Aggregate Risk and the Choice between Cash and Lines of Credit

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Abstract

We model corporate liquidity policy and show that aggregate risk exposure is a key determinant of how firms choose between cash and bank credit lines. Banks create liquidity for firms by pooling their idiosyncratic risks. As a result, firms with high aggregate risk find it costly to get credit lines and opt for cash in spite of higher opportunity costs and liquidity premium. Likewise, in times when aggregate risk is high, firms rely more on cash than on credit lines. We verify these predictions empirically. Cross-sectional analyses show that firms with high exposure to systematic risk have a higher ratio of cash to credit lines and face higher costs on their lines. Time-series analyses show that firms' cash reserves rise in times of high aggregate volatility and in such times credit lines initiations fall, their spreads widen, and maturities shorten. Also consistent with the mechanism in the model, we find that exposure to undrawn credit lines increases bank-specific risks in times of high aggregate volatility.

Key words: Bank lines of credit, cash holdings, liquidity management, systematic risk, loan spreads, loan maturity, asset beta.

JEL classification: G21, G31, G32, E22, E5.

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Abstract

We model corporate liquidity policy and show that aggregate risk exposure is a key determinant of how firms choose between cash and bank credit lines. Banks create liquidity for firms by pooling their idiosyncratic risks. As a result, firms with high aggregate risk find it costly to get credit lines and opt for cash in spite of higher opportunity costs and liquidity premium. Likewise, in times when aggregate risk is high, firms rely more on cash than on credit lines. We verify these predictions empirically. Cross-sectional analyses show that firms with high exposure to systematic risk have a higher ratio of cash to credit lines and face higher costs on their lines. Time-series analyses show that firms' cash reserves rise in times of high aggregate volatility and in such times credit lines initiations fall, their spreads widen, and maturities shorten. Also consistent with the mechanism in the model, we find that exposure to undrawn credit lines increases bank-specific risks in times of high aggregate volatility.

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"A Federal Reserve survey earlier this year found that about one-third of U.S. banks have tightened their standards on loans they make to businesses of all sizes. And about 45% of banks told the Fed that they are charging more for credit lines to large and midsize companies. Banks such as Citigroup Inc., which has been battered by billions of dollars in write-downs and other losses, are especially likely to play hardball, resisting pleas for more credit or pushing borrowers to pay more for loan modifications."

— *The Wall Street Journal, March 8, 2008*

How do firms manage their liquidity needs? This question has become increasingly important for both academic research and corporate finance in practice. Survey evidence indicates that liquidity management tools such as cash and credit lines are essential components of a firm's financial policy (see Lins, Servaes, and Tufano (2010) and Campello, Giambona, Graham, and Harvey (2010)). Consistent with the evidence from surveys, a number of studies show that the funding of investment opportunities is a key determinant of corporate cash policy (e.g., Opler, Pinkowitz, Stulz, and Williamson (1999), Almeida, Campello, and Weisbach (2004, 2009), and Duchin (2009)). Recent work also shows that bank lines of credit have become an important source of firm financing (Sufi (2009), Disatnik, Duchin, and Schmidt (2010)). The evidence further suggests that credit lines played a crucial role in the liquidity management of firms during the recent credit crisis (Ivashina and Scharfstein (2010)).

In contrast to the growing empirical literature, there is limited theoretical work on the reasons why firms may use "pre-committed" sources of funds (such as cash or credit lines) to manage their liquidity needs. In principle, a firm can use other sources of funding for long-term liquidity management, such as future operating cash flows or proceeds from debt issuances. However, these alternatives expose the firm to additional risks because their availability depends on firm performance. Holmstrom and Tirole (1997, 1998), for example, show that relying on future issuance of external claims is insufficient to provide liquidity for firms that face costly external financing. Similarly, Acharya, Almeida, and Campello (2007) show that cash holdings dominate spare debt capacity for financially constrained firms that have their financing needs concentrated in states of the world where cash flows are low. Notably, these models of liquidity insurance are silent on the trade-offs between cash and credit lines.[1]

This paper attempts to fill this gap in the liquidity management literature. Building on Holmstrom and Tirole (1998) and Tirole (2006), we develop a model of the trade-offs firms face when choosing between holding cash and securing a credit line. The key insight of our argument is that a firm's exposure to aggregate risks — its "beta" — is a fundamental determinant of liquidity choices. The intuition is straightforward. In the presence of a liquidity premium (e.g., a low return on cash holdings), firms find it costly to hold cash. Firms may instead manage their liquidity needs using bank credit lines, which do not require them to hold liquid assets. Under a credit line agreement, the bank provides the firm with funds when the firm faces a liquidity shortfall. In exchange, the bank collects payments from the firm in states of the world in which the firm does not need the funds under the line (e.g., commitment fees). The credit line can thus be seen as an insurance contract. Provided that the bank can offer this insurance at "actuarially fair" terms, lines of credit will dominate cash holdings in corporate liquidity management.

The drawback of credit lines, however, is that banks may not be able to provide liquidity insurance for all firms in the economy at all times. Consider, for example, a situation in which a large fraction of the corporate sector is hit by a liquidity shock. In this state of the world, banks might become unable to guarantee liquidity since the demand for funds under the outstanding lines (drawdowns) may exceed the supply of funds coming from healthy firms. In other words, the ability of the banking sector to meet corporate liquidity needs depends on the extent to which firms are subject to correlated (systematic) liquidity shocks. Aggregate risk thus creates a cost to credit lines.

We explore this trade-off between aggregate risk and liquidity premia to derive optimal corporate liquidity policy. We do this in an equilibrium model in which firms are heterogeneous with respect to their exposure to aggregate risks (firms have different betas). We show that while low beta firms manage their liquidity through bank credit lines, high beta firms optimally choose to hold cash, despite the liquidity premium. Because the banking sector manages primarily idiosyncratic risk, it

[1] A recent paper by Bolton, Chen, and Wang (2011) introduces both cash and credit lines in a dynamic investment framework with costly external finance. In their model, the size of the credit line facility is given exogenously, thus they do not analyze the ex-ante trade-off between cash and credit lines (see also DeMarzo and Fishman (2007)).

can provide liquidity for low beta firms even in bad states of the world. In equilibrium, low beta firms therefore face better contractual terms when initiating credit lines, demand more lines, and hold less cash in equilibrium. On the flip side, high beta firms face worse contractual terms, demand less lines, and hold more cash. This logic suggests that firms' exposure to systematic risks increases the demand for cash and reduces the demand for credit lines. In a similar fashion, when there is an increase in aggregate risk there is greater aggregate reliance on cash relative to credit lines.

In addition to this basic result, the model generates a number of insights on liquidity management. These, in turn, motivate our empirical analysis. First, the model suggests that exposure to risks that are systematic to the banking industry should affect corporate liquidity policy. In particular, firms that are more sensitive to banking industry downturns should be more likely to hold cash for liquidity management. Second, the trade-off between cash and credit lines should be more important for firms that find it more costly to raise external capital. Third, the effect of aggregate risk exposure on liquidity policy should be stronger for firms that have high aggregate risk, as these firms have the strongest impact on bank liquidity constraints. Fourth, lines of credit should be more expensive for firms with greater aggregate risk and in times of higher aggregate volatility.

We test these cross-sectional and time-series implications using data from the 1987–2008 period.[2] For the cross-sectional analysis, we use two alternative data sources to construct proxies for the availability of credit lines. Our first sample is drawn from the LPC-DealScan database. These data allow us to construct a large sample of credit line initiations. The LPC-DealScan data, however, have two limitations. First, they are largely based on syndicated loans, thus biased towards large deals (consequently large firms). Second, they do not reveal the extent to which existing lines have been used (drawdowns). To overcome these issues, we also use an alternative sample that contains detailed information on the credit lines initiated and used by a random sample of 300 firms between 1996 and 2003. These data are drawn from Sufi (2009). Using both LPC-DealScan and Sufi's data sets, we measure the fraction of corporate liquidity that is provided by lines of credit as the ratio of total credit lines to the sum of total credit lines plus cash. For short, we call this variable *LC-to-Cash* ratio. While some firms may have higher demand for total liquidity due to variables such as better investment opportunities, the *LC-to-Cash* ratio isolates the *relative* usage of lines of credit versus cash in corporate liquidity management.

Our main hypothesis is that a firm's exposure to aggregate risk should be negatively related to its *LC-to-Cash* ratio. In the model, the relevant aggregate risk is the correlation of a firm's financing needs with those of other firms in the economy. While this could suggest using a "cash flow beta," note that cash flow-based measures are slow-moving and available only at low frequency. Under the

[2] To be precise, we use a panel dataset to test the model's cross-sectional implications. However most of the variation in our proxies for firm-level systematic risk exposure is cross-sectional in nature.

assumption that a firm's financing needs go up when its stock return falls, the relevant beta is the traditional beta of the firm with respect to the overall stock market. Accordingly, we employ a standard stock market-based beta as our baseline measure of risk exposure. For robustness, however, we also use cash flow-based betas.[3] To test the prediction that a firm's exposure to banking sector's risk should influence the firm's liquidity policy, we measure "bank beta" as the beta of a firm's returns with respect to the banking sector aggregate return.

Our market-based measures of beta are asset (i.e., unlevered) betas. While equity betas are easy to compute using stock price data, they are mechanically related to leverage (high leverage firms will tend to have larger betas). Since greater reliance on credit lines will typically increase the firm's leverage, the "mechanical" leverage effect may bias our estimates. To overcome this problem, we unlever equity betas by using a Merton-KMV-type model for firm value, or alternatively we compute betas using data on firm asset returns (from Choi (2009)). We also tease out the relative importance of systematic and idiosyncratic risk for corporate liquidity policy, by decomposing total asset risk on its systematic and idiosyncratic components.

We test the theory's cross-sectional implications by relating systematic risk exposure to *LC-to-Cash* ratios. In a nutshell, all of our tests lead to a similar conclusion: exposure to systematic risk has a statistically and economically significant impact on the fraction of corporate liquidity that is provided by credit lines. Using the LPC-DealScan sample, for example, we find that an increase in beta from 0.8 to 1.5 (this is less than a one-standard deviation change in beta) decreases a firm's reliance on credit lines by 0.06 (approximately 15% of the standard deviation and 20% of the sample average value of *LC-to-Cash*). We also find that the systematic component of asset variance has a negative and significant effect on the *LC-to-Cash* ratio. These findings support our theory's predictions. Notably, the inferences we draw hold across both the larger LPC-DealScan dataset and the smaller, more detailed data constructed by Sufi (both for total and unused credit lines).

The negative relation between systematic risk exposure and *LC-to-Cash* holds for all different proxies of betas that we employ, including Choi's (2009) asset-return based betas, betas that are unlevered using net rather than gross debt (to account for a possible effect of cash on asset betas), equity (levered) betas, and cash flow-based betas. The results also hold for "bank betas" (suggesting that firms that are more sensitive to banking industry downturns are more likely to hold cash for liquidity management) and "tail betas" (suggesting that a firm's sensitivity to market downturns affects corporate liquidity policy). These estimates agree with our theory and imply a strong economic relation between exposure to aggregate risk and liquidity management.

In additional tests, we sort firms according to observable proxies of financing constraints to study

[3] In addition, we employ a "tail beta" that uses data from the days with the worst returns in the year to compute beta (cf. Acharya, Pedersen, Philippon, and Richardson (2010)). This beta proxy captures the idea that a firm's exposure to systematic risks matters mostly on the downside (because a firm may need liquidity when other firms face problems).

whether the effect of beta on *LC-to-Cash* is driven by firms that are likely to be constrained. As predicted by our model, the relation between beta and the use of credit lines only holds in samples of likely constrained firms (e.g., across small and low payout firms). When we sort firms in "high beta" and "low beta" groups, we find that the effect of beta on the *LC-to-Cash* ratio is significantly stronger in the sample of high beta firms (consistent with our story). Finally, we study the relation between firms' beta and the fees and spreads that they commit to pay on bank lines of credit. We find that high beta firms pay significantly higher fees on their undrawn balances, and also higher spreads when drawing on their credit lines. This is direct evidence that it is more costly for banks to provide liquidity insurance for aggregate risky firms.

Next, we examine our model's time-series implications. These tests gauge aggregate risk using *VIX*, the implied volatility of the stock market index returns from options data. *VIX* captures both aggregate volatility as well as the financial sector's appetite to bear that risk. In addition, we examine whether expected volatility in the banking sector drives time-series variation in corporate liquidity policy. Given limited historical data on implied volatility for the banking sector, we construct *Bank VIX*, the expected banking sector volatility, using a GARCH model.

Controlling for real GDP growth and flight-to-quality effects (see Gatev and Strahan (2005)), we find that an increase in *VIX* and/or *Bank VIX* reduces credit line initiations and raises firms' cash reserves (Figure 4 provides a visual illustration). The maturity of credit lines shrinks as aggregate volatility rises, and new credit lines become more expensive in those times (see Figure 5). We confirm that these effects are not due to an overall increase in the cost of debt by showing that firms' debt issuances are not affected by *VIX*. In other words, the negative impact of *VIX* on new debt operates through availability of lines of credit. These results point out that an increase in aggregate risk in the economy is an important limitation of bank-provided liquidity insurance to firms.

Finally, we provide evidence for the mechanism that drives corporate liquidity choices in our model. The model suggests that an increase in aggregate risk in the economy creates liquidity risk for banks that are exposed to undrawn corporate credit lines. Thus, banks increase the cost of credit lines for aggregate risky firms, which in turn move towards cash holdings. Nevertheless, a possible alternative interpretation for the results is related to the risk of covenant violations (as in Sufi (2009)). For example, if firms are more likely to violate covenants in times when aggregate risk is high, then "high beta" firms may move to cash holdings not because of banks' liquidity constraint as in our model, but because of the risk of covenant violations.

In order to disentangle these two stories, we devise a direct test of the prediction that aggregate risk exposure tightens banks' liquidity constraints through a credit line channel. The link between credit line exposure and bank risk has been studied by Gatev, Schuermann, and Strahan (2009). They find that bank risk, as measured by stock return volatility, increases with unused credit lines that the bank has agreed to extend to the corporate sector. The mechanism in our model would then suggest that the impact of credit line exposure on bank risk should increase during periods of high aggregate risk. We test and confirm this prediction using bank-level data (taken from "call reports"). In addition, we examine the hypothesis that covenant violations (or credit line revocations conditional on violations) increase during periods of high aggregate volatility (or for firms with high aggregate risk exposure). Our results suggest that aggregate risk does not increase the sensitivity of covenant violations to profitability shocks. In addition, the effect of covenant violations on credit line revocations is largely independent of firms' aggregate risk exposures.[4] These results provide additional evidence that the link between liquidity management and aggregate risk uncovered in our tests indeed due to the effect of aggregate risk on banks' liquidity constraints.

Our work has connections with recent literature that discusses firms' liquidity choices and it is important that we highlight our contributions. Relative to Sufi (2009), our contribution is to show that the (largely idiosyncratic) risk of covenant violations is not the only type of risk that affects firms' choice between cash and credit lines. Firms' exposure to aggregate risk, and the ensuing effects on banks' liquidity constraints are also key forces that drive corporate liquidity policy. Relative to the growing new literature on firms' choices between credit lines and cash (e.g., Lins, Servaes, and Tufano (2010), Campello, Giambona, Graham, and Harvey (2010), and Disatnik, Duchin, and Schmidt (2010)), we are the first to advance and test a full-fledged theory explaining how corporate exposure to aggregate risk drives their liquidity management. We also provide a novel assessment of the importance of financial intermediary risk to the choice between cash and lines. In fact, papers in the cash–credit line choice generally abstract from connections between the macroeconomy, banks, and firms when examining liquidity management.[5] We believe our paper represents a step forward in establishing a theoretical framework describing these connections and in showing how they operate. Understanding and characterizing these links should be of interest for future research, especially around important episodes such as financial crises.

The paper is organized as follows. In the next section, we develop our model and derive its empirical implications. We present the empirical tests in Section II.. Section III. offers concluding remarks.

I. Model

Our model is based on Holmstrom and Tirole (1998) and Tirole (2006), who consider the role of aggregate risk in affecting corporate liquidity policy. We introduce firm heterogeneity in their

[4]Since a credit line is a loan commitment, it may not be easy for the bank to revoke access to the line once it is initiated. In order for the bank to revoke access, the firm must be in violation of a covenant. Given that covenant violations are unrelated to systematic risk after controlling for firm profitability (as the evidence in this paper suggests), banks do not revoke access simply because aggregate risk is high.

[5]Exceptions are papers written on the 2008-9 crisis, such as Campello, Giambona, Graham, and Harvey (2010) and Ivashina and Scharfstein (2010).

framework to analyze the trade-offs between cash and credit lines.

The economy has a unit mass of firms. Each firm has access to an investment project that requires fixed investment I at date 0. The investment opportunity also requires an additional investment at date 1, of uncertain size. This additional investment represents the firms' liquidity need at date 1. We assume that the date-1 investment need can be either equal to ρ, with probability λ, or 0, with probability $(1-\lambda)$. There is no discounting and everyone is risk-neutral, so that the discount factor is one.

Firms are symmetric in all aspects, with one important exception. They differ in the extent to which their liquidity shocks are correlated with each other. A fraction θ of the firms has perfectly correlated liquidity shocks; that is, they all either have a date-1 investment need, or not. We call these firms *systematic firms*. The other fraction of firms $(1-\theta)$ has independent investment needs; that is, the probability that a firm needs ρ is independent of whether other firms need ρ or 0. These are the *non-systematic firms*. We can think of this set up as one in which an aggregate state realizes first. The realized state then determines whether or not systematic firms have liquidity shocks.

We refer to states as follows. We let the aggregate state in which systematic firms have a liquidity shock be denoted by λ^{θ}. Similarly, $(1-\lambda^{\theta})$ is the state in which systematic firms have no liquidity demand. After the realization of this aggregate state, non-systematic firms learn whether they have liquidity shocks. The state in which non-systematic firms do get a shock is denoted as λ and the other state as $(1-\lambda)$. Note that the likelihood of both λ and λ^{θ} states is λ. In other words, to avoid additional notation, we denote states by their probability, but single out the state in which systematic firms are all hit by a liquidity shock with the superscript θ. The set up is summarized in Figure 1.

– Figure 1 about here –

A firm will only continue its date-0 investment until date 2 if it can meet the date-1 liquidity need. If the liquidity need is not met, then the firm is liquidated and the project produces a cash flow equal to zero. If the firm continues, the investment produces a date-2 cash flow R which obtains with probability p. With probability $1-p$, the investment produces nothing. The probability of success depends on the input of specific human capital by the firms' managers. If the managers exert high effort, the probability of success is equal to p_G. Otherwise, the probability is p_B, but the managers consume a private benefit equal to B. While the cash flow R is verifiable, the managerial effort and the private benefit are not verifiable and contractible. Because of the moral hazard due this private benefit, managers must keep a high enough stake in the project to be induced to exert effort. We assume that the investment is negative NPV if the managers do not exert effort, implying the following incentive constraint: $p_G R_M \geq p_B R_M + B$, or $R_M \geq \frac{B}{\Delta p}$, where R_M is the managers' compensation and $\Delta p = p_G - p_B$. This moral hazard problem implies that the firms' cash flows cannot be pledged in their entirety to outside investors. Following Holmstrom and Tirole, we define:

$$\rho_0 \equiv p_G(R - \frac{B}{\Delta p}) < \rho_1 \equiv p_G R. \tag{1}$$

The parameter ρ_0 represents the investment's pledgeable income, and ρ_1 its total expected payoff.

In addition, we assume that the project can be partially liquidated at date 1. Specifically, a firm can choose to continue only a fraction $x < 1$ of its investment project, in which case (in its liquidity shock state, λ or λ^θ) it requires a date-1 investment of $x\rho$. It then produces total expected cash flow equal to $x\rho_1$, and pledgeable income equal to $x\rho_0$. In other words, the project can be linearly scaled down at date 1. We make the following assumption:

$$\rho_0 < \rho < \rho_1. \tag{2}$$

The assumption that $\rho < \rho_1$ implies that the efficient level of x is $x^{FB} = 1$. However, the firm's pledgeable income is lower than the liquidity shock. This might force the firm to liquidate some of its projects and thus have $x^* < 1$ in equilibrium. For each x, they can raise $x\rho_0$ in the market at date-1. As in Holmstrom and Tirole, we assume that the firm can fully dilute the date-0 investors at date-1, i.e., the firm can issue securities that are senior to the date-0 claim to finance a part of the required investment $x\rho$ (alternatively, we can assume efficient renegotiation of the date-0 claim).

