Aggregate Risk and the Choice between Cash and Lines of Credit*

Viral V. Acharya
NYU–Stern, CEPR,
ECGI & NBER
vacharya@stern.nyu.edu

Heitor Almeida
University of Illinois
& NBER
halmeida@illinois.edu

Murillo Campello
University of Illinois
& NBER
campello@illinois.edu

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 spreads 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. Our theory and evidence shed new insights on the relation between macroeconomic risk, financial intermediation, and firm financial decisions.

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 spreads 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. Our theory and evidence shed new insights on the relation between macroeconomic risk, financial intermediation, and firm financial decisions.

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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*

1 Introduction

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) and Disatnik, Duchin, and Schmidt (2010)). The available evidence further suggests that credit lines played a crucial role in the liquidity management of industrial 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 future debt issuances. However, these alternatives expose the firm to additional risks because their availability depends directly 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 expect to 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 model is that a firm's exposure to aggregate risks — its "beta" — is a fundamental determinant of liquidity choices.

[1] A recent paper by Bolton, Chen, and Wang (2009) 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)).

The intuition for our main result 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 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 shortfall. 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 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 these basic results, the model generates a number of new 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 model implies that the lines of credit should be more expensive for firms with greater aggregate risk and in times of higher aggregate volatility.

We test our model's 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 states 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," we note that cash flow-based measures are slow-moving and available only at low frequency. Under the 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.[3] For robustness, however, we also use cash flow-based betas. 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 would then bias our estimates of the effect of betas on corporate liquidity management. To overcome this problem, we unlever equity betas in two alternative ways. First, we back out and eliminate the leverage effect using a Merton-KMV-type model for firm value. Second, we compute betas using data on firm *asset returns*. Our data on

[2] To be precise, we use a panel dataset to test the model's cross-sectional implications. Since most of the variation in our proxies for systematic risk exposure is cross-sectional in nature, we refer to this analysis as "cross-sectional" to clearly distinguish from the time-series analysis.

[3] In addition, we use a "tail beta" that essentially uses data from the days with the 5% 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 are likely to be in trouble).

this alternative beta proxy come from Choi (2009), who computes bond and bank loan returns and combines them with stock returns into an asset return measure that uses relative market values of the different financial claims as weights. We also tease out the relative importance of systematic and idiosyncratic risk for corporate liquidity policy. We do this by decomposing total asset risk on its systematic and idiosyncratic components. The systematic component is estimated as squared asset beta times the unlevered variance of market returns. The idiosyncratic component is equal to total variance minus the systematic component.

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, while the idiosyncratic component is positively related to this ratio. These findings support our theory's prediction that firms use credit lines to manage idiosyncratic risk, but they are increasingly likely to use cash as systematic risk exposure increases. 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. Importantly, 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 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). Our model also suggests that firms with high aggregate risk exposure hold more cash because it is more costly for banks to provide them with liquidity. To investigate this channel, we study the relation between firms' beta and the spreads that they commit to pay on bank lines of credit. Indeed, we find that high beta firms pay significantly higher spreads when opening and drawing on their credit lines.

Finally, we examine our model's time-series implications. Our macro time-series 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. Since there is no available historical data on implied volatility for the banking sector, we construct expected banking sector volatility using a GARCH model. We call this variable *Bank VIX*.

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.

Our work has strong connections with recent literature that discusses firms' liquidity choices and it is important that we highlight our contributions. Sufi (2009) examines the choice between cash and credit lines and shows that firms that are at risk of losing access to those facilities due to a covenant violation and firms with more cash flow volatility are less likely to use credit lines. Campello, Giambona, Graham, and Harvey (2010) study survey data collected during the financial crisis and describe how cash flows and cash stocks influence firms' demand for credit lines. The authors show that the relation between cash flows and lines of credit is modulated by the level of cash savings: profitable firm are less (more) likely to use credit lines when they have more (less) cash. Looking at international survey data, Lins, Servaes, and Tufano (2010) document that cash and credit lines are used for different purposes. Managers say that non-operational cash is used to guard against future cash flow shocks in bad times, while credit lines are used to fund business opportunities that arise in good times. Disatnik, Duchin, and Schmidt (2010) investigate the role of hedging in shaping firms' liquidity preferences. The authors point to the importance of hedging in reducing firms' precautionary demand for cash and increasing preference towards credit lines.

