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Three Essays on Corporate Liquidity, Financial Crisis, and Real Estate

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THREE ESSAYS ON CORPORATE LIQUIDITY, FINANCIAL CRISIS, AND REAL ESTATE

by

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ABSTRACT

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The first essay examines why firms with access to lines of credit (LOC) have different drawdowns and their implications for asset pricing, investment and profitability. Utilizing a hand-collected LOC dataset that extends the sample of Sufi (2009) to 2010, our principal finding is that firms with greater LOC usage are more financially constrained than firms with lower LOC usage. We also document that high users of credit lines have higher risk-adjusted returns, less investment in capital expenditures and employment, and lower profitability than low LOC users. An interesting implication of our evidence is that high LOC drawdowns could serve as an alternative financial constraint measure.

The second essay shows that firms are unable to utilize credit lines to prevent decreases in investment during the 2008 financial crisis. Theory predicts that credit lines provide liquidity insurance that allows firms to invest during periods of limited credit availability; however, we do not find evidence in support of the theoretical predictions. To the contrary, we find strong evidence that credit lines do not enable firms to maintain investment during the crisis. With a unique dataset that includes bank line of credit drawdowns and hedging data, we study the relationship between credit line usage and

corporate investment. Our results suggest that credit lines may be unable to provide adequate liquidity insurance to allow firms to continue investment during tough economic environments.

In the third essay, we examine linkages between the real estate and stock markets before and after the delisting of Lehman Brothers to determine if the 2008 financial crisis had an effect on the degree of integration between these two markets. Using several different models, we find that real estate returns subsequently influence stock market returns, a unique result when compared to past financial crises, but consistent with recent findings of increased systematic risk in REITs. These tests were made possible through the employment of a new daily transaction-based commercial real estate return series.

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CHAPTER I

BANK LINES OF CREDIT AND DRAWDOWNS

INTRODUCTION

The subject of credit lines has received increasing attention in the corporate finance literature since Sufi's (2009) seminal work. The previous literature concentrates on whether or not a firm has access to lines of credit (LOC) and whether they possess liquidity insurance properties. Sufi (2009) also argues that lack of access to a line of credit could be a more powerful measure of financial constraints than traditional measures used in the literature.[1] While these studies are insightful about the role of LOC in corporate finance, when firms with access to LOCs realize the benefits of liquidity insurance remains unknown. The reason is that previous studies simply assume that access to lines of credit automatically yields liquidity insurance benefits. We argue that the liquidity insurance function of lines of credit can be assessed by focusing on LOC drawdowns. Moreover, studying the usage of lines of credit is expected to allow us to gain insights into the financial status of firms with access to lines of credit.[2] This paper sheds light on these issues by addressing the question: why do some firms with access to lines of credit use them more extensively than others? The answer to this important question is expected to let us know when the liquidity insurance function of credit lines is performed effectively.

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[1] See, Sufi (2009), Yun (2009), Ivashina and Scharfstein (2010), Almeida, Campello and Hackbarth (2011), and Campello, Giambona, Graham and Harvey (2011). The key variable in most of these studies is the extent to which firms use lines of credit as a percentage of the firm's total liquidity, measured as lines of credit divided by lines of credit plus cash.

[2] Using survey data, Campello, Graham and Harvey (2010) report that financially constrained firms planned to use more LOCs and cash during the 2008 financial crisis than firms that were more financially healthy.

Several theoretical studies suggest that lines of credit are used as a hedge against a possible reduction in availability of future funds (Campbell (1978), Hawkins (1982), Holmstrom and Tirole (1998)). Shockley and Thakor (1997) argue that LOCs may be used as liquidity insurance to protect a firm's ability to invest during states of the economy when credit is difficult to obtain. Likewise, anecdotal reports from the CFO magazine[3] state that firms increase LOCs before investment, possibly indicating that they are used as a hedge against an increase in interest rates. Additionally, several recent survey-based and empirical studies have found that a firm's access to credit lines may increase investment. By interviewing CFOs regarding investment plans and line of credit usage for future investment, Campello, Giambona, Graham and Harvey (2011) find that access to LOCs may allow firms to increase investment to levels higher than what could have been achieved with cash alone. Specifically, they find that firms that are more reliant on credit lines for liquidity are able to engage in more investment than firms that rely more heavily on cash. Almeida, Campello and Hackbarth (2011) provide further e0vidence that the existence of LOCs can boost a firm's investment activities. Furthermore, they find that use of credit lines is more prevalent in industries in which liquidity-seeking mergers take place. It is important to note that these studies focus primarily on the proportion of corporate liquidity that is satisfied by either LOCs or cash. That is, they study credit lines and cash as complementary or substitute corporate liquidity components. Taken together, these studies confirm that credit lines can be a form of liquidity insurance that enables firms to engage in investment activities.