Finally, we assume that even when $x = 1$, each project produces enough pledgeable income to finance the initial investment I, and the date-1 investment ρ:

$$I < (1 - \lambda)\rho_0 + \lambda(\rho_0 - \rho). \tag{3}$$

In particular, notice that this implies that $(1 - \lambda)\rho_0 > \lambda(\rho - \rho_0)$.

A. The role of liquidity management

Before we characterize the optimal solution using credit lines and cash, it is worth exploring the common feature to both of them, which is their role as pre-committed financing. This discussion also clarifies why alternative strategies such as excess debt capacity are imperfect substitutes for pre-committed financing through cash or credit lines.

In order to see this, consider what happens to the firm when it carries no cash and no credit line, but saves maximum future debt capacity by borrowing as little as it can today (that is, exactly I). The firm plans to borrow on the spot debt market at date-1, once the liquidity shock materializes (in state λ). Given the assumptions above, this debt capacity strategy is bound to fail. Even under the assumption of full dilution of date-0 investors, the maximum amount that the firm can borrow in the spot market at date-1 for a given x is $x\rho_0$. But since $x\rho_0 < x\rho$ for all x, the firm does not have enough funds to pay for the liquidity shock, and must liquidate the project. In other words, in the absence of cash and/or a credit line, $x^* = 0$.

The problem with this "wait and see" strategy is that it does not generate enough debt capacity in future liquidity states, while at the same time wasting debt capacity in states of the world with no liquidity shock. Notice that in the no-liquidity-shock state (state $1 - \lambda$), the firm has debt capacity equal to ρ_0, but no required investments. In this context, the role of corporate liquidity policy (that is, cash and credit lines) is to transfer financing capacity from the good to the bad state of the world. The firm accomplishes this transfer using cash by borrowing more than I at date 0, and promising a larger payment to investors in the good future state of the world, state $1-\lambda$. The firm accomplishes this transfer using credit lines by paying a commitment fee to banks in future good states of the world, in exchange for the right to borrow in the bad state of the world. The difference between standard debt issuance and a credit line is that the latter is pre-committed, while the former must be contracted on the spot market (thus creating potential liquidity problems).

B. *Solution using credit lines*

We assume that the economy has a single, large intermediary who will manage liquidity for all firms ("the bank") by offering lines of credit. The credit line works as follows. The firm commits to making a payment to the bank in states of the world in which liquidity is not needed. We denote this payment ("commitment fee") by y. In return, the bank commits to lending to the firm at a pre-specified interest rate, up to a maximum limit. We denote the maximum size of the line by w. In addition, the bank lends enough money (I) to the firms at date 0 so that they can start their projects, in exchange for a promised date-2 debt payment D.

To fix ideas, let us imagine for now that firms have zero cash holdings. In the next section we will allow firms to both hold cash, and also open bank credit lines.

In order for the credit line to allow firms to invest up to amount x in state λ, it must be that:

$$w(x) \geq x(\rho - \rho_0). \tag{4}$$

In return, in state $(1 - \lambda)$, the financial intermediary can receive up to the firm's pledgeable income, either through the date-1 commitment fee y, or through the date-2 payment D. We thus have the budget constraint:

$$y + p_G D \leq \rho_0. \tag{5}$$

The intermediary's break even constraint is:

$$I + \lambda x(\rho - \rho_0) \leq (1 - \lambda)\rho_0. \tag{6}$$

Finally, the firm's payoff is:

$$U(x) = (1-\lambda)\rho_1 + \lambda(\rho_1 - \rho)x - I. \tag{7}$$

Given assumption (3), equation (6) will be satisfied by $x = 1$, and thus the credit line allows firms to achieve the first-best investment policy.

The potential problem with the credit line is adequacy of *bank* liquidity. To provide liquidity for the entire corporate sector, the intermediary must have enough available funds in all states of the world. Since a fraction θ of firms will always demand liquidity in the same state, it is possible that the intermediary will run out of funds in the bad aggregate state. In order to see this, notice that in order obtain $x = 1$ in state λ^{θ}, the following inequality must be obeyed:

$$(1-\theta)(1-\lambda)\rho_0 \geq [\theta + (1-\theta)\lambda](\rho - \rho_0). \tag{8}$$

The left-hand side represents the total pledgeable income that the intermediary has in that state, coming from the non-systematic firms that do not have liquidity needs. The right-hand side represents the economy's total liquidity needs, from the systematic firms and from the fraction of non-systematic firms that have liquidity needs. Clearly, from (3) there will be a $\theta^{\max} > 0$, such that this condition is met for all $\theta < \theta^{\max}$. This leads to an intuitive result:

PROPOSITION 1 *The intermediary solution with lines of credit achieves the first-best investment policy if and only if systematic risk is sufficiently low ($\theta < \theta^{\max}$), where $\theta^{\max} = \frac{\rho_0 - \lambda\rho}{(1-\lambda)\rho}$.*

C. The choice between cash and credit lines

We now allow firms to hold both cash and open credit lines, and analyze the properties of the equilibria that obtain for different parameter values. Analyzing this trade-off constitutes the most important and novel theoretical contribution of our paper.

Firms' optimization problem. To characterize the equilibria, we introduce some notation. We let L^{θ} (alternatively, $L^{1-\theta}$) represent the cash demand by systematic (non-systematic) firms. Similarly, x^{θ} ($x^{1-\theta}$) represents the investment level that systematic (non-systematic) firms can achieve in equilibrium. In addition, the credit line contracts that are offered by the bank can also differ across firm types. That is, we assume that a firm's type is observable by the bank at the time of contracting. Thus, $(D^{\theta}, w^{\theta}, y^{\theta})$ represents the contract offered to systematic firms, and $(D^{1-\theta}, w^{1-\theta}, y^{1-\theta})$ represents the contract offered to non-systematic firms. For now, we assume that the bank cannot itself carry cash and explain later why this is in fact the equilibrium outcome in the model.

As in Holmstrom and Tirole (1998), we assume that there is a supply L^s of a liquid and safe asset (such as treasury bonds) that the firm can buy at date-0 and hold until date-1 to implement a given cash policy L. This asset trades at a price equal to q at date 0. In the absence of a liquidity premium, this safe asset should have a price equal to $q = 1$. The price q will be determined in equilibrium in our model, and in some cases may be greater than one. If so, then holding cash is costly for the firm.

Firms will optimize their payoff subject to the constraint that they must be able to finance the initial investment I, and the continuation investment x. In addition, the bank must break even. For each firm type $i = (\theta, 1-\theta)$, the relevant constraints can be written as:

$$\begin{aligned} w^i + L^i &= x^i(\rho - \rho_0) \\ I + qL^i + \lambda w^i &= (1-\lambda)(L^i + y^i + p_G D^i) \\ y^i + p_G D^i &\leq \rho_0. \end{aligned} \tag{9}$$

The first equation ensures that the firm can finance the continuation investment level x^i, given its liquidity policy (w^i, L^i). The second equation is the bank break-even constraint. The bank provides financing for the initial investment and the cash holdings qL^i, and in addition provides financing through the credit line in state λ (equal to w^i). In exchange, the bank receives the sum of the firm's cash holdings, the credit line commitment fee, and the date-2 debt payment D^i. The third inequality guarantees that the firm has enough pledgeable income to make the payment $y^i + p_G D^i$ in the state when it is not hit by the liquidity shock.

In addition to the break-even constraint, the bank must have enough liquidity to honor its credit line commitments, in both aggregate states. As explained above, this constraint can bind in state λ^θ, in which all systematic firms may demand liquidity. Each systematic firm demands liquidity equal to $x^\theta(\rho - \rho_0) - L^\theta$, and there is a mass θ of such firms. In addition, non-systematic firms that do not have an investment need demand liquidity equal to $x^{1-\theta}(\rho - \rho_0) - L^{1-\theta}$. There are $(1-\theta)\lambda$ such firms. To honor its credit lines, the bank can draw on the liquidity provided by the fraction of non-systematic firms that does not need liquidity, a mass equal to $(1-\theta)(1-\lambda)$. The bank receives a payment equal to $L^{1-\theta} + y^{1-\theta} + p_G D^{1-\theta}$ from each of them, a payment that cannot exceed $L^{1-\theta} + \rho_0$. Thus, the bank's liquidity constraint requires that:

$$\theta[x^\theta(\rho - \rho_0) - L^\theta] + (1-\theta)\lambda[x^{1-\theta}(\rho - \rho_0) - L^{1-\theta}] \leq (1-\theta)(1-\lambda)[L^{1-\theta} + \rho_0]. \tag{10}$$

As will become clear below, this inequality will impose a constraint on the maximum size of the credit line that is available to systematic firms. For now, we write this constraint as $w^\theta \leq w^{\max}$.

We collapse the constraints (9) into a single constraint, and write the firm's problem as:

$$\begin{aligned} \max_{x^i, L^i} U^i &= (1-\lambda)\rho_1 + \lambda(\rho_1 - \rho)x^i - (q-1)L^i - I \quad \text{s.t.} \\ I + (q-1)L^i + \lambda x^i \rho &\leq (1-\lambda)\rho_0 + \lambda x^i \rho_0 \ , \\ w^\theta &\leq w^{\max}. \end{aligned} \tag{11}$$

This problem determines firms' optimal cash holdings and continuation investment, which are a function of the liquidity premium, $L^i(q)$ and $x^i(q)$. In equilibrium, the total demand from cash coming from systematic and non-systematic firms cannot exceed the supply of liquid funds:

$$\theta L^{\theta}(q) + (1-\theta)L^{1-\theta}(q) \leq L^s. \tag{12}$$

This condition determines the cost of holding cash, q. We denote the equilibrium price by q^*.

Optimal firm policies. The first point to notice is that non-systematic firms will never find it optimal to hold cash. In the optimization problem (11), firms' payoffs decrease with cash holdings L^i if $q^* > 1$, and they are independent of L^i if $q^* = 1$. Thus, the only situation in which a firm might find it optimal to hold cash is when the constraint $x^{\theta}(\rho - \rho_0) - L^{\theta} \leq w^{\max}$ is binding. But this constraint can only bind for systematic firms. Notice also that if $L^i = 0$ the solution of the optimization problem (11) is $x^i = 1$ (the efficient investment policy). Thus, non-systematic firms always invest optimally, $x^{1-\theta} = 1$.

Given that non-systematic firms use credit lines to manage liquidity and invest optimally, we can rewrite constraint (10) as:

$$x^{\theta}(\rho - \rho_0) - L^{\theta} \leq \frac{(1-\theta)(\rho_0 - \lambda\rho)}{\theta} \equiv w^{\max}.$$

This expression gives the maximum size of the credit line for systematic firms, $w^{\max}$. The term $(1-\theta)(\rho_0 - \lambda\rho)$ represents the total amount of excess liquidity that is available from non-systematic firms in state λ^{θ}. By equation (3), this is positive. The bank can then allocate this excess liquidity to the fraction θ of firms that are systematic.

Lemma 1 states the optimal policy of systematic firms, which we prove in Appendix A.

LEMMA 1 *Investment policy of systematic firms, x^{θ}, depends upon the liquidity premium, q, as:*

1. *If $\rho - \rho_0 \leq w^{\max}$, then $x^{\theta}(q) = 1$ for all q.*

2. *If $\rho - \rho_0 > w^{\max}$, define two threshold values of q, q_1 and q_2 as follows:*

$$q_1 = 1 + \frac{\rho_0 - \lambda\rho - I}{\rho - \rho_0 - w^{\max}}, \text{ and } q_2 = 1 + \frac{\lambda(\rho_1 - \rho)}{\rho - \rho_0}. \tag{13}$$

Then, x^{θ} satisfies:

$$\begin{aligned} x^{\theta}(q) &= 1 \text{ if } q \leq \min(q_1, q_2) \\ &= \frac{(1-\lambda)\rho_0 - I + (q-1)w^{\max}}{(\lambda + q - 1)(\rho - \rho_0)} \text{ if } q_2 \geq q > q_1 \\ &\in [0,1] \text{ (indifference over entire range) if } q_1 > q = q_2 \\ &= 0 \text{ if } q > q_2. \end{aligned} \tag{14}$$

In words, systematic firms will invest efficiently if their total liquidity demand $(\rho - \rho_0)$ can be satisfied by credit lines (of maximum size $w^{\max}$), or if the cost of holding cash q is low enough. If the maximum available credit line is low, and the cost of carrying cash is high, then systematic firms will optimally reduce their optimal continuation investment ($x^\theta < 1$). If the cost of carrying cash is high enough, then systematic firms may need to fully liquidate their projects ($x^\theta = 0$).

Given the optimal investment in Lemma 1, the demand for cash is given by $L^\theta(q) = 0$ if $\rho - \rho_0 \leq w^{\max}$, and by the following condition

$$L^\theta(x^\theta) = x^\theta(\rho - \rho_0) - w^{\max}, \tag{15}$$

when $\rho - \rho_0 > w^{\max}$, for the optimal $x^\theta(q)$ in Lemma 1.

Equilibria. The particular equilibrium that obtains in the model will depend on the fraction of systematic firms in the economy (θ), and the supply of liquid funds (L^s).

First, notice that if $\rho - \rho_0 \leq w^{\max}$ (that is, if the fraction of systematic firms in the economy is small, ($\theta \leq \theta^{\max}$), then there is no cash demand and the equilibrium liquidity premium is zero ($q^* = 1$). Firms use credit lines to manage liquidity and they invest efficiently ($x^\theta = x^{1-\theta} = 1$).

On the flip side, if $\rho - \rho_0 > w^{\max}$ (that is, $\theta > \theta^{\max}$), then systematic firms will need to use cash in equilibrium. Equilibrium requires that the demand for cash does not exceed supply:

$$\theta L^\theta(q) = \theta[x^\theta(q)(\rho - \rho_0) - w^{\max}] \leq L^s. \tag{16}$$

Given this equilibrium condition, we can find the minimum level of liquidity supply L^s, such that systematic firms can sustain an efficient investment policy, $x^\theta(q) = 1$. This is given by:

$$\theta[(\rho - \rho_0) - w^{\max}] = L_1^s(\theta). \tag{17}$$

If $L^s \geq L_1^s(\theta)$, then systematic firms invest efficiently, $x^\theta = 1$, demand a credit line equal to $w^{\max}$, and have cash holdings equal to $L^\theta = (\rho - \rho_0) - w^{\max}$. The equilibrium liquidity premium is zero, $q^* = 1$. When L^s drops below $L_1^s(\theta)$, then the cash demand by systematic firms must fall to make it compatible with supply. This is accomplished by an increase in the liquidity premium that reduces cash demand. In equilibrium, we have $q^* > 1$, $x^\theta(q^*) < 1$, and equation (16) holding with equality (such that the demand for cash equals the reduced supply):[6]

$$\theta[x^\theta(q^*)(\rho - \rho_0) - w^{\max}] = L^s. \tag{18}$$

[6] There are two cases to consider here, depending on whether q_1 is higher or lower than q_2. Please see the online appendix for details.

D. *Summary of results*

We summarize the model's results in the following detailed proposition:

PROPOSITION 2 *When firms choose between cash holdings and bank-provided lines of credit, following equilibria arise depending on the extent of aggregate risk and the supply of liquid assets:*

1. *If the amount of systematic risk in the economy is low ($\theta \leq \theta^{\max}$), where $\theta^{\max}$ is as given in Proposition 1, then all firms use credit lines to manage their liquidity. They invest efficiently and credit line contracts are independent of firms' exposure to systematic risk.*

2. *If the amount of systematic risk in the economy is high ($\theta > \theta^{\max}$), then firms that have more exposure to systematic risk are more likely to hold cash (relative to credit lines) in their liquidity management. Given bank's liquidity constraint, credit line contracts discriminate between idiosyncratic and systematic risk. There are two sub-cases to consider according to the supply of liquid assets in the economy (see Figure 2 for the case when $q_1 < q_2$):*

   (a) *If the supply of liquid assets is higher than a minimum cutoff $L_1^s(\theta)$ defined by $L_1^s(\theta) = \theta[(\rho - \rho_0) - w^{\max}(\theta)]$ and $w^{\max}(\theta) = \frac{(1-\theta)(\rho_0 - \lambda\rho)}{\theta}$, then in equilibrium all firms invest efficiently (irrespective of their exposure to systematic risk), and there is no liquidity premium. Firms use both cash and credit lines to manage systematic risk, and they use credit lines to manage idiosyncratic risk.*

   (b) *If the supply of liquid assets is lower than $L_1^s(\theta)$, then systematic liquidity risk generates a liquidity premium; and, firms that have greater exposure to systematic risk hold more cash and less credit lines, and under-invest in the event of a liquidity shock.*

– Figure 2 about here –

Notice that the maximum credit line that is available to each systematic firm, $w^{\max}(\theta)$, is decreasing in θ. The aggregate demand for credit lines from systematic firms is given by $\theta w^{\max}(\theta) = (1-\theta)(\rho_0 - \lambda\rho)$, which is also decreasing in θ. It follows that the aggregate demand for credit lines decreases when the fraction of systematic firms in the economy goes up.

In all of these situations, there is no role for cash held inside the intermediary. In equilibrium, cash is held only to manage systematic risk. Thus, firms gain no diversification benefits by depositing the cash with the intermediary (they all need the cash in the same state of the world, and so the intermediary must carry the same amount of cash that the firms do). Firms would benefit from diversification when managing non-systematic risk, but for that they are always better off using the credit line (which does not involve a liquidity premium).

E. Empirical implications

The model generates the following implications, which we examine in the next section:

(1) *An increase in a firm's exposure to systematic risk increases its propensity to use cash reserves for corporate liquidity management, relative to bank-provided lines of credit.* We test this prediction by relating the fraction of total corporate liquidity that is held in the form of credit lines to proxies for a firm's systematic risk exposure (e.g., beta).

(2) *A firm's exposure to risks that are systematic to the banking industry is particularly important for the determination of its liquidity policy.* In the model, bank systematic risk has a one-to-one relation with firm systematic risk, given that there is only one source of risk in the economy (firms' liquidity shock). However, one might imagine that in reality banks face other sources of systematic risk (coming, for example, from consumers' liquidity demand) and that firms are differentially exposed to such risks. Accordingly, a "firm-bank asset beta" should also drive corporate liquidity policy. Firms that are more sensitive to banking industry downturns should be more likely to hold cash for liquidity management.

(3) *The trade-off between cash and credit lines is more important for firms that find it more costly to raise external capital.* In the absence of financing constraints, there is no role for corporate liquidity policy, thus the choice between cash and credit lines becomes irrelevant. We test this model implication by sorting firms according to observable proxies for financing constraints, and examining whether the effect of systematic risk exposure on the choice between cash and credit lines is driven by firms that are likely to be financially constrained.

(4) *The effect of systematic risk exposure on corporate liquidity policy should be greater among firms with high systematic risk.* In the model, the effect of systematic risk on corporate liquidity policy is non-linear (convex). If aggregate risk exposure is low (for example, if θ is low, then the bank's liquidity constraint does not bind, and thus variation in systematic risk exposure does not matter. After θ reaches the threshold level $\theta^{\max}$, further increases in aggregate risk exposure tighten the bank's liquidity constraint and thus forces firms to switch to cash holdings. We test this implication by examining whether the effect of aggregate risk exposure (beta) on liquidity policy is concentrated among firms with high systematic risk exposure (e.g., beta).[7]

(5) *Firms with higher systematic risk exposure should face worse contractual terms when raising bank credit lines.* In the model, if the amount of systematic risk in the economy is high, then the

[7] Strictly speaking, in the model the variable θ captures the amount of systematic risk in the economy as a whole. In addition, the model only allows for two types of firms (systematic and idiosyncratic). However, a similar implication would hold in a version of the model in which firms varied continuously with respect to their aggregate risk exposure. Low beta firms create little liquidity risk for the bank, and thus there would be a cutoff below which all firms would have access to cheap credit lines. Only high beta firms would be driven out of bank credit lines, and more so the greater the value of beta.

bank's liquidity constraint requires that credit line contracts discriminate between idiosyncratic and systematic risk. Systematic firms should face worse contractual terms since they are the ones that drive the bank's liquidity constraint. We test this implication by relating asset beta to credit line spreads and fees, after controlling for firm characteristics and other credit line contractual terms.

