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

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Abstract

We argue that a firm's aggregate risk is a key determinant of whether it manages its future liquidity needs through cash reserves or bank lines of credit. 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 from banks and opt for cash reserves in spite of higher opportunity costs and liquidity premium. We verify our model's hypothesis empirically by showing that firms with high asset beta have a higher ratio of cash reserves to lines of credit, controlling for other determinants of liquidity policy. This effect of asset beta on liquidity management is economically significant, especially for financially constrained firms; is robust to variation in the proxies for firms' exposure to aggregate risk and availability of credit lines; works at the firm level as well as the industry level; and is significantly stronger in times when aggregate risk is high.

Key words: Bank lines of credit, cash holdings, liquidity premium, lending channel, asset beta.

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

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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 tightening of credit by once-patient lenders is why Standard & Poor's and Moody's Investors Service have projected corporate defaults to grow fivefold or more from the record lows of 2007."

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

1 Introduction

How do firms manage their future liquidity needs? This question has become increasingly important for both academic research and corporate finance in practice. Survey evidence from CFOs indicates that liquidity management tools such as cash and credit lines are essential components of a firm's financial policy (Lins, Servaes, and Tufano (2007), Campello, Giambona, Graham, and Harvey (2009)).[1] Consistent with the survey evidence, the empirical literature also suggests that the financing of future investments is a key determinant of corporate cash policy (e.g., Opler, Pinkowitz, Stulz, and Williamson (1999), Almeida, Campello, and Weisbach (2004, 2009), Denis and Sibilikov (2007), and Duchin (2009)). More recently, bank lines of credit have been shown to be an important source of financing for many companies in the U.S. (see Sufi (2009) and Yun (2009)). Despite this growing literature, we still know little about what are the fundamental determinants of the choice between cash holdings and bank credit lines in corporate liquidity management.[2]

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 future liquidity needs.[3] 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

[1]For example, the CFOs in Lins et al.'s survey argue that credit lines are used to finance future growth opportunities, while cash is used to withstand negative liquidity shocks.

[2]The results in Sufi suggest that cash and credit lines are substitutes for firms that perform poorly. If firms' cash flows deteriorate, their access to outstanding lines of credit is restricted by covenants, forcing firms to switch to cash. Sufi's analysis does not explain how firms choose between cash and credit lines in the first place.

[3]A typical line of credit is a borrowing facility with a maximum amount that a financial institution is committed to lend to the borrower over a given period and a pre-specified interest rate (usually specified as a fixed spread over some reference rate, such as LIBOR). These facilities include various fees charged by the lender including an up-front annual fee on the total amount committed and a usage annual fee on the available unused portion. They also include a material adverse change (MAC) clause that allows the financial institution to deny credit if the borrower's financial condition has deteriorated substantially. See Shockley and Thakor (1997) for a detailed discussion.

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 in which their cash flows are low. Notably, these models of liquidity insurance are silent on the trade-offs between cash and credit lines.

This paper attempts to fill this important 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 (say, its "beta") is a fundamental determinant of its liquidity management choices. The intuition for our main result is as follows. In the presence of a liquidity premium (e.g., a low return on corporate cash holdings), firms find it costly to hold cash. Firms may instead prefer to manage their liquidity through bank credit lines, which do not require them to hold liquid assets. Under a credit line agreement, the bank only needs to provide 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 credit line (e.g., commitment fees). The line of credit can thus be seen as an insurance contract. Provided that the bank can offer this insurance at "actuarially fair" terms, lines of credit will strictly dominate cash holdings in corporate liquidity management.

The drawback of credit lines arises from the observation 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 the *entire* corporate sector has a liquidity shortfall. In this state of the world, banks will be unable to provide liquidity to the corporate sector because the demand for funds under the credit line facilities (drawdowns) will sharply exceed the supply of funds coming from the healthy firms. In other words, the ability of the banking sector to meet corporate liquidity needs will depend on the extent to which firms are subject to correlated (systematic) liquidity shocks. Aggregate risk will thus create a cost of credit lines.

We explore this trade-off between aggregate risk and liquidity premia to derive optimal corporate liquidity policy in an equilibrium model in which firms are heterogeneous in their (unlevered) *asset beta*; that is, in the extent to which they are exposed to aggregate risk. Our main result is that while low beta firms will manage their liquidity through bank credit lines, high beta firms may optimally choose to hold cash in equilibrium, despite the existence of liquidity premia. Specifically, high beta firms will optimally face worse contractual terms when opening bank credit lines and will thus demand less credit lines and more cash in equilibrium, relative to low beta firms. Because the banking sector manages mostly idiosyncratic risk, it can provide liquidity for firms in bad states of the world, sustaining the equilibrium. In short, firm exposure to systematic risks increases the demand for cash and reduces the demand for credit lines.[4]

In addition to this basic result, the model generates a couple of new economic insights. These insights motivate some of our empirical analysis. First, the trade-off between cash and credit lines becomes more important as the amount of systematic risk in the economy increases. Second, the trade-off between cash and credit lines should be more important for firms that find it more costly to raise external capital. In the absence of costly external financing there is no role for corporate liquidity policy, and thus the choice between cash and credit lines becomes irrelevant. Third, the model suggests that a firm's exposure to risks that are systematic to the banking industry should affect the determination of its liquidity policy. In particular, firms that are more sensitive to banking industry downturns should be more likely to hold cash for liquidity management.

We test our model's implications using data over the 1987–2008 period. We use two alternative data sources to construct a proxy for the availability of credit lines. Our first sample is drawn from the LPC-Deal Scan database. These data allow us to construct a large sample of credit line initiations. However, the LPC-Deal Scan data have two potential drawbacks. 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-Deal Scan 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. As discussed by Sufi, 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 systematic risk should be negatively related to its *LC-to-Cash*. We measure this exposure using asset betas. While equity betas are easy to compute using stock price data, they are mechanically related to leverage due to simple leverage effects (high leverage firms will tend to have larger betas). Since 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. To overcome this problem, 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. We call the set of betas that we obtain using this method *Beta KMV*. The second way to unlever betas and variances is

[4] Broadly speaking, the result that bank lines of credit will be more expensive for firms with greater aggregate risk can be interpreted as a greater cost of purchasing insurance from the intermediation sector against states with greater aggregate risk (manifesting as a higher risk premium in out-of-the-money put options on the stock market index as a whole, documented by Bondarenko (2003), among others.

to directly compute data on firm *asset* returns. Our data on this alternative beta measure 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 test the model's central result by relating asset betas to *LC-to-Cash* ratios. Figure 3 below, which is based on industry-averages for the whole time period of 1987 to 2008, gives a visual illustration of our main result: exposure to systematic risk (*asset betas*) has a statistically and economically significant effect on the fraction of corporate liquidity that is provided by credit lines *LC-to-Cash*. To give a concrete example, consider a comparison between the SIC 344 industry (Fabricated Metals) and SIC 367 (Electronic Components). The former industry is characterized by heavy reliance on credit lines for liquidity management (average *LC-to-Cash* is 0.43 in our time period), while the latter shows greater reliance on cash (*LC-to-Cash* = 0.18). These LC/cash choices correspond to the differences in unlevered industry betas across the two industries. SIC 344 has an average *Beta KMV* of 0.83 in our time period, while SIC 367's average asset beta equals 1.56.[5] These liquidity patterns are explained by the model we introduce in this paper.

We also run a battery of empirical specifications that controls for other potential determinants of the fraction of corporate liquidity that is provided by credit lines. First, similarly to Sufi (2009), we use panel data to show that profitable, large, low Q, low net worth firms are more likely to use bank credit lines. These patterns hold both in the LPC-Deal Scan and also in Sufi's data, indicating that the large sample of line of credit usage that is based on LPC-Deal Scan has similar empirical properties to the smaller, more detailed data constructed by Sufi. More importantly, we find that the relationship between aggregate risk and the choice between cash and credit lines holds after controlling for total risk and the variables considered in previous work on credit lines. For example, in our benchmark specification (which uses *Beta KMV* and the LPC-Deal Scan proxy for *LC-to-Cash*), we find that an increase in asset beta from 0.8 to 1.5 (this is less than a one-standard deviation in beta in our sample) decreases a firm's reliance on credit lines by approximately 0.06 (approximately 15% of the standard deviation and 20% of the average value of the *LC-to-Cash* variable in our sample).

