

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

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First draft: September 2009; This Draft: November 2009

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 this 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. The effect of aggregate risk on liquidity management is economically significant, and is robust to variation in the proxies for firms' exposure to aggregate risk, and availability of credit lines. This effect is true at the firm level as well as the industry level, and it is significantly stronger in times when aggregate risk is higher. The positive relation between a preference for cash and asset risk is particularly strong for firms that are more likely to be financially constrained (small, non-rated, low payout firms).

Key words: Bank lines of credit, Cash holdings, Liquidity premium, Lending channel, Asset beta.

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

*We thank Florin Vasvari and Anurag Gupta for help with the data on lines of credit and Michael Roberts and Florin Vasvari for matching of these data to COMPUSTAT. Quoc Nguyen provided excellent research assistance. We are also grateful to Jaewon Choi and Thomas Philippon for sharing with us the data on firm betas.

“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 corporations in the US (e.g., Sufi (2009) and Yun (2009)).² 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.³

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. In principle firms 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

¹For 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.

²A 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 the London Inter-Bank Offered Rate). These facilities also 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, and finally, 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.

³The 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 loan 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.

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 cash holding 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.

However, the cost of a credit line arises from the observation that banks may not be able to provide such 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.

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.

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 DealScan and Sufi’s data sets, we measure the fraction of corporate liquidity that is provided by lines of credit as the ratio of total credit lines to the sum of total credit lines plus cash. For short, we call this variable *LC-to-Cash* ratio. 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 several 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 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. Third, we compute “cash-adjusted” betas by unlevering equity betas using net debt (e.g., debt minus cash) rather than gross debt in the Merton-KMV calculations.⁴ All of these

⁴Given the potentially endogenous relationship between cash-adjusted betas and firm cash holdings, we use the

betas are measured in a yearly basis.

One important methodological issue that arises when using asset beta data in panel regressions is that such betas are likely to be measured with error, thus biasing down the coefficient of OLS regressions of *LC-to-Cash* on betas. Our empirical methodology addresses this point explicitly by using in our panel regressions an OLS-IV estimator in which the current values of betas are instrumented with their two first lags. As shown by Griliches and Hausman (1986), under the assumption that the measurement error in betas is independently and identically distributed over time, such an approach will produce consistent estimates of the relation between betas and *LC-to-Cash*.

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) 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 355 industry (Special Industry Machinery) and SIC 201 (food products). The former industry is characterized by heavy reliance on cash for liquidity management (*LC-to-Cash* = 0.155), while the latter shows greater reliance on credit lines (*LC-to-Cash* = 0.35). These LC/cash choices correspond to the differences in unlevered industry betas across the two industries. SIC 355 has a *Beta KMV* of 1.59, while SIC 201’s beta equals 0.68. 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 a panel 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 complete and 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). These results hold for all different proxies of asset betas and line of credit usage that we employ.

We also provide evidence for the auxiliary implications of the model. We examine, for example, whether the effect of asset beta on the choice between cash and credit lines increases during times

median (3-digit) SIC industry beta in lieu of firm betas in this calculation.

when aggregate risk is likely to matter 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 aggregate volatility (as measured by *VIX*). The results indicate that a firm’s exposure to systematic risk matters most in times when *VIX* is high. 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). These results suggest that cross-sectional variation in the exposure to systematic risk is a more important determinant of liquidity policy among constrained firms, and in times when systematic risk is likely to increase.

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 during crises, banks experience an inflow of deposits coming from the commercial paper market. 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. 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 present the basic model and derive its empirical implications. We present the empirical tests in Section 3, and offer some concluding remarks in Section 4.

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:

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

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:

$$\rho_0 < \rho < \rho_1. \quad (3)$$

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 :

$$I - A < (1 - \lambda)\rho_0 + \lambda(\rho_0 - \rho). \quad (4)$$

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 the 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 exchange for that, 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:

$$w(x) \geq x(\rho - \rho_0). \quad (5)$$

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 that:

$$y + p_G D \leq \rho_0. \quad (6)$$

The intermediary's break even constraint is:

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

Finally, the firm's payoff is:

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

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:

$$(1 - \theta)(1 - \lambda)\rho_0 \geq [\theta + (1 - \theta)\lambda](\rho - \rho_0). \quad (9)$$

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 θ^{\max} is given by the condition:*

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

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:

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

The first equation ensures that the firm can finance the continuation investment level x^i , given its liquidity policy (w^i, L^i) . The second equation is the bank break-even constraint. The bank provides financing for the initial investment and the liquid holdings qL^i , and in addition provides financing through the credit line in state λ (equal to w^i). In exchange, the bank receives the sum of the firm's liquid holdings, the credit line commitment fee, and the date-2 debt payment D^i . The third inequality guarantees that the firm has enough pledgeable income to make the payment $y^i + p_G D^i$ in 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 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:

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

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

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

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:

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

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 a case, both systematic and non-systematic firms can use credit lines to manage liquidity. Notice that this corresponds to cases 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:

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

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 $q = 1$. 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:

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

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

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:*

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

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:

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

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:

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

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:

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

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 $q = 1$.⁵

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 θ^{\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 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 –

⁵Notice that $x^\theta(q_2) < 1$.