However, in order for credit lines to provide effective liquidity insurance, sufficient unused credit must be available. A near fully-used credit line does not provide

[3] See June 2008 issue of CFO magazine.

a firm with the ability to receive additional liquidity and therefore cannot be used as a hedge. Firms that choose to draw down their credit lines extensively may forfeit the liquidity insurance benefit of credit lines. Therefore, we hypothesize that only firms that have used a low percentage of their credit lines are employing credit lines as liquidity insurance.

Liquidity insurance may be one reason firms pursue access to LOCs. However, there may be other reasons LOCs are utilized. Some firms may use their credit lines to meet day to day liquidity requirements, including investment. Sufi (2009) finds that LOCs may be more useful to firms with high cash flow due to debt covenants. Debt covenants often require that firms maintain high performance in order to retain access to credit lines. However, among firms that have credit lines, those that have relatively low levels of cash flow and little access to capital markets may be expected to make greater use of their credit lines than more financially robust firms. There is some non-US evidence that supports this supposition. In a sample of Spanish firms, Jimenez, Lopez and Saurina (2009) argue that whether or not a firm is able to meet its debt obligations influences credit line usage. They find firms that are unable to make timely payments use a higher percentage of their credit lines. Similarly, Acharya, Almeida, Ippolito and Perez (2012) find that firms with high hedging needs use less of their credit lines. That is, firms with a lower correlation between cash flow and investment have more undrawn lines of credit.

Given these two competing uses of credit lines (liquidity insurance and corporate investment) we propose that there are two different types of firms, each having access to credit lines but choosing to use them differently: high LOC users and low LOC users.

Firms that are high users extensively draw down their LOCs resulting in a high percentage of the total available LOCs being used. Low LOC users make less use of their LOCs and therefore have a low percentage of used LOCs. High users may have limited access to the capital markets because they possess high idiosyncratic risk. Hence, they use LOCs because of limited alternative credit options. Consequently, for this type of firm, LOCs cannot be viewed as a credit hedge. In fact, these firms may be viewed as financially constrained. The less-risky low users have a lower need to deploy their lines of credit because they have more access to capital markets and lower financing costs. These firms may be viewed as buying liquidity insurance against a future liquidity or credit squeeze that may have an adverse effect on their investment or operating cash flow needs. That is, they are using LOCs as a hedge.

Furthermore, to the extent that the financial constraint argument is true, LOC usage should be priced in the cross section of returns. Since financially constrained firms have higher returns than non-financially constrained firms (Whited and Wu (2006), Livdan, Sapriza and Zhang (2009)), we expect that high LOC users will command a higher return than low LOC users. That is, investors are expected to perceive high-users of lines of credit as more risky than firms that make less use of their LOCs. Accordingly, we conjecture that investors will demand higher returns in order to hold equity shares of high LOC firms.

These arguments are based on extant theoretical literature. Although Modigliani and Miller (1958) argue that in efficient markets, capital structure does not influence a firm's ability to invest; more recent research demonstrates that in the presence of market frictions, capital structure may have an impact on a firm's investment decisions and operating performance. Several studies suggest that increased leverage is associated with lower levels of investment (Myers (1977), Lang, Ofek and Stulz (1996)). Almeida and Campello (2007) propose and test a theory that market frictions influence corporate investment. Furthermore, Hahn and Lee (2009) extend the Almeida and Campello (2007) model and find that the risk of not having sufficient funds for investment is priced in the cross-section of returns for financially constrained firms. Taken together, these studies imply that in the presence of market frictions, access to additional financing (or the risk associated with the lack of additional funding) influences both investment and the cross-section of returns. Since constrained firms have fewer options and are more reliant on LOCs, we expect that constrained firms use them more extensively. Hence, using LOC usage as an indication of a firm's access to additional funds, we empirically examine whether or not the theoretical prediction that high LOCs users are constrained is confirmed in the data.

To address these issues, we begin by creating a dataset that builds upon line of credit information from Amir Sufi's 2009 study, which he generously made available on his website. However, his data only covers the time period of 1996-2003. Since we want to ensure that our results encompass the effects of the 2008 financial crisis, we hand-collected additional LOC data from firm 10-Ks, extending the dataset to 2010. We completed the unique dataset by combining the 1997-2010 LOC data with returns and other corporate financial data from CRSP and Compustat.[4] The longer time series of information allows us to examine LOC usage over periods of both stable and tumultuous credit markets, providing a more accurate understanding of the ways LOCs are used.