(6) *An increase in the amount of systematic risk in the economy increases firms' reliance on cash and reduces their reliance on credit lines for liquidity management.* The model shows that when economy-wide aggregate risk is low, firms can manage their liquidity using only credit lines because the banking sector can provide them at actuarially fair terms. When aggregate risk increases beyond a certain level, firms must shift away from credit lines and towards cash so that the banking sector's liquidity constraint is satisfied.[8] In addition, the greater is the amount of systematic risk in the economy, the lower is the amount of liquidity that is provided by bank credit lines. We test this implication by examining how aggregate cash holdings and credit line initiations change with *VIX*, the implied volatility of the stock market index returns from options data. In addition, and similarly to Implication 2 above, we also examine whether "*Bank VIX*", a measure we compute of the expected volatility in the banking sector, drives time-series variation in corporate liquidity policy.

(7) *An increase in the amount of systematic risk in the economy worsens firms' contractual terms when raising bank credit lines.* We test this implication by examining how credit line spreads and maturities change with changes in economy-wide risk (*VIX*) and banking sector (*Bank VIX*) aggregate risk.[9]

II. Empirical tests

A. Data

We use two alternative sources to construct our line of credit data. Our first sample (which we call *LPC Sample*) is drawn from LPC-DealScan. These data allow us to construct a large sample of credit line initiations. We note, however, that the LPC-DealScan data have two potential drawbacks. First, they are mostly based on syndicated loans, thus are potentially biased towards large deals and consequently towards large firms. Second, they do not allow us to measure line of credit drawdowns (the fraction of existing lines that has been used in the past). To overcome these issues, we also construct an alternative sample that contains detailed information on the credit lines initiated and used by a random sample of 300 COMPUSTAT firms. These data are provided by

[8] In section C.3., we provide evidence that exposure to undrawn corporate credit lines increases bank stock return volatility in times of high aggregate risk. This result is consistent with the mechanism suggested by the model, whereby credit line exposure poses risks to banks when corporate liquidity shocks become correlated.

[9] Our model has the additional empirical implication that the liquidity risk premium is higher when there is an economic downturn since in such times there is greater aggregate risk and lines of credit become more expensive. This is similar to the result of Eisfeldt and Rampini (2009), but in their model, the effect arises from the fact that firms' cash flows are lower in economic downturns and they are less naturally hedged against future liquidity needs.

Amir Sufi on his website and were used on Sufi (2009). We call this sample *Random Sample*. Using these data reduces the sample size for our tests. In particular, since this sample only contains seven years (1996-2003), in our time-series tests we use only *LPC sample*. We regard these two samples as providing complementary information on the usage of credit lines for the purposes of this paper. The data construction criteria are described in detail in Appendix B.

B. *Variable definitions*

Our main variables of interest are described below. All of our control variables in tests are as in Sufi (2009). Detailed description of the variables is in Appendices C, D and E.

Line of credit data. When using *Random Sample*, we measure the fraction of total corporate liquidity that is provided by credit lines for firm i in year t using the ratios of both total and unused credit lines to the sum of credit lines plus cash. As discussed by Sufi, while some firms may have higher demand for total liquidity due to better investment opportunities, these *LC-to-Cash* ratios should isolate the *relative* usage of lines of credit versus cash in corporate liquidity management.

When using *LPC Sample*, we construct a proxy for line of credit usage in the following way. For each firm-quarter, we measure credit line availability at date t by summing all existing credit lines that have not yet matured ($Total\ LC$). We convert these firm-quarter measures into firm-year measures by computing the average value of $Total\ LC$ in each year. We then measure the fraction of corporate liquidity that is provided by lines of credit by computing the ratio of $Total\ LC$ to the sum of $Total\ LC$ plus cash.

In addition, to examine the time-series impact of systematic risk on liquidity management we construct aggregate changes in credit lines and cash, scaled by assets ($LC\ Initiation_t$ and $Change\ in\ Cash_t$). These ratios capture the economy's total demand for cash and credit lines in a given year, scaled by total assets.

Data on betas and variances. We measure firms' exposure to systematic risk using asset (unlevered) betas.[10] While equity betas are easy to compute using stock price data, they are mechanically related to leverage: high leverage firms will tend to have larger betas. Because greater reliance on credit lines will typically increase the firm's leverage, the leverage effect would then bias our estimates of the effect of betas on corporate liquidity management. Nonetheless, we also present results using standard equity betas (*Beta Equity*).

We unlever equity betas in two alternative ways. First, we use a Merton-KMV type model to unlever Betas (*Beta KMV*), and total asset volatility (*Var KMV*). Second, we use Choi (2009) betas

[10] Similar to the COMPUSTAT data items, all measures of beta described below are winsorized at a 5% level.

and asset variance (denoted *Beta Asset* and *Var Asset*). Because of data availability, we use *Beta KMV* as our benchmark measure of beta, but we verify that the results are robust to the use of this alternative unlevering method.

One potential concern with theses beta measures is that they may be mechanically influenced by a firm's cash holdings. Since corporate cash holdings are typically held in the form of riskless securities, high cash firms could have lower asset betas. Thus, we also compute KMV-type asset betas that are unlevered using net debt (e.g., debt minus cash) rather than gross debt. We call this variable *Beta Cash*, which is computed at the level of the industry to mitigate endogeneity. We also compute a firm's "bank beta" (which we call *Beta Bank*) to test the model's implication that a firm's exposure to banking sector's risks should influence the firm's liquidity policy. In the model, a firm's exposure to systematic risks matters mostly on the downside (because a firm may need liquidity when other firms are likely to be in trouble). To capture a firm's exposure to large negative shocks, we follow Acharya, Pedersen, Philippon, and Richardson (2010) and compute the firm's *Beta Tail*.

All of the betas described above are computed using market prices. As discussed in the introduction, using market data is desirable because of their high frequency, and because they also reflect a firm's financing capacity that is tied to its long-run prospects. However, the model's argument is based on the correlation between a firm's liquidity needs, and the liquidity need for the overall economy (which affects the banking sector's ability to provide liquidity). While market-based betas should capture this correlation, it is desirable to verify whether a beta that is based more directly on cash flows and financing needs also contains information about firm's choices between cash and credit lines. In order to do this, we compute two alternative beta proxies (*Beta Gap* and *Beta Cash Flow*).

Decomposing total risk into idiosyncratic and systematic components. In addition to using asset and cash flow betas to measure systematic risk exposure, we alternatively use a measure of systematic risk which is computed by decomposing total asset risk on its systematic and idiosyncratic components. Using the Merton-KMV betas and variances, the systematic component for firm j at time t can be estimated as:

$$SysVar\ KMV_{j,t} = (Beta\ KMV_{j,t})^2 \times \overline{Var\ KMV_t}, \tag{19}$$

where $\overline{Var\ KMV_t}$ is the unlevered variance of the market. We compute $\overline{Var\ KMV_t}$ as the value-weighted average of firm-level asset variances, *Var KMV* $_{j,t}$. The systematic component is essentially the variance of asset returns that is explained by the market. Given this formula, the idiosyncratic component can be computed as total asset variance $Var\ KMV_{j,t}$ minus $SysVar\ KMV_{j,t}$.

Notice that since idiosyncratic variance is a function of total and systematic variance, we do not need to include it separately in the corporate liquidity regressions. Rather, we experiment with specifications in which we include both total and systematic variance (or beta) in the regressions explaining corporate liquidity.

Addressing measurement error. A common shortcoming of the measures of systematic risk we constructed is that they are noisy and subject to measurement error. This problem can be ameliorated by adopting a strategy dealing with classical errors-in-variables. We follow the standard Griliches and Hausman (1986) approach to measurement problem and instrument the endogenous variable (e.g., our beta proxies) with lags of itself. We experimented with alternative lag structures and chose a parsimonious form that satisfies the restriction conditions needed to validate the approach.[11] Throughout the analysis, we report auxiliary statistics that speak to the relevance (first-stage F-tests) and validity (Hansen's J-stats) of our instrumental variables regressions.

Time-series variables. We proxy for the extent of aggregate risk in the economy by using VIX (the implied volatility on S&P 500 index options). *VIX* captures both aggregate volatility, as well as the financial sector's appetite to bear that risk. We also add other macroeconomic variables to our tests, including the commercial paper–Treasury spread (Gatev and Strahan (2005)) to capture the possibility that funds may flow to the banking sector in times of high aggregate volatility, and real GDP growth to capture general economic conditions.

In addition, we proxy for the extent of aggregate risk in the banking sector by computing *Bank* VIX (the expected volatility on an index of bank stock returns). Since there are no available historical data on implied volatility for an aggregate bank equity index, we compute expected volatility using a GARCH (1,1) model and the Fama-French index of bank stock returns. The online appendix details the procedure that we use.

C. Empirical tests and results

Summary statistics. We start by summarizing our data in Table 1. Panel A reports summary statistics for the LPC-DealScan sample (for firm-years in which *Beta* KMV data are available), and Panel B uses Sufi's sample. Notice that the size of the sample in Panel A is much larger, and that the data for *Beta Asset* are available only for approximately one third of the firm-years for which *Beta* KMV data are available. As expected, the average values of asset betas are very close to each other, with average values close to one. The two alternative measures of variance also appear to be very close to each other. The spread and fee data are available at the deal-level, and thus the number of observations reflect the number of different credit line deals in our sample.

– Table 1 about here –

[11] An alternative way to address measurement error is to compute betas at a "portfolio," rather than at a firm-level. We explore this idea as well, using industry betas rather than firm-level betas in some specifications below.

Comparing Panel A and Panel B, notice that the distribution for most of the variables is very similar across the two samples. The main difference between the two samples is that the LPC-DealScan data is biased towards large firms (as discussed above). For example, median assets are equal to 270 million in *LPC Sample*, and 116 million in *Random Sample*. Consistent with this difference, the firms in *LPC Sample* are also older, and have higher average *Qs* and EBITDA volatility. The measure of line of credit availability in *LPC Sample* (*LC-to-Cash*) is lower than those in *Random Sample* (*Total LC-to-Cash* and *Unused LC-to-Cash*). For example, the average value of *LC-to-Cash* in *LPC Sample* is 0.33, while the average value of *Total LC-to-Cash* is 0.51. This difference reflects the fact that LPC-DealScan may fail to report some credit lines that are available in Sufi's data, though it could also reflect the different sample compositions.

In Table 2, we examine the correlation among the different betas that we use in this study. We also include the asset variance proxies (*Var KMV*, *Var Asset*, and *SysVar KMV*). Not surprisingly, all the beta proxies that are based on asset return data are highly correlated. The lowest correlations are those between the cash flow-based betas (*Beta Gap* and *Beta Cash Flow*) and the asset-return based betas (approximately 0.10). The correlations among the other betas (all of them based on asset return data) hover between 0.3 and 0.9.

– Table 2 about here –

To examine the effect of aggregate risk on the choice between cash and credit lines, we perform a number of different sets of tests. We describe these tests in turn.

C.1. Firm-level regressions

Our benchmark empirical specification closely follows of Sufi (2009). We expand his specification by including our measure of systematic risk:

$$\begin{aligned} \textit{LC-to-Cash}_{i,t} \;=\; & \alpha + \beta_1 BetaKMV_{i,t} + \beta_2 \ln(Age)_{i,t} + \beta_3 (Profitability)_{i,t-1} \\ & + \beta_4 Size_{i,t-1} + \beta_5 Q_{i,t-1} + \beta_6 Networth_{i,t-1} + \beta_7 IndSalesVol_{j,t} \\ & + \beta_8 ProfitVol_{i,t} + \sum_t Year_t + \epsilon_{i,t}, \end{aligned} \tag{20}$$

where *Year* absorbs time-specific effects, respectively. Our theory predicts that the coefficient β_1 should be negative. We also run the same regression replacing *Beta KMV* with our other proxies for a firm's exposure to systematic and idiosyncratic risks (see Section B.). And we use different proxies for *LC-to-Cash*, which are based both on LPC-DealScan and Sufi's data. We also include industry dummies (following Sufi we use 1-digit SIC industry dummies) and the variance measures that are based on stock and asset returns (*Var KMV* and *Var Asset*).

The results for the *KMV-Merton* betas and variances, and LPC-DealScan data are presented in Table 3. In column (1), we replicate Sufi's (2009) results (see his Table 3). Just like Sufi, we find that profitable, large, low Q, low net worth, low cash flow volatility firms are more likely to use bank credit lines. The fact that we can replicate Sufi's results is important, given that our dependent variable is not as precisely measured as that in Sufi. In column (2), we introduce asset variance (*Var KMV*) in the model. *Var KMV* is negatively correlated with the *LC-to-Cash* ratio, and it drives out the significance of Sufi's profit volatility variable. This finding suggests that *Var KMV* is a better measure of total risk than the profit volatility variable used by Sufi.

– Table 3 about here –

Next, we introduce our measures of systematic risk in the regressions. The coefficient on *Beta KMV* in column (3) suggests that systematic risk is negatively related to the *LC-to-Cash* ratio. The size of the coefficient implies that a one-standard deviation increase in asset beta (approximately 1) decreases firm's reliance on credit lines by approximately 0.08 (about 20% of the standard deviation of the *LC-to-Cash* variable). In column (4) we use *SysVar KMV* in the regressions rather than *Beta KMV*. The results again suggest that systematic risk exposure is negative correlated to the *LC-to-Cash* ratio. Finally, in column (5) we report a specification that includes both *Beta KMV* and *Var KMV* together in the same regressions. The coefficient on *Beta KMV* drops to approximately 0.06 and continues to be statistically significant (p-value equal to 1.78). The coefficient on *Var KMV* remains negative but is not statistically significant.

Table 4 uses Sufi's (2009) measures of *LC-to-Cash* rather than LPC-DealScan data. In columns (1) to (4) we use *Total LC-to-Cash*, and in columns (5) to (8) we use *Unused LC-to-Cash.* Columns (1) and (5) replicate the results in Sufi's Table 3. Notice that the coefficients are virtually identical to those in Sufi. We then introduce our KMV-based proxies for total, and aggregate risk exposures. As in Table 3, the evidence suggests that systematic risk exposure is negatively correlated with the use of credit lines. We reach this conclusion both when we use *Beta KMV* (columns (2) and (6)) and *SysVar KMV* (columns (3) and (7)) to proxy for systematic risk exposure. In addition, aggregate risk exposure continues to be significantly related to the *LC-to-Cash* ratio after controlling for *Var KMV* (columns (4) and (8)). These results suggest that the cross-sectional relationship between systematic risk exposure and liquidity management is economically significant and robust to different ways of computing exposure to systematic risk and reliance on credit lines.[12]

– Table 4 about here –

[12] In our model, both cash and credit lines are used by the firm to hedge liquidity shocks. This raises the question of whether derivatives-based hedging would affect our results. We believe this is unlikely for a couple of reasons. First, notice that the use of derivatives and other forms of hedging should be reflected in the betas that we observe. Second, while derivatives hedging is only feasible in certain industries (such as those that are commodity-intensive), our results hold across and within industries, for a broad set of industries.

It is important that we consider the validity of our instrumental variables approach to the mismeasurement problem. The first statistic we consider in this examination is the first-stage exclusion F-tests for our set of instruments. Their associated p-values are all lower to 1% (confirming the explanatory power of our instruments). We also examine the validity of the exclusion restrictions associated with our set of instruments. We do this using Hansen's (1982) J-test statistic for overidentifying restrictions. The p-values associated with Hansen's test statistic are reported in the last row of Tables 3 and 4. We generally find high p-values (particularly when using Sufi's sample in Table 4). These reported statistics suggest that we do not reject the joint null hypothesis that our instruments are uncorrelated with the error term in the leverage regression and the model is well-specified.

Table 5 replaces *Beta KMV* with our alternative beta measures using the LPC-Deal Scan sample.[13] The results in the first column of Table 5 suggest that the results reported in Table 3 are robust to the method used to unlever betas. *Beta Asset* (which is based directly on asset return data) has a similar relation to liquidity policy as that uncovered in Table 2. The economic magnitude of the coefficient on *Beta Asset* is in fact larger than that reported in Table 2. Using industry-level cash-adjusted betas, *Beta Cash*, also produces similar results (column (2)). In column (3), we show that a firm's exposure to banking sector risks (*Beta Bank*) affects liquidity policy in a way that is consistent with the theory. The coefficients are also economically significant. Specifically, a one-standard deviation increase in *Beta Bank* (which is equal to 0.7) decreases *LC-to-Cash* by 0.21, which is half of the standard deviation of the *LC-to-Cash* variable. Column (4) shows that a firm's exposure to tail risks is also correlated with liquidity policy. Firms which tend to do poorly during market downturns have a significantly lower *LC-to-Cash* ratio. In column (5), we use equity (levered) betas instead of asset betas. The coefficient on beta is comparable to the similar specification in Table 3 (which is in column (3)), though somewhat smaller. Thus, adjusting for the leverage effect increases the effect of beta on the *LC-to-Cash* ratio (as expected). However, even the equity beta shows a negative relation to the fraction of credit lines used in liquidity management. Columns (6) and (7) replace market-based beta measures with cash flow-based betas computed at the industry level (*Beta Gap* and *Beta Cash Flow*). Consistent with the theory, cash flow betas are significantly related to the *LC-to-Cash* ratio, though economic significance is smaller than for the market measures.[14] Finally, in column (8) we use value-weighted industry betas rather than firm-level betas in the regression. Using industry betas is an alternative way to address the possibility that firm-level betas are measured with error. Thus, in column (6) we do not instrument betas with the first two lags (as we do in the other columns).

[13] We obtain similar results when using Sufi's sample (see the internet appendix).

[14] The coefficient in column (7), for example, suggests that a one-standard deviation increase in *Beta Gap* decreases *LC-to-Cash* by approximately 1.5%.

The results again suggest a significant relation between asset beta and the *LC-to-Cash* ratio.

– Table 5 about here –

The regressions on Tables 3 and 4 suggest that total risk is not robustly related to corporate liquidity policy, after introducing proxies for systematic risk exposure (such as *Beta KMV*). In other words, firms' idiosyncratic or non-systematic risk is not robustly related to cross-sectional variation in liquidity policy. This result may appear to contradict the results in Sufi (2009), who suggests that riskier firms should shy away from credit lines due to the risk of covenant violations. However, Sufi (2009) also shows that the *level* of profitability proxies for the risk of covenant violations and credit line revocations. In particular, the level of profitability is the key variable that predicts covenant violations (as shown in Sufi's Table 6). The results above are consistent with Sufi's profitability results, since the level of profitability in our results too is positively related to the LC-Cash ratio, particularly so in the LPC sample (Tables 3 and 5), suggesting that the risk of credit line revocation is being captured by variation in the level of profitability, rather than non-systematic risk.

Sorting firms according to proxies for financing constraints and beta. One of the implications of the model in Section I. is that the choice between cash and credit lines should be most relevant for firms that are financially constrained (Implication 3). This line of argument suggests that the relation that we find above should be driven by firms that find it more costly to raise external funds. In addition, the theory suggests that the effect of systematic risk exposure on corporate liquidity policy should primarily arise among firms with high systematic risk (Implication 4). In this section we attempt to test both implications. We follow prior studies (e.g., Almeida, Campello and Weisbach (2004)) in using three alternative schemes to partition our sample in order to test Implication 3:

(1) We rank firms based on their payout ratio and assign to the financially constrained (unconstrained) group those firms in the bottom (top) three deciles of the annual payout distribution.

(2) We rank firms based on their asset size, and assign to the financially constrained (unconstrained) group those firms in the bottom (top) three deciles of the size distribution. The argument for size as a good observable measure of financial constraints is that small firms are typically young, less well known, and thus more vulnerable to credit imperfections.

(3) We rank firms based on whether they have bond and commercial paper ratings. A firm is deemed to be constrained if it has neither a bond nor a commercial paper rating. it is unconstrained if it has both a bond and a commercial paper rating.

To test Implication 4, we partition the sample into two groups. "High Beta" firms are those that have beta greater than one. "Low Beta" firms are those that have beta less than one (the average value of *Beta KMV* according to Table 1).

We repeat the regressions performed above, but now separately for financially constrained and unconstrained subsamples and for Low Beta and High Beta sub-samples. To measure systematic risk, we use both *Beta KMV* and *Beta Tail* (which measures firms' exposure to tail risks).