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.⁶
3. *The trade-off between cash and credit lines is more important for firms that find it more costly to raise external capital.* In the absence of financing constraints there is no role for corporate liquidity policy, thus the choice between cash and credit lines becomes irrelevant. We test this model implication by sorting firms according to observable proxies for financing constraints, and examining whether the effect of 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 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

⁶Empirical 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.

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 “sample A”) 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, and 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 between 1996 and 2003. These data are provided by Amir Sufi on his website, and were used on Sufi (2009). We call this sample “sample B.” 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 sample A, 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).⁷ We drop utilities, quasi-public and financial firms from the sample (SIC codes greater than 5999 and lower than 7000, greater than 4899 and lower than 5000, and greater than 8999). We consider only short term and long term credit lines, which are defined as those that have the LPC field “*loantype*” equal to “*364-day Facility*,” “*Revolver/Line < 1 Yr*,” “*Revolver/Line >= 1 Yr*,” or “*Revolver/Line*.” We drop loans that appear to be repeated (same *gvkey* and *loan_id*). In some cases, the same firm has more than one credit line initiation in the same quarter. In these cases, we sum the facility amounts (the total available credit in each line) for each firm-quarter, and average the other variables using the facility amount as weights. We let $LC_{i,t}$ denote the total value of credit lines initiated in quarter t by firm i , and let $Maturity_{i,t}$ denote the average maturity of these lines in quarters. This sample is then matched to COMPUSTAT annual data, as described below.

To construct sample B, we start from the “random sample” used in Sufi (2009), which contains

⁷We use several procedures to obtain *gvkeys*, 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.

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 (described below). 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, $(Assets + prcc_fc \times sho - ceq) / Assets$.⁸ *NetWorth* is defined as $(ceq - che) / Assets$. *Profitability* is the ratio of EBITDA over assets. *Age* is measured as the difference between the current year and the first year in which the firm appeared in COMPUSTAT. Industry sales volatility (*IndSaleVol*) is the (3-digit SIC) industry median value of the within-year standard deviation of quarterly changes in firm sales ($saleq$ minus its lagged value) scaled by the average asset value (atq) in the year. Profit volatility (*ProfitVol*) is the firm-level standard deviation of annual changes in the level of EBITDA, calculated using four lags, and scaled by average assets in the lagged period. We winsorize all COMPUSTAT variables at the 5th and 95th percentiles.

3.2.2 Line of credit data

When using sample B, 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:

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

⁸Sufi (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.

and:

$$Unused\ LC\text{-to-Cash}_{i,t} = \frac{Unused\ Line_{i,t}}{Unused\ Line_{i,t} + Cash_{i,t}}. \quad (23)$$

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 sample A (LPC-Deal Scan data), we construct a proxy for line of credit usage in the following way. For each firm-quarter, we measure credit line availability at date t by summing all existing credit lines that have not yet matured. This calculation assumes that LCs remain open until they mature. Specifically, we define our measure of line of credit availability for each firm-quarter (j, s) as:

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

where $\Gamma(\cdot)$ 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:

$$LC\text{-to-Cash}_{j,t} = \frac{Total\ LC_{j,t}}{Total\ LC_{j,t} + Cash_{j,t}}. \quad (25)$$

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. 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.

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.⁹ We call the set of betas that we obtain using this method *Beta KMV*. We also compute a measure of total asset

⁹This is a known rule-of-thumb used to fit a KMV-type model to an annual horizon.

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.¹⁰

One potential concern with these beta measures is that they may be mechanically influenced by a firm’s cash holdings. Since corporate cash holdings are typically held in the form of riskless securities, high cash firms could have lower asset betas. Notice that this possibility would make it *less* likely for us to find a positive 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.

Finally, 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 (from Kenneth French’s website).

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. 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.

¹⁰We refer the reader to Choi’s original paper for further details on the construction of *Beta Asset*.

3.3 Empirical tests and results

3.3.1 Summary statistics

We start by summarizing the data described above, 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 268 million in sample A, and 116 million in sample B. Consistent with this difference, the firms in sample A are also older, and have higher average *Qs* and EBITDA volatility. The measure of line of credit availability in sample A (*LC-to-Cash*) is lower than those in sample B (*Total LC-to-Cash* and *Unused LC-to-Cash*). For example, the average value of *LC-to-Cash* in sample A is 0.32, 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 order to examine the effect of aggregate risk on the choice between cash and credit lines, we perform a number of different sets of tests, which we describe now.