The negative relationship between asset beta and *LC-to-Cash* holds for all different proxies of asset betas and line of credit usage that we employ. First, we show that this result also holds when we use Sufi's (2009) sample to calculate firms' reliance on credit lines for liquidity management, both for total and unused credit lines. Second, the results are also robust to variations in the methodology used to compute betas, 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), "tail betas" (that capture a firm's exposure to systematic risks in bad times), and cash flow-based betas (com-

[5] These betas represent the 1987-2008 average, unlevered, value-weighted industry betas for the respective industries.

puted by relating a firm's financing needs to the aggregate financing need in the entire universe of firms in the sample).

We also provide evidence for the auxiliary implications of the model. First, we compute a firm's "bank beta" to test the model's implication that a firm's exposure to banking sector's risks should influence the firm's liquidity policy. Our evidence suggests that firms that are more sensitive to banking industry downturns are more likely to hold cash for liquidity management. We also sort firms according to observable proxies for financing constraints to test whether the effect of asset beta on *LC-to-Cash* is driven by firms that are likely to be financially constrained. The relationship between asset beta and the usage of credit lines holds only in the "constrained" subsamples (e.g., those containing only small and low payout firms). Finally, we examine whether the effect of asset beta on the choice between cash and credit lines increases during times when aggregate risk is likely to matter the most. In particular, we estimate cross-sectional regressions of *LC-to-Cash* on betas every year, and we relate the time series variation in the coefficient to the level of aggregate risk, as measured by *VIX*, the implied volatility of the stock market index returns from options data, which captures both the aggregate volatility as well as the financial sector's appetite to bear that risk. The results indicate that a firm's exposure to systematic risk matters most in times when *VIX* is high, .

In addition to the literatures discussed above, our paper is related to existing work on bank lending during liquidity crises. Gatev and Strahan (2005) and Gatev, Schuermann, and Strahan (2005), show that when commercial paper to treasury bill spread widens, banks experience an inflow of deposits. This, in turn, helps them to honor their loan commitments. The flight of depositors to banks may be due to banks having greater expertise in screening borrowers during stress times (cf. Kashyap, Rajan, and Stein (2002)). Alternatively, the flight to bank deposits may be explained by the FDIC insurance (see Pennacchi (2006) for evidence). This line of research helps explain why banks are the natural providers of liquidity insurance for the corporate sector. In particular, the flight to bank deposits in bad times may counteract the effect of agggregate risk in liquidity management that we identify. To address this, we confirm that in times of high aggregate volatility (*VIX*), firm's liquidity management responds more to aggregage risk exposure, even after controlling for flight to quality, captured by a widening of the commercial paper (CP) to treasury bill spread. Our paper contributes to this literature by pointing out to an important limitation of bank-provided liquidity insurance: firms' exposure to systematic risks.

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. The firms' date-0 wealth is $A < I$. 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 using probabilities, so 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 set up is summarized in Figure 1.

– Figure 1 about here –

A firm will only continue its date-0 investment until date 2 if it can meet the date-1 liquidity need. If the liquidity need is not met, then the firm is liquidated and the project produces a cash flow equal to zero. If the firm continues, the investment produces a date-2 cash flow R which obtains with probability p. With probability $1 - p$, the investment produces nothing. The probability of success depends on the input of specific human capital by the firms' managers. If the managers exert high effort, the probability of success is equal to p_G. Otherwise, the probability is p_B, but the managers consume a private benefit equal to B. Because of the private benefit, managers must keep a high enough stake in the project to induce 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 state λ) 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:

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

This means that the efficient level of x is $x^{FB} = 1$. However, the firm's pledgeable income is lower than the liquidity shock in state λ. 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).

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:

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

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 to the firms at date 0 so that they can start their projects $(I - A)$, 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.

Firms have a shortfall equal to $x(\rho - \rho_0)$ in state λ. 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 $x\rho$ in state λ (alternatively, we can assume efficient renegotiation of the date-0 claim). However, this external financing is not sufficient to pay for the required investment $x\rho$. 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:

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

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, $(D_2^{\theta}, w^{\theta}, y^{\theta})$ represents the contract offered to systematic firms and $(D_2^{1-\theta}, w^{1-\theta}, y^{1-\theta})$ 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:

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

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 state $(1-\lambda)$.

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:

$$w^{\theta}=x^{\theta}(\rho-\rho_0)-L^{\theta}\leq w^{\max}. \tag{13}$$

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

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

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:

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

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 systematic firms. Since there are θ of them, the maximum credit line that can be provided to systematic firms is given by $w^{\max}$, equal to $\frac{(1-\theta)(\rho_0-\lambda\rho)}{\theta}$.

We can now derive the optimal policy of systematic firms. 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:

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

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 above.

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:

$$L^\theta(x^\theta)=x^\theta(\rho-\rho_0)-w^{\max}. \tag{16}$$

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 (16). 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:

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

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:

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

$$x^\theta \leq \frac{(1-\lambda)\rho_0-(I-A)+(q-1)w^{\max}}{(\lambda+q-1)(\rho-\rho_0)}. \tag{17}$$

The right-hand side of equation (17) is greater than one since $(1-\lambda)\rho_0 - (I-A) - \lambda(\rho - \rho_0) > 0$ (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:

$$q_1 = 1 + \frac{\rho_0 - \lambda\rho - (I-A)}{\rho - \rho_0 - w^{\max}}.$$

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. Thus, we have:

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

$$\begin{aligned}
x^\theta(q) &= 1 \textit{ if } \rho - \rho_0 \leq w^{\max} \qquad (18)\\
x^\theta(q) &= 1 \textit{ if } \rho - \rho_0 > w^{\max} \textit{ and } q \leq \min(q_1, q_2)\\
x^\theta(q) &= \frac{(1-\lambda)\rho_0 - (I-A) + (q-1)w^{\max}}{(\lambda + q - 1)(\rho - \rho_0)} \textit{ if } \rho - \rho_0 > w^{\max} \textit{ and } q_2 \geq q > q_1\\
x^\theta(q) &\in [0,1] \textit{ if } \rho - \rho_0 > w^{\max} \textit{ and } q_1 > q = q_2\\
x^\theta(q) &= 0 \textit{ if } q > q_2.
\end{aligned}$$

Finally, the demand for cash is given by $L^\theta(q) = 0$ if $\rho - \rho_0 \leq w^{\max}$, and by equations (16) and (18) when $\rho - \rho_0 > w^{\max}$.

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 use cash in equilibrium. Equilibrium requires that:

$$\theta L^\theta(q) = \theta[x^\theta(q)(\rho - \rho_0) - w^{\max}] \leq L^s. \qquad (19)$$

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

$$\theta[(\rho - \rho_0) - w^{\max}] = L_1^s. \qquad (20)$$

If $L^s \geq L_1^s$, 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, 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 (according to equations 16 and 18). The easiest case is when $q_1 > q_2$, such that the firm's budget constraint never binds in equilibrium. In this case, if $L^s < L_1^s$ we will have that $q = q_2 > 1$, and the cash demand for systematic firms is such that liquidity supply equals demand:

$$\theta[x^\theta(q_2)(\rho - \rho_0) - w^{\max}] = L^s. \tag{21}$$

Since systematic firms are indifferent between any x^θ between 0 and 1 when $q = q_2$, this is the unique equilibrium of the model. 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 liquidity premium would drop to $q = 1$.[6]

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):*

   (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*

[6] Notice that $x^\theta(q_2) < 1$.

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 under-invest in the event of a liquidity shock.

– Figure 2 about here –

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 a firm's asset beta.

2. *The trade-off between cash and credit lines becomes more important as the amount of systematic risk in the economy increases.* Following previous research, we test this implication by examining whether the effect of asset beta on the choice between cash and credit lines increases during economic downturns.[7]

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,

[7] Empirical asset pricing research has found that (i) aggregate volatility rises during downturns (see, e.g., Bekaert and Wu (2000)) and (ii) correlation of stock returns with market returns also rises during downturns (e.g., Ang and Chen (2002)). Both these effects increase the amount of systematic risk of firms in the economy during downturns.

and examining whether the effect of asset beta on the choice between cash and credit lines is driven by firms that are likely to be financially constrained.

4. *A firm's exposure to risks that are systematic to the banking industry is be 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 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-Deal Scan. These data allow us to construct a large sample of credit line initiations. We note, however, that the LPC-Deal Scan 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. 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-Deal Scan in the period of 1987 to 2008 for which we can obtain the firm identifier *gvkey* (which we later use to match to COMPUSTAT).[8] 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

[8] 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.

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. This sample is then matched to COMPUSTAT annual data, as described below.