Table 6 presents the results we obtain. Panel A presents results for *Beta KMV*, and Panel B shows the *Beta Tail* results. Results for the other beta proxies are generally similar, and are presented in the internet appendix. The first six columns in Panel A show that the negative relation between systematic risk and the usage of credit lines obtains only in the constrained samples. The coefficient on *Beta KMV* for the constrained samples is negative and significant for the small and low payout samples, but is insignificant for large, high payout, and rated firms. Column (5) shows that the coefficient is negative but not significant for non-rated firms (t-stat of 1.47). The coefficients are also significantly different across constrained and unconstrained samples, with exception of the ratings sorting. The p-values from Wald tests that the coefficients are significantly different from each other range from 0.198 (ratings sorting) to 0.005 (payout sorting). Panel B shows similar results for the *Beta Tail* variable. The main differences are that the coefficient on *Beta Tail* for the non-rated sub-sample is now significantly negative (t-stat of -4.56), while the coefficient for the high-payout sample is now negative and significant. However, even for the payout sorting there is (weak) evidence that the coefficient is larger for the constrained sample. The p-value from a Wald test that the coefficient for the low payout sample is different from that for the high payout sample is 0.104. The p-values are higher for the ratings (p-value of 0.037) and the size sortings (p-value of 0.003), indicating that the coefficient on Beta for constrained samples is indeed more negative than that for unconstrained samples. These results are consistent with Implication 3.

– Table 6 about here –

Columns (7) and (8) of each Panel show that the negative relationship between beta and the *LC-Cash* ratio is much stronger in the sample of firms with high exposure to aggregate risk. When using *Beta KMV*, the negative coefficient on beta obtains only in the High Beta sample. The coefficient is negative and significant for the Low Beta sample when using *Beta Tail*, but its magnitude is substantially smaller than the coefficient that obtains in the High Beta sample. The p-value from a Wald test that the coefficients on *Beta Tail* are different from each other is 0.024, indicating that the coefficients are statiscally distinguishable from each other. These results support Implication 4.

The non-linearity of the relationship between beta and the *LC-Cash* ratio can also be illustrated with a graph. In Figure 3, we sort the sample into quintiles based on the average value for *Beta KMV* for each firm during the entire sample period. Then, we calculate the average value of the *LC-Cash* ratio in each of these quintiles of beta. Figure 3 shows that the average *LC-Cash* ratio barely changes as one moves from the first to the third quintile of Beta (the average *LC-Cash* ratio in the first three quintiles is approximately 0.35). However, the average ratio in the highest quintile drops to less than 0.2. This figure gives a visual illustration that the effect of beta on the *LC-Cash* ratio is concentrated among firms with high exposure to systematic risk (Implication 4 of the theory).

– Figure 3 about here –

Asset beta and the cost of credit lines. The empirical findings so far all suggest that firms with high aggregate risk exposure hold more cash relative to lines of credit. This effect arises in our theoretical model since firms with greater aggregate risk exposure face a higher cost of bank lines of credit. We perform an additional test to further investigate this channel. Specifically, we provide evidence on the relation between all-in drawn spreads and undrawn fees paid by firms on their credit lines, and systematic risk. To do this, we regress the average annual spreads and fees paid by firm i in deals initiated in year t,[15] on systematic risk proxies and controls. We control for the size of credit line facilities raised in year t scaled by assets ($\frac{LC_{i,t}}{Assets_{i,t}}$), and the level of the $LIBOR$ in the quarter when the credit line was raised.[16] Our empirical model has the following form:

$$Cost_{i,t} = \mu_0 + \mu_1 Beta_{i,t} + \mu_2 (\frac{LC_{i,t}}{Assets_{i,t}}) + \mu_3 LIBOR_{i,t} + \boldsymbol{\mu}_4 \mathbf{X}_{i,t} + \sum_t Year_t + \epsilon_{i,t}, \tag{21}$$

where $\mathbf{X}$ is the vector of firm characteristics used in equation (20). We use both *All-in drawn spread* and *Undrawn fee* as alternative dependent variables to measure the cost of credit lines. We focus on a set of three risk proxies (namely, *Beta KMV*, *Beta Tail*, and *SysVar KMV*), and present results for the other proxies in the internet appendix.

Our findings are presented in Table 7. The coefficients on systematic risk proxies in columns (1) to (3) suggest that *All-in drawn spread* is higher for firms with greater exposure to systematic risk (though statistical significance for the coefficient on *Beta KMV* is weaker).[17] For example, the coefficient estimate of 10 on *SysVar KMV* indicates that a one-standard deviation change in systematic risk exposure (equal to 0.018 according to Table 1) is associated with an increase of 18 basis points on credit line spreads (approximately 16% of the standard deviation in *All-in drawn spread*). Columns (4) through (6) show similar results for *Undrawn fee*. The evidence suggests that an increase of one standard deviation in systematic risk exposure increases undrawn fees by 6 basis points, 35% of the standard deviation reported in Table 1. These results provide evidence that firms with high exposure to systematic risk face worse contractual terms when initiating credit lines.

– Table 7 about here –

[15] This annual average is weighted by the amount raised in each credit line deal.

[16] The data on LIBOR refers to the level of LIBOR in the quarter in which firm i initiates the credit line. We annualize this variable by computing the facility size-weighted, firm-year average ($LIBOR_{i,t}$). Notice that since firms initiate credit lines in different quarters, this proxy varies both over time and across firms.

[17] We obtain generally similar results for the other systematic risk proxies (see the internet appendix).

C.2. Time-series tests

In this section, we examine the time-series implications of the model. The model suggests that an increase in aggregate risk makes it more difficult for the banking sector to provide new credit lines. Accordingly, high aggregate risk should be associated with lower credit line initiations, and worse terms for new credit lines (for example, higher spreads and shorter maturities). In response, firms should attempt to build up cash reserves. The model also suggests that both economy-wide and banking sector risk should matter for corporate liquidity policy. We examine these dynamics in turn.

We focus first on the impact of aggregate risk on credit line initiations and changes in cash holdings (defined in equation (38) in the appendix). To do so, we run the following time-series SUR model:

$$\begin{aligned} LCInitiation_t &= \varsigma_0 + \varsigma_1 VIX_{t-1} + \varsigma_2 TimeTrend_t + \boldsymbol{\varsigma}_3 \mathbf{Controls}_{t-1} + \varpi_t \\ Change\ in\ Cash_t &= \gamma_0 + \gamma_1 VIX_{t-1} + \gamma_2 Time\ Trend_t + \boldsymbol{\gamma}_3 \mathbf{Controls}_{t-1} + \upsilon_t. \end{aligned} \tag{22}$$

To allow for variation in our tests, in some specifications we replace VIX (a measure of economy-wide aggregate risk) with $Bank\ VIX$ (expected volatility of banking sector equity returns).[18] We also include both volatility measures together in the regressions in some specifications. Our model would suggest that $\varsigma_1 < 0$, and $\gamma_1 > 0$. The control variables are the 3-month commercial paper–Treasury spread and real GDP growth. Previous banking literature suggests that during crises, banks experience an inflow of deposits coming from the commercial paper market. This effect, in turn, helps them honor their loan commitments (e.g., Gatev and Strahan (2005)). Banks' increased ability to honor their commitments during bad times may then counteract the effect of VIX on corporate liquidity management. As shown by Gatev and Strahan, this inflow effect tends to happen in times when the spread of commercial paper over Treasury rates is high. Real GDP growth captures general economic conditions and investment opportunities. We lag both VIX and the control variables one period, since it may take time for macroeconomic conditions to affect corporate liquidity management variables. Also, corporate variable may be measured at different times of the year based on fiscal-year ends.

Before reporting the results, we examine the relation between VIX, $LC\ Initiation$, and $Change\ in\ Cash$ in a simple plot. Figure 4 shows a clear negative correlation between VIX and credit line initiations in our sample period. The correlation between VIX and changes in cash is less clear, but there seems to be a positive correlation throughout the sample period.

– Figure 4 about here –

Table 8 reports the regression outputs. The results for credit lines are presented in Panel A, and those for cash are in Panel B (recall that each equation is estimated using a SUR procedure).

[18] The correlation between VIX and $Bank\ VIX$ in our time-series data is equal to 0.39.

Column (1) shows that the negative relation between VIX and *LC Initiation* is statistically significant. The coefficient on VIX suggests that a one-standard deviation increase in VIX (which is equal to 0.07) decreases *LC Initiation* by approximately 0.7 standard deviations of that variable. This effect is economically relevant. In addition, VIX has a positive relation with aggregate change in cash holdings. The coefficient on Panel B suggests that a one-standard deviation in VIX increases aggregate cash holdings by 0.43 standard deviations of that variable. Column (2) suggests that *Bank* VIX also has a negative relation with *LC Initiation*. However, the coefficient on the cash regression is virtually zero. When we include both VIX and *Bank* VIX together in the same regression (see column (3)), we find that both are negatively related to *LC Initiation*, suggesting that banking sector matters for credit line provision, over and above economy-wide aggregate risk. This result supports the implications of our model.

– Table 8 about here –

One potential issue with the results above is that the right-hand side variables are simple aggregates (see equation (38)). In particular, these results leave open the possibility that contemporaneous changes in other firm-level variables may affect our inferences. In order to address this possibility, in columns (4) to (6) we use the average residual value of firm-level cash holdings and credit line initiations to compute our aggregate quantities. The firm-level residual values are computed using the same explanatory variables as in equation (20) (excluding year effects and *Beta*). Columns (4) through (6) show that our results become even stronger after this change in the specification. While the relation between VIX, *LC Initiation*, and *Change in Cash* is robust to this modification (column (4)), column (5) shows that *Bank* VIX is now positively correlated with *Change in Cash*. In addition, column (6) suggests that both VIX and *Bank* VIX seem to matter for corporate liquidity policy in the way suggested by our theory.[19]

Table 8 suggests that in times of high aggregate risk, new credit line initiations decrease and cash holdings increase. Thus, firms appear to be substituting cash holdings for credit lines when aggregate risk is high. This pattern is consistent with our model, which predicts that the banking sector's ability to provide new credit lines decreases when aggregate risk is high. However, there are other explanations for the correlations depicted in Table 8. For example, even though we control for GDP growth, it is possible that VIX is capturing general economic conditions, which reduce investment opportunities and firms' demand for new credit lines. Second, it is possible that aggregate risk increases the cost of debt for corporations, causing firms to reduce demand for any type of

[19] We also performed tests of joint significance for VIX and *Bank* VIX in the regressions depicted in columns (3) and (6), both for credit line initiations and cash (Panels A and B). In all cases we reject the hypothesis that the coefficients on VIX and *Bank* VIX are jointly equal to zero (the highest p-value that we obtain is approximately 0.03, in the cash regression in column (3)).

debt (including credit lines).[20] It is thus important that we perform tests that are designed to help counter these alternative explanations and provide additional support for our model.

To address the possibility that the results in Table 8 capture a decrease in overall demand for credit and liquidity in the economy, we examine aggregate changes in credit line contractual terms (spreads and maturities). The idea is as follows. If the reduction in credit line initiations reflects a decline in demand that is caused by poor investment opportunities, then we would expect the spreads on new credit lines to *decrease* as well (as the economy moves along the supply curve, and adjusts to the reduction in credit line demand). On the other hand, if the underlying cause for the decline in observed initiations is as suggested by our model, then we would expect credit line spreads to increase following an increase in *VIX*. In addition, according to our model, we would also expect other contractual terms such as credit line maturities to become tighter (e.g., shorter maturities).

We examine the relation between VIX, $Bank\ VIX$, and credit line terms in the four first columns of Table 9. To do so, we measure the average credit line maturity and all-in drawn spread (weighted by the size of the credit line facility) in each year of our sample. We then estimate a SUR model in which average maturities and spreads are used as dependent variables:

$$\begin{aligned} Average\ Maturity_t &= \psi_0 + \psi_1 VIX_{t-1} + \psi_2 TimeTrend_t + \psi_3 \mathbf{Controls}_{t-1} + \varkappa_t \\ Average\ Spread_t &= \varrho_0 + \varrho_1 VIX_{t-1} + \varrho_2 TimeTrend_t + \varrho_3 \mathbf{Controls}_{t-1} + \phi_t. \end{aligned} \tag{23}$$

The demand-investment opportunity story would suggest that $\psi_1 > 0$ and $\varrho_1 < 0$, while our model would predict $\psi_1 < 0$ and $\varrho_1 > 0$.

The main result is presented in Table 9 and Figure 5. Notably, aggregate risk appears to tighten credit line contractual terms. In other words, following increases in aggregate volatility, credit line spreads increase, and maturities decrease. This result is visually obvious in Figure 5, and it is confirmed in Table 9 (first four columns). In addition, notice that the impact of aggregate risk on credit line contracts is economically substantial. A one-standard deviation increase in VIX decreases average credit line maturity by approximately 60% of its standard deviation, and increases average spread by 50% of its standard deviation.[21] The results are similar for $Bank\ VIX$, though the coefficient on the spread regression is not statistically significant.

– Figure 5 about here –

– Table 9 about here –

[20]For example, one argument is that financial distress costs are systematic and increase in times of high aggregate risk (see Almeida and Philippon (2007) and Chen (2010)).

[21]For example, the standard deviation in VIX is 0.07. Multiplying by the coefficient of -26 on the maturity regression gives 1.82, which is 61% of the standard deviation of the maturity variable (which is equal to 3).

While these results are consistent with our model, they can still be explained by an overall increase in the cost of debt for corporations, following an increase in aggregate risk. A simple way to examine whether this is a plausible explanation for the results is to replace credit line initiations with aggregate changes in *total* debt, and see whether lagged changes in aggregate risk also predict reductions in total debt in the economy. We test this idea by estimating a debt-taking model in which the dependent variable is computed similarly to changes in cash holdings:

$$Change\ in\ Debt_t = \frac{\sum_j (Debt_{j,t} - Debt_{j,t-1})}{\sum_j Assets_{j,t}}. \tag{24}$$

In this equation, we define debt as the sum of short- and long-term debt from COMPUSTAT. We then replace $LCInitiation_t$ in Equation 22 above with $Change\ in\ Debt_t$.

Columns (5) and (6) of Table 9 report the results for the debt regression, using both VIX (column (5)) and $Bank\ VIX$ (column (6)). The SUR model also includes an equation for $Change\ in\ Cash$, but coefficients are not reported since they are identical to those reported in Table 9 (columns (1) and (2)). As it turns out, neither lagged VIX nor $Bank\ Vix$ predict an overall reduction in debt in the economy. The coefficient on the $Change\ in\ Debt$ variable is positive, economically small, and statistically insignificant in column (5), and negative and statistically insignificant in column (6). These results suggest that the negative impact of aggregate risk on new debt is strongest for credit line initiations. This is consistent with our model's suggestion that increases in aggregate risk compromise the baking sector's ability to provide credit lines for liquidity management.

C.3. Covenant violation risk or banks' liquidity constraints?

The results above suggest that firms hold more cash and less credit lines when their aggregate risk exposure is high, and when economy-wide aggregate risk increases. Our interpretation of these findings is that aggregate risk increases the correlation among firms' liquidity shocks, and tightens banks' liquidity constraints, constraining banks' ability to provide liquidity insurance to firms through credit lines. Nevertheless, a possible alternative interpretation for the results is related to the risk of covenant violations (as in Sufi (2009)). If firms are more likely to violate covenants in times when aggregate risk is high, then "high beta" firms may shy away from credit lines not because of banks' liquidity constraint as in our model, but because of the risk of covenant violations. In this section, we attempt to provide additional evidence that the link between liquidity management and aggregate risk that our results uncovered is indeed due to the effect of aggregate risk on banks' liquidity constraints.

Bank-level evidence on the link between credit line exposure and aggregate risk. First, we devise a direct test of the prediction that aggregate risk exposure tightens banks' liquidity constraints through a credit line channel. The link between credit line exposure and bank risk has been studied by Gatev, Schuermann, and Strahan (2009). They find that bank risk, as measured by stock return volatility, increases with unused credit lines that the bank has agreed to extend to the corporate sector. The mechanism in our model would then suggest that the impact of credit line exposure on bank risk should *increase* during periods of high aggregate risk. When aggregate risk goes up, firm-level liquidity risks become more correlated. Thus, banks with larger credit line exposure should be more strongly affected by increases in aggregate risk.

In order to implement this new test, we employ bank Call Reports (the same source used by Gatev et al.). Call Reports contain detailed information on bank's assets and liabilities (significantly more detail than one can obtain from Bank COMPUSTAT). In particular, there is information on total unused credit lines at the bank level. We follow Gatev et al. to construct our variables and empirical specifications. The dependent variable is a measure of bank stock return volatility ($Bank\ Vol$), while the main independent variable is the ratio of unused credit lines to the sum of unused credit lines plus other loans ($Commitments$). The definition of credit lines in these tests eliminates credit cards and family residential commitment (such as home equity credit lines), to make sure that the results are coming from exposure to corporate credit lines. The set of controls resemble those used in Gatev et al. Specifically, we estimate the following empirical model:

$$Bank\ Vol_{i,t} = \alpha + \beta Commitments_{i,t-1} + \text{Bank-level and Market-level Control Variables} + \epsilon_{i,t} \quad (25)$$

Our model predicts that the coefficient β, which measures the effect of undrawn credit line exposure on bank risk, should increase during times of high aggregate risk. In addition, recall that the model suggests that aggregate volatility should have a non-linear impact on bank's liquidity constraints in that these constraints will bind only if aggregate risk is sufficiently high. To capture this potential non-linearity, we split the sample into months with the 20% highest and 20% lowest levels of VIX, and estimate equation 25 separately for these sub-samples. The results are not sensitive to the particular choice of cut-off (using alternative cut-offs of 10% or 25% produce similar results, as we show in the internet appendix).

Following Gatev et al., the variable $Bank\ Vol$ is measured as the annualized monthly average of bank squared returns (that is, the unit of observation for these tests is a bank-month). The variable $Commitments$ is constructed using information on undrawn credit lines and other loans from the previous quarter. The set of control variables follows those in Gatev et al.'s Tables 3 and 4.[22] Our sample construction also follows Gatev et al. We use data from the largest 100 publicly traded banks

[22] The market-level control variables include VIX itself, the paper-bill spread (the spread on 3-month commercial paper over treasuries), and the yield on the 3-month t-bill. Bank-level controls include the lagged ratio of transaction deposits to total deposits (*Deposit base*), the ratio of cash plus securities to total assets (liquid asset measure), and the ratio of capital to assets (capital adequacy measure). Gatev et al. provide evidence that bank deposits provide insurance for banks against credit line exposure. Following their paper, we also interact *Deposit base* with *Commitments* to capture this insurance effect.

from 1990 to 2007, and drop all banks that were engaged in mergers and acquisitions in that year (using SDC Merger&Acquisition data).[23]

The results, reported in Table 10, show that exposure to unused credit lines increases bank risk, but only when VIX is high (columns (1) to (4)). In high VIX months, the effect of lagged credit line exposure on bank stock return volatility is positive and significant irrespective of the set of controls that we use, including market-level controls (column (2)) and both market-level and bank-level controls (column (3) and (4)). In particular, this result continues to hold after controlling for a bank's deposit base and its interaction with credit line exposure (column (4)). In contrast, credit line exposure has an insignificant effect on bank risk when VIX is low (columns (5) to (8)). In addition, the difference in the sensitivity of bank risk to credit line exposure between high VIX and low VIX periods is statistically significant (the lowest clustered t-statistic is 1.8, for the difference in coefficients between columns (4) and (8)).

– Table 10 about here –

The effect of credit line exposure on bank risk is also economically significant. During high-VIX months, a one standard deviation increase in credit line exposure increases $Bank\ Vol$ by 7.85% (column (3)). The lowest economic effect of credit lines on bank risk is on column (4). When we include $Depositbase$ and its interaction with $Commitments$, one standard deviation increase of loan commitments results in an increase in $Bank\ Vol$ of 6.88%, holding $Deposit\ Base$ at 0.183 (our sample mean for high-VIX months).

These results suggest that exposure to credit lines only matters in times when several firms are likely to have negative shocks at the same time. It thus provides direct evidence on the link between aggregate risk and the banking sector's liquidity constraint that underlies our results.