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* against average industry betas (measured using *Beta KMV*). 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 SIC 355 (Special Industry Machinery, Except Metalworking) and SIC 201 (Meat Products). The former industry is characterized by heavy reliance on cash for liquidity management (*LC-to-Cash* = 0.155), while the latter is characterized by greater reliance on credit lines (*LC-to-Cash* = 0.35). These LC/cash patterns directly correspond to the differences in unlevered industry betas across the two industries: SIC 355 shows an industry *Beta KMV* equal to 1.59 while SIC 201 shows an industry beta equal to 0.68. This empirical relation

supports the implications of the model developed in Section 2.

— Figure 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:

$$\begin{aligned}
 LC\text{-to-Cash}_{i,t} = & \alpha + \beta_1 \ln(Age)_{i,t} + \beta_3(Profitability)_{i,t-1} \\
 & + \beta_4 Size_{i,t-1} + \beta_5 Q_{i,t-1} + \beta_6 Networth_{i,t-1} + \beta_7 IndSalesVol_{j,t} \\
 & + \beta_8 ProfitVol_{i,t} + \beta_9 BetaKMV_{i,t} + \sum_t Year_t + \epsilon_{i,t},
 \end{aligned}
 \tag{26}$$

where *Year* absorbs industry- and 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 *Beta Market* and *Beta Market*. 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*).

The results for the *Beta KMV* and LPC-Deal Scan data are presented in Table 2. 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 0.085 (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.

It is important that we consider the validity of our instrumental variables approach to the mis-measurement problem. The first statistic we consider in this examination is the first-stage exclusion F -tests for our set of instruments. Their the 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 2. 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 2 about here –

Table 3 replaces the KMV measure of beta with that from Choi (i.e., *Beta Market*), and also employs cash-adjusted and bank betas. The results in the first three columns suggest that *Beta Market* has a similar relationship to liquidity policy as that uncovered in Table 2. The economic magnitude of the coefficient on *Beta Market* is in fact larger than that reported in Table 2. These results hold before and after using industry-dummies, and also after instrumenting the associated variance measure (*Var Asset*) using its first two lags. Using industry-level cash-adjusted betas, *Beta Cash*, also produces similar results (columns (4) and (5)) . Finally, notice that there is also some evidence that a firm’s exposure to banking sector risks (*Beta Bank*) affects liquidity policy, though the coefficient is not significant after controlling for total variance (columns (6) and (7)).

– Table 3 about here –

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 2, 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 –

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, so we believe the *LC-to-Cash* is appropriate for our goals.

Still, 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. The results are presented in Table 5.

— Table 5 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)).

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 is 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. These results are once again consistent with the model in Section 2.

– Table 6 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 (??) every year between 1988 and 2007, collect the coefficients β_9 , and examine their relationship to a proxy for overall risk in the economy, *VIX* (the implied volatility on S&P 500 index options).¹¹ We also include a time trend, and a dummy that takes the value of one in the recession years of 1990, 1991 and 2001. We obtain the following result, which we report in the text. The t-statistics associated with each estimate are reported in parenthesis:

$$\beta_9 = 0.035 - 0.143 \cdot \text{VIX} - 0.011 \cdot \text{Recession Dummy} - 0.001 \cdot \text{Time Trend}$$

$$(2.90) \quad (-2.64) \quad (-1.20) \quad (-2.08) \quad (27)$$

This regression shows that the coefficient on *Beta_KMV* is significantly more negative in periods when *VIX* is high.

4 Concluding Remarks

We show in this paper that aggregate risk affects firms' choice between cash and credit lines. For firms with high exposure to systematic risks, the folk statement that "*cash is king*" appears to be

¹¹We divide *VIX* by 100 to increase the magnitude of the coefficients.

true. In contrast, for firms that only need to manage their idiosyncratic liquidity risks, bank credit lines dominate cash holdings due to a liquidity premium. In our empirical tests we measure a firm's exposure to systematic risk using asset, or unlevered betas. 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 a line of 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 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 aggregate risky firms, and potentially lead to excessive aggregate risk in the economy. We believe 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. *ProfitVol* is the firm-level standard deviation of annual changes in the level of EBITDA, calculated using four lags, and scaled by average gross assets in the lagged period. *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. *betaKMV_{asset}* 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.

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	0.782	44628
CashHold_A	0.148	0.216	0.053	0.016	0.173	44847
Total LC	0.146	1.316	0.000	0.000	0.174	44847
Tangibility	0.350	0.232	0.297	0.164	0.497	43281
Assets	2470.109	16411.354	268.335	67.994	1077.531	43340
Q	1.960	1.312	1.476	1.113	2.227	43319
Networth	0.382	0.248	0.404	0.255	0.558	43319
Profitability	0.137	0.120	0.141	0.085	0.203	43340
IndSalesVol	0.043	0.031	0.034	0.022	0.050	44856
ProfitVol	0.063	0.053	0.044	0.024	0.083	44854
Firm age	18.779	14.278	14.000	7.000	29.000	44858
betaKMV	0.987	1.029	0.857	0.288	1.545	44473
betaCash	0.969	0.572	0.920	0.596	1.287	44741
betaBank	0.009	0.011	0.008	0.002	0.015	44399
varKMV	0.017	0.019	0.009	0.005	0.020	44858
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	1.009	1.066	0.817	0.293	1.614	1553
varKMV	0.026	0.026	0.015	0.007	0.038	1567