To construct the *Random Sample*, we start from the sample used in Sufi (2009), which contains 1,908 firm-years (300 firms) between 1996 and 2003. Sufi's data set includes information on the total credit line facilities available to firm j in the random sample during an year t between 1996 to 2003 ($Total\ Line_{j,t}$), and the amount of credit in these lines that is still available to firm j in year t ($Unused\ Line_{j,t}$). We use this information to construct our proxies for credit line usage. 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, $(Assets + prcc\_fc \times sho - ceq)/Assets$.[9] *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

[9] 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.

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:

$$Total\ LC\text{-}to\text{-}Cash_{i,t} = \frac{Total\ Line_{i,t}}{Total\ Line_{i,t} + Cash_{i,t}}, \tag{22}$$

$$Unused\ LC\text{-}to\text{-}Cash_{i,t} = \frac{Unused\ Line_{i,t}}{Unused\ Line_{i,t} + Cash_{i,t}}. \tag{23}$$

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:

$$Total\ LC_{j,s} = \sum_{t \leq s} LC_{j,t}\Gamma(Maturity_{j,t} \geq s - t), \tag{24}$$

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:

$$LC\text{-}to\text{-}Cash_{j,t} = \frac{Total\ LC_{j,t}}{Total\ LC_{j,t} + Cash_{j,t}}. \tag{25}$$

This ratio is closely related to the *Total LC-to-Cash* ratio of equation (22).

3.2.3 Data on betas and volatilities

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

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

To overcome this problem, 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). 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.[11] We call the set of betas that we obtain using this method *Beta KMV*. We also compute a measure of total asset volatility, which is used as a control in some of the regressions below. This measure (denoted *Var KMV*) is estimated yearly using the past 12 monthly stock returns and the KMV-Merton model.

The second way to unlever betas and variances is to directly compute data on firm *asset* returns. The data we use come from Choi (2009). Choi computes bond and bank loan returns using several data sources and then combines them with stock returns into an asset return measure that uses relative market values of the different financial claims as weights. 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.[12] 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 is 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 relationship 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-Deal Scan 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.

[11] This is a knwon rule-of-thumb used to fit a KMV-type model to an annual horizon.

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

In the model, a firm's exposure to systematic risks matters mostly on the downside (because a firm may need liquidity when other firms are likely to be in trouble). To capture a firm's exposure to large negative shocks, we follow Acharya, Pedersen, Philippon and Richardson (2010) and compute the firm's *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 then unlevered using the same procedure used to compute *Beta KMV*.

All of the betas described above are computed using market prices. Using market data is desirable because of their high frequency. However, the model's argument is based on the correlation between a firm's liquidity needs (the difference between required investments and pledgeable cash flows) 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 investment also contains information about firm's choices between cash and credit lines.[13] In order to do this, we compute each 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*).[14] 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 gap to mitigate the endogeneity of firm-specific investment, and to reduce the error in measuring the gap betas.[15]

One shortcoming of the measures of systematic risk that we construct is that they are noisy and prone 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 traditional 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.[16] Throughout the tests performed below, we report auxiliary statistics that speak to the relevance (first-stage F-tests) and validity (Hansen's J-stats) of our instrumental variables regressions.

[13] We thank Ran Duchin for suggesting this analysis.

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

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

[16] 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, by using industry betas rather than firm-level betas in some specifications below.

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-Deal Scan 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.

– 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-Deal Scan 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-Deal Scan 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 volatility proxies (*Var KMV* and *Var Asset*). Not surprisingly, all the beta proxies that are based on asset return data are highly correlated. The lowest correlations are those between *Beta Gap* 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 0.4 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 Industry analysis

To provide a visual illustration of the effect of betas on corporate liquidity management, we plot in Figure 3 the average industry value for *LC-to-Cash* for our entire time period of 1987 to 2008, against average (value-weighted) industry asset betas (using *Beta KMV*).[17] The figure depicts a strong negative relation between asset betas and the usage of credit lines. The effect of beta on liquidity management also appears to be economically significant. To give a concrete example, consider a comparison between the SIC 344 industry (Fabricated Metals) and SIC 367 (Electronic Components). The former industry is characterized by heavy reliance on credit lines for liquidity management (average *LC-to-Cash* is 0.43 in our time period), while the latter shows greater reliance on cash (*LC-to-Cash* = 0.18). These LC/cash choices correspond to the differences in unlevered industry betas across the two industries. SIC 344 has an average *Beta KMV* of 0.83 in our time period, while SIC 367's average asset beta equals 1.56. We also report the output of a simple regression of *LC-to-Cash* on *Beta KMV*. This regression slope is -0.09, significant at a 1% level (t-stat $= -2.76$). This empirical relation supports the implications of the model developed in Section 2.

– Table 3 about here –

3.3.3 Firm-level regressions

The plot in Figure 3 uses raw data and thus does not address the possibility that the relation between aggregate risk and line of credit may be driven by other variables. For example, the evidence in Sufi (2009) suggests that risky firms (equivalent to *ProfitVol* above) are less likely to use credit lines. Since betas are correlated with total risk, it is important to show that the relation between beta and credit line usage remains after controlling for risk.

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

$$\begin{aligned} LC\text{-}to\text{-}Cash_{i,t} \;&=\; \alpha + \beta_1 BetaKMV_{i,t} + \beta_2 \ln(Age)_{i,t} + \beta_3 (Profitability)_{i,t-1} \\ &\quad + \beta_4 Size_{i,t-1} + \beta_5 Q_{i,t-1} + \beta_6 Networth_{i,t-1} + \beta_7 IndSalesVol_{j,t} \\ &\quad + \beta_8 ProfitVol_{i,t} + \sum_t Year_t + \epsilon_{i,t}, \end{aligned} \tag{26}$$

where *Year* absorbs time-specific effects, respectively. Our model 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 risk (see Section 3.2.3). And we use different proxies for *LC-to-Cash*, which are based both on LPC-Deal Scan and Sufi's data. In some specifications we also include industry dummies (following Sufi we use 1-digit SIC industry dummies in our empirical models) and the variance measures that are based on stock and asset returns (*Var KMV* and *Var Asset*).

[17] Below, we also examine whether the industry betas depicted in Figure 3 are correlated with *LC-to-Cash* after controlling for other firm-level determinants of liquidity management.

The results for the *Beta KMV* and LPC-Deal Scan 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, seasonal firms are more likely to use bank credit lines. This is particularly important given the fact that our dependent variable is not as precisely measured as that in Sufi. In column (2) we introduce our measure of systematic risk and find that the choice between lines of credit and cash is heavily influenced by that measure. Specifically, the coefficient on *Beta KMV* suggests that a one-standard deviation increase in asset beta (approximately one) decreases firm's reliance on credit lines by approximately 0.089 (more than 20% of the standard deviation of the *LC-to-Cash* variable). This result is robust to the inclusion of industry dummies (column (3)), and stock-return based variance measures (column (4)). Since the variance measures are computed in a similar way to beta, in columns (5) and (6) we experiment with a specification in which the variance measure is also instrumented with its two first lags. This change in specification has no significant effect on the *Beta KMV* coefficients.

– Table 3 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 Table 3. The high p-values reported in the table imply the acceptance of the null hypothesis that the identification restrictions that justify the instruments chosen are met in the data. Specifically, these reported statistics suggest that we do not reject the joint null hypothesis that our instruments are uncorrelated with the error term in the leverage regression and the model is well-specified.

Table 4 uses Sufi's (2009) measures of *LC-to-Cash* rather than LPC-Deal Scan data. In the first two columns, we replicate the results in Sufi's Table 3, for both total and unused measures of *LC-to-Cash*. Notice that the coefficients are virtually identical to those in Sufi. We then introduce our KMV-based proxy for aggregate risk exposure (*Beta KMV*). As in Table 3, the coefficients are statistically and economically significant, both before and after controlling for asset variance (*Var KMV*). These results suggest that the relation between asset betas 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 for liquidity management.

– Table 4 about here –

Tables 5 and 6 replace *beta KMV* with our alternative beta measures. Table 5 shows the results for the LPC-Deal Scan sample,[18] 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 relationship to liquidity policy as that uncovered in Table 2. The economic magnitude of the coefficient on *Beta Asset* is in fact larger than that reported in Table 2. Using industry-level cash-adjusted betas, *Beta Cash*, also produces similar results (column (2)). In column (3), we show that a firm's exposure to banking sector risks (*Beta Bank*) affects liquidity policy in a way that is consistent with the theory. The coefficients are also economically significant. Specifically, a one-standard deviation increase in *Beta Bank* (which is equal to 0.7) decreases *LC-to-Cash* by 0.21, which is half of the standard deviation of the *LC-to-Cash* variable. Column (4) shows that a firm's exposure to tail risks is also correlated with liquidity policy. Firms which tend to do poorly during market downturns have a significantly lower *LC-to-Cash* ratio. Column (5) replaces market-based beta measures with the financing gap beta (*Beta Gap*). Consistent with the theory, *Beta Gap* is significantly related to the *LC-to-Cash* ratio, though economic significance is smaller than for the market measures (possibly due to residual measurement error in these cash-flow based betas).[19] Finally, 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 relationship between asset beta and the *LC-to-Cash* ratio.