Covenant violation, credit line revocations and aggregate risk. To complement the evidence above, in this section we examine the hypothesis that covenant violations (or credit line revocations conditional on violations) increase during systemic downturns.

To test these hypotheses, we use data from Sufi (2009). We start from the specifications reported in Sufi's Table 6, and then examine whether aggregate risk (VIX) and aggregate risk exposure ($Beta$) help explain covenant violations and credit line revocations. To do so, we use the data provided in

[23] Gatev et al. use lead bank characteristics as proxies for the characteristics of bank holding companies. Since we do not have the bank holding data, for each bank holding company and each reporting quarter we use the bank with the largest asset level among all member banks as the lead bank. Finally, we use CRSP to compute the bank-level measures of stock return volatility. The summary statistics (available from the authors) is generally similar to those reported in Gatev et al.'s Table 2. For example the commitment ratio, excluding retail commitments, is 0.24 (0.22 in Gatev et al.'s paper); the deposit base is 0.20 in our sample, which is slightly smaller than Gatev et al.'s. The discrepancy probably come from difference in sample period in our study and in Gatev et al.'s. Our sample period is from 1990 to 2007, whereas theirs' only lasts until 2002.

Sufi's website and consider the following specifications. First, for covenant violations:

$$\begin{aligned} Covenant\ Violation_{i,t} &= a + b\frac{EBITDA_t}{Assets_{t-1}} + cVIX_t + d\frac{EBITDA_t}{Assets_{t-1}} * VIX_t + \\ &\quad + \text{Firm-level controls} + \zeta_{i,t}. \end{aligned} \tag{26}$$

The coefficient c measures whether firms are more likely to violate covenants in times of high aggregate risk, controlling for profitability and other firm-level variables. The coefficient d measures whether profitability shocks have a larger effect on covenant violations, in times of high aggregate risk. If coefficients c and/or d were positive, there would be evidence that covenant violation risk may confound our main hypothesis. Alternatively, we replace VIX with $Beta\ KMV$ in the equation above to examine whether high beta firms are more likely to violate covenants, and whether covenant violations are more sensitive to profitability shocks for such firms. As in Sufi, all regressions contain firm-fixed effects, and are estimated only in a sample of firms with credit lines in year t. The regressions that contain VIX are estimated without year fixed effects.

To measure credit line revocations, we use a few alternative specifications. First, and following Sufi (2009), we examine the change in the availability of credit lines as a function of covenant violations and VIX. We employ unused credit lines (scaled by assets) in our main specification, but also examine total credit lines in robustness checks (see the internet appendix):

$$\begin{aligned} Unused\ LC\text{-}Assets_{i,t} &= \vartheta + \kappa Covenant\ Violation_{t-1} + \nu VIX_{t-1} + \\ &\quad + \xi Covenant\ Violation_{t-1} * VIX_{t-1} + \text{Firm-level controls} + \varpi_{i,t} \end{aligned} \tag{27}$$

This regression is estimated for a sample of firms that has a credit line in year $t-1$, and includes firm fixed effects. The coefficient κ thus measures the impact of a covenant violation on year $t-1$, on the *change* in credit line availability for an individual firm in year t. Similarly, the coefficient ξ captures whether violations have a greater impact on credit line availability in years of high aggregate risk, and the coefficient ν captures the direct impact of VIX. As in Equation 26, we also replace VIX with $Beta\ KMV$ to examine whether high beta firms are differentially affected by covenant violations.

While changes in credit line availability are certainly related to credit line revocations, the measures of change in credit line availability used by Sufi (2009) are also affected by variables such as maturing credit lines and initiations of new lines. In order to try to improve our proxy for credit line revocations, we take advantage of the fact that the LPC-Deal Scan data does provide information on credit line maturity and new initiations. Since the LPC data do not capture revocation of existing lines, implementing this strategy forces us to examine a sub-sample of firm-years that are present in both Sufi's and the LPC-Deal Scan sample. For this sub-sample, we construct the following additional proxies.

First, we deduct the annual amount of maturing credit lines (measured using LPC) from the annual decrease in credit line availability (measured using Sufi's data). That is, we create the following variable:

$$Revocation_{i,t} = -(Change\ in\ Credit\ Line\ Availability)_{i,t} - (Maturing\ Credit\ Lines)_{i,t} \quad (28)$$

This calculation helps ensure that the measured decreases in credit line availability in Sufi's (2009) data are not simply due to the maturity of existing credit lines (measured using LPC-Deal Scan). We compute this variable both for total (*Revocation Total*) and unused (*Revocation Unused*) credit lines. These variables are scaled by lagged assets.

One remaining issue with these proxies is that they are also potentially affected by new credit line initiations. In order to address this possibility, we make use of the data on credit line initiations that is available from LPC-Deal Scan. First, we restrict our sample to firm-years in which there are no credit line initiations in LPC. This filter helps ensure that the relations that we measure are coming from credit line revocations. Second, we construct a measure that is based on an indication that an existing credit line was revoked. To do so, we construct a dummy variable that takes the value of one when the variable *Revocation* defined in Equation 28 above takes a positive value, and zero otherwise. That is, this dummy variable takes the value of one when there is a decline in credit line availability that is greater than the amount of maturing lines, indicating a possible revocation. Following the strategy above, we restrict the sample to firm-years in which there are no credit line initiations measured from the LPC data. We create these dummy variables starting both from total (*Revocation Dummy Total*) and unused (*Revocation Dummy Unused*) credit lines.

Since these alternative proxies for revocation are based on changes in credit line availability, we estimate models similar to Equation 27, but where we control for changes in firm characteristics, and do not include firm fixed effects.

The results are reported in Table 11 (covenant violations) and Table 12 (credit line revocations). In column (1) of Table 11 we are able to replicate Sufi's main result: profitability is the main determinant of whether a firm violates a covenant or not. We then introduce our proxies for aggregate risk (VIX) and aggregate risk exposure (*Beta KMV*). Column (2) shows that VIX has virtually no effect on covenant violations, after controlling for its main firm-level determinants. VIX also does not affect the relationship between profitability and violations (column (3)). The results for *Beta KMV* suggest that high *Beta KMV* firms are if anything less likely to violate covenants than other firms, and are less sensitive to declines in profitability (columns (4) and (5)). The interaction between *Beta KMV* and profitability is positive in column (5), suggesting that aggregate risk exposure may mitigate the effect of profitability on covenant violations. This result likely reflects the results that we report earlier: High beta firms have smaller credit lines and pay more for these credit lines *ex-ante*, and are thus less likely to violate covenants ex-post.

– Table 11 about here –

We examine changes in credit line availability and credit line revocations in Table 12. In Panel A, we report the results of estimating Equation 27. The results show that covenant violations cause subsequent reductions in credit line availability, as emphasized by Sufi. Column (1) replicates the result in Sufi's column (4). In these regressions, neither VIX nor *Beta* help explain changes in credit line availability, suggesting that aggregate risk and aggregate risk exposure are not important predictors of credit line revocations after controlling for their main firm-level determinants.

– Table 12 about here –

In Panel B, we use our alternative proxies for credit line revocations as dependent variables. Notice that the sample size in this Panel decreases since we only use firms that are present in both LPC-Deal Scan and Sufi's datasets. Columns (1) and (2) focus on $Revocation\ Total$. The results again suggest that covenant violations are associated with subsequent credit line revocations, but that revocations are not significantly related to VIX. Column (3) shows a similar result for the dummy variable that indicates a credit line revocation ($Revocation\ Dummy\ Total$). Columns (4) to (6) replace $Revocation\ Total$ and $Revocation\ Dummy\ Total$ with $Revocation\ Unused$ and $Revocation\ Dummy\ Unused$. There is again no clear link between credit line revocations and aggregate risk. Notice also that covenant violations are not significantly related to credit line revocations when we use $Revocation\ Unused$ and $Revocation\ Dummy\ Unused$.[24]

Interpretation. These results broadly confirm those in Sufi (2009). Covenant violations are associated with declines in firm profitability, but appear to be unrelated to both time-series and cross-sectional variation in aggregate risk. Covenant violations seem to predict subsequent credit line revocations, for most of the alternative empirical specifications that we use. In addition, there is no evidence that systematic risk proxies are related to credit line revocations after controlling for covenant violations. These results are robust to the usage of different proxies for the availability of credit lines, and they generally survive after controlling for the potential effect of maturity and initiations on credit line availability.

While the lack of relationship between systematic risk and credit line revocations may seem surprising at first glance, there is a natural interpretation that is consistent with the evidence in Tables 11 and 12. Since a credit line is a loan commitment, it may not be easy for the bank to revoke access

[24] We obtain similar results when we use Beta instead of VIX in the regressions of Panel B. We also interact systematic risk proxies with covenant violations and find no evidence of a positive coefficient on the interaction terms. See the internet appendix.

to the line once it is initiated. In order for the bank to revoke access, the firm must be in violation of a covenant. Given that covenant violations are unrelated to systematic risk after controlling for firm profitability (Table 11), the bank cannot revoke access simply because aggregate risk is high (even though the bank may like to do so). Thus, after controlling for covenant violations, there is no association between aggregate risk and credit line revocations (Table 12).[25]

Recent evidence on the role of credit lines during the recent financial crisis agrees with the evidence that access to credit lines is unlikely to be restricted solely because of aggregate economic conditions. Looking at banks, Ivashina and Scharfstein (2010) document a steep increase in loan volumes during the crisis. That increase, however, was not caused by fresh bank lending, but instead by high drawdown activity of pre-existing lines. Indeed, the authors estimate that some US$119 Billion dollars were added to bank loan portfolios by force of credit lines drawdowns. Campello, Giambona, Graham, and Harvey (2011) report that 18.6% of the sample firms with credit lines officially violated a covenant during the crisis, while 9.1% had their lines cancelled. Campello et al. conclude that outright cancellations were relatively rare during the crisis (only 2% of the firms in their sample reporting having all of their lines cancelled). The evidence in their paper, however, makes it clear that firms with low cash flows were those more likely not to renew their lines, to pay higher commitment fees, markup fees and to report more difficulties in renewing their lines.

Overall, these results help rule out the hypothesis that covenant violations and the resulting credit line revocations explain the link between systematic risk and credit line usage that we report as our main finding in the paper.

III. Concluding Remarks

We show theoretically and empirically that aggregate risk affects firms' choice between cash and credit lines. Our results show a negative, statistically significant and economically large effect of systematic risk exposure on the fraction of total liquidity that is held via credit lines. We also measure time-series changes in aggregate volatility using VIX, and show that firms tend to hold more cash and initiate fewer credit lines when aggregate risk rises. Finally, we report results that suggest that the impact of aggregate risk on corporate liquidity policy is consistent with the mechanism suggested in our model that aggregate risk tightens banks' liquidity constraints due to the ensuing correlation in credit line drawdowns. In equilibrium, firms with the highest aggregate risk exposure move out of bank-managed liquidity insurance (credit lines) and into self-insurance (cash holdings). For these firms, the folk statement that *"cash is king"* appears to be true.

[25] Given that credit line drawdowns in times of high aggregate risk are specially costly for the bank (as suggested by our model), banks are forced to price systematic risk exposure *ex ante* through an increase in credit line spreads and lower initiations of credit lines for aggregate risky firms. The evidence in this paper supports the pricing of systematic risk by banks ex ante (see, e.g., Table 7), but not ex post through revocations.

There are many ways in which our paper can be extended. One of the most interesting extensions has to do with the role of *bank capital* for corporate liquidity management. The current framework has no role for bank capital, given that cash can be efficiently held inside the corporate sector. However, in a more general framework this conclusion may not hold. If aggregate risk (proportion θ of systematic firms in our model) were uncertain, then bank capital or excess liquidity buffers can enable the economy to transfer resources from low aggregate risk states to high aggregate risk states. Further, a firm's decision to manage liquidity needs through cash holdings or lines of credit should be affected by unexpected shocks to capital of its relation bank(s), especially during crises (when other better-capitalized banks also find it difficult to offer further lines of credit given heightened aggregate risk levels). Finally, the anticipation of government bailouts during aggregate crises can lead to ex-ante under-investment in bank capital, generate moral hazard in the form of banks issuing excessive lines of credit to risky firms, and potentially lead to excessive aggregate risk in the economy. Over all, it seems important for researchers and policy-makers to better understand the dynamics of liquidity management in the economy as aggregate risk varies.

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Appendix A. Proofs

Proof of Lemma 1: First, notice that if $w^\theta \leq w^{\max}$ is satisfied for $x^\theta = 1$ and $L^\theta = 0$, then systematic firms will not find it optimal to hold cash (since the solution to (11) would then be equivalent to that of non-systematic firms). This situation arises when:

$$\rho - \rho_0 \leq w^{\max}. \tag{29}$$

In such case, both systematic and non-systematic firms can use credit lines to manage liquidity. Notice that this corresponds to scenarios in which $\theta \leq \theta^{\max}$ in Proposition 1.

If in turn $\rho - \rho_0 > w^{\max}$, systematic firms will generally demand cash in addition to credit lines. For each x^θ, their cash demand is given by equation (15).

Next, we consider the firm's optimal investment policy x^θ as a function of the liquidity premium q, $x^\theta(q)$. The firm's liquidity demand can then be derived from equation (15). To find the firm's optimal policy, notice that the firm's payoff increases with x^θ as long as $q < q_2$ which is defined as:

$$q_2 = 1 + \frac{\lambda(\rho_1 - \rho)}{\rho - \rho_0}. \tag{30}$$

In the range of prices such that $q < q_2$, the firm's optimal choice would be $x^\theta = 1$. If $q > q_2$, the firm's optimal choice is $x^\theta = 0$. The firm is indifferent between all $x^\theta \in [0, 1]$ when $q = q_2$. In addition to these payoff considerations, the budget constraint in problem (11) can also bind for a positive level of x^θ. The budget constraint can be written as:

$$I + (q-1)\left[x^\theta(\rho - \rho_0) - w^{\max}\right] + \lambda x^\theta \rho \leq (1-\lambda)\rho_0 + \lambda x^\theta \rho_0, \text{ or} \tag{31}$$

$$x^\theta \leq \frac{(1-\lambda)\rho_0 - I + (q-1)w^{\max}}{(\lambda + q - 1)(\rho - \rho_0)}. \tag{32}$$

The right-hand side of equation (32) is greater than one since $(1-\lambda)\rho_0 - I - \lambda(\rho - \rho_0) > 0$ (by (3)). Thus, there exists a maximum level of q such that the budget constraint is obeyed for $x^\theta = 1$. Call this level q_1. We can solve for q_1 as:

$$q_1 = 1 + \frac{\rho_0 - \lambda\rho - I}{\rho - \rho_0 - w^{\max}}. \tag{33}$$

Clearly, for $q < \min(q_1, q_2)$ we will have $x^\theta(q) = 1$. As q increases, either the firm's budget constraint binds, or its payoff becomes decreasing in cash holdings. The firm's specific level of $x(q)$ will then depend on whether q_1 is larger than q_2.

Appendix B. Data construction

To construct the *LPC Sample*, we start from a sample of loans in LPC-DealScan in the period of 1987 to 2008 for which we can obtain the firm identifier *gvkey* (which we later use to match to COMPUSTAT).[26] We drop utilities, quasi-public and financial firms from the sample (SIC codes greater than 5999 and lower than 7000, greater than 4899 and lower than 5000, and greater than 8999). We consider only short term and long term credit lines, which are defined as those that have the LPC field "*loantype*" equal to "*364-day Facility*," "*Revolver/Line < 1 Yr*," "*Revolver/Line >= 1 Yr*," or "*Revolver/Line*." We drop loans that appear to be repeated (same *gvkey* and *loan_id*). In some cases, the same firm has more than one credit line initiation in the same quarter. In these cases, we sum the facility amounts (the total available credit in each line) for each firm-quarter, and average the other variables using the facility amount as weights. We let $LC_{i,t}$ denote the total value of credit lines initiated in quarter t by firm i, and let $Maturity_{i,t}$ denote the average maturity of these lines in quarters. We also collect data on the spreads paid by firms when raising these lines. *All-in drawn spread* captures the total annual spread paid over LIBOR for each dollar drawn down from the facility. *Undrawn fee* is the total annual fee paid by the firm for each dollar available under commitment. *Maturity* is the maturity of the credit line in quarters from initiation. This sample is then matched to COMPUSTAT annual data, as described below.

To construct the *Random Sample*, we start from the sample used in Sufi (2009), which contains 1,908 firm-years (300 firms) between 1996 and 2003. Sufi's data set includes information on the total credit line facilities available to firm j in the random sample during an year t between 1996 to 2003 ($Total\ Line_{j,t}$), and the amount of credit in these lines that is still available to firm j in year t ($Unused\ Line_{j,t}$). We use this information to construct our proxies for credit line usage and availability. Sufi's sample also contains information on whether a firm is in violation of a covenant in a given year ($Covenant\ Violation_{j,t}$). These data are then matched to annual data from COMPUSTAT.

Finally, we merge these data with data on firm-level betas and stock-price based volatility measures. These data are described in more detail below.

Appendix C. Variable definitions

When using *Random Sample*, we measure the fraction of total corporate liquidity that is provided by credit lines for firm i in year t using:

$$Total\ LC\text{-}to\text{-}Cash_{i,t} = \frac{Total\ Line_{i,t}}{Total\ Line_{i,t} + Cash_{i,t}}, \tag{34}$$

$$Unused\ LC\text{-}to\text{-}Cash_{i,t} = \frac{Unused\ Line_{i,t}}{Unused\ Line_{i,t} + Cash_{i,t}}. \tag{35}$$

When using *LPC Sample*, we construct a proxy for line of credit usage by defining a measure of line of credit availability for each firm-quarter (j, s) as:

$$Total\ LC_{j,s} = \sum_{t \le s} LC_{j,t}\Gamma(Maturity_{j,t} \ge s - t), \tag{36}$$

where $\Gamma(.)$ represents the indicator function, and the variables LC and $Maturity$ are defined above. We convert these firm-quarter measures into firm-year measures by computing the average value of

[26] We use several procedures to obtain *gvkey*s, including a file provided by Michael Roberts, which was used in Chava and Roberts (2008), firm tickers (which are available in LPC), and manual matching using firm names.

$Total\ LC$ in each year. We then measure the fraction of corporate liquidity that is provided by lines of credit for firm j in quarter s using the following variable:

$$LC\text{-}to\text{-}Cash_{j,t} = \frac{Total\ LC_{j,t}}{Total\ LC_{j,t} + Cash_{j,t}}. \tag{37}$$

To examine the time-series impact of systematic risk on liquidity management we construct aggregate changes in credit lines and cash, scaled by assets ($LC\ Initiation_t$ and $Change\ in\ Cash_t$).

$$\begin{aligned} LC\ Initiation_t &= \frac{\sum_j LC_{j,t}}{\sum_j at_{j,t}}, \\ Change\ in\ Cash_t &= \frac{\sum_j (Cash_{j,t} - Cash_{j,t-1})}{\sum_j at_{j,t}}. \end{aligned} \tag{38}$$

Appendix D. Construction of control variables

We follow Sufi (2009) in the definitions of the variables that we use as control variables for our credit line tests. We use a book asset measure that deducts the amount of cash holdings, that is, firm *Assets* are defined as *at* – *che.* The other COMPUSTAT-based variables that we examine in our tests are defined as follows (in terms of annual COMPUSTAT fields). *Cash* is given by *che*. *Tangibility* is equal to *ppent* scaled by assets. *Size* is defined as the log of assets. Q is defined as a cash-adjusted, market-to-book asset ratio, (*Assets* + *prcc_fc*×*sho* – *ceq*)/*Assets*.[27] *NetWorth* is defined as (*ceq* – *che*)/*Assets*. *Profitability* is the ratio of EBITDA over assets. *Age* is measured as the difference between the current year and the first year in which the firm appeared in COMPUSTAT. Industry sales volatility (*IndSaleVol*) is the (3-digit SIC) industry median value of the within-year standard deviation of quarterly changes in firm sales (*saleq* minus its lagged value) scaled by the average asset value (*atq*) in the year. Profit volatility (*ProfitVol*) is the firm-level standard deviation of annual changes in the level of EBITDA, calculated using four lags, and scaled by average assets in the lagged period. We winsorize all COMPUSTAT variables at the 5^{th} and 95^{th} percentiles.