While our work relates to this growing empirical literature, we are the first to advance and test a full-fledged theory explaining how corporate exposure to aggregate risk drives the choice between cash and credit lines. 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.[4] 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 3. Section 4 offers concluding remarks.

2 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 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.[5] 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 –

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

[5] In Tirole (2006), the firm has date-0 wealth A but this plays no significant role in our model. Hence, we have set it equal to zero.

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:

$$\begin{aligned} p_G R_M &\geq p_B R_M + B, \text{ or} \\ R_M &\geq \frac{B}{\Delta p}, \end{aligned} \tag{1}$$

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:

$$\rho_0 \equiv p_G(R - \frac{B}{\Delta p}) < \rho_1 \equiv p_G R. \tag{2}$$

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:

$$\rho_0 < \rho < \rho_1. \tag{3}$$

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. In particular, in the absence of liquidity management we would have $x^* = 0$ (since $x\rho > x\rho_0$ for all positive x). In particular, firms have a shortfall equal to $x(\rho - \rho_0)$ when hit by a liquidity shock. 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.

In other words, 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:

$$I < (1 - \lambda)\rho_0 + \lambda(\rho_0 - \rho). \tag{4}$$

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

2.1 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:

$$w(x) \geq x(\rho - \rho_0). \tag{5}$$

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:

$$y + p_G D \leq \rho_0. \tag{6}$$

The intermediary's break even constraint is:

$$I + \lambda x(\rho - \rho_0) \leq (1 - \lambda)\rho_0. \tag{7}$$

Finally, the firm's payoff is:

$$U(x) = (1 - \lambda)\rho_1 + \lambda(\rho_1 - \rho)x - I. \tag{8}$$

Given assumption (4), equation (7) 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:

$$(1-\theta)(1-\lambda)\rho_0 \geq [\theta + (1-\theta)\lambda]\,(\rho - \rho_0). \tag{9}$$

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 (4) 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 $\theta^{\max}$ is given by the condition:*

$$\theta^{\max} = \frac{\rho_0 - \lambda\rho}{(1-\lambda)\rho}. \tag{10}$$

2.2 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 contribution of our paper.

2.2.1 Firms' optimization problem

In order to characterize the different equilibria, we start by introducing some notation. We let L^{θ} (alternatively, $L^{1-\theta}$) represent the liquidity 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 (under their preferred liquidity policy). 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. This assumption implies that the credit line contract is also indexed by firm type; specifically, $(D^{\theta}, w^{\theta}, y^{\theta})$ 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 liquid funds and explain later why this is in fact the equilibrium outcome in the model.

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:

$$\begin{aligned} w^i + L^i &= x^i(\rho - \rho_0) \\ I + qL^i + \lambda w^i &= (1-\lambda)(L^i + y^i + p_G D^i) \\ y^i + p_G D^i &\leq \rho_0. \end{aligned} \tag{11}$$

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 liquid 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 liquid 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:

$$\theta[x^\theta(\rho - \rho_0) - L^\theta] + (1-\theta)\lambda[x^{1-\theta}(\rho - \rho_0) - L^{1-\theta}] \leq (1-\theta)(1-\lambda)[L^{1-\theta} + \rho_0]. \tag{12}$$

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 follows:

$$w^\theta \leq w^{\max}. \tag{13}$$

We can collapse the constraints in (11) into a single constraint, and thus write the firm's optimization problem as follows:

$$\begin{aligned} \max_{x^i, L^i} U^i &= (1-\lambda)\rho_1 + \lambda(\rho_1 - \rho)x^i - (q-1)L^i - I \quad \text{s.t.} \\ I + (q-1)L^i + \lambda x^i \rho &\leq (1-\lambda)\rho_0 + \lambda x^i \rho_0 \\ w^\theta &\leq w^{\max} \end{aligned} \tag{14}$$

This optimization problem determines firms' optimal cash holdings and continuation investment, which we write as 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:

$$\theta L^{\theta}(q) + (1-\theta)L^{1-\theta}(q) \leq L^{s}. \tag{15}$$

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

2.2.2 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 (14), 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 (14) 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 (12) in simpler form as:

$$\begin{aligned} \theta[x^{\theta}(\rho - \rho_0) - L^{\theta}] + (1-\theta)\lambda(\rho - \rho_0) \quad &\leq \quad (1-\theta)(1-\lambda)\rho_0, \text{ or} \\ x^{\theta}(\rho - \rho_0) - L^{\theta} \quad &\leq \quad \frac{(1-\theta)(\rho_0 - \lambda\rho)}{\theta} \equiv w^{\max}. \end{aligned} \tag{16}$$

Thus, the maximum size of the credit line for systematic firms is $w^{\max} = \frac{(1-\theta)(\rho_0 - \lambda\rho)}{\theta}$. 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 (4), 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 the appendix.