– Table 5 about here –

Table 6 replicates the analysis in Table 5 for Sufi's (2009) sample. The results show that the relationship 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, relative to Table 5.

– Table 6 about here –

[18] To economize space we do not report the results using industry dummies in Table 5. All results continue to hold if we do so.

[19] The coefficient in column (5) suggests that a one-standard deviation increase in *Beta Gap* decreases *LC-to-Cash* by approximately 1.5%.

3.3.4 SUR models for cash and credit lines

As discussed by Sufi (2009), the variable *LC-to-Cash* has the advantage of isolating the relative importance of credit lines versus cash for corporate liquidity management, while controlling for the firm's total liquidity demand. Our theory also makes predictions about the relative usage of cash versus credit lines. Accordingly, our tests focus on *LC-to-Cash*.

Naturally, it is interesting to examine how asset betas impact the firm's choice of cash and credit lines separately. In order to do this, we use a seemingly unrelated regression (SUR) model, in which we regress measures of line of credit usage and cash holdings (both scaled by assets net of cash) on betas and the control variables listed in equation (26). To address measurement error, these regressions use predicted values of beta on the right-hand side, using a model that includes two lags of beta and the other control variables. The results are presented in Table 7.

– Table 7 about here –

When using the LPC-Deal Scan data, we find that asset betas impact mostly the firm's cash holdings, while they are insignificantly related to the firm's demand for credit lines. However, using Sufi's data (in particular the measure that includes all credit lines, both used and unused) we find evidence that asset betas both increase cash and also reduce the demand for credit lines (see columns (5) and (6)). One possible explanation for this finding is the better coverage of line of credit data in Sufi's sample. These results are interesting in their own right and more fully charcterize our main insights.

3.3.5 Sorting firms according to proxies for financing constraints

As the model in Section 2 makes it clear, the choice between cash and credit lines should be most relevant for firms that are financially constrained. This line of argument suggests that the relationship 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:

- 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 in Table 2, but now separately for financially constrained and unconstrained subsamples. Table 6 presents the results we obtain. The table shows that the relationship between beta and the usage of credit lines holds only in the constrained samples, for all criteria.[20] These results are once again consistent with the model in Section 2.

– Table 8 about here –

3.3.6 Year-by-year regressions and macroeconomic effects

Finally, we provide evidence on the time variation of the relationship between systematic risk (*Beta KMV*) and credit line usage (*LC-to-Cash*). To do this, we run the regression in equation (26) every year between 1988 and 2008, collect the coefficients β_1 for each time period, and examine their relationship to a proxy for overall risk in the economy, VIX (the implied volatility on S&P 500 index options).[21] A simple regression of $\beta_{1,t}$ on VIX_t produces a negative coefficient of -0.094, with a t-statistic of 1.87. This suggests that when VIX goes up, the effect of beta on the LC-to-Cash ratio (captured by $\beta_{1,t}$) becomes more pronounced.

In addition to this simple regression, we also experiment with alternative specifications in which we include additional macroeconomic variables. For example, 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 to honor their loan commitments (e.g., Gatev and Strahan (2005)). Banks' increased ability to honor their loan commitments during bad times may then counteract the effect of VIX on corporate liquidity management. As shown by Gaten and Srahan, this inflow

[20] While the beta coefficient for the non-rated sample is only marginally significant (p-value of 0.107), its magnitude is much larger than that of the sub-sample of firms that have both bond and commercial paper ratings.

[21] We divide *VIX* by 100 to increase the magnitude of the coefficients.

effect tends to happen in times when the spread of commercial paper over treasury rates is high. Accordingly, we include the CP–treasury spread in the regression that explains the time variation in $\beta_{1,t}$.[22] We also include a time trend, and real GDP growth to capture general economic conditions. We obtain the following result, which we report in the text. The t-statistics associated with each estimate are reported in parenthesis:

$$\beta_{1,t} = \underset{(0.94)}{0.015} - \underset{(-1.87)}{0.099} \times VIX_t - \underset{(-0.35)}{0.088} \times GDPgrowth_t + \underset{(1.16)}{0.021} \times CP\text{–}Treasury\ Spread_t - \underset{(-1.49)}{0.001} \times TimeTrend_t \quad (27)$$

This regression shows that the the *Beta KMV* coefficient is significantly more negative in periods when *VIX* is high, controlling for variation in other economic variables. That is, riskier firms resort more to cash (as opposed to lines of credit) in periods of elevated aggregate risk. The positive coefficient on the *CP–Treasury Spread* indicates that the flight to bank deposits in bad times does mitigate some of the effect of VIX on liquidity management (consistent with arguments in the existing literature).

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 a firm's exposure to systematic risk using asset. Our results show a negative, statistically significant and economically large effect of asset betas on the fraction of total liquidity that is held via credit lines. This effect increases during times when systematic risk is high, and is stronger among groups of firms that are more likely to be financially constrained (such as small firms). 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 (beta) 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. In order for banks to be able to build an "excess" liquidity buffer and help in aggregate crises, they must be special and earn some rents (such as information rents). Such an argument suggests that securitization may limit the ability of banks to intermediate in aggregate crises. Bank rents can also come from market concentration. This argument suggests that concentrated and scope-restricted banks may be

[22] The CP-treasury spread is measured using 3-month CP and treasury rates (data from the FRB).

able to intermediate better in aggregate crises. In either case, 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 relationship bank(s), especially during crises (when other better-capitalized banks also find it difficult to offer further lines of credit given heightened aggregate risk levels). Finally, 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 these dynamics of liquidity management in the economy.

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Table 1: Summary statistics

This table reports basic summary statistics for empirical proxies related to firm characteristics. *LC-to-Cash* is the fraction of corporate liquidity that is provided by lines of credit, specifically the ratio of the firm's total amount of open credit lines to the sum of open credit lines plus cash balances. *Assets* are firm assets net of cash, measured in millions of dollars. *Tangibility* is PPE over assets. *Q* is defined as a cash-adjusted, market-to-book assets ratio. *NetWorth* is the book value of equity minus cash over total assets. *Profitability* is the ratio of EBITDA over net assets. Industry sales volatility (*IndSaleVol*) is the (3-digit SIC) industry median value of the within-year standard deviation of quarterly changes in firm sales, scaled by the average quarterly gross asset value in the year. *Profitability* is the firm-level standard deviation of annual changes in the level of EBITDA, calculated using four lags, and scaled by average gross assets in the lagged period. *Firm Age* is measured as the difference between the current year and the first year in which the firm appeared in COMPUSTAT. *Unused LC-to-Cash* and *Total LC-to-Cash* measure the fraction of total corporate liquidity that is provided by credit lines using unused and total credit lines respectively. *BetaKMV* is the firm's asset (unlevered) beta, calculated from equity (levered) betas and a Merton-KMV formula. *betaAsset* is another proxy for the firm's asset (unlevered) beta, calculated directly from data on asset returns as in Choi (2009). *VarKMV* and *varAsset* are the corresponding values for total asset variance. *BetaCash* is the (3-digit SIC industry median) asset Beta, adjusted for cash holdings. *BetaBank* is the firm's beta with respect to an index of bank stock returns. *BetaTail* is a measure of beta that is based on the average stock return of a firm in the days in which the stock market had its worst 5% returns in the year. *BetaGap* is computed using the difference between investment and cash flows at the 3-digit SIC level, and the aggregate financing gap.