Table 2: 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		-0.086*** (-5.459)	-0.080*** (-4.752)	-0.110*** (-4.597)	-0.066** (-2.154)	-0.057* (-1.734)
varKMV				1.691*** (2.798)	-1.430 (-1.069)	-1.613 (-1.155)
Profitability	0.130*** (5.210)	0.087*** (2.885)	0.098*** (3.204)	0.124*** (4.073)	0.055 (1.433)	0.063 (1.640)
Tangibility	0.011 (0.577)	0.028 (1.340)	0.004 (0.197)	0.027 (1.294)	0.029 (1.367)	0.004 (0.190)
Size	0.044*** (16.49)	0.053*** (17.06)	0.052*** (16.29)	0.057*** (14.80)	0.050*** (9.801)	0.048*** (8.893)
Networth	-0.138*** (-9.799)	-0.124*** (-7.470)	-0.132*** (-7.972)	-0.120*** (-7.070)	-0.126*** (-7.359)	-0.134*** (-7.850)
Q	-0.055*** (-23.94)	-0.050*** (-15.13)	-0.051*** (-14.53)	-0.051*** (-15.85)	-0.050*** (-15.93)	-0.050*** (-15.29)
IndSalesVol	-0.190 (-1.298)	-0.048 (-0.353)	-0.236 (-1.456)	-0.063 (-0.458)	-0.036 (-0.261)	-0.226 (-1.391)
ProfitVol	-0.245*** (-3.679)	0.037 (0.418)	0.027 (0.304)	-0.050 (-0.636)	0.111 (1.210)	0.111 (1.206)
Ln Firm age	-0.047*** (-7.858)	-0.051*** (-6.817)	-0.052*** (-6.879)	-0.049*** (-6.614)	-0.052*** (-7.002)	-0.054*** (-7.098)
Constant	0.373*** (5.632)	0.547*** (16.96)	0.459*** (5.975)	0.504*** (15.80)	0.584*** (13.06)	0.503*** (5.973)
Industry Fixed-effect	No	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		0.247	0.306	0.322	0.018	0.022
Observations	43039	35460	35460	35460	35460	35460
R^2	0.173	0.496	0.500	0.484	0.501	0.506

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

Table 3: 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. The dependent variable is *LC-to-Cash*, defined in Table 1. *betaKMV_{asset}* is a proxy for the firm's asset (unlevered) beta, calculated directly from data on asset returns as in Choi (2009). *Var_{asset}* is the corresponding value for total asset variance. *VarKMV* is the proxy for total asset variance calculated from KMV data. *BetaCash* is the (3-digit SIC industry median) asset Beta, adjusted for cash holdings, and *BetaBank* is the firm's beta with respect to an index of bank stock returns. All Beta measures are instrumented with their first two lags. In columns (3), (4) and (6) the variance measures are also instrumented with their first two lags. All other variables are described in Table 1.

	Dependent variable: LC-to-Cash						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
betaAsset	-0.156*** (-7.582)	-0.137*** (-6.006)	-0.131*** (-4.399)				
betaCash				-0.126*** (-9.207)	-0.129*** (-7.053)		
betaBank						-5.608** (-2.068)	-1.288 (-0.327)
var_asset			-2.768* (-1.805)				
Profitability	0.055 (0.860)	0.042 (0.675)	-0.010 (-0.154)	0.116*** (5.082)	0.082** (2.457)	0.115*** (3.870)	0.018 (0.472)
Tangibility	0.015 (0.364)	-0.017 (-0.400)	0.011 (0.283)	-0.004 (-0.245)	-0.001 (-0.0376)	0.042** (1.963)	0.040* (1.894)
Size	0.043*** (7.126)	0.042*** (6.965)	0.038*** (5.392)	0.050*** (19.95)	0.047*** (14.36)	0.049*** (16.48)	0.042*** (10.22)
Networth	-0.103*** (-3.346)	-0.127*** (-4.169)	-0.094*** (-3.071)	-0.109*** (-8.628)	-0.127*** (-8.092)	-0.137*** (-8.085)	-0.139*** (-8.091)
Q	-0.051*** (-8.631)	-0.050*** (-8.136)	-0.047*** (-8.297)	-0.049*** (-23.04)	-0.053*** (-18.89)	-0.060*** (-22.28)	-0.053*** (-16.12)
IndSalesVol	-0.079 (-0.304)	-0.341 (-1.029)	-0.058 (-0.221)	-0.131 (-1.098)	-0.131 (-0.962)	0.040 (0.293)	0.027 (0.197)
Profitability	-0.156 (-0.855)	-0.315* (-1.747)	-0.015 (-0.0804)	-0.014 (-0.209)	0.141 (1.599)	-0.103 (-1.088)	0.150* (1.665)
Ln Firm age	-0.027** (-1.995)	-0.029** (-2.064)	-0.030** (-2.194)	-0.048*** (-8.490)	-0.049*** (-6.676)	-0.047*** (-6.205)	-0.052*** (-7.078)
varKMV					-1.483** (-2.156)		-3.726*** (-3.061)
Constant	0.581*** (9.837)	0.448** (2.529)	0.615*** (9.787)	0.613*** (21.42)	0.681*** (18.10)	0.524*** (15.11)	0.629*** (15.51)
Industry Fixed-effect	No	Yes	Yes	No	No	Yes	No
Year Fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First-stage F-stat p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Hansen J-stat p-value	0.101	0.158	0.053	0.012	0.005	0.279	0.005
Observations	9536	9536	9536	46862	35637	35464	35386
R ²	0.574	0.587	0.580	0.498	0.507	0.503	0.508