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

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:*

$$q_1 = 1 + \frac{\rho_0 - \lambda\rho - I}{\rho - \rho_0 - w^{\max}}, \tag{17}$$

$$q_2 = 1 + \frac{\lambda(\rho_1 - \rho)}{\rho - \rho_0}. \tag{18}$$

Then, x^θ satisfies:

$$
\begin{aligned}
x^\theta(q) &= 1 \textit{ if } q \leq \min(q_1, q_2) \\
&= \frac{(1-\lambda)\rho_0 - I + (q-1)w^{\max}}{(\lambda + q - 1)(\rho - \rho_0)} \textit{ if } q_2 \geq q > q_1 \\
&\in [0,1] \textit{ (indifference over entire range) if } q_1 > q = q_2 \\
&= 0 \textit{ if } q > q_2.
\end{aligned}
\tag{19}
$$

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

$$L^\theta(x^\theta) = x^\theta(\rho - \rho_0) - w^{\max}, \tag{20}$$

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

2.2.3 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:

$$\theta L^\theta(q) = \theta[x^\theta(q)(\rho - \rho_0) - w^{\max}] \leq L^s. \tag{21}$$

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:

$$\theta[(\rho - \rho_0) - w^{\max}] = L_1^s(\theta). \tag{22}$$

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 (21) holding with equality (such that the demand for cash equals the reduced supply):[6]

$$\theta[x^\theta(q^*)(\rho - \rho_0) - w^{\max}] = L^s. \tag{23}$$

2.3 Summary of results

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

Proposition 2 *When firms can choose between both cash holdings and bank-provided lines of credit, the following equilibria are possible depending on the extent of aggregate risk and the supply of liquid assets in the economy:*

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 can 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 will be more likely to hold cash (relative to credit lines) in their liquidity management. The bank's liquidity constraint requires that credit line contracts discriminate between idiosyncratic and systematic risk. There are two sub-cases to consider, which vary 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 investment distortions. 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.*

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

– 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).

2.4 Empirical implications

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

1. *A firm's exposure to systematic risk is an important determinant of whether it manages its future liquidity needs through cash reserves or bank-provided lines of credit.* In particular, an increase in a firm's exposure to aggregate risk should increase its propensity to use cash for corporate liquidity management, relative to credit lines. 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. *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 bank's liquidity constraint requires that credit line contracts discriminate between idiosyncratic and systematic risk. In particular, 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 spreads, after controlling for firm characteristics and other credit line contractual terms.

5. *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.[7] 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. 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.[8] We test this implication by examining how aggregate cash holdings and credit line initiations change with aggregate risk. We measure aggregate risk using *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.

6. *An increase in the amount of systematic risk in the economy worsens firms' contractual terms when raising bank credit lines.* In the model, an increase in the cost of credit lines is the mechanism that induces firms to shift into cash for their liquidity management. Thus, when aggregate risk increases, credit line contractual terms worsen.[9] We test this implication by examining how credit line spreads and maturities change with changes in economy-wide (*VIX*), and banking sector (*Bank VIX*) aggregate risk.[10]

[7] Recall that in the model, economy-wide aggregate risk is captured by the fraction of firms that are systematic, θ.

[8] As explained above, the aggregate demand for credit lines is a decreasing function of θ.

[9] Specifically, as the demand for cash increases the liquidity premium goes up. Thus, credit line terms must worsen in equilibrium.

[10] 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.

3 Empirical tests

3.1 Sample selection criteria

The main implication of our model is that firms are more likely to use cash in their liquidity management if they are subject to a greater amount of systematic risk. 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 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. In addition, this allows us to document that several previously reported patterns prevail in both samples.

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).[11] 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 (fees and interests) annual spread paid over LIBOR for each dollar drawn down from the facility. *Undrawn spread* is the total (fees and interest) annual spread over LIBOR, 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.