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[4] Due to computational requirements to produce risk-adjusted returns, this portion of our study begins with 1997 data.

While previous studies examine LOCs as a percentage of total liquidity, our key measure is an indicator variable that reflects whether or not a firm is a high LOC user. We limit our study to firms with access to LOCs to tease out the information provided by the extent of LOC usage, rather than merely access to LOCs. We then divide the data into two sub-samples: firms that have a high percentage (above the sample median) of used lines of credit and those that have a low percentage (below the sample median) of used lines of credit. The splitting of the sample allows us to examine differences in the high and low users. We then create three different indicator variables, reflecting alternative measures of high/low users to ensure that our results are robust. Each indicator variable takes the value of 1 if a firm is classified as a high LOC user and 0 otherwise.

With this unique dataset we are able to investigate differences in LOC usage. We find strong support for our hypothesis that there are significant differences between firms that use a high percentage of their credit lines (high users) and those that do not (low users). Not only do high users have more book leverage and less liquidity than low users, but they also have lower bond ratings and less access to commercial paper. These differences provide early evidence that high LOC users may be financially constrained and support our later findings that firms that use their credit lines more have higher risk-adjusted returns, less corporate investment and lower profitability than low LOC users.

We begin by examining Sufi's results over time. His main finding is that cash flow is a crucial determinant in a firm's decision to use cash or credit lines to satisfy liquidity requirements. After extending the dataset to 2010, we confirm Sufi's results. We find that cash flow remains an important indicator of a firm's liquidity choice and that firms with higher cash flow volatility prefer to use cash for liquidity. Our results also indicate that credit line usage plays a role in firms' liquidity choice. When we add credit line usage to Sufi's regression specification, we find that in addition to cash flow, credit line usage is a significant factor in a firm's liquidity choice. Credit line usage is significant in a firm's liquidity choice, even after controlling for cash flow hedging. These findings suggest that credit line drawdown warrants further investigation.

We subsequently examine whether high and low LOC users are subject to different financial constraints. To address this issue we utilize existing measures from the previous literature (Gilchrist and Himmelberg (1995), Fazzari, Hubbard and Petersen (1988), Whited (1992), Kashyap and Lamont (1994), Calomiris, Himmelberg and Wachtel (1995), Almeida, Campello and Weisbach (2004), Hahn and Lee (2009)) and find that high LOC users have less access to capital markets than low LOC users. In particular, high LOC users are less likely to have a bond rating and access to commercial paper.

Next, we examine the relationship between LOC usage and the cross section of returns. Using monthly data combined with CRSP, we regress a high LOC indicator variable against risk- adjusted returns. We find that high LOC users have higher risk-adjusted returns than low LOC users. We verify that this result is not sensitive to the definition of high/low users by investigating alternate classification schemes. We also confirm that the relationship between LOC usage and return is robust to other measures of risk by controlling for common measures of financial constraints and market movements. These results are consistent with the idea that high LOC users are more financially constrained and, therefore, why investors require a higher return to hold these firms.

Finally, we examine the differences in the level of corporate investment and degree of profitability in high and low LOC users. If high users face greater difficulty in accessing capital markets, they are expected to be less able to engage in corporate investment activities and have lower levels of accounting profitability. Our results support this supposition. Specifically, we find that high users have lower levels of capital expenditures and employment than low LOC users. High users also have lower profitability as measured by ROA, EBITDA (scaled by total assets), and ROE.

This current paper adds to the literature in several important ways. First, our empirical evidence shows that even among firms with access to LOCs, the different levels of LOC usage indicate that firms operate under different levels of financial constraints. Firms that use a high (low) percentage of their LOCs are more (less) financially constrained. Second, by adding seven additional years of data, we are able to confirm Sufi's main result that cash flow is an important determinant of a firm's liquidity choice. We also find evidence that LOC usage influences a firm's choice to use cash or bank lines of credit for liquidity. Third, this paper documents the previously unexplored relationship between the cross section of returns and LOCs. Reflecting their level of financial constraint, firms exhibiting high usage of LOCs have higher risk-adjusted returns than firms with low LOC usage. Investors demand higher returns to compensate for the higher levels of risk. Finally, we find evidence suggesting that high usage of LOCs reduces the ability of the firm to engage in corporate investment, specifically capital expenditure and employment. High users employ LOCs to cover cash flow and short term operating requirements. They do not benefit from the investment-increasing liquidity insurance that credit lines offer to low LOC users. Altogether, our results provide strong and consistent evidence that a firm's choice of credit line usage reflects its level of financial constraint.