* 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			-0.334*** (-5.499)	-0.422*** (-2.826)	-0.267*** (-4.895)	-0.325** (-2.469)
varKMV				3.327 (0.693)		1.967 (0.458)
Profitability	0.078** (2.269)	0.061* (1.955)	-0.018 (-0.322)	-0.002 (-0.0377)	-0.019 (-0.395)	-0.010 (-0.189)
Tangibility	0.040 (0.560)	0.025 (0.371)	-0.094 (-1.169)	-0.084 (-0.972)	-0.094 (-1.229)	-0.089 (-1.102)
Size	0.047*** (5.110)	0.053*** (6.106)	0.074*** (5.945)	0.086*** (3.790)	0.077*** (7.036)	0.085*** (4.268)
Networth	-0.097** (-2.293)	-0.054 (-1.396)	-0.078 (-1.404)	-0.073 (-1.185)	-0.046 (-0.911)	-0.043 (-0.783)
Q	-0.036*** (-8.495)	-0.029*** (-7.263)	-0.019*** (-2.677)	-0.015 (-1.525)	-0.016** (-2.431)	-0.013 (-1.492)
IndSalesVol	1.094* (1.691)	1.042 (1.549)	-0.292 (-0.405)	-0.285 (-0.385)	-0.191 (-0.244)	-0.196 (-0.250)
ProfitVol	-0.596*** (-3.209)	-0.554*** (-3.162)	0.298 (0.952)	0.246 (0.779)	0.165 (0.584)	0.147 (0.532)
Ln Firm age	-0.039* (-1.846)	-0.023 (-1.125)	-0.086*** (-2.813)	-0.083*** (-2.714)	-0.063** (-2.190)	-0.062** (-2.160)
Constant	0.748*** (8.612)	0.148 (1.377)	0.291** (2.246)	0.234 (1.417)	0.156 (1.265)	0.126 (0.845)
Industry Fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes
First-stage F-stat p-value			0.000	0.016	0.000	0.016
Hansen J-stat p-value			0.234	0.503	0.147	0.268
Observations	1905	1903	1313	1313	1311	1311
R^2	0.401	0.371	0.640	0.559	0.643	0.592

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

Table 5: 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.