[11] 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.

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. 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.

3.2 Variable definitions

Our tests combine data that comes from multiple sources. It is useful to explain in detail how we construct our variables.

3.2.1 COMPUSTAT variables

We follow Sufi (2009) in the definitions of the variables that we use 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, $(Assets + prcc\_fc{\times}sho - ceq)/Assets$.[12] *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.

3.2.2 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 both total and unused credit lines:

$$Total\ LC\text{-}to\text{-}Cash_{i,t} = \frac{Total\ Line_{i,t}}{Total\ Line_{i,t} + Cash_{i,t}}, \tag{24}$$

[12] 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.

$$Unused\ LC\text{-}to\text{-}Cash_{i,t} = \frac{Unused\ Line_{i,t}}{Unused\ Line_{i,t} + Cash_{i,t}}. \quad (25)$$

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. This calculation assumes that LCs remain open until they mature. Specifically, we define our measure of line of credit availability for each firm-quarter (j, s) as:

$$Total\ LC_{j,s} = \sum_{t \leq s} LC_{j,t} \Gamma(Maturity_{j,t} \geq s - t), \quad (26)$$

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 $Total\ LC$ in each year.

We then measure the fraction of corporate liquidity that is provided by investment-related lines of credit for firm j in quarter s using the following variable:

$$LC\text{-}to\text{-}Cash_{j,t} = \frac{Total\ LC_{j,t}}{Total\ LC_{j,t} + Cash_{j,t}}. \quad (27)$$

This ratio is closely related to the *Total LC-to-Cash* ratio of equation (24).

In addition, to examine the time-series impact of systematic risk on liquidity management we construct aggregate changes in credit lines and cash as follows:

$$\begin{aligned} LC\ Initiation_t &= \frac{\sum_j LC_{j,t}}{\sum_j at_{j,t}}, \quad (28) \\ Change\ in\ Cash_t &= \frac{\sum_j (Cash_{j,t} - Cash_{j,t-1})}{\sum_j at_{j,t}}. \end{aligned}$$

These ratios capture the economy's total demand for cash and credit lines in a given year, scaled by total assets.

3.2.3 Data on betas and variances

We measure firms' exposure to systematic risk using asset (unlevered) betas.[13] 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*).

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

We unlever equity betas in two alternative ways. 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 appendix details the procedure that we used to compute this set of asset betas and volatilities.

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.[14] The firm-level asset return measure 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. 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. Notice that this possibility would make it *less* likely for us to find a positive relation between asset betas and cash. However, we also verify whether this effect has a significant bearing on our results by computing 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 further mitigate endogeneity. Specifically, we measure *Beta Cash* as the median cash-adjusted asset beta in the firm's 3-digit SIC industry.

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. We compute this beta 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*.

In the model, a firm's exposure to systematic risks matters mostly on the downside (because a

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

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 *Tail Beta*. The firm's 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*.

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 to alternative beta proxies. First, 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 (*at*).[15] 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.[16] Second, we use a similar procedure to compute an industry-level cash flow beta. 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.

3.2.4 Decomposing total risk into idiosyncratic and systematic components

In addition to using asset and cash flow betas to measure systematic risk exposure, we also attempt to tease out the relative importance of systematic and idiosyncratic risk for corporate liquidity policy. We do this 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

[15] We use COMPUSTAT item *capx* to measure investment (*ib*), and define cash flow as earnings before extraordinary items (*ib*).

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

estimated as:[17]

$$SysVar\ KMV_{j,t} = (Beta\ KMV_{j,t})^2 \times \overline{Var\ KMV_t}, \tag{29}$$

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 the asset variance that is not explained by the market:

$$IdVar\ KMV_{j,t} = Var\ KMV_{j,t} - SysVar\ KMV_{j,t}. \tag{30}$$

3.2.5 Addressing measurement error

One common shortcoming of the measures of systematic risk that we construct is that they are noisy and subject to measurement error. While this problem cannot be fully resolved, it 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 (our beta proxy) 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.[18] 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.

3.2.6 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.[19] Appendix D details the procedure that we use.

[17] We focus on the KMV measures to decompose variances, but the results are robust across different measures.

[18] 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.

[19] We also use a Risk Metrics procedure to compute expected volatility, and obtain virtually identical results.