Appendix E. Computing asset betas and variances

The simplest way to unlever betas is to use a model that backs out the "mechanical" effect of leverage, using for example a Merton-KMV type model for firm value. Our first set of betas is computed using such a model, starting from yearly equity betas that are estimated using the past 12 monthly stock returns for each firm (using CRSP data). We call the set of betas that we obtain using this method *Beta KMV*. We also compute a measure of total asset volatility, which is used as a control in some of the regressions below. This measure (denoted *Var KMV*) is estimated yearly using the past 12 monthly stock returns and the KMV-Merton model.

The second way to unlever betas and variances is to directly compute data on firm *asset* returns. The data we use come from Choi (2009). Choi computes bond and bank loan returns using several data sources and then combines them with stock returns into an asset return measure that uses relative market values of the different financial claims as weights.[28] The firm-level asset return measure

[27] Sufi (2009) also deducts deferred taxes from the numerator. We excluded deferred taxes from this calculation because including it causes a significant drop in the number of observations when using sample B.

[28] We refer the reader to Choi's original paper for further details on the construction of *Beta Asset*.

is then used to compute annual betas against the aggregate equity market. We call this beta measure *Beta Asset*, and the associated return variance measure *Var Asset*. Given the stricter requirements (including some proprietary information), these data are only available for a subset of our firms.

We compute *Beta Bank* by unlevering the firm's equity beta relative to an index of bank stock returns, which is computed using a value-weighted average of the stock returns of all banks that are present in the LPC-DealScan database. We use the LPC banks to compute the aggregate bank stock return to ensure that our measure of the banking sector's risk captures a risk that is relevant for the firms in our sample. This beta is unlevered using the same procedure to compute *Beta KMV*.

Tail Beta is defined as the ratio of Marginal Expected Shortfall (MES) of a firm, divided by Expected Shortfall (ES) of the market, where MES is the average percentage loss suffered by a firm on days when the CRSP value-weighted market return is in its worst 5% days in the previous year, and ES is the average percentage loss suffered by the market on those same days. MES is a common risk measure used by firms for enterprise-wide risk aggregation. This beta is unlevered using an identical procedure used to compute *Beta KMV* and *Beta Bank*.

We compute a firm's financing gap beta (*Beta Gap*) in the following way. In each year, we compute a firm's financing gap at the level of the 3-digit SIC industry by taking the difference between total industry investment and total industry cash flow, scaled by assets. Then we compute the beta of the firm's financing gap with respect to the aggregate financing gap (the difference between investment and cash flows for the entire COMPUSTAT sample), using 10 years of data. We define the firm's financing gap at the industry level to mitigate the endogeneity of firm-specific investment, and to reduce the error in measuring the gap betas.[29] Second, we use a similar procedure to compute an industry-level cash flow beta (*Beta Cash Flow*). That is, we compute the beta of the firm's 3-digit industry cash flow, against the aggregate cash flow across all COMPUSTAT firms, using 10 years of past data.

[29] We restrict the sample to industry-years with at least 15 firms to further improve measurement.

Table 1: Summary statistics

This table reports summary statistics for empirical proxies related to firm characteristics. *LC-to-Cash* is the fraction of corporate liquidity that is provided by lines of credit, specifically the ratio of the firm's total amount of open credit lines to the sum of open credit lines plus cash balances. *Assets* are firm assets net of cash, measured in millions of dollars. *Tangibility* is PPE over assets. Q is defined as a cash-adjusted, market-to-book assets ratio. *NetWorth* is the book value of equity minus cash over total assets. *Profitability* is the ratio of EBITDA over net assets. Industry sales volatility (*IndSaleVol*) is the (3-digit SIC) industry median value of the within-year standard deviation of quarterly changes in firm sales, scaled by the average quarterly gross asset value in the year. *ProfitVol* is the firm-level standard deviation of annual changes in the level of EBITDA, calculated using four lags, and scaled by average gross *Assets* in the lagged period. *Age* is measured as the difference between the current year and the first year in which the firm appeared in COMPUSTAT. *Unused LC-to-Cash* and *Total LC-to-Cash* measure the fraction of total corporate liquidity that is provided by credit lines using unused and total credit lines respectively. *Beta KMV* is the firm's asset (unlevered) beta, calculated from equity (levered) betas and a Merton-KMV formula. *Beta Asset* is another proxy for the firm's asset (unlevered) beta, calculated directly from data on asset returns as in Choi (2009). *Var KMV* and *Var Asset* are the corresponding values for total asset variance. *Beta Cash* is the (3-digit SIC industry median) asset Beta, adjusted for cash holdings. *Beta Bank* is the firm's beta with respect to an index of bank stock returns. *Beta Tail* is a measure of beta that is based on the average stock return of a firm in the days in which the stock market had its worst 5% returns in the year. *Beta Gap* is computed using the difference between investment and cash flows at the 3-digit SIC level, and the aggregate financing gap. *Beta Cash Flow* is computed using industry cash flows at the 3-digit SIC level, and aggregate cash flows. *Beta Equity* is the equity (levered) beta. *SysVar KMV* is a measure of firm-level systematic variance of asset returns. *All-in drawn spread* is the spread on credit lines drawdowns, measured relative to LIBOR. *Undrawn fee* is the total annual fee on the undrawn balance of the credit line. Both spreads and fees are measured in percentage, and come from LPC-Deal Scan.

Panel A: LPC credit line data

Variables	Mean	StDev	Median	Firm-years
Panel A: LPC credit line data				
LC-to-Cash	0.325	0.404	0.000	44598
Tangibility	0.350	0.232	0.297	43250
Assets	2,594	17,246	270	43309
Q	1.961	1.314	1.475	43288
Networth	0.381	0.248	0.404	43288
Profitability	0.137	0.120	0.141	43309
IndSalesVol	0.043	0.031	0.034	44823
ProfitVol	0.063	0.053	0.044	44821
Age	18.855	14.339	14.000	44825
Beta KMV	0.986	1.032	0.856	44402
Beta Cash	0.970	0.574	0.920	44714
Beta Bank	0.445	0.703	0.390	44440
Beta Tail	0.742	0.567	0.697	44367
Beta Gap	0.906	1.420	0.681	35532
Beta Cash Flow	0.926	1.397	0.697	35532
Beta Equity	1.110	1.319	1.037	44402
Beta Asset	0.919	0.926	0.756	14646
Var KMV	0.017	0.019	0.009	44825
Var Asset	0.012	0.017	0.005	14646
SysVar KMV	0.013	0.018	0.006	44402
All-in drawn spread	1.771	1.124	1.750	11408
Undrawn fee	0.315	0.167	0.300	9865

Panel B: Sufi data

Variables	Mean	StDev	Median	Firm-years
Panel B: Sufi data				
Unused LC-to-Cash	0.450	0.373	0.455	1906
Total LC-to-Cash	0.512	0.388	0.569	1908
Unused LC-to-Assets	0.122	0.225	0.078	1908
Covenant Violation	0.080	0.271	0.000	1908
Tangibility	0.332	0.230	0.275	1908
Assets	1,441	7,682	116	1908
Q	2.787	3.185	1.524	1905
Networth	0.426	0.300	0.453	1905
Profitability	0.015	0.413	0.126	1908
IndSalesVol	0.043	0.026	0.036	1908
ProfitVol	0.089	0.078	0.061	1908
Age	16.037	13.399	10.000	1908
Beta KMV	1.002	1.068	0.804	1559
Beta Cash	0.974	0.639	0.915	1881
Beta Bank	0.479	0.756	0.400	1561
Beta Tail	0.631	0.494	0.584	1003
Beta Gap	1.000	1.755	0.892	1677
Beta Cash Flow	0.904	1.549	0.733	1677
Beta Equity	1.086	1.280	0.968	1596
Beta Asset	0.957	0.995	0.705	643
Var KMV	0.026	0.026	0.015	1568
Var Asset	0.023	0.025	0.011	643
SysVar KMV	0.019	0.023	0.008	1559

Table 2: Correlations

This table shows the correlations for the different proxies of asset beta, idiosyncratic and systematic risk. See Table 1 for a description of the variables.

	Beta Asset	*Beta Cash*	*Beta Bank*	*Beta Tail*	*Beta Equity*	*Beta Gap*	*Beta Cash Flow*	*Beta KMV*	*Var KMV*	*SysVar KMV*
Beta Cash	0.4627									
Beta Bank	0.5591	0.2795								
Beta Tail	0.4685	0.3302	0.2215							
Beta Equity	0.817	0.371	0.6213	0.3124						
Beta Gap	0.1809	0.232	0.0955	0.0863	0.0849					
Beta Cash Flow	0.1684	0.196	0.0982	0.0828	0.0747	0.6114				
Beta KMV	0.8889	0.4502	0.6416	0.3865	0.9444	0.1131	0.0925			
Var KMV	0.4001	0.2165	0.2585	0.2	0.2804	0.1144	0.096	0.3803		
SysVar KMV	0.7086	0.3469	0.463	0.2859	0.596	0.1285	0.0977	0.7374	0.6337	
Var Assets	0.4414	0.238	0.2633	0.2584	0.2978	0.1511	0.1491	0.3872	0.9181	0.6149

Table 3: The choice between cash and credit lines: LPC-Deal Scan sample

This Table reports regressions of a measure of line of credit usage in corporate liquidity policy on proxies for asset beta, asset variance and controls. The dependent variable is *LC-to-Cash*, defined in Table 1. *Beta KMV* is the firm's asset (unlevered) beta, calculated from equity (levered) betas and a Merton-KMV formula. *Var KMV* is the corresponding value for total asset variance. *SysVar KMV* is a measure of firm-level systematic variance of asset returns. All proxies for Beta and variances are instrumented with their first two lags. All other variables are described in Table 1. Robust t-statistics presented in parenthesis.

	Dependent variable: *LC-to-Cash*				
	(1)	(2)	(3)	(4)	(5)
Beta KMV			-0.083***		-0.059*
			(-4.947)		(-1.778)
Var KMV		-3.920***			-1.681
		(-7.010)			(-1.209)
SysVar KMV				-6.213***	
				(-8.231)	
Profitability	0.136***	0.031	0.101***	0.044	0.063
	(5.435)	(0.959)	(3.274)	(1.396)	(1.633)
Tangibility	0.012	0.005	0.004	0.002	0.004
	(0.606)	(0.215)	(0.173)	(0.072)	(0.168)
Size	0.044***	0.039***	0.051***	0.047***	0.047***
	(16.151)	(12.285)	(16.151)	(16.045)	(8.726)
Networth	-0.138***	-0.146***	-0.132***	-0.133***	-0.136***
	(-9.817)	(-9.253)	(-8.008)	(-8.259)	(-7.883)
Q	-0.055***	-0.052***	-0.050***	-0.046***	-0.049***
	(-23.840)	(-18.017)	(-14.211)	(-14.156)	(-14.941)
IndSalesVol	-0.197	-0.206	-0.219	-0.202	-0.208
	(-1.343)	(-1.271)	(-1.349)	(-1.241)	(-1.279)
ProfitVol	-0.250***	0.148*	0.033	0.221**	0.121
	(-3.751)	(1.673)	(0.380)	(2.492)	(1.316)
Age	-0.047***	-0.054***	-0.052***	-0.056***	-0.053***
	(-7.933)	(-7.165)	(-6.819)	(-7.394)	(-7.049)
Constant	0.379***	0.568***	0.465***	0.514***	0.511***
	(5.710)	(7.307)	(6.044)	(6.704)	(6.064)
Industry Fixed-effect	Yes	Yes	Yes	Yes	Yes
Year Fixed-effect	Yes	Yes	Yes	Yes	Yes
First-stage F-stat p-value		0.000	0.000	0.000	0.000
Hansen J-stat p-value		0.001	0.385	0.001	0.013
Observations	43009	35374	35372	35372	35372
R^2	0.173	0.167	0.168	0.169	0.169

* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 4: The choice between cash and credit lines: Sufi's (2009) sample

This table reports regressions of a measure of line of credit usage in corporate liquidity policy on proxies for asset beta, asset variance and controls. The dependent variables are *Unused LC-to-Cash* and *Total LC-to-Cash*, defined in Table 1. *Beta KMV* is the firm's asset (unlevered) beta, calculated from equity (levered) betas and a Merton-KMV formula. *Var KMV* is the corresponding value for total asset variance. *SysVar KMV* is a measure of firm-level systematic variance of asset returns. All proxies for Beta and variances are instrumented with their first two lags. All other variables are described in Table 1. Robust t-statistics presents in parenthesis.

	Dependent variable: *Total LC-to-Cash*				Dependent variable: *Unused LC-to-Cash*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Beta KMV		-0.336***	-0.419***			-0.270***	-0.322**	
		(-5.489)	(-2.801)			(-4.893)	(-2.438)	
Var KMV			3.114				1.649	
			(0.654)				(0.387)	
SysVar KMV				-17.119***				-15.026***
				(-5.789)				(-5.327)
Profitability	0.078**	-0.013	0.003	-0.004	0.061*	-0.012	-0.004	-0.008
	(2.269)	(-0.226)	(0.052)	(-0.083)	(1.955)	(-0.238)	(-0.074)	(-0.176)
Tangibility	0.040	-0.089	-0.081	-0.110	0.025	-0.091	-0.088	-0.113
	(0.560)	(-1.098)	(-0.938)	(-1.318)	(0.371)	(-1.184)	(-1.092)	(-1.439)
Size	0.047***	0.071***	0.083***	0.055***	0.053***	0.074***	0.081***	0.062***
	(5.110)	(5.593)	(3.621)	(4.593)	(6.106)	(6.481)	(3.992)	(5.687)
Networth	-0.097**	-0.077	-0.072	-0.071	-0.054	-0.043	-0.040	-0.036
	(-2.293)	(-1.345)	(-1.141)	(-1.231)	(-1.396)	(-0.819)	(-0.708)	(-0.678)
Q	-0.036***	-0.019***	-0.016	-0.018**	-0.029***	-0.016**	-0.013	-0.013*
	(-8.495)	(-2.656)	(-1.516)	(-2.472)	(-7.263)	(-2.398)	(-1.479)	(-1.918)
IndSalesVol	1.094*	-0.156	-0.138	-0.345	1.042	-0.073	-0.075	-0.278
	(1.691)	(-0.215)	(-0.186)	(-0.484)	(1.549)	(-0.093)	(-0.095)	(-0.355)
ProfitVol	-0.596***	0.315	0.272	0.548*	-0.554***	0.198	0.192	0.461
	(-3.209)	(1.022)	(0.887)	(1.694)	(-3.162)	(0.711)	(0.716)	(1.512)
Age	-0.039*	-0.086***	-0.083***	-0.097***	-0.023	-0.061**	-0.061**	-0.074**
	(-1.846)	(-2.818)	(-2.731)	(-3.028)	(-1.125)	(-2.101)	(-2.102)	(-2.438)
Constant	0.748***	0.306**	0.250	0.294**	0.148	0.165	0.141	0.172
	(8.612)	(2.359)	(1.516)	(2.306)	(1.377)	(1.332)	(0.945)	(1.404)
Ind. Fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First-stage F-stat p-val.		0.000	0.000	0.000	0.000	0.000	0.000	0.000
Hansen J-stat p-value		0.283	0.788	0.059		0.174	0.296	0.033
Observations	1905	1321	1321	1321	1903	1319	1319	1319
R^2	0.401	0.437	0.444	0.445	0.3713	0.399	0.406	0.411

* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 5: The Choice Between Cash and Credit Lines - Varying Betas

This table reports regressions of a measure of line of credit usage in corporate liquidity policy on asset (unlevered) beta and controls. *Beta KMV (Industry)* is the value-weighted average (3-digit SIC) industry *Beta KMV*. All other variables are described in Table 1. In columns (1) to (7), beta measures are instrumented with their first two lags. In column (8), we use an industry beta rather than the firm-level instrumented beta in the regression. Robust t-statistics presented in parenthesis.

	Dependent variable: *LC-to-Cash*							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Beta Asset	-0.137***							
	(-6.006)							
Beta Cash		-0.127***						
		(-9.258)						
Beta Bank			-0.291***					
			(-4.952)					
Beta Tail				-0.137***				
				(-7.417)				
Beta Equity					-0.054***			
					(-3.453)			
Beta Gap						-0.010***		
						(-3.428)		
Beta Cash Flow							-0.013***	
							(-4.515)	
Beta KMV (Industry)								-0.029***
								(-4.919)
Profitability	0.042	0.116***	0.078**	0.128***	0.113***	0.117***	0.118***	0.124***
	(0.675)	(5.088)	(2.284)	(4.364)	(3.878)	(4.779)	(4.853)	(5.008)
Tangibility	-0.017	-0.004	-0.015	-0.001	0.006	0.025	0.026	0.048**
	(-0.400)	(-0.239)	(-0.629)	(-0.027)	(0.269)	(1.320)	(1.372)	(2.400)
Size	0.042***	0.050***	0.055***	0.059***	0.052***	0.049***	0.049***	0.042***
	(6.965)	(19.963)	(15.334)	(16.679)	(15.804)	(17.865)	(17.905)	(14.520)
Networth	-0.127***	-0.109***	-0.120***	-0.118***	-0.149***	-0.124***	-0.125***	-0.114***
	(-4.169)	(-8.612)	(-6.836)	(-7.169)	(-9.720)	(-9.080)	(-9.162)	(-8.204)
Q	-0.050***	-0.049***	-0.048***	-0.044***	-0.053***	-0.056***	-0.056***	-0.052***
	(-8.136)	(-23.028)	(-12.198)	(-12.330)	(-17.681)	(-25.415)	(-25.507)	(-22.093)
IndSalesVol	-0.341	-0.128	-0.156	-0.174	-0.190	-0.187	-0.172	0.132
	(-1.029)	(-1.066)	(-0.936)	(-1.063)	(-1.207)	(-1.356)	(-1.255)	(0.826)
ProfitVol	-0.315*	-0.013	0.120	0.065	-0.065	-0.254***	-0.254***	-0.198***
	(-1.747)	(-0.199)	(1.168)	(0.797)	(-0.780)	(-3.608)	(-3.592)	(-2.785)
Age	-0.029**	-0.048***	-0.054***	-0.053***	-0.053***	-0.042***	-0.043***	-0.046***
	(-2.064)	(-8.494)	(-6.916)	(-7.005)	(-7.535)	(-6.678)	(-6.710)	(-6.902)
Constant	0.448**	0.614***	0.468***	0.415***	0.477***	0.453***	0.454***	0.362***
	(2.529)	(21.435)	(5.800)	(5.613)	(6.472)	(16.661)	(16.738)	(13.516)
Industry Fixed-effect	Yes	No	Yes	Yes	Yes	No	Yes	No
Year Fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First-stage F-stat p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	
Hansen J-stat p-value	0.158	0.005	0.586	0.000	0.156	0.8728	0.001	
Observations	9536 31811	46865	35499	35343	38397	37485	37485	31811
R^2	0.211	0.162	0.166	0.170	0.166	0.155	0.155	0.166

* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 6: Sorting on proxies for financing constraints and beta

This table reports regressions of a measure of line of credit usage in corporate liquidity policy on different proxies for asset beta and controls. The dependent variable is *LC-to-Cash*, defined in Table 1. *Beta KMV* is the firm's asset (unlevered) beta, calculated from equity (levered) betas and a Merton-KMV formula. *Var KMV* is the corresponding value for total asset variance. *Beta Tail* is a measure of beta that is based on the average stock return of a firm in the days in which the stock market had its worst 5% returns in the year. All beta and variance measures are instrumented with their first two lags. In column (1) we use a sample of small firms (those with Assets in the 30th percentile and lower). In column (2) we use a sample of large firms (those with Assets in the 70th percentile and higher). In column (3) we use a sample of firms with low payouts (those with payout in the 30th percentile and lower). In column (4) we use a sample of firms with high payouts (those with payout in the 70th percentile and higher). In column (5) we use a sample of firms that have neither a bond, nor a commercial paper rating. In column (6) we use a sample of firms that have both bond and commercial paper ratings. In column (7) we use a sample of firms with beta greater than one. In column (8) we use a sample of firms with beta lower than one. Panel A reports results using *Beta KMV*, and Panel B reports results using *Beta Tail.* All other variables are described in Table 1. Robust t-statistics presented in parenthesis.