	Total LC		Dependent variable:			
	(1)	(2)	Unused LC-to-Cash (3)	(4)	Total LC-to-Cash (5)	(6)
betaKMV	0.024 (0.573)	0.033 (0.753)	-0.001 (-0.068)	-0.007 (-0.355)	-0.337*** (-8.595)	-0.303*** (-7.416)
varKMV		-0.888* (-1.696)		0.075 (0.349)		-1.593*** (-3.803)
Profitability	-0.150* (-1.869)	-0.179** (-2.157)	0.015 (1.049)	0.012 (0.789)	-0.020 (-0.690)	-0.035 (-1.165)
Tangibility	-0.061 (-1.576)	-0.064 (1.632)	-0.051** (2.340)	-0.055** (-2.469)	-0.103** (-2.392)	-0.113*** (-2.588)
Size	-0.013** (-2.228)	-0.015** (2.449)	0.007** (2.370)	0.007** (2.199)	0.076*** (12.860)	0.070*** (11.410)
Networth	-0.162*** (-4.681)	-0.163*** (-4.527)	-0.016 (-1.067)	-0.016 (-1.012)	-0.086*** (-2.890)	-0.084*** (-2.789)
Q	-0.032*** (-3.561)	-0.031*** (-3.359)	-0.007*** (-3.522)	-0.007*** (-3.428)	-0.020*** (-4.851)	-0.021*** (-5.253)
IndSalesVol	0.140 (0.457)	0.151 (0.482)	0.413** (2.120)	0.405** (2.047)	-0.375 (-0.971)	-0.354 (-0.912)
ProfitVol	-0.184 (-0.892)	-0.113 (0.531)	-0.022 (0.265)	-0.022 (0.256)	0.305* (-1.823)	0.370** (-2.159)
Ln Firm age	-0.009 (-0.668)	-0.010 (-0.716)	-0.028*** (-3.858)	-0.029*** (-3.832)	-0.085*** (-5.850)	-0.087*** (-5.953)
Constant	0.481*** (3.508)			0.169*** (2.873)	0.386*** (3.338)	
Observations	36390	35611	1341	1313	1341	1313
R-squared	0.005	0.005	0.087	0.087	0.443	0.451
Dependent variable: CashHold_A						
betaKMV	0.128*** (25.280)	0.118*** (22.860)	0.351*** (6.845)	0.344*** (6.485)	0.351*** (6.845)	0.344*** (6.485)
varKMV		0.831*** (13.460)		0.227 (0.417)		0.227 (0.417)
Profitability	-0.036*** (-3.700)	-0.019* (-1.928)	-0.188*** (-5.044)	-0.139*** (-3.598)	-0.188*** (-5.044)	-0.139*** (-3.598)
Tangibility	-0.013*** (-2.870)	-0.013*** (-2.733)	-0.003 (-0.057)	0.020 (0.357)	-0.003 (-0.057)	0.020 (0.357)
Size	-0.027*** (-37.060)	-0.025*** (-33.640)	-0.106*** (-13.710)	-0.107*** (-13.500)	-0.106*** (-13.710)	-0.107*** (-13.500)
Networth	-0.049*** (-11.910)	-0.055*** (-12.980)	-0.294*** (-7.588)	-0.324*** (-8.283)	-0.294*** (-7.588)	-0.324*** (-8.283)
Q	0.054*** (50.570)	0.054*** (50.510)	0.046*** (8.809)	0.048*** (9.033)	0.046*** (8.809)	0.048*** (9.033)
IndSalesVol	0.029 (0.775)	0.022 (0.592)	0.897* (1.778)	0.645 (1.280)	0.897* (1.778)	0.645 (1.280)
ProfitVol	0.089*** (3.569)	0.054** (2.153)	-0.968*** (-4.428)	-0.930*** (-4.178)	-0.968*** (-4.428)	-0.930*** (-4.178)
Ln Firm age	0.005*** (3.066)	0.006*** (3.991)	0.084*** (4.402)	0.085*** (4.476)	0.084*** (4.402)	0.085*** (4.476)
Constant		0.116*** (6.917)		0.804*** (5.362)	0.771*** (5.109)	0.775*** (5.181)
Observations	36390	35611	1341	1313	1341	1313
R-squared	0.330	0.339	0.527	0.530	0.527	0.530

Table 6: 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) Small firms	(2) Large firms	(3) Low payout firms	(4) High payout firms	(5) Non-rated firms	(6) Rated firms
betaKMV	-0.207** (-2.088)	-0.028 (-0.545)	-0.175*** (-3.541)	0.003 (0.0679)	-0.065 (-1.523)	0.082 (0.776)
varKMV	5.758 (1.488)	-6.113** (-2.192)	2.219 (1.097)	-4.388** (-2.014)	-0.710 (-0.395)	-15.888** (-2.222)
Profitability	0.121* (1.683)	0.172* (1.745)	0.198*** (3.684)	-0.044 (-0.734)	0.025 (0.589)	0.123 (0.483)
Tangibility	-0.011 (-0.350)	0.020 (0.517)	0.010 (0.387)	0.049 (1.593)	0.034 (1.459)	0.015 (0.205)
Size	0.104*** (5.001)	0.008 (0.772)	0.072*** (8.295)	0.040*** (5.790)	0.057*** (6.885)	0.004 (0.190)
Networth	-0.062** (-2.143)	-0.168*** (-4.317)	-0.083*** (-3.634)	-0.155*** (-5.788)	-0.119*** (-6.194)	-0.237*** (-2.981)
Q	-0.008 (-0.765)	-0.067*** (-9.717)	-0.028*** (-4.994)	-0.051*** (-10.76)	-0.045*** (-11.68)	-0.051*** (-3.092)
IndSalesVol	0.241 (0.993)	-0.045 (-0.186)	0.082 (0.442)	-0.166 (-0.859)	0.062 (0.401)	0.082 (0.185)
ProfitVol	-0.180 (-0.980)	0.418** (2.012)	-0.077 (-0.656)	0.181 (1.222)	0.143 (1.413)	0.598 (0.971)
Ln Firm age	-0.005 (-0.290)	-0.041*** (-3.167)	-0.037*** (-3.811)	-0.048*** (-4.540)	-0.053*** (-5.852)	-0.051* (-1.934)
Constant	-0.022 (-0.148)	0.925*** (10.12)	0.373*** (5.128)	0.636*** (10.55)	0.495*** (7.459)	0.962*** (4.540)
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	0.877	0.002	0.222	0.022	0.419	0.155
Observations	8473	12554	14965	14172	22631	4343
R^2	0.019	0.592	0.406	0.516	0.406	0.601