3.3 Empirical tests and results

3.3.1 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 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 –

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*, *SysVar KMV* and *IdVar 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.

3.3.2 Firm-level regressions

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

$$\begin{aligned} \textit{LC-to-Cash}_{i,t} \;=\; & \alpha + \beta_1 \textit{BetaKMV}_{i,t} + \beta_2 \ln(\textit{Age})_{i,t} + \beta_3 (\textit{Profitability})_{i,t-1} \\ & + \beta_4 \textit{Size}_{i,t-1} + \beta_5 Q_{i,t-1} + \beta_6 \textit{Networth}_{i,t-1} + \beta_7 \textit{IndSalesVol}_{j,t} \\ & + \beta_8 \textit{ProfitVol}_{i,t} + \sum_t \textit{Year}_t + \epsilon_{i,t}, \end{aligned} \tag{31}$$

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 Sections 3.2.3 and 3.2.4). 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. Since *Var KMV* contains both systematic and idiosyncratic risk, it is not clear which type of risk explains this negative coefficient.

– Table 3 about here –

Next, we introduce our measures of systematic and idiosyncratic 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 columns (4) and (5) we introduce *SysVar KMV* and *IdVar KMV* in the regressions. The results suggest that while systematic risk exposure is negative correlated to the *LC-to-Cash* ratio, idiosyncratic risk is positively correlated with the use of credit lines in corporate liquidity policy. Finally, in columns (5) and (6) we report results of specifications that include both *Beta KMV* and *Var KMV* (column (5)), and *SysVar KMV* and *IdVar KMV* together in the same regressions. The results support our model's implication that systematic risk exposure reduces firms' reliance on credit lines for liquidity management. In addition, the evidence suggests that idiosyncratic risk exposure is positively correlated with the usage of credit lines.

Table 4 uses Sufi's (2009) measures of *LC-to-Cash* rather than LPC-DealScan data. In Panel A we use *Total LC-to-Cash*, and in Panel B we use *Unused LC-to-Cash.* Column (1) in both tables replicates 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, aggregate, and idiosyncratic 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 (3) and (6)) and *SysVar KMV* (columns (4) and (7)) to proxy for systematic risk exposure. Idiosyncratic risk exposure is positively correlated to credit line usage, though statistical significant is weaker than in Table 3 (t-statistics are close to 1.6 for *IdVar KMV*). These results suggest that the relation between systematic risk exposure and liquidity management that we uncover in this paper is economically significant and robust to different ways of computing exposure to systematic risk and reliance on credit lines.[20]

– Table 4 about here –

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.

Tables 5 and 6 replace *Beta KMV* with our alternative beta measures.[21] Table 5 shows the results for the LPC-DealScan sample, while Table 6 shows the results for Sufi's (2009) sample. 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

[20] 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.

[21] We obtain similar results when using *SysVar KMV* to measure systematic risk exposure.

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. In column (6) 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). The results again suggest a significant relation between asset beta and the *LC-to-Cash* ratio. Columns (7) and (8) replace market-based beta measures with cash flow-based betas (*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.[22]

– Table 5 about here –

Table 6 replicates the analysis in Table 5 for Sufi's (2009) sample. The results show that the relation between beta and liquidity management also holds when using that sample, for both measures of liquidity management (using total and unused credit lines). The only difference between the results in Table 5 and Table 6 is that in some cases the statistical significance of the beta coefficients is lower in Table 6 (such as for *Beta Bank* and *Beta Gap*). This difference is probably due to the decrease in the number of observations in Table 6.

– Table 6 about here –

3.3.3 Sorting firms according to proxies for financing constraints

One of the implications of the model in Section 2 is that the choice between cash and credit lines should be most relevant for firms that are financially constrained. 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 this section we employ specifications in which we sort firms into "financially constrained" and "financially unconstrained" categories. We do not have strong priors about which approach is best and follow prior studies in using multiple alternative schemes to partition our sample:

[22] 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%.

- Scheme #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. The intuition that financially constrained firms have significantly lower payout ratios follows from Fazzari et al. (1988), among many others, in the financial constraints literature. In the capital structure literature, Fama and French (2002) use payout ratios as a measure of difficulties firms may face in assessing the financial markets.

