[t-statistic]
Credit Line				
All-In Drawn Spread	123.605	122.870	0.735	[0.47]
Facility Size	7.806	6.230	1.596***	[8.60]
Maturity	43.659	43.921	-0.263	[-0.76]
Secured	0.491	0.481	0.009	[0.87]
Borrower				
Age	28.470	28.346	0.124	[0.38]
Sales	2745.881	2192.902	553.279***	[5.76]
Leverage	0.306	0.292	0.013***	[4.13]
Market to Book	1.715	1.743	-0.029*	[-1.71]
Interest Coverage	29.272	29.730	-0.457	[-0.10]
Net Working Capital	3.841	3.822	0.019	[0.41]
Tangibles	0.477	0.484	-0.006	[-1.51]
Investment Grade	0.467	0.547	-0.078***	[9.70]
Bank				
Assets	698.774	1021.60	-322.826	[-0.46]
Return on Assets	0.007	0.009	-0.002	[-1.23]
Deposits	0.654	0.705	-0.051	[-1.21]
Core Deposits	0.255	0.310	-0.056	[-0.93]
Subordinated Debt	0.023	0.010	0.0123	[1.68]
Equity	0.117	0.115	0.002	[0.07]
Loan Losses	0.002	0.001	0.001	[0.27]
Observations				
Loans	4,141	3,090		
Firms	1,182	944		
Banks	53	53		
Loan-Firm-Bank Triples	6,250	8,950		

Variables appearing in this table are defined in Table 1. For Panel A, I split the sample according to whether the borrower shows up only once ("Non-Repeat") or multiple times ("Repeat") between 2003Q1 and 2009Q4. For Panel B, banks with low exposure have *Exposure* in the first/bottom tercile of the *Exposure* distribution during the post-event window. Banks with high exposure have *Exposure* in the third/top tercile of the *Exposure* distribution. Values in the *Low* and *High* columns are simple averages across observations in the pre-event window. For borrower characteristics, an observation is a loan-firm-bank triple at time of origination; for lender characteristics, an observation is the time-series average of quarterly observations of bank characteristics. The difference-in-means test is simple (equal/pooled variance). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.