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

Figure 1: Timeline of the model

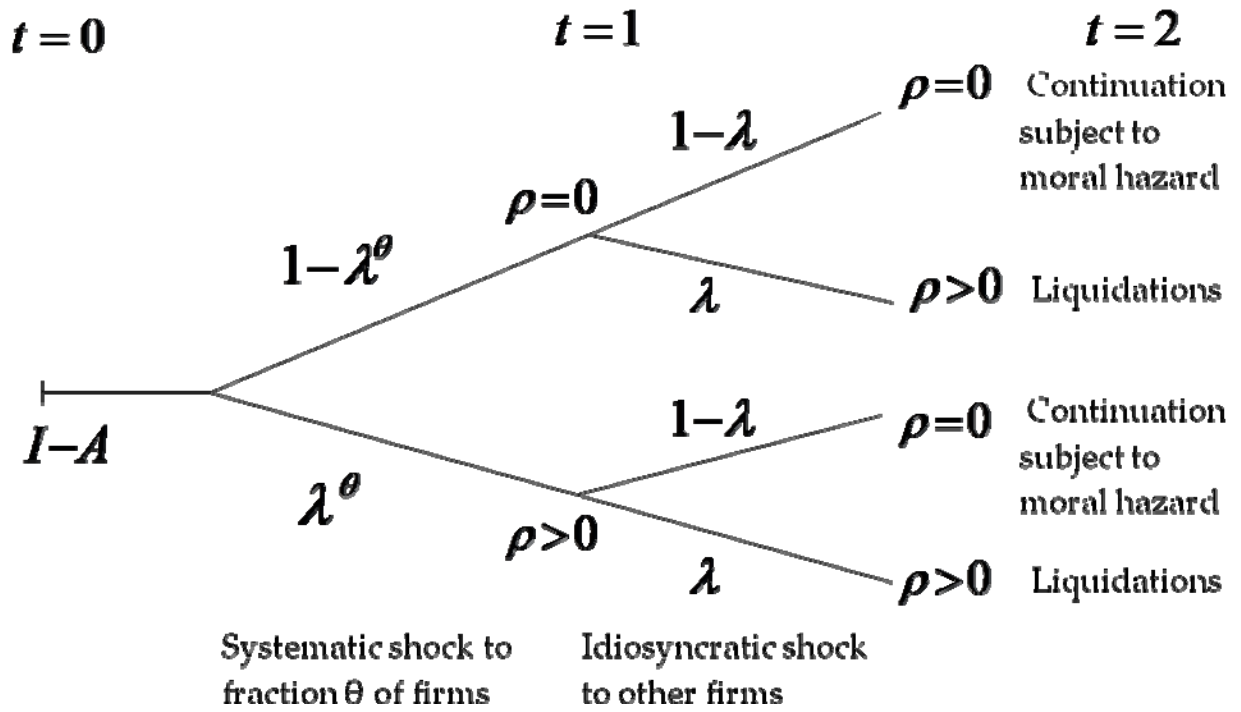


Figure 2: Equilibrium with cash holdings for systematic firms when systematic risk is high ($\theta \geq \theta^{\max}$)