- Scheme #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. This approach resembles that of Gilchrist and Himmelberg (1995), who also distinguish between groups of financially constrained and unconstrained firms on the basis of size. Fama and French (2002) and Frank and Goyal (2003) also associate firm size with the degree of external financing frictions. 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.

- Scheme #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.

We repeat the regressions performed above, but now separately for financially constrained and unconstrained subsamples. Due to space constraints we report only results for the LPC-Deal Scan sample, though results are similar for Sufi's sample. To measure systematic risk, we use both *Beta KMV* and *Beta Tail* (which measures firms' exposure to tail risks). The results are qualitatively similar if we use the other proxies used above.

Table 7 presents the results we obtain. Panel A presents results for *Beta KMV*, and Panel B shows the *Beta Tail* results. The table shows that the negative relation between systematic risk and the usage of credit lines obtains only in the constrained samples (the exception is the coefficient for the high-payout sample when using *Beta Tail*). These results are once again consistent with the model in Section 2.

– Table 7 about here –

3.3.4 Asset beta and loan spreads

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 spreads paid by firms on their credit lines and systematic risk. To do this, we regress the average annual spreads paid by firm i in deals initiated in year t,[23] 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.[24] Our empirical model has the following form:

$$Spread_{i,t}=\mu_0 + \mu_1 Beta_{i,t} + \mu_2(\frac{LC_{i,t}}{Assets_{i,t}}) + \mu_3 LIBOR_{i,t} + \boldsymbol{\mu}_4 \mathbf{X}_{i,t} + \sum_t Year_t + \epsilon_{i,t}, \tag{32}$$

where $\mathbf{X}$ is the vector of firm characteristics used in equation (31). To save space, the analysis in this section focuses on a set of three risk proxies (namely, *Beta KMV*, *Beta Tail*, and *SysVar KMV*), but our results hold robustly across different proxies for systematic risk.

Our findings are presented in Table 8. 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). 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 the alternative spread measure (*Undrawn spread*). The evidence suggests that an increase of one standard deviation in systematic risk exposure increases undrawn spreads 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 8 about here –

3.3.5 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

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

[24] 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.

holdings (defined in equation (28) above). To do so, we run the following time-series SUR model:

$$\begin{aligned} LCInitiation_t &= \varsigma_0 + \varsigma_1 VIX_{t-1} + \varsigma_2 TimeTrend_t + \boldsymbol{\varsigma}_3 \mathbf{Controls}_{t-1} + \varpi_t \\ Change\ in\ Cash_t &= \gamma_0 + \gamma_1 VIX_{t-1} + \gamma_2 Time\ Trend_t + \boldsymbol{\gamma}_3 \mathbf{Controls}_{t-1} + \upsilon_t. \end{aligned} \tag{33}$$

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).[25] 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 3 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 3 about here –

Table 9 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). 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

[25] The correlation between VIX and *Bank* VIX in our time-series data is equal to 0.39.

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 9 about here –

One potential issue with the results above is that the right-hand side variables are simple aggregates (see equation (28)). 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 (31) (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.[26]

Table 9 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 9. 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 debt (including credit lines).[27] 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 9 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

[26] 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)).

[27] 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)).

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 10. To do so, we measure the average credit line maturity and 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:

$$\begin{aligned} Average\ Maturity_t &= \psi_0 + \psi_1 VIX_{t-1} + \psi_2 TimeTrend_t + \psi_3 \mathbf{Controls}_{t-1} + \varkappa_t \\ Average\ Spread_t &= \varrho_0 + \varrho_1 VIX_{t-1} + \varrho_2 TimeTrend_t + \varrho_3 \mathbf{Controls}_{t-1} + \phi_t. \end{aligned} \quad (34)$$

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 10 and Figure 4. 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 4, and it is confirmed in Table 10 (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.[28] The results are similar for $Bank\ VIX$, though the coefficient on the spread regression is not statistically significant.[29]

– Figure 4 about here –

– Table 10 about here –

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:

$$Change\ in\ Debt_t = \frac{\sum_j (Debt_{j,t} - Debt_{j,t-1})}{\sum_j Assets_{j,t}}. \quad (35)$$

[28] 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).

[29] We have also used an alternative specification that controls for other firm-specific variables (similar to Table 9), with virtually identical results.

In this equation, we define debt as the sum of short- and long-term debt from COMPUSTAT. We then replace $LCInitiation_t$ in Equation 33 above with $Change\ in\ Debt_t$.