Panel A: LPC credit line data

Variables	Mean	StDev	Median	25%	75%	Firm-years
LC-to-Cash	0.325	0.404	0.000	0.000	0.781	44598
CashHold_A	0.148	0.216	0.053	0.016	0.173	44817
Total LC	0.146	1.316	0.000	0.000	0.173	44817
Tangibility	0.350	0.232	0.297	0.164	0.498	43250
Assets	2594.093	17246.889	270.431	68.545	1094.000	43309
Q	1.961	1.314	1.475	1.114	2.227	43288
Networth	0.381	0.248	0.404	0.254	0.558	43288
Profitability	0.137	0.120	0.141	0.085	0.203	43309
IndSalesVol	0.043	0.031	0.034	0.022	0.050	44823
ProfitVol	0.063	0.053	0.044	0.024	0.083	44821
Firm age	18.855	14.339	14.000	7.000	29.000	44825
betaKMV	0.986	1.032	0.856	0.290	1.545	44402
betaCash	0.970	0.574	0.920	0.602	1.292	44714
betaBank	0.445	0.703	0.390	0.013	0.813	44440
betaTail	0.742	0.567	0.697	0.324	1.099	44367
betaGap	0.928	3.018	1.156	-1.268	4.000	44825
varKMV	0.017	0.019	0.009	0.005	0.020	44825
betaAsset	0.919	0.926	0.756	0.303	1.343	14646
varAsset	0.012	0.017	0.005	0.003	0.013	14646

Panel B: Sufi data

Variables	Mean	StDev	Median	25%	75%	Firm-years
Unused LC-to-Cash	0.450	0.373	0.455	0.000	0.822	1906
Total LC-to-Cash	0.512	0.388	0.569	0.000	0.900	1908
Tangibility	0.332	0.230	0.275	0.146	0.481	1908
Assets	1441.409	7682.261	116.411	23.981	522.201	1908
Q	2.787	3.185	1.524	1.069	2.726	1905
Networth	0.426	0.300	0.453	0.284	0.633	1905
Profitability	0.015	0.413	0.126	0.040	0.198	1908
IndSalesVol	0.043	0.026	0.036	0.024	0.051	1908
ProfitVol	0.089	0.078	0.061	0.028	0.126	1908
Firm age	16.037	13.399	10.000	6.000	23.000	1908
betaKMV	1.002	1.068	0.804	0.286	1.609	1559
varKMV	0.026	0.026	0.015	0.007	0.038	1568

Table 2: Correlations among different proxies for asset beta.

See Table 1 for a description of the variables.

	betaKMV	betaCash	betaBank	betaTail	betaGap	betaAsset	varAsset
betaCash	0.4255						
betaBank	0.6598	0.3129					
betaTail	0.4421	0.3734	0.2484				
betaGap	0.1022	0.3016	0.0828	0.1432			
betaAsset	0.9000	0.4596	0.6718	0.5204	0.2072		
varAsset	0.5002	0.4712	0.2253	0.3594	0.2593	0.5554	
varKMV	0.5541	0.4094	0.2710	0.2877	0.1233	0.5306	0.9597

Table 3: The Choice Between Cash and Credit Lines - KMV Betas

This Table reports regressions of a measure of line of credit usage in corporate liquidity policy on asset (unlevered) beta and controls. The dependent variable is *LC-to-Cash*, defined in Table 1. *betaKMV* is the firm's asset (unlevered) beta, calculated from equity (levered) betas and a Merton-KMV formula. *varKMV* is the corresponding value for total asset variance. *BetaKMV* is instrumented with its first two lags in all regressions. In columns (5) and (6) we also instrument *varKMV* with its first two lags. All other variables are described in Table 1.

	Dependent variable: LC-to-Cash					
	(1)	(2)	(3)	(4)	(5)	(6)
betaKMV		-0.089***	-0.083***	-0.113***	-0.067**	-0.059*
		(-5.626)	(-4.947)	(-4.749)	(-2.181)	(-1.778)
varKMV				1.721***	-1.506	-1.681
				(2.906)	(-1.133)	(-1.209)
Profitability	0.136***	0.089***	0.101***	0.128***	0.055	0.063
	(5.435)	(2.962)	(3.274)	(4.194)	(1.430)	(1.633)
Tangibility	0.012	0.030	0.004	0.030	0.031	0.004
	(0.606)	(1.437)	(0.173)	(1.393)	(1.467)	(0.168)
Size	0.044***	0.053***	0.051***	0.057***	0.049***	0.047***
	(16.15)	(16.87)	(16.15)	(14.70)	(9.612)	(8.726)
Networth	-0.138***	-0.124***	-0.132***	-0.120***	-0.127***	-0.136***
	(-9.817)	(-7.500)	(-8.008)	(-7.080)	(-7.389)	(-7.883)
Q	-0.055***	-0.050***	-0.050***	-0.051***	-0.049***	-0.049***
	(-23.84)	(-14.88)	(-14.21)	(-15.56)	(-15.65)	(-14.94)
IndSalesVol	-0.197	-0.031	-0.219	-0.047	-0.018	-0.208
	(-1.343)	(-0.227)	(-1.349)	(-0.336)	(-0.130)	(-1.279)
ProfitVol	-0.250***	0.051	0.033	-0.037	0.129	0.121
	(-3.751)	(0.581)	(0.380)	(-0.467)	(1.408)	(1.316)
Ln Firm age	-0.047***	-0.051***	-0.052***	-0.049***	-0.052***	-0.053***
	(-7.933)	(-6.787)	(-6.819)	(-6.579)	(-6.989)	(-7.049)
Constant	0.379***	0.552***	0.465***	0.508***	0.591***	0.511***
	(5.710)	(17.05)	(6.044)	(15.86)	(13.20)	(6.064)
Industry Fixed-effect	Yes	No	Yes	No	No	Yes
Year Fixed-effect	No	Yes	Yes	Yes	Yes	Yes
First-stage F-stat p-value		0.000	0.000	0.000	0.000	0.000
Hansen J-stat p-value		0.312	0.385	0.396	0.011	0.013
Observations	43009	35372	35372	35372	35372	35372
R^2	0.173	0.495	0.499	0.482	0.501	0.505

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

Table 4: Using Sufi's (2009) line of credit data

This Table reports regressions of a measure of line of credit usage in corporate liquidity policy on asset (unlevered) beta and controls. The dependent variables are *Unused LC-to-Cash* and *Total LC-to-Cash*, defined in Table 1. *betaKMV* is the firm's asset (unlevered) beta, calculated from equity (levered) betas and a Merton-KMV formula. *varKMV* is the corresponding value for total asset variance. All Beta measures are instrumented with their first two lags. In columns (4) and (6) the variance measures are also instrumented with their first two lags. All other variables are described in Table 1.

	Dependent variable:					
	Total LC-to-Cash (1)	Unused LC-to-Cash (2)	Total LC-to-Cash (3)	Total LC-to-Cash (4)	Unused LC-to-Cash (5)	Unused LC-to-Cash (6)
betaKMV			-0.336***	-0.419***	-0.270***	-0.322**
			(-5.489)	(-2.801)	(-4.893)	(-2.438)
varKMV				3.114		1.649
				(0.654)		(0.387)
Profitability	0.078**	0.061*	-0.013	0.003	-0.012	-0.004
	(2.269)	(1.955)	(-0.226)	(0.0518)	(-0.238)	(-0.0736)
Tangibility	0.040	0.025	-0.089	-0.081	-0.091	-0.088
	(0.560)	(0.371)	(-1.098)	(-0.938)	(-1.184)	(-1.092)
Size	0.047***	0.053***	0.071***	0.083***	0.074***	0.081***
	(5.110)	(6.106)	(5.593)	(3.621)	(6.481)	(3.992)
Networth	-0.097**	-0.054	-0.077	-0.072	-0.043	-0.040
	(-2.293)	(-1.396)	(-1.345)	(-1.141)	(-0.819)	(-0.708)
Q	-0.036***	-0.029***	-0.019***	-0.016	-0.016**	-0.013
	(-8.495)	(-7.263)	(-2.656)	(-1.516)	(-2.398)	(-1.479)
IndSalesVol	1.094*	1.042	-0.156	-0.138	-0.073	-0.075
	(1.691)	(1.549)	(-0.215)	(-0.186)	(-0.0927)	(-0.0951)
ProfitVol	-0.596***	-0.554***	0.315	0.272	0.198	0.192
	(-3.209)	(-3.162)	(1.022)	(0.887)	(0.711)	(0.716)
Ln Firm age	-0.039*	-0.023	-0.086***	-0.083***	-0.061**	-0.061**
	(-1.846)	(-1.125)	(-2.818)	(-2.731)	(-2.101)	(-2.102)
Constant	0.748***	0.148	0.306**	0.250	0.165	0.141
	(8.612)	(1.377)	(2.359)	(1.516)	(1.332)	(0.945)
Industry Fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed-effect	No	No	Yes	Yes	Yes	Yes
First-stage F-stat p-value			0.000	0.016	0.000	0.016
Hansen J-stat p-value			0.283	0.569	0.174	0.295
Observations	1905	1903	1321	1321	1319	1319
R^2	0.401	0.371	-0.066	-0.294	0.051	-0.074

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

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

This Table reports regressions of a measure of line of credit usage in corporate liquidity policy on asset (unlevered) beta and controls. All variables are described in Table 1. In columns (1) to (5), Beta measures are instrumented with their first two lags. In column (6), we use an industry beta rather than the firm-level instrumented beta in the regression.