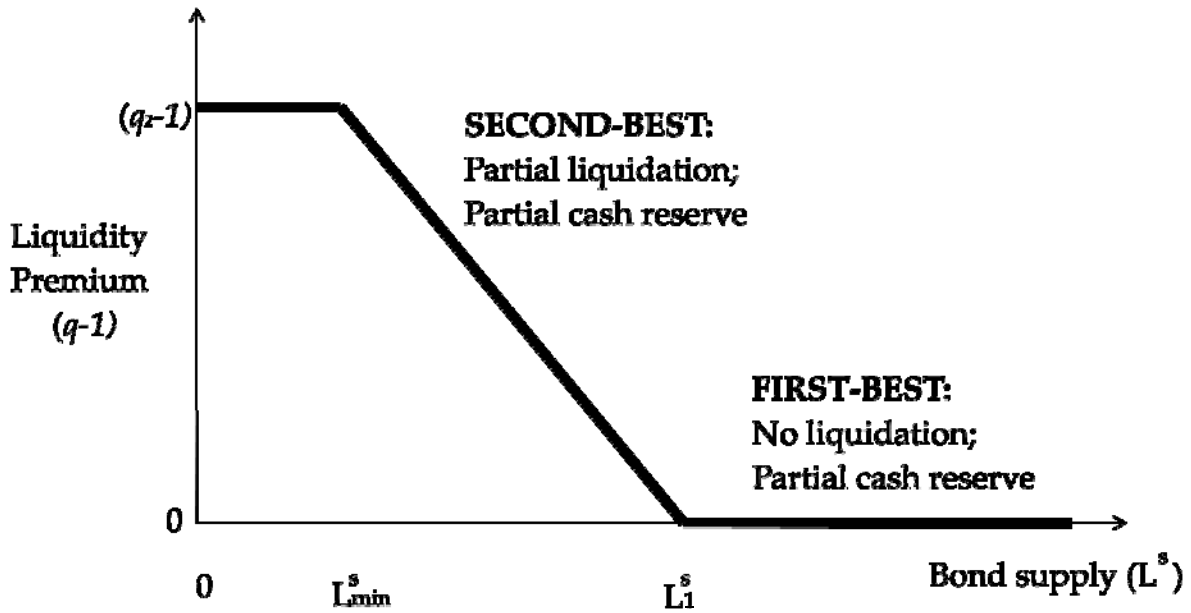
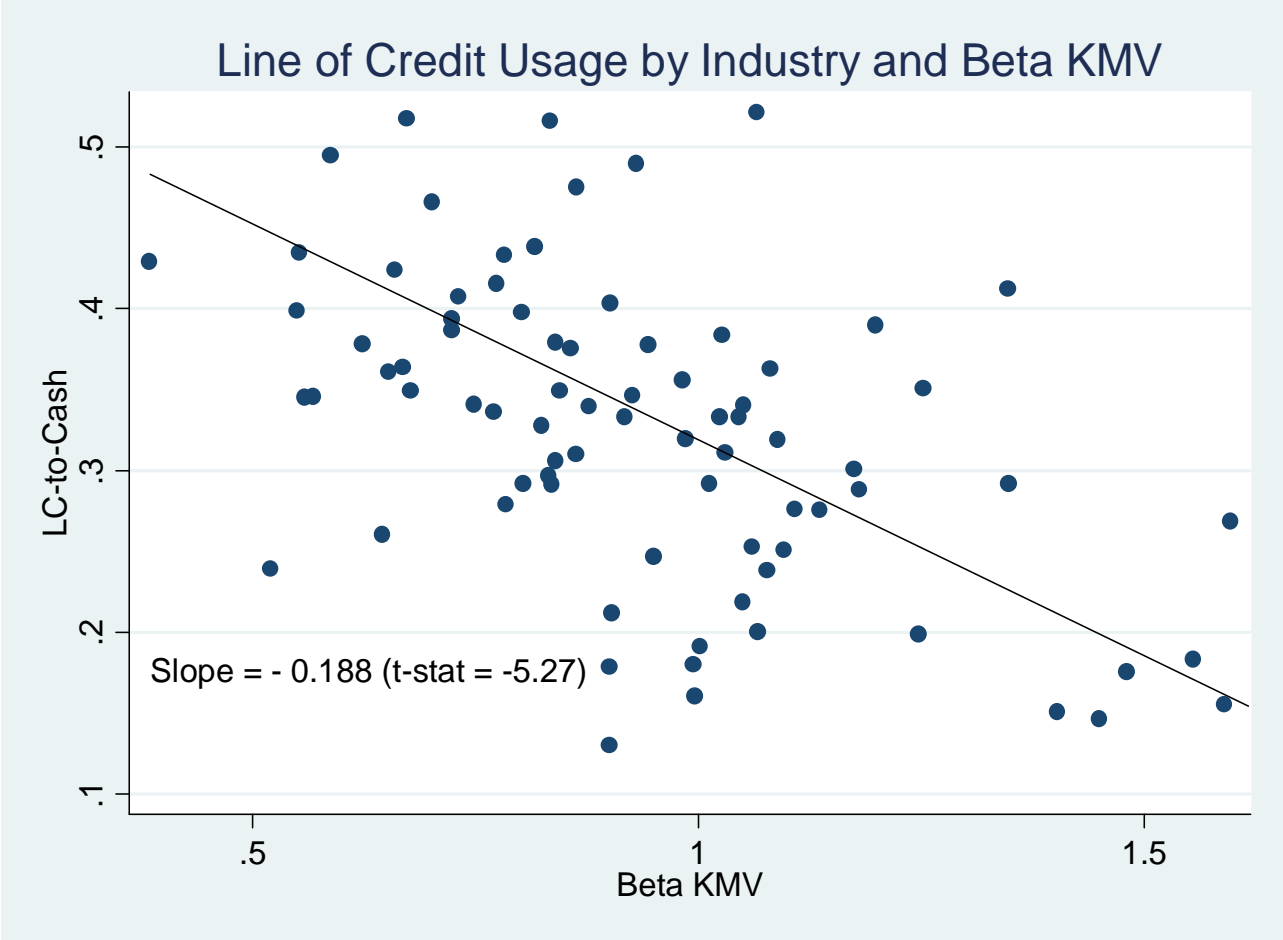


Figure 3: Aggregate risk and the choice between cash and credit lines at the industry level.



This figure displays the average industry value for *LC-to-Cash*, plotted against average industry betas (across our entire sample period). *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, and we require an industry to have at least 15 firms for it to appear in Figure 2. We also report the slope of a simple regression of *LC-to-Cash* on *beta KMV*, and its t-stat.