Panel A - Beta KMV

	(1) Small firms	(2) Large firms	(3) Low payout firms	(4) High payout firms	(5) Non-rated firms	(6) Rated firms	(7) High beta firms	(8) Low beta firms
Beta KMV	-0.236**	-0.002	-0.191***	0.027	-0.069	0.092	-0.348***	0.067
	(-2.077)	(-0.029)	(-3.483)	(0.492)	(-1.467)	(0.789)	(-4.188)	(0.390)
Var KMV	6.628	-6.751**	2.739	-4.972**	-0.634	-14.317*	5.013*	-2.759**
	(1.523)	(-2.387)	(1.260)	(-2.170)	(-0.329)	(-1.706)	(1.883)	(-2.559)
Profitability	0.136*	0.156	0.217***	-0.039	0.029	0.038	0.075	0.067
	(1.663)	(1.560)	(3.882)	(-0.640)	(0.670)	(0.155)	(1.488)	(1.138)
Tangibility	-0.011	-0.003	-0.011	0.036	0.013	0.007	0.001	0.007
	(-0.338)	(-0.080)	(-0.404)	(1.112)	(0.532)	(0.089)	(0.024)	(0.265)
Size	0.109***	0.004	0.072***	0.036***	0.056***	0.010	0.043***	0.042***
	(4.655)	(0.447)	(7.508)	(4.897)	(6.109)	(0.496)	(7.488)	(3.710)
Networth	-0.060**	-0.186***	-0.080***	-0.174***	-0.119***	-0.267***	-0.101***	-0.183***
	(-2.008)	(-4.821)	(-3.463)	(-6.371)	(-6.235)	(-3.478)	(-5.515)	(-6.988)
Q	-0.006	-0.066***	-0.026***	-0.053***	-0.044***	-0.054***	-0.042***	-0.054***
	(-0.458)	(-9.372)	(-4.273)	(-10.778)	(-10.392)	(-3.140)	(-10.105)	(-13.284)
IndSalesVol	0.188	-0.149	0.000	-0.581**	-0.090	0.104	-0.200	-0.190
	(0.668)	(-0.474)	(0.002)	(-2.454)	(-0.494)	(0.199)	(-1.020)	(-0.971)
ProfitVol	-0.201	0.365*	-0.047	0.192	0.164	0.154	0.075	0.148
	(-1.012)	(1.732)	(-0.394)	(1.266)	(1.611)	(0.249)	(0.666)	(1.162)
Age	-0.009	-0.039***	-0.037***	-0.051***	-0.054***	-0.048*	-0.049***	-0.060***
	(-0.521)	(-2.995)	(-3.741)	(-4.793)	(-6.044)	(-1.800)	(-5.357)	(-6.623)
Constant	-0.046	0.819***	0.293**	0.548***	0.437***	0.551***	0.851***	0.487***
	(-0.231)	(5.966)	(2.239)	(4.288)	(4.389)	(2.389)	(9.623)	(5.031)
Industry Fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First-stage F-stat p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Hansen J-stat p-value	0.913	0.001	0.284	0.012	0.400	0.262	0.050	0.498
Observations	8436	12578	14908	14162	22546	4344	15212	20160
R^2	0.105	0.148	0.182	0.170	0.138	0.164	0.187	0.187

* significant at 10%; ** significant at 5%; *** significant at 1%.

Panel B - Beta Tail

	(1) Small firms	(2) Large firms	(3) Low payout firms	(4) High payout firms	(5) Non-rated firms	(6) Rated firms	(7) High Beta firms	(8) Low Beta firms
Beta Tail	-0.228***	-0.019	-0.178***	-0.091**	-0.151***	0.077	-0.574***	-0.162**
	(-4.518)	(-0.385)	(-4.452)	(-2.481)	(-4.556)	(0.736)	(-4.793)	(-2.525)
Var KMV	2.578*	-6.301***	-0.305	-1.787	0.199	-12.204*	1.145	-1.265
	(1.833)	(-3.194)	(-0.260)	(-1.319)	(0.193)	(-1.766)	(0.654)	(-1.260)
Profitability	0.133***	0.161	0.207***	0.013	0.077*	0.061	0.043	0.164***
	(2.621)	(1.589)	(4.448)	(0.228)	(1.943)	(0.248)	(0.919)	(3.255)
Tangibility	-0.010	-0.005	-0.012	0.030	0.005	0.008	-0.003	-0.010
	(-0.353)	(-0.122)	(-0.461)	(0.928)	(0.221)	(0.098)	(-0.101)	(-0.379)
Size	0.109***	0.006	0.070***	0.048***	0.069***	0.006	0.035***	0.064***
	(8.191)	(0.541)	(9.223)	(7.639)	(9.636)	(0.301)	(5.622)	(8.554)
Networth	-0.076***	-0.182***	-0.083***	-0.150***	-0.103***	-0.276***	-0.064***	-0.143***
	(-3.878)	(-4.730)	(-4.063)	(-5.829)	(-5.789)	(-3.430)	(-3.042)	(-6.633)
Q	-0.003	-0.066***	-0.025***	-0.048***	-0.036***	-0.061***	-0.038***	-0.051***
	(-0.520)	(-9.072)	(-4.638)	(-9.650)	(-8.922)	(-4.136)	(-8.973)	(-12.136)
IndSalesVol	0.155	-0.142	0.156	-0.560**	-0.073	0.052	0.056	-0.296
	(0.592)	(-0.450)	(0.724)	(-2.370)	(-0.406)	(0.100)	(0.247)	(-1.599)
ProfitVol	0.012	0.375*	0.079	0.161	0.186**	0.179	0.195	0.146
	(0.095)	(1.793)	(0.773)	(1.062)	(1.972)	(0.291)	(1.606)	(1.297)
Age	-0.023*	-0.038***	-0.043***	-0.050***	-0.057***	-0.050*	-0.047***	-0.058***
	(-1.679)	(-2.956)	(-4.465)	(-4.736)	(-6.458)	(-1.852)	(-4.391)	(-6.768)
Constant	0.047	0.810***	0.334***	0.474***	0.358***	0.600***	1.203***	0.399***
	(0.404)	(5.787)	(2.820)	(3.693)	(3.921)	(2.369)	(10.152)	(4.253)
Industry Fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First-stage F-stat p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Hansen J-stat p-value	0.084	0.001	0.000	0.076	0.000	0.345	0.000	0.0223
Observations	8418	12573	14892	14151	22528	4344	10679	24664
R^2	0.108	0.149	0.184	0.171	0.140	0.164	0.191	0.160

* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 7: Aggregate risk exposure and the cost of credit lines

This table reports regressions of line of credit spreads and fees on systematic risk exposure and controls. *LIBOR* is the level of the LIBOR (in percentage) in the quarter in which a deal was initiated, for each firm. *New LC* is the total size of deals initiated in a firm-year, scaled by assets. All other variables are described in Table 1. All proxies for beta are instrumented with their first two lags. Robust z-statistics presented in parenthesis.

	Dependent variables:					
	All-in drawn spread			Undrawn fee		
	(1)	(2)	(3)	(4)	(5)	(6)
Beta KMV	0.104			0.051***		
	(1.525)			(3.560)		
SysVar KMV		10.029***			3.124***	
		(2.740)			(4.047)	
Beta Tail			0.142**			0.047***
			(2.347)			(4.077)
LIBOR	-0.005	-0.005	-0.001	0.003	0.001	0.005
	(-0.242)	(-0.230)	(-0.051)	(0.631)	(0.188)	(1.291)
New LC	-0.236***	-0.237***	-0.240***	-0.018***	-0.020***	-0.020***
	(-3.355)	(-3.555)	(-3.503)	(-5.102)	(-6.620)	(-6.954)
Profitability	-1.852***	-1.732***	-1.897***	-0.095***	-0.073**	-0.120***
	(-11.885)	(-10.871)	(-12.435)	(-3.163)	(-2.359)	(-4.351)
Tangibility	0.131**	0.142**	0.140**	0.027**	0.030**	0.030**
	(2.192)	(2.390)	(2.367)	(2.205)	(2.451)	(2.555)
Size	-0.368***	-0.362***	-0.376***	-0.046***	-0.044***	-0.049***
	(-45.526)	(-48.126)	(-41.431)	(-27.482)	(-26.389)	(-26.738)
Networth	-1.212***	-1.217***	-1.237***	-0.193***	-0.188***	-0.196***
	(-20.204)	(-21.222)	(-20.412)	(-17.657)	(-18.006)	(-18.657)
Q	-0.150***	-0.164***	-0.154***	-0.036***	-0.038***	-0.035***
	(-10.034)	(-10.493)	(-11.052)	(-12.703)	(-12.967)	(-14.002)
IndSalesVol	0.238	0.219	0.131	-0.057	-0.046	-0.099
	(0.521)	(0.488)	(0.291)	(-0.629)	(-0.512)	(-1.149)
ProfitVol	2.266***	1.823***	2.275***	0.128*	0.047	0.173***
	(6.337)	(4.695)	(7.392)	(1.880)	(0.623)	(2.978)
Constant	4.790***	4.726***	4.828***	0.668***	0.659***	0.683***
	(21.626)	(22.075)	(22.695)	(18.972)	(19.000)	(21.034)
Year Fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes
Fst.-stage F-stat p-val	0.000	0.000	0.000	0.000	0.000	0.000
Hansen J-stat p-value	0.017	0.082	0.652	0.942	0.753	0.381
Observations	6799	6895	6774	5977	6084	5973
R^2	0.559	0.550	0.559	0.404	0.405	0.405

* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 8: Aggregate risk and the choice between cash and credit lines: Time-series tests

This table reports regressions of aggregate credit line initiations and changes in aggregate cash holdings on macroeconomic variables. We estimate the SUR (seemingly-unrelated regression model) in equation (33) in the text. The dependent variable in columns (1) to (3) of Panel A is *LCInitiations*, which is defined as the sum of all credit line initiations in the LPC-Deal Scan sample in a given year, scaled by aggregate assets. The dependent variable in columns (1) to (3) in Panel B is *Change in Cash*, which is defined as the change in aggregate cash holdings in the LPC-Deal Scan sample scaled by aggregate assets, see equation (28) in the text. The dependent variable in columns (4) to (6) of Panel A (Panel B) is the average residual value of *LC Initiations* (*Change in Cash*) after controlling for the firm characteristics in equation (31), excluding Beta and year fixed effects. The independent variables are VIX, the implied volatility on S&P 500 index options, $BankVIX$, the expected volatility on an index of bank stock returns (computed using a GARCH model), *CP Spread*, the 3-month commercial paper-treasury spread, *Real GDP Growth*, and a time trend. All independent variables are lagged one period. Robust z-statistics presented in parenthesis.

	Dependent Variables:					
		LC Initiations			*Resid. LC Init.*	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A:						
VIX_{t-1}	-0.040***		-0.022**	-0.054***		-0.022
	(-3.856)		(-2.259)	(-2.632)		(-1.064)
$Bank\ VIX_{t-1}$		-0.033***	-0.024***		-0.053***	-0.044***
		(-4.944)	(-3.463)		(-4.122)	(-3.005)
$CP\ \ Spread_{t-1}$	0.002	0.007**	0.006*	0.001	0.010	0.008
	(0.459)	(2.116)	(1.887)	(0.122)	(1.503)	(1.309)
$Real\ GDP\ Growth_{t-1}$	0.087*	-0.013	0.013	0.159	-0.002	0.024
	(1.756)	(-0.261)	(0.300)	(1.592)	(-0.022)	(0.252)
$Time\ Trend_{t-1}$	-0.066	0.282**	0.192*	0.429**	0.989***	0.899***
	(-0.631)	(2.430)	(1.726)	(2.051)	(4.412)	(3.847)
$Constant$	0.014***	0.020***	0.021***	0.000	0.013*	0.013**
	(4.512)	(5.733)	(6.580)	(0.023)	(1.860)	(1.989)
Observations	20	20	20	20	20	20
R-squared	0.487	0.598	0.679	0.404	0.566	0.589
		Chg. Cash			*Resid. Chg. Cash*	
Panel B:						
VIX_{t-1}	0.040**		0.054***	0.092**		0.060
	(2.213)		(2.642)	(2.358)		(1.367)
$Bank\ VIX_{t-1}$		0.002	-0.019		0.066**	0.042
		(0.120)	(-1.299)		(2.328)	(1.321)
$CP\ \ Spread_{t-1}$	-0.003	-0.003	0.001	0.006	-0.005	-0.001
	(-0.448)	(-0.383)	(0.078)	(0.449)	(-0.342)	(-0.085)
$Real\ GDP\ Growth_{t-1}$	-0.084	-0.078	-0.143	0.057	0.258	0.186
	(-0.959)	(-0.728)	(-1.498)	(0.301)	(1.246)	(0.907)
$Time\ Trend_{t-1}$	0.058	0.039	0.265	0.223	-0.478	-0.227
	(0.316)	(0.150)	(1.114)	(0.565)	(-0.963)	(-0.447)
$Constant$	0.000	0.007	0.006	-0.024**	-0.035**	-0.036**
	(0.043)	(0.944)	(0.885)	(-2.086)	(-2.303)	(-2.509)
Observations	20	20	20	20	20	20
R-squared	0.240	0.054	0.299	0.240	0.235	0.301

* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 9. Aggregate risk, credit line contractual terms and changes in total debt

This table reports regressions of credit line contractual terms (maturity and spreads) and changes in aggregate debt on macroeconomic variables. In columns (1) and (2), and (3) and (4), we estimate the SUR (seemingly-unrelated regression model) in equation (34) in the text. The dependent variable in columns (1) and (3) is $AverageMaturity$, which is defined as the average maturity (weighted by the size of the facility) in the LPC-Deal Scan sample for each year in the sample period. The dependent variable in columns (2) and (4) is $AverageSpread$, which is defined as the average all-in-drawn spread (weighted by the size of the facility) in the LPC-Deal Scan sample for each year in the sample period. In columns (5) and (6) we estimate a SUR model such as that in equation (33) in the text, replacing $LCInitiations$ with $ChangeinDebt$, which is defined in equation (35) in the text. The variable represents the aggregate change in total debt (short plus long term) in the LPC-Deal Scan sample for each year, scaled by aggregate assets. The independent variables are VIX, the implied volatility on S&P 500 index options, $BankVIX$, the expected volatility on an index of bank stock returns (computed using a GARCH model, $CPspread$, the 3-month commercial paper-treasury spread, *Real GDP Growth*, and a time trend. All independent variables are lagged one period. Robust z-statistics presented in parenthesis.

	Dependent Variables:					
	Avg. Maturity	Avg. Spread	Avg. Maturity	Avg. Spread	Agg. Change in total debt	Agg. Change in total debt
	(1)	(2)	(3)	(4)	(5)	(6)
VIX_{t-1}	-26.192***	1.756**			0.026	
	(-3.808)	(2.284)			(0.668)	
$Bank\ VIX_{t-1}$			-12.269**	0.733		-0.011
			(-2.063)	(1.214)		(-0.390)
$CP\ \ Spread_{t-1}$	-4.475*	0.500*	-2.483	0.382	0.025*	0.027*
	(-1.870)	(1.869)	(-0.817)	(1.238)	(1.809)	(1.832)
$Real\ GDP\ Growth_{t-1}$	55.280*	-4.497	17.584	-2.243	0.601***	0.567***
	(1.661)	(-1.209)	(0.403)	(-0.506)	(3.178)	(2.709)
$Time\ Trend_{t-1}$	-184.984***	2.416	-53.980	-5.414	-0.787**	-0.669
	(-2.650)	(0.310)	(-0.516)	(-0.510)	(-1.984)	(-1.333)
$Constant$	17.892***	0.567**	18.138***	0.590*	-0.002	0.008
	(8.898)	(2.523)	(5.732)	(1.836)	(-0.140)	(0.556)
Observations	20	20	20	20	20	20
R-squared	0.582	0.328	0.405	0.211	0.516	0.509

* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 10: Aggregate Risk and Banks' Liquidity Constraints

This table reports regressions of bank stock return volatility on bank exposure to undrawn corporate credit lines, and other bank-level and macroeconomic variables. The variable definitions follow Gatev, Schuermann, and Strahan (2009). The dependent variable is the annualized monthly average of bank squared returns. $Commitments_{t-1}$ is the lagged ratio of undrawn credit lines for each bank, divided by the sum of undrawn credit lines plus other loans. Retail loan commitments are excluded from both the numerator and denominator. $Deposit\ Base_{t-1}$ is the lagged ratio of transaction deposits to total deposits.Paper-Bill spread is the spread on 3-month commercial paper rates over treasuries.High (Low)-VIX months are those with the 20% highest (lowest) values of VIX in the sample. T-statistics are reported in parenthesis. Standard errors are clustered by bank.

	Dependent variable: *Annualized monthly average of bank squared returns*							
	High VIX periods				Low VIX periods			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Commitments_{t-1}$	0.494**	0.530**	0.534*	0.931**	-0.129	0.007	-0.121	-0.057
	(2.195)	(2.008)	(1.976)	(2.398)	(-0.624)	(0.032)	(-0.509)	(-0.142)
$Commitments_{t-1}$ ×				-2.529				-0.301
$Deposit\ base_{t-1}$				(-1.498)				(-0.240)
$Deposit\ base_{t-1}$				0.018				0.071
				(0.038)				(0.181)
$Log(VIX)_{t-1}$		0.843***	0.846***	0.859***		0.287	0.299	0.304
		(10.166)	(10.226)	(10.431)		(1.413)	(1.547)	(1.615)
Paper bill spread		-0.080	-0.080	-0.075		-0.068	-0.052	-0.050
		(-1.324)	(-1.331)	(-1.255)		(-0.684)	(-0.528)	(-0.531)
Yield on 3-month T-bill		0.084***	0.086***	0.092***		-0.043**	-0.034*	-0.034*
		(7.724)	(7.300)	(7.611)		(-2.205)	(-1.791)	(-1.808)
Log of assets		-0.031	-0.029	-0.030		-0.069***	-0.068***	-0.069**
		(-1.142)	(-1.000)	(-1.120)		(-2.857)	(-2.624)	(-2.471)
$(Cash + securities)/assets$			0.013	0.031			0.388	0.383
			(0.057)	(0.148)			(1.353)	(1.323)
Equity/assets			0.353	0.319			-0.382	-0.389
			(0.828)	(0.776)			(-0.982)	(-1.013)
Constant	-1.226***	-3.948***	-4.041***	-4.093***	-1.573***	-1.020	-1.156*	-1.162*
	(-21.810)	(-7.495)	(-6.981)	(-7.593)	(-25.948)	(-1.643)	(-1.750)	(-1.758)
Observations	1,600	1,600	1,600	1,600	1,590	1,590	1,561	1,561
R^2	0.024	0.143	0.144	0.157	0.002	0.045	0.064	0.064

* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 11. Covenant violations and aggregate risk

This table reports fixed-effect regressions of covenant violations on firm characteristics. The dependent variable is *Covenant Violation*, which is a dummy indicating whether there was a covenant violation in that firm-year. All regressions include firm fixed effects. The sample is restricted to firm-years in which the firm has a credit line. Thus, the regressions measure the effect of a change in firm characteristics and VIX on the probability of covenant violations. The variables are described in Table 1, Panel B (Sufi's sample).