	Dependent variable: LC-to-Cash					
	(1)	(2)	(3)	(4)	(5)	(6)
betaAsset	-0.156***					
	(-7.582)					
betaCash		-0.127***				
		(-9.258)				
betaBank			-0.297***			
			(-5.573)			
betaTail				-0.146***		
				(-8.133)		
betaGap					-0.010***	
					(-3.428)	
betaMKV						-0.029***
						(-4.919)
Profitability	0.055	0.116***	0.070**	0.117***	0.117***	0.124***
	(0.860)	(5.088)	(2.141)	(4.041)	(4.779)	(5.008)
Tangibility	0.015	-0.004	-0.001	0.028	0.025	0.048**
	(0.364)	(-0.239)	(-0.0483)	(1.331)	(1.320)	(2.400)
Size	0.043***	0.050***	0.055***	0.061***	0.049***	0.042***
	(7.126)	(19.96)	(16.40)	(17.53)	(17.87)	(14.52)
Networth	-0.103***	-0.109***	-0.114***	-0.110***	-0.124***	-0.114***
	(-3.346)	(-8.612)	(-6.534)	(-6.685)	(-9.080)	(-8.204)
Q	-0.051***	-0.049***	-0.048***	-0.043***	-0.056***	-0.052***
	(-8.631)	(-23.03)	(-12.99)	(-12.50)	(-25.42)	(-22.09)
IndSalesVol	-0.079	-0.128	0.012	0.020	-0.187	0.132
	(-0.304)	(-1.066)	(0.0895)	(0.144)	(-1.356)	(0.826)
ProfitVol	-0.156	-0.013	0.114	0.083	-0.254***	-0.198***
	(-0.855)	(-0.199)	(1.152)	(1.012)	(-3.608)	(-2.785)
Ln Firm age	-0.027**	-0.048***	-0.053***	-0.052***	-0.042***	-0.046***
	(-1.995)	(-8.494)	(-6.842)	(-7.038)	(-6.678)	(-6.902)
Constant	0.581***	0.614***	0.543***	0.503***	0.453***	0.362***
	(9.837)	(21.43)	(16.69)	(16.49)	(16.66)	(13.52)
Industry Fixed-effect	No	No	No	No	No	No
Year Fixed-effect	Yes	Yes	Yes	Yes	Yes	No
First-stage F-stat p-value	0.000	0.000	0.000	0.000	0.000	
Hansen J-stat p-value	0.101	0.005	0.555	0.000	0.873	
Observations	9536	46865	35499	35343	37485	31811
R^2	0.574	0.497	0.393	0.503	0.502	0.164

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

Table 6: The Choice Between Cash and Credit Lines - Varying Betas, Sufi (2009) sample

This Table reports regressions of measures of line of credit usage in corporate liquidity policy on asset (unlevered) beta and controls. All variables are described in Table 1. In both panels, in columns (1) to (5) Beta measures are instrumented with their first two lags. In column (6), we use an industry beta rather than the firm-level instrumented beta in the regression.

Panel A

	Dependent variable: LC-to-Cash					
	(1)	(2)	(3)	(4)	(5)	(6)
betaAsset	-0.265***					
	(-3.330)					
betaCash		-0.238***				
		(-5.327)				
betaBank			-0.619***			
			(-2.866)			
betaTail				-0.285**		
				(-2.326)		
betaGap					-0.012	
					(-1.318)	
betaKMV						-0.096***
						(-3.616)
Profitability	-0.134**	0.100***	0.048	0.229**	0.061*	0.108***
	(-2.094)	(2.762)	(0.845)	(2.489)	(1.760)	(2.843)
Tangibility	-0.079	-0.030	-0.026	0.037	0.088	0.098
	(-0.651)	(-0.433)	(-0.273)	(0.343)	(1.183)	(1.117)
Size	0.109***	0.048***	0.077***	0.032*	0.047***	0.037***
	(7.573)	(5.025)	(4.474)	(1.882)	(4.852)	(3.242)
Networth	-0.090	-0.057	-0.127*	-0.159	-0.076*	-0.103**
	(-1.157)	(-1.356)	(-1.912)	(-1.430)	(-1.814)	(-2.378)
Q	-0.015*	-0.031***	-0.031***	-0.033***	-0.038***	-0.035***
	(-1.957)	(-7.147)	(-3.938)	(-2.731)	(-8.880)	(-8.413)
IndSalesVol	1.299	0.452	0.370	0.245	1.471**	1.790**
	(1.375)	(0.845)	(0.467)	(0.318)	(2.541)	(2.373)
profitVol	1.033*	-0.252	0.236	-0.241	-0.655***	-0.381*
	(1.922)	(-1.224)	(0.604)	(-0.821)	(-3.131)	(-1.734)
Ln Firm Age	-0.040	-0.041**	-0.080**	-0.077**	-0.032	-0.030
	(-1.006)	(-1.961)	(-2.344)	(-2.363)	(-1.450)	(-1.156)
Constant		0.680***	0.367*		0.371***	0.565***
		(6.857)	(1.955)		(4.093)	(5.174)
Industry Fixed-effect	Yes	No	Yes	Yes	No	No
Year Fixed-effect	Yes	Yes	Yes	Yes	Yes	No
First-stage F-stat p-value	0.004	0.000	0.011	0.000	0.000	
Hansen J-stat p-value	0.063	0.041	0.043	0.086	0.023	
Observations	434	1866	1322	866	1659	1241
R^2	0.250	0.767	0.501	0.211	0.754	0.383

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

Panel B

	Dependent variable: Unused LC-to-Cash					
	(1)	(2)	(3)	(4)	(5)	(6)
betaAsset	-0.257***					
	(-3.591)					
betaCash		-0.170***				
		(-3.879)				
betaBank			-0.523**			
			(-2.406)			
betaTail				-0.210		
				(-1.422)		
betaGap					-0.013	
					(-1.302)	
betaKMV						-0.073***
						(-2.854)
Profitability	-0.127**	0.084**	0.036	0.247**	0.049	0.081**
	(-2.175)	(2.500)	(0.636)	(2.384)	(1.516)	(2.358)
Tangibility	-0.220*	-0.027	-0.057	0.058	0.054	0.040
	(-1.889)	(-0.367)	(-0.584)	(0.411)	(0.687)	(0.483)
Size	0.100***	0.045***	0.068***	0.016	0.049***	0.041***
	(6.858)	(4.669)	(4.026)	(0.857)	(5.103)	(4.007)
Networth	-0.094	-0.044	-0.132**	-0.181*	-0.052	-0.083**
	(-1.203)	(-1.152)	(-2.159)	(-1.740)	(-1.341)	(-2.130)
Q	-0.012	-0.025***	-0.025***	-0.028**	-0.029***	-0.029***
	(-1.591)	(-6.459)	(-3.772)	(-2.244)	(-7.449)	(-7.450)
IndSalesVol	3.049**	0.820	0.438	0.054	1.420**	1.652**
	(2.209)	(1.183)	(0.385)	(0.0415)	(2.170)	(2.160)
profitVol	0.787	-0.259	0.200	-0.389	-0.518**	-0.373*
	(1.502)	(-1.269)	(0.562)	(-1.253)	(-2.541)	(-1.769)
Ln Firm Age	-0.053	-0.017	-0.063	-0.048	-0.012	-0.008
	(-1.306)	(-0.727)	(-1.487)	(-1.074)	(-0.491)	(-0.320)
Constant		0.458***	0.304		0.232***	0.402***
		(4.695)	(1.373)		(2.632)	(3.977)
Industry Fixed-effect	Yes	No	Yes	Yes	No	No
Year Fixed-effect	Yes	Yes	Yes	Yes	Yes	No
First-stage F-stat p-value	0.003	0.000	0.022	0.000	0.000	
Hansen J-stat p-value	0.081	0.337	0.080	0.155	0.262	
Observations	348	1437	963	574	1396	1241
R^2	0.219	0.695	0.368	0.211	0.691	0.352

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

Table 7: SUR models for cash and credit lines

This Table reports seemingly unrelated regressions of line of credit usage and cash holdings on asset (unlevered) beta and controls. The dependent variables in columns (1) to (4) are *Total LC* (total lines of credit divided by assets net of cash), and *cash* (cash holdings divided by assets net of cash). In columns (1) and (2) we measure *Total LC* using the LPC-Deal Scan sample (described in Panel A of Table 1), and in columns (3) and (4) we use Sufi (2009) data, described in Panel B of Table 1. The dependent variables in columns (5) to (6) are *Unused LC* (total lines of credit divided by assets net of cash), and cash (cash holdings divided by assets net of cash). *betaKMV* is the firm's asset (unlevered) beta, calculated from equity (levered) betas and a Merton-KMV formula. *varKMV* is the corresponding value for total asset variance. All Beta measures are instrumented with their first two lags. All other variables are described in Table 1.