Columns (5) and (6) of Table 10 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.[30]

4 Concluding Remarks

We show that aggregate risk affects firms' choice between cash and credit lines. For firms with high exposure to systematic risk, the folk statement that *"cash is king"* appears to be true. In contrast, for firms that only need to manage their idiosyncratic liquidity risk, bank credit lines dominate cash holdings. In our empirical tests we measure firm-level exposure to systematic risk using asset betas and systematic variance (the component of firm-level variance that is explained by aggregate variance). 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. These results shed light on an important trade-off between cash and credit lines for corporate liquidity management, and they suggest a new role for aggregate risk exposure in corporate finance.

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

[30] We have also examined the relationship between VIX and aggregate corporate liquidity instruments separately for different sample partitions (those in Section 3.3.3). We find that the negative relationship between VIX (or $Bank\ VIX$) and credit line initiations is stronger for small, low-payout and non-rated firms.

other better-capitalized banks also find it difficult to offer further lines of credit given heightened aggregate risk levels). Finally, in such a framework of bank capital, government bailouts and/or guarantees during aggregate crises can lead to ex-ante under-investment in bank capital, generate moral hazard in the form of banks issuing lines of credit to risky firms, and potentially lead to excessive aggregate risk in the economy. In all, these arguments highlight that it is 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 Proof of Lemma 1

First, notice that if constraint (13) 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 (14) would then be equivalent to that of non-systematic firms). This situation arises when:

$$\rho - \rho_0 \leq w^{\max}. \tag{36}$$

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 (20).

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 (20). 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:

$$q_2 = 1 + \frac{\lambda(\rho_1 - \rho)}{\rho - \rho_0}. \tag{37}$$

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 (14) can also bind for a positive level of x^θ. The budget constraint can be written as:

$$I + (q-1)\left[x^\theta(\rho - \rho_0) - w^{\max}\right] + \lambda x^\theta \rho \leq (1-\lambda)\rho_0 + \lambda x^\theta \rho_0, \text{ or} \tag{38}$$

$$x^\theta \leq \frac{(1-\lambda)\rho_0 - I + (q-1)w^{\max}}{(\lambda + q - 1)(\rho - \rho_0)}. \tag{39}$$

The right-hand side of equation (39) is greater than one since $(1-\lambda)\rho_0 - I - \lambda(\rho - \rho_0) > 0$ (by (4)). 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:

$$q_1 = 1 + \frac{\rho_0 - \lambda\rho - I}{\rho - \rho_0 - w^{\max}}. \tag{40}$$

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 Characterization of the equilibrium when $L^s < L_1^s(\theta)$

Suppose first that $q_1 > q_2$, such that the firm's budget constraint never binds in equilibrium. In this case, if $L^s < L_1^s$ we will have that $q^* = q_2 > 1$. To see why, notice that if $q < q_2$ then systematic firms would choose $x^\theta = 1$, which is not compatible with equilibrium. If $q > q_2$, then $x^\theta = 1$, generating an excess supply of cash. Thus, we must have $q^* = q_2$. Since systematic firms are indifferent between any x^θ between 0 and 1 when $q = q_2$, we can sustain an equilibrium such that:

$$\theta[x^\theta(q_2)(\rho - \rho_0) - w^{\max}] = L^s. \tag{41}$$

This is the unique equilibrium of the model. To see why, notice that for $x^\theta > x^\theta(q_2)$, cash demand would be larger than supply, and if $x^\theta < x^\theta(q_2)$, cash supply would be greater than demand and thus the cost of cash would drop to $q = 1$.

If $q_1 < q_2$, then the firm's budget constraint will bind in equilibrium, and we will have $q_1 < q^* \leq q_2$. The cost of cash q^* is such that the demand for cash exactly equals supply:

$$\theta[x^\theta(q^*)(\rho - \rho_0) - w^{\max}] = L^s. \tag{42}$$

Since $q_1 < q^*$, then $x^\theta(q^*) < 1$. Since $q^* \leq q_2$, then systematic firms would like to increase their demand for cash beyond $x^\theta(q^*)$, but they cannot afford to do so. Thus, q^* is the equilibrium cost of cash in this case.