LITERATURE REVIEW

Theoretical Basis for Hypothesis

Our main hypothesis addresses the question of why firms with access to lines of credit have different drawdowns. Since LOCs are debt instruments, we look to the theory of capital structure for guidance in understanding how firms use credit lines. The literature addresses capital structure implications for both returns and investment.

We first address the cross-section of returns. In their seminal paper, Modigliani and Miller (1958) find that in a world with perfectly efficient markets, capital structure of the firm should have no impact on returns. However, allowing for market frictions, Stiglitz and Weiss (1981) argue that credit rationing can occur in equilibrium with bank lending. Welch (2004) finds that capital structure changes (proxied by the debt ratio) are primarily influenced by changes in the value of equity due to market performance. Hahn and Lee (2009) provide further evidence of the effect of capital structure on the cross sectional returns of constrained firms. By examining manufacturing firms from 1973 to 2001, they find that debt capacity is a predictor of cross-sectional returns only in firms that are financially constrained. Financial constraints are modeled in four different ways: Asset size, payout ratio, bond rating, and commercial paper rating. This finding shows that in the presence of market imperfections, higher debt capacity is associated with higher returns. However, such a relationship only exists in financially constrained firms. That is, the higher debt capacity provides a higher level of exposure to risks of changes in interest rates or a reduced availability of funds required for future investment. They find that this risk is indeed priced in the market. Debt capacity predicts cross-sectional returns, but only in financially constrained firms, as theory conjectures. Because High LOC users have little access to additional liquidity, they should be associated with higher returns in the cross-section than Low LOC users since investors view them as riskier due to lack of access to credit for investment not having sufficient slack to mitigate the risk of default due to fluctuations in cash flows.

Next, we turn to the theoretical literature that examines the relationship between debt and investment. Once again when market frictions like agency costs and information asymmetries are introduced to the perfect markets of Modigliani and Miller (1958), studies have shown that capital structure changes may impact investment. Managers may under-invest in an effort to shift wealth to shareholders (Myers (1977). These managers may choose to pay dividends rather than invest in positive net present value projects. Lang, Ofek and Stulz (1996) find that leverage is negatively related to investment, but only in low Q firms. They find that in the presence of increased leverage, corporate investment is not reduced in well-managed (high Q) firms. Bradley, Jarrell and Kim (1984) and Titman and Wessels (1988) also document a negative relationship between leverage and investment in research and development (R&D). Specifically, a lower debt ratio leads to higher R&D expenditures. In a more recent paper. Almeida and Campello (2007) propose a theory that access to additional financing can increase investment in constrained firms. Their empirical tests provide evidence suggesting that financial constraints do affect corporate investment.

Taken together, the literature suggests that debt, including credit lines, is more likely to be used by financially constrained firms because they have fewer alternative funding options. If LOC usage reflects a firm's level of financial constraints, then high LOC users should have a similar relationship to the cross-section of returns and investment as other constrained firms. Specifically, they should be associated with higher returns and less corporate investment then less constrained firms such as low LOC users.

Previous LOC Literature

The use of credit lines as liquidity insurance is richly documented in the theoretical literature (Campbell (1978), Hawkins (1982). Shockley and Thakor (1997), Holmstrom and Tirole (1998)). Firms may use credit lines as a cost effective way to ensure liquidity is available in the event that cash or other forms of financing are not readily available. DeMarzo and Fishman (2007) create a model that examines the heterogeneity of debt. They develop the terms of optimal contracts for long-term debt, credit lines, and equity and argue that credit lines may be used to provide the firm sufficient slack so that it is not at risk of default due to fluctuations in cash flows. That is, lines of credit can also be used as insurance against the possibility of a decrease in cash flows. A common feature in all these studies is that they treat credit lines as a dichotomous variable: either firms have access to credit lines or they do not. In reality, firms with access to credit lines may not have limited or very little access to additional liquidity if they have experienced high drawdowns. That is, if a firm uses a high percentage of its credit lines, its access to additional liquidity via credit lines is diminished because it has already employed the majority of its credit lines.

The liquidity literature has recently seen a surge in papers examining credit lines. Most of these studies focus on a firm's choice of credit lines or cash to meet liquidity requirements. The first comprehensive empirical study of LOC was conducted by Sufi (2009) in which he found that LOCs are useful only to firms with positive cash flow. Specifically, his findings indicate that firms with low cash flow are unable to use LOCs due to restrictive loan covenants. However, his results do not shed light on the question why some firms with access to credit lines make greater usage of LOCs than others. Sufi's evidence suggests that firms that are unable to use LOCs may have exhausted their LOCs, which warrants a formal investigation.