	Dependent variables:			
	Total LC		Total LC-to-Cash	
	(1)	(2)	(3)	(4)
BetaKMV	0.020	0.030	-0.338***	-0.302***
	(0.55)	(0.72)	(8.70)	(7.51)
varKMV		-0.84		-1.687***
		(-1.63)		(-4.12)
Profitability	-0.148*	-0.177**	-0.010	-0.030
	(-1.84)	(-2.13)	(-0.42)	(-1.03)
Tangibility	-0.060	-0.060	-0.097**	-0.107**
	(-1.53)	(-1.590)	(-2.240)	(-2.46)
Size	-0.014**	-0.016**	0.073***	0.067***
	(-2.31)	(-2.51)	(12.29)	(11.00)
Networth	-0.163***	-0.164***	-0.084***	-0.084***
	(-4.71)	(-4.56)	(-2.82)	(-2.80)
Q	-0.032***	-0.031***	-0.020***	-0.022***
	(-3.53)	(-3.33)	(-4.94)	(-5.39)
IndSalesVol	0.140	0.150	-0.220	-0.220
	(0.46)	(0.48)	(-0.58)	(-0.57)
ProfitVol	-0.180	-0.12 0	0.317*	0.384**
	(-0.89)	(-0.54)	(1.90)	(2.26)
Ln Firm age	-0.01	-0.01	-0.086***	-0.088***
	(-0.66)	(-0.69)	(-5.85)	(-6.00)
Constant		0.512***	0.384***	0.422***
		(3.59)	(3.30)	(3.65)
Observations	36315	35524	1348	1321
R^2	0.01	0.01	0.44	0.45
	Dependent variable: CashHold_A			
betaKMV	0.128***	0.118***	0.350***	0.341***
	(25.26)	(22.89)	(6.971)	(6.572)
varKMV		0.821***		0.28
		(13.48)		(0.520)
Profitability	-0.035***	-0.018*	-0.190***	-0.142***
	(-3.626)	(-1.842)	(-5.133)	(-3.684)
Tangibility	-0.013***	-0.013***	0	0.03
	(-2.907)	(-2.714)	(0.00936)	(0.448)
Size	-0.026***	-0.025***	-0.105***	-0.106***
	(-36.86)	(-33.47)	(-13.66)	(-13.46)
Networth	-0.049***	-0.054***	-0.291***	-0.319***
	(-11.73)	(-12.82)	(-7.548)	(-8.191)
Q	0.054***	0.054***	0.046***	0.048***
	(50.22)	(50.10)	(8.911)	(9.110)
IndSalesVol	0.03	0.02	0.76	0.52
	(0.704)	(0.536)	(1.522)	(1.030)
ProfitVol	0.086***	0.052**	-0.960***	-0.943***
	(3.468)	(2.065)	(-4.464)	(-4.304)
Ln Firm age	0.005***	0.006***	0.085***	0.084***
	(2.935)	(3.847)	(4.449)	(4.436)
Constant		0.150***	0.244*	
		(9.507)	(1.934)	
Observations	36315	35524	1348	1321
R^2	0.33	0.34	0.53	0.53

z-statistics in parentheses .* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 8: Sorting on Proxies for Financing Constraints

This Table reports regressions of a measure of line of credit usage in corporate liquidity policy on asset (unlevered) beta and controls. The dependent variable is *LC-to-Cash*, defined in Table 1. *betaKMV* is the firm's asset (unlevered) beta, calculated from equity (levered) betas and a Merton-KMV formula. *varKMV* is the corresponding value for total asset variance. All beta and variance measures are instrumented with their first two lags. In column (1) we use a sample of small firms (those with assets in the 30th percentile and lower). In column (2) we use a sample of large firms (those with assets in the 70th percentile and higher). In column (3) we use a sample of firms with low payouts (those with payout in the 30th percentile and lower). In column (4) we use a sample of firms with high payouts (those with payout in the 70th percentile and higher). In column (5) we use a sample of firms that have neither a bond, nor a commercial paper rating. In column (6) we use a sample of firms that have both bond and commercial paper ratings. All other variables are described in Table 1.

	Dependent variable: LC-to-Cash					
	(1)	(2)	(3)	(4)	(5)	(6)
	Small firms	Large firms	Low payout firms	High payout firms	Non-rated firms	Rated firms
betaKMV	-0.227**	-0.020	-0.184***	0.006	-0.070	0.073
	(-2.206)	(-0.392)	(-3.655)	(0.115)	(-1.613)	(0.639)
varKMV	6.282	-6.350**	2.404	-4.494**	-0.701	-13.558
	(1.587)	(-2.267)	(1.178)	(-2.100)	(-0.389)	(-1.596)
Profitability	0.128*	0.174*	0.208***	-0.048	0.023	0.191
	(1.723)	(1.749)	(3.765)	(-0.786)	(0.528)	(0.742)
Tangibility	-0.009	0.022	0.009	0.051*	0.036	0.030
	(-0.286)	(0.582)	(0.360)	(1.650)	(1.519)	(0.403)
Size	0.107***	0.004	0.073***	0.038***	0.056***	0.005
	(4.917)	(0.444)	(8.187)	(5.632)	(6.611)	(0.281)
Networth	-0.054*	-0.174***	-0.082***	-0.157***	-0.116***	-0.235***
	(-1.810)	(-4.512)	(-3.535)	(-5.895)	(-5.991)	(-3.064)
Q	-0.006	-0.065***	-0.027***	-0.050***	-0.045***	-0.054***
	(-0.523)	(-9.407)	(-4.709)	(-10.64)	(-11.37)	(-3.151)
IndSalesVol	0.256	-0.028	0.085	-0.153	0.093	0.145
	(1.044)	(-0.116)	(0.449)	(-0.788)	(0.600)	(0.325)
ProfitVol	-0.182	0.416**	-0.052	0.176	0.152	0.386
	(-0.954)	(1.976)	(-0.440)	(1.186)	(1.512)	(0.640)
Ln Firm age	-0.005	-0.038***	-0.038***	-0.047***	-0.054***	-0.048*
	(-0.329)	(-2.978)	(-3.837)	(-4.433)	(-5.975)	(-1.811)
Constant	-0.035	0.939***	0.374***	0.644***	0.507***	0.918***
	(-0.223)	(10.23)	(5.080)	(10.75)	(7.605)	(4.359)
Year Fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes
First-stage F-stat p-value	0.003	0.000	0.000	0.000	0.000	0.000
Hansen J-stat p-value	0.904	0.001	0.248	0.011	0.346	0.223
Observations	8436	12578	14908	14162	22548	4344
R^2	-0.378	0.125	-0.007	0.158	0.103	0.127

Robust z-statistics in parentheses .* significant at 10%; ** significant at 5%; *** significant at 1%.