Finally, notice that since the cost of cash cannot be greater than q_2, there is a level of liquidity supply (denoted by $L^s_{\min}$) such that for all $L^s < L^s_{\min}$, the equilibrium is $q^* = q_2$. $L^s_{\min}$ is such that the maximum level of x^θ that satisfies the budget constraint when $q = q_2$ yields a demand for cash exactly equal to $L^s_{\min}$:

$$\theta[x^\theta(q_2)(\rho - \rho_0) - w^{\max}] = L^s_{\min}. \tag{43}$$

Appendix C Computing *Beta KMV* and *Var KMV*

To compute *Beta KMV* and *Var KMV* we make the following assumptions. First, suppose that the total value of a firm follows:

$$\frac{dV}{V} = \mu dt + \sigma_V dW \tag{44}$$

where V is the total value, μ is the expected continuously compounded return on V, σ_V is the volatility of firm value, and dW is a standard Wiener process. In addition, assume that the firm issued one discount bond maturing in T periods. Under these assumptions, the equity of the firm is a call option on the underlying value of the firm with a strike price equal to the face value of the firm's debt and a time-to-maturity of T. The value of the "call option" is:

$$E = VN(d_1) - e^{-rT} FN(d_2) \tag{45}$$

where E is the market value of a firm's equity, F is the face value of the firm's debt, r is the instantaneous risk-free rate, $N(.)$ is the cumulative standard normal distribution function, d_1 is given by

$$d_1 = \frac{ln(V/F) + (r + \frac{1}{2}\sigma_V^2)T}{\sigma_V\sqrt{T}}, \tag{46}$$

and d_2 is given by

$$d_2 = d_1 - \sigma_V\sqrt{T}$$

Given the value of equity, the underlying value of the firm, or market value of asset is:

$$V = \frac{E + e^{-rT} FN(d_2)}{N(d_1)} \tag{47}$$

Since the value of equity is a function of the value of the firm and time, using Ito's lemma we obtain:

$$\sigma_E = \frac{V}{E}\frac{\partial E}{\partial V}\sigma_V = \frac{V}{E}\frac{1}{N(d_1)}\sigma_V \tag{48}$$

To implement the model, we need to simultaneously solve equations (47) and (48). We follow Bharath and Shumway (2008), and adopt an iterative procedure as follows. First, equity volatility σ_E is estimated from historical stock returns. We use the last 12 months to do so (e.g., $T = 12$ months). We also set $r = 0.03$. To compute the face value of debt for each firm, we use the firm's total book value of short-term debt plus one-half of the book value of long-term debt. This is a known rule-of-thumb used to fit a KMV-type model to an annual horizon. Then, we propose an initial value for asset volatility, σ_V, which is computed as:

$$\sigma_V = \sigma_E \frac{E}{E+F} \tag{49}$$

We use this value of σ_V, and equation (47) to infer the market value of the firm's assets for every month. We then calculate the implied log monthly return on assets, and use that return series to generate new estimates of σ_V and μ. Finally, we iterate on σ_V until the procedure converges. Similarly to unlevering volatility using (48), asset beta is then unlevered using:

$$\beta_{Asset} = \beta_{Equity} \frac{E}{V} N(d_1) \tag{50}$$

Finally, we let $Var\ KMV = \sigma_V$, and $Beta\ KMV = \beta_{Asset}$.

Appendix D Computing *Bank VIX*

Three distinct forecasts of daily bank return volatility are computed. The purpose is to construct a forecast of volatility on day $t+1$ given all information up to and including day t.

First, the daily estimates of volatility are computed using the return series available for the financial sector index from Kenneth French's website. The data span July 1st 1963 through October 29th 2010.

Next, we compute a volatility forecast based on a Gaussian GARCH(1,1) model. This procedure is a fully parametric one and uses a statistical model to forecast future volatilities. The parametric approach requires the estimation of model parameters for which all data up to time t are used. In the case of value-weighted financial sector return series, at least 105 days of observations were required to obtain reliable estimates of the parameters. Hence, the first run of the model uses the sample window $[t_0, t_{105}]$ to estimate the model parameters and subsequently forecasts the volatility on day t_{106}. To obtain volatility forecasts for all dates, the procedure is repeated for each individual day on an expanding sample size basis.

Finally, we compute the average yearly value of the expected volatility series (*Bank VIX*) to match the frequency of the other data that we use.