	Dependent Variables: *Covenant Violation*				
	(1)	(2)	(3)	(4)	(5)
$EBITDA_t/Assets_{t-1}$	-0.586***	-0.585***	-0.947	-0.555***	-0.695***
	(-5.143)	(-4.642)	(-1.628)	(-4.299)	(-4.663)
$Debt_t/Assets_t$	0.402*	0.404	0.401	0.363*	0.341
	(1.791)	(1.642)	(1.627)	(1.670)	(1.583)
$Networth_t/Assets_t$	-0.175	-0.174	-0.177	-0.154	-0.174
	(-0.829)	(-0.747)	(-0.759)	(-0.727)	(-0.839)
Q	-0.007	-0.006	-0.006	-0.009	-0.010
	(-0.746)	(-0.669)	(-0.630)	(-0.992)	(-1.067)
Size	0.040*	0.040	0.036	0.053**	0.053**
	(1.833)	(1.494)	(1.330)	(2.205)	(2.203)
VIX		0.000	-0.002		
		(0.097)	(-0.352)		
$VIX * EBITDA_t/Assets_{t-1}$			0.014		
			(0.626)		
Beta KMV				-0.012	-0.023
				(-0.955)	(-1.522)
$Beta\ KMV * EBITDA_t/Assets_{t-1}$					0.103**
					(2.193)
Constant	-0.041	-0.045	0.028	-0.107	-0.070
	(-0.210)	(-0.208)	(0.111)	(-0.504)	(-0.334)
Year Fixed-effect	Yes	No	No	Yes	Yes
Firm Fixed-effect	Yes	Yes	Yes	Yes	Yes
Observations	1,425	1,425	1,425	1,186	1,186
R-squared	0.103	0.382	0.383	0.096	0.100

* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 12. Credit line revocations and aggregate risk

This table reports regressions of measures of credit line availability on covenant violations, firm characteristics and VIX. The sample is restricted to firm-years in which a credit line was presented in year t-1. In Panel A the dependent variable is *Unused LC-to-Assets*, the ratio of unused credit lines to lagged assets. All regressions in Panel A include firm fixed effects. The variables in Panel A are described in Table 1, Panel B (Sufi's sample). In Panel B we consider alternative measures of credit line revocations. In columns (1) and (2) the dependent variable is *Revocation Total*, which is equal to the decrease in the amount of total credit lines in year t relative to year t-1, minus the dollar amount of credit lines that matures in year t. In column (3) we use the variable *Revocation Dummy Total*, which is a dummy variable that takes the value of one for firm-years in which *Revocation Total* is positive (that is, there is a reduction in availability of existing credit lines that have not yet matured). In columns (4) and (5) we use the variable *Revocation Unused*, which is the equivalent of *Revocation Total*, but based on changes in unused credit lines. We use the dummy variable *Revocation Dummy Unused* in column (6), which is the equivalent of *Revocation Dummy Total*, but based on changes in unused credit lines. The sample in columns (2), (3), (5) and (6) is restricted to firm-years with no credit line initiations. Firm-level controls are all in differenced form (the change in year t relative to year t-1). The data on changes in total and unused credit lines are drawn from Sufi (2009), and described in Table 1, Panel B. The data required to compute maturing credit lines and credit line initiations is drawn from LPC-Deal Scan, described in Table 1, Panel A

Panel A

	Dependent Variables: *Unused LC-to-Assets*				
	(1)	(2)	(3)	(4)	(5)
Covenant Violation$_{t-1}$	-0.041***	-0.041***	-0.081	-0.040***	-0.043***
	(-3.411)	(-3.041)	(-0.719)	(-3.768)	(-3.221)
$EBITDA_{t-1}/Assets_{t-2}$	0.095**	0.091*	0.090*	0.062	0.062
	(2.135)	(1.784)	(1.775)	(1.355)	(1.356)
$Debt_{t-1}/Assets_{t-1}$	0.048	0.040	0.040	0.064	0.063
	(0.365)	(0.266)	(0.266)	(0.406)	(0.396)
$Networth_{t-1}/Assets_{t-1}$	0.048	0.041	0.042	-0.012	-0.013
	(0.503)	(0.392)	(0.393)	(-0.156)	(-0.171)
Q_{t-1}	0.007	0.007	0.007	0.007	0.007
	(1.182)	(1.001)	(0.997)	(1.027)	(1.029)
$Size_{t-1}$	-0.120***	-0.117***	-0.117***	-0.089***	-0.089***
	(-4.143)	(-3.501)	(-3.511)	(-3.465)	(-3.464)
VIX_{t-1}		-0.001	-0.001		
		(-0.495)	(-0.552)		
$VIX_{t-1} * Covenant\ Violation_{t-1}$			0.002		
			(0.355)		
$Beta\ KMV_{t-1}$				0.001	0.001
				(0.229)	(0.138)
$Beta\ KMV_{t-1} * Covenant\ Violation_{t-1}$					0.004
					(0.529)
Constant	0.754***	0.760***	0.762***	0.617***	0.618***
	(5.435)	(4.907)	(4.897)	(4.459)	(4.452)
Year Fixed-effect	Yes	No	No	Yes	Yes
Firm Fixed-effect	Yes	Yes	Yes	Yes	Yes
Observations	1,206	1,206	1,206	1,010	1,010
R-squared	0.170	0.607	0.607	0.131	0.131

* significant at 10%; ** significant at 5%; *** significant at 1%.

Panel B

	Dependent Variables:					
	Revocation Total		*Revocation Dummy Total*	*Revocation Unused*		*Revocation Dummy Unused*
	(1)	(2)	(3)	(4)	(5)	(6)
$Covenant\ Violation_{t-1}$	0.044**	0.039*	0.178***	0.009	0.013	0.088
	(2.104)	(1.815)	(2.780)	(0.502)	(0.731)	(1.478)
Vix_{t-1}	0.001	0.001	0.007	0.001	-0.000	-0.001
	(0.672)	(0.532)	(1.413)	(0.468)	(-0.093)	(-0.163)
$\Delta EBITDA_{t-1}/Assets_{t-1}$	0.093	0.050	0.072	-0.022	-0.006	-0.155
	(1.227)	(0.682)	(0.373)	(-0.316)	(-0.078)	(-0.775)
$\Delta Debt_{t-1}/Assets_{t-1}$	0.340***	0.250**	0.545	0.050	-0.033	0.060
	(3.215)	(2.201)	(1.639)	(0.488)	(-0.299)	(0.142)
$\Delta Networth_{t-1}/Assets_{t-1}$	0.084	0.069	0.058	-0.028	-0.047	-0.085
	(0.870)	(0.632)	(0.220)	(-0.264)	(-0.398)	(-0.259)
ΔQ_{t-1}	-0.015**	-0.010	-0.041**	-0.004	-0.007	-0.003
	(-2.220)	(-1.566)	(-2.070)	(-0.717)	(-1.084)	(-0.138)
$\Delta Size_{t-1}$	-0.086***	-0.057**	-0.103	-0.001	-0.009	-0.077
	(-3.816)	(-2.336)	(-1.447)	(-0.033)	(-0.440)	(-1.337)
Constant	-0.092*	-0.078	0.123	-0.072*	-0.039	0.396***
	(-1.871)	(-1.363)	(0.955)	(-1.882)	(-0.870)	(3.014)
Observations	877	700	700	877	700	700
R-squared	0.038	0.025	0.042	0.005	0.003	0.010

* significant at 10%; ** significant at 5%; *** significant at 1%.

Figure 1: Timeline of the model

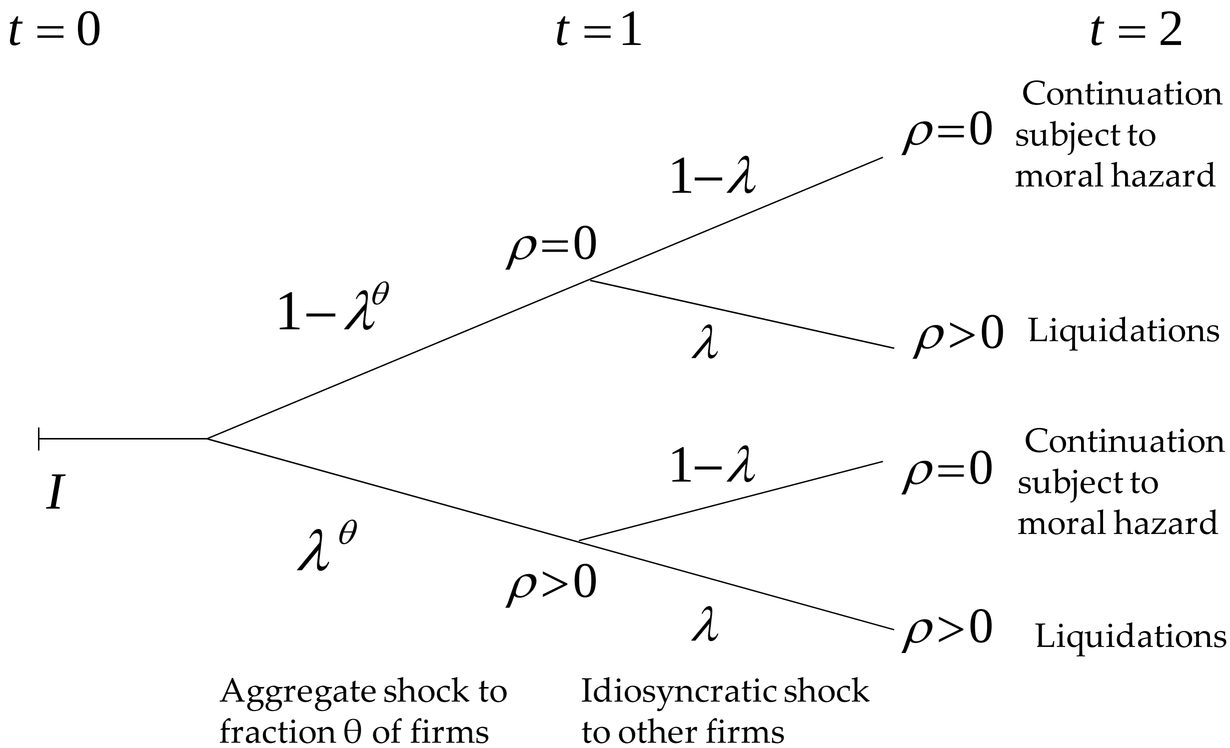

Figure 2: Equilibrium with cash holdings for systematic firms when systematic risk is high ($\theta \geq \theta^{max}$)

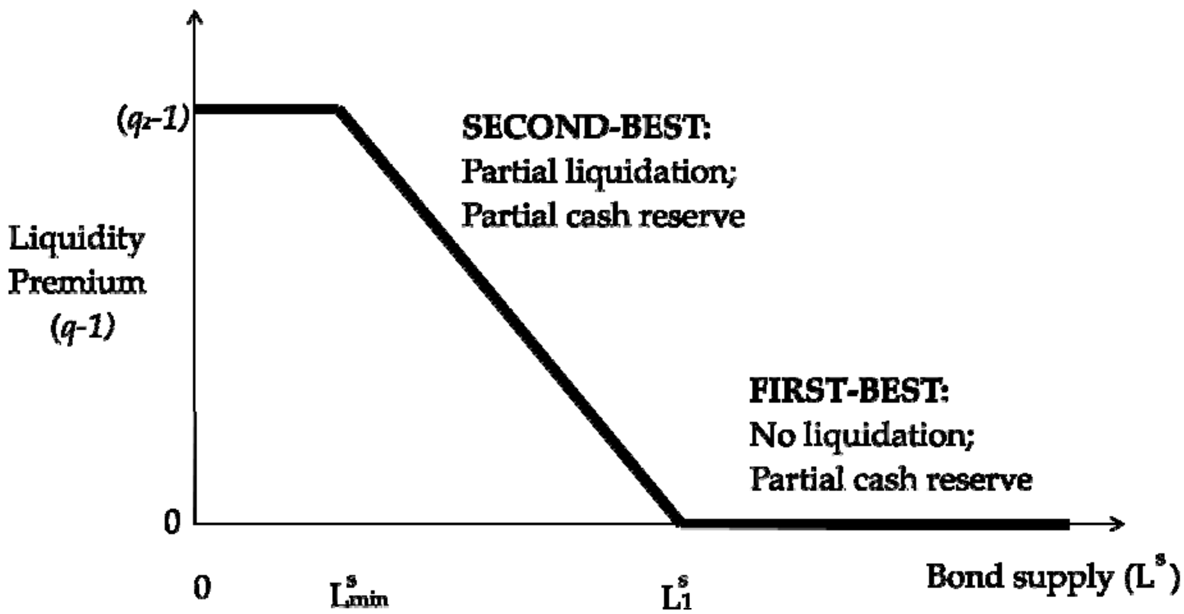

Figure 3: Average *LC-Cash* ratios for different quintiles of *Beta KMV*

This figure reports the average *LC-Cash* ratio for firms in different quintiles of *Beta KMV*. The sample is sorted into quintiles based on the average value of *Beta KMV* for each firm during the entire sample period. Then, we calculate the average value of the *LC-Cash* ratio in each of these quintiles of beta.

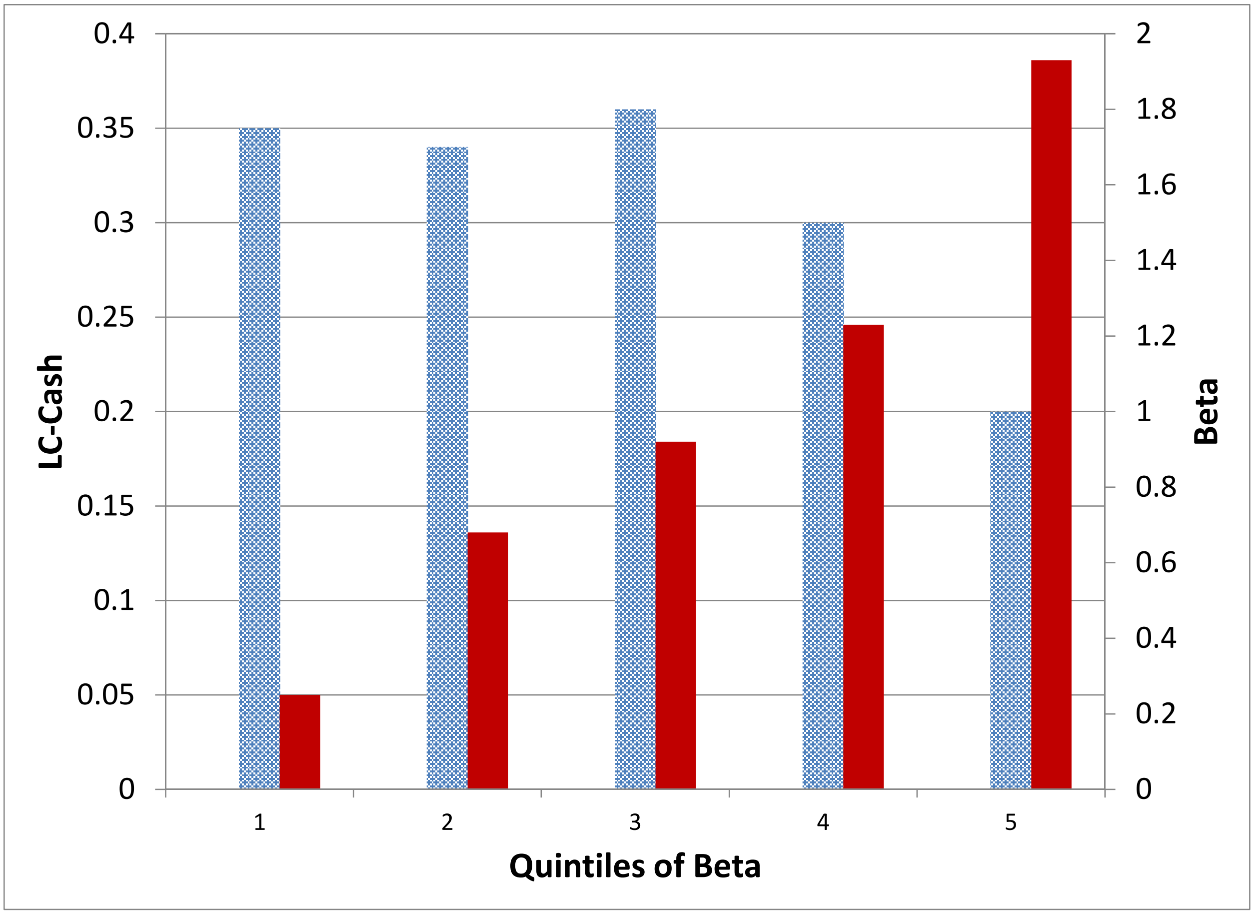

Figure 4: Aggregate risk and time series changes in cash and credit line initiations

This figure reports changes in aggregate credit line initiations and changes in aggregate cash holdings. *LC Initiations* is defined as the sum of all credit line initiations in the LPC-Deal Scan sample in a given year, scaled by aggregate assets. *Change in Cash* is defined as the change in aggregate cash holdings in the LPC-Deal Scan sample scaled by aggregate assets. *VIX* is the implied volatility on S&P 500 index options, lagged one period (VIX is divided by 10 in this figure).

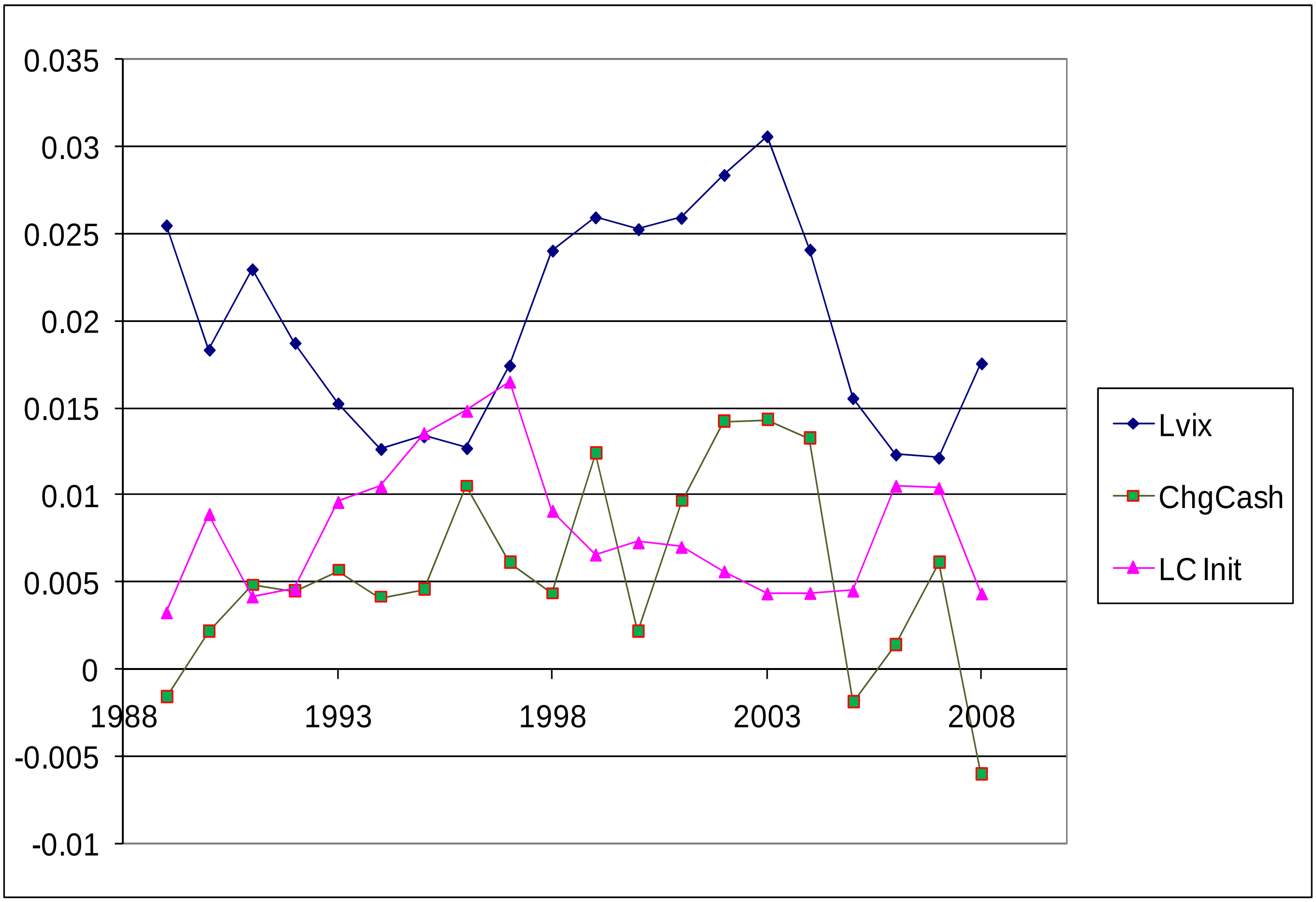

Figure 5: Aggregate risk and time series changes in credit line contractual terms

This table reports over-time changes in credit line contractual terms (maturity and spreads). *Average Maturity* is defined as the average maturity (weighted by the size of the facility) in the LPC-Deal Scan sample for each year in the sample period. *Average Spread* is defined as the average all-in-drawn spread (weighted by the size of the facility) in the LPC-Deal Scan sample for each year in the sample period. It is expressed in basis points and divided by 10. *VIX* is the implied volatility on S&P 500 index options, lagged one period. *VIX* is expressed in percentage points, and divided by two.