Figure 1: Timeline of the model

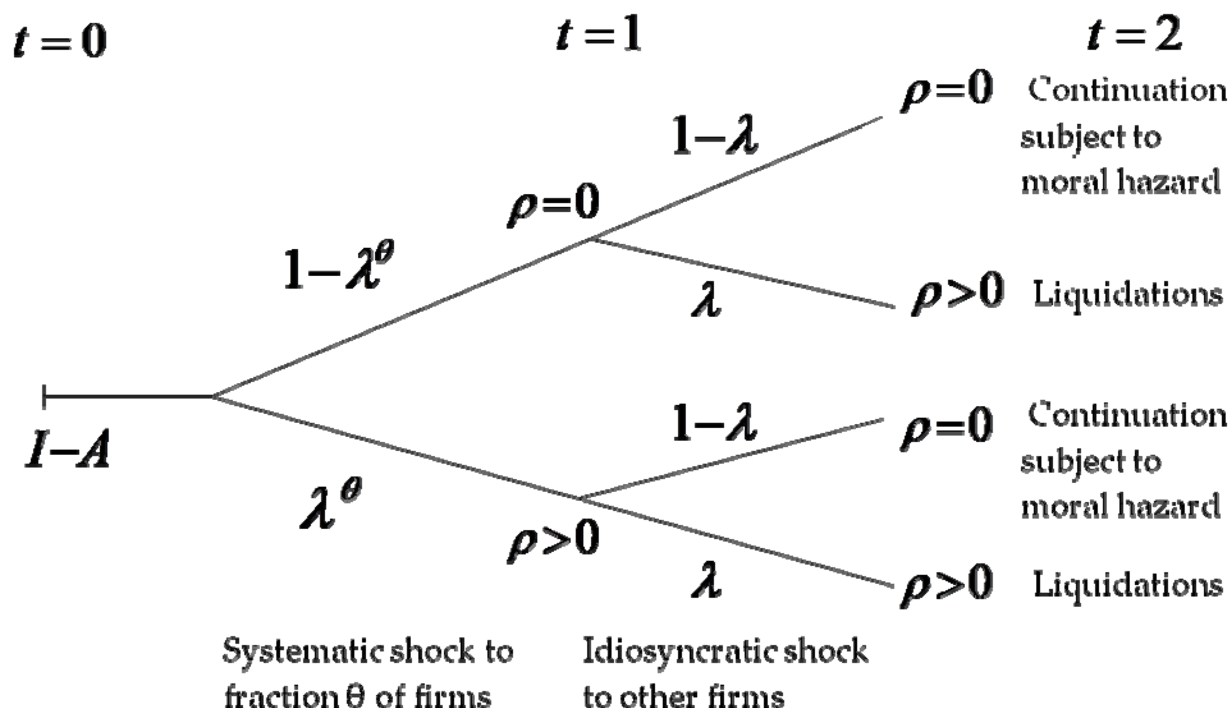


Figure 2: Equilibrium with cash holdings for systematic firms when systematic risk is high ($\theta \geq \theta^{max}$)

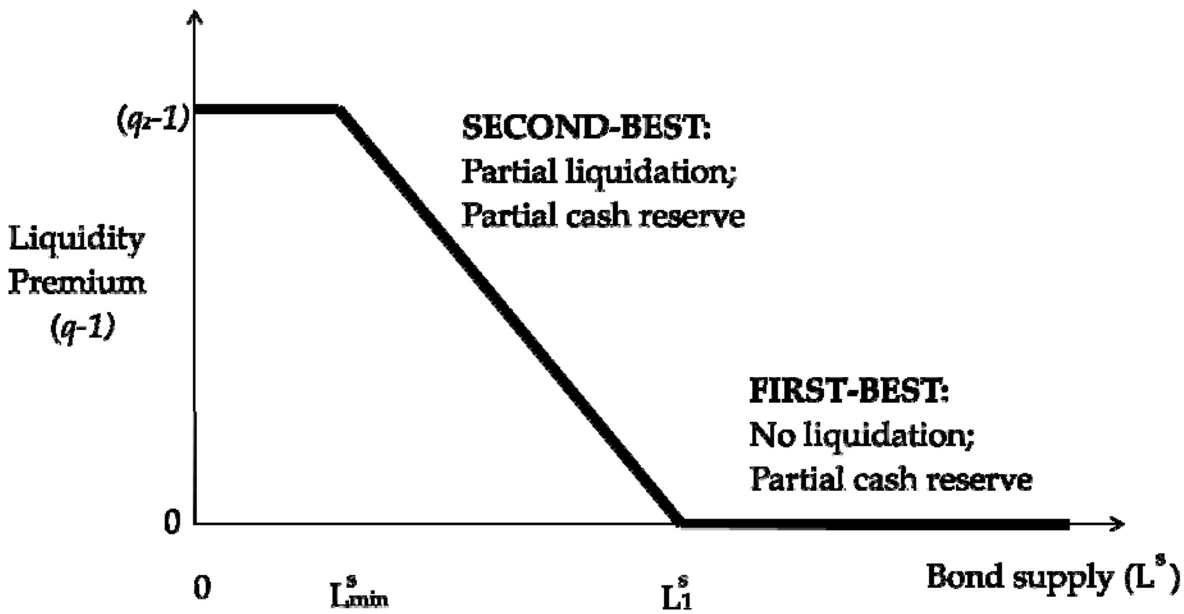
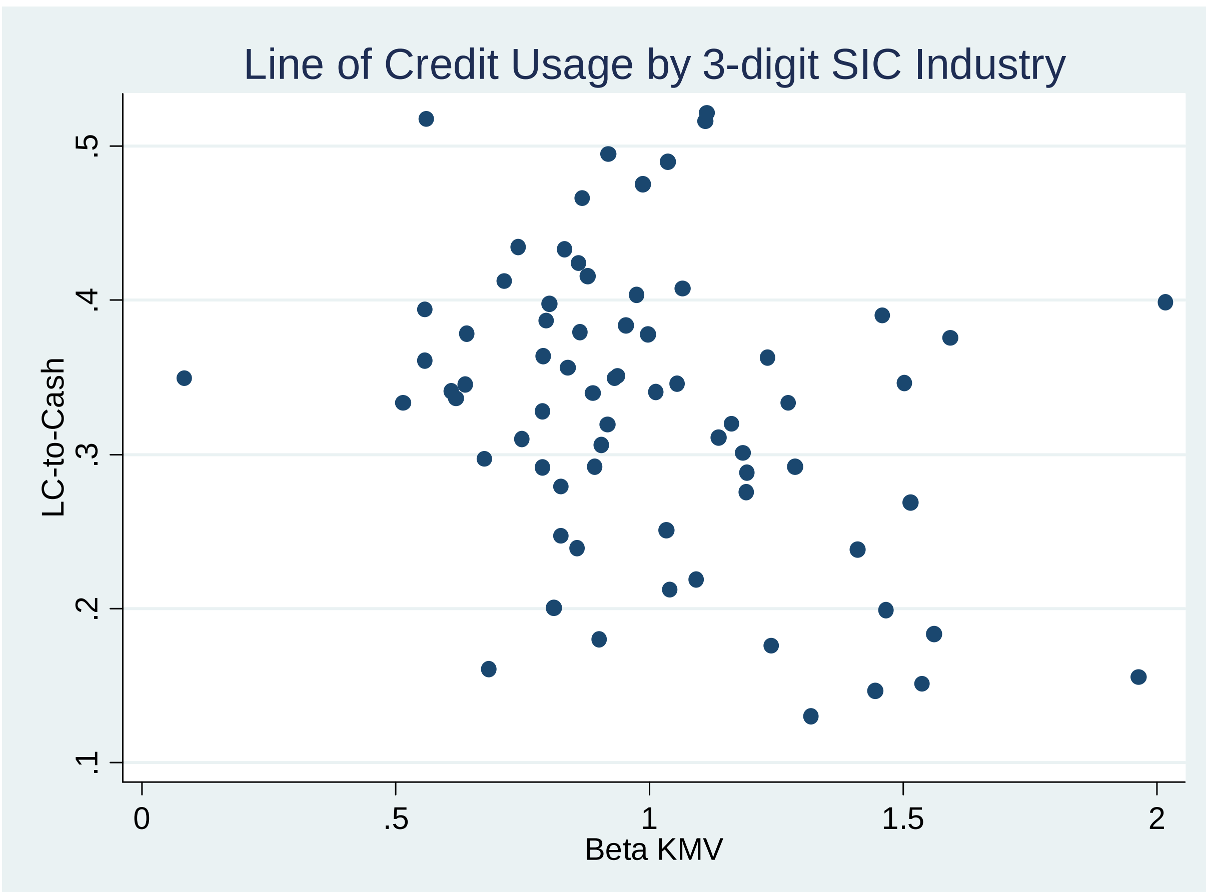


Figure 3: Aggregate risk and the choice between cash and credit lines at the industry level.

This figure displays the average industry value for *LC-to-Cash,* plotted against average industry betas (across our entire sample period of 1987 to 2008). *LC-to-Cash* is the ratio of the firm's total amount of open credit lines divided by total liquidity, which is defined as total open credit lines plus cash balances. We use the *beta KMV* in this Figure. *Beta KMV* is the firm's asset (unlevered) beta, calculated from equity (levered) betas and a Merton-KMV formula. The industry is defined at the 3-digit SIC level. Industry betas are computed using value-weighted industry stock returns, and unlevered using the industry's leverage ratio. Industry-years with less than 15 firms are dropped from the calculations. We also report the output of a simple regression of *LC-to-Cash* on *beta KMV*.



LC-to-Cash = 0.42 - 0.09*Beta KMV
(12.3) (-2.8)