Since Sufi (2009), there have been several other empirical studies concerning the role of lines of credit. For example, Yun (2009) examines the relationship between credit lines and corporate governance. He finds that firms with poor corporate governance prefer to use credit lines for liquidity than cash. He suggests that using credit lines reduces the prospect of opportunistic managers squander cash. Almeida, Campello and Hackbarth (2011) find that credit lines are used to finance liquidity mergers, or acquisitions undertaken in an effort to increase bidder's liquidity. Lins, Servaes and Tufano (2010) survey international CFOs to examine whether or not cash and credit lines are used for the same purpose. They find evidence suggesting that credit lines are used to facilitate corporate investment in positive economic times, but that firms rely more on cash during hard times. This is a novel finding suggesting that credit lines may be used for purposes other than liquidity insurance. Continuing in this line of research, Campello, Giambona, Graham and Harvey (2011) investigate whether access to lines of credit influenced planned investment during the recent financial crisis. Using survey data from

2008-2009, they find that credit lines can allow firms to increase investment over what they could have achieved with cash alone, but that the existence of credit lines, by itself, does not increase investment during a crisis. Whereas these papers examine the firm's choice of liquidity (cash versus credit lines), this current paper looks into the degree to which firms use credit lines and the whether LOC usage lessens financial constraints.

Two recent papers are more related to this article in that they address different uses of credit lines: Acharya, Almeida, Ippolito and Perez (2012) and Jimenez, Lopez and Saurina (2009). The first paper, Acharya, Almeida, Ippolito and Perez (2012), puts forth a theory in which credit lines are a monitored source of liquidity insurance. Like Sufi (2009), they argue that banks have the ability to control firm behavior through the use of credit line covenants. As in previous studies, they examine the choice of cash or credit lines for liquidity, using the credit lines as a percentage of total liquidity measure. They find that firms with greater liquidity risk are more likely to use cash for liquidity requirements in order to avoid the high monitoring costs that using credit lines entails. Firms with lower liquidity risk are more likely to use credit lines because they incur lower monitoring costs. This paper provides important evidence pertaining to this current study because it provides the first model to allow for different purposes for credit lines. Acharya, Almeida, Ippolito and Perez (2012) suggest that credit lines are used not only to help firms during times of limited liquidity, but also to make investments that support their future growth. Although their paper focuses on the liquidity choice rather than extent of use, their model provides theoretical support for recognizing different uses of credit lines as we do in this current paper. The second study, Jimenez, Lopez and Saurina (2009), investigates credit line usage in Spain. This paper is unique among the extant literature because it examines the percentage of credit lines that are used, instead of a firm's choice of cash or credit for liquidity. Using Spanish banking data from 1984 to 2005, they find that firms that fail to meet required debt payments use more of the credit lines than firms that never miss a payment. They also find that smaller, less profitable firms also use a higher percentage of their credit lines. These findings are consistent with our hypothesis that credit line usage is indicative of a firm's level of financial constraints, but they do not address that firms may be using credit lines for different reasons. Neither Acharya, Almeida, Ippolito and Perez (2012) nor Jimenez, Lopez and Saurina (2009) addresses the differences between high LOC users and low LOC users; specifically that high LOC users may be financially constrained. They also do not examine the relationship between credit line drawdowns and the cross section of returns, corporate investment and profitability[5].

DATA

We construct our unique dataset spanning the 1997-2010 period using Sufi (2009)'s random sample of 300 firms. Firm-year data concerning the amount of credit lines used and total credit lines from 1997-2003 were obtained from Sufi's website[6]. Following the procedures outlined in Sufi (2009), we then hand-collected used and total credit line data from the sample firms' annual reports for 2004-2010. This drawdown information required to evaluate high and low credit line users is not available in the LPC-DealScan dataset (Almeida, Campello and Hackbarth (2011)). Since we are

[5] See Demiroglu, C., and C. James. 2011, The use of bank lines of credit in corporate liquidity management: A review of empirical evidence, *Journal of Banking & Finance* 35, 775-782. for more review on the LOC literature.
[6] http://faculty.chicagobooth.edu/amir.sufi/data.htm

interested in the different uses of credit lines, the final sample includes only firms that had access to credit lines at some point during the period 1997-2010. We then combined this data with firm accounting data from Compustat. In order to examine the relationship between credit line usage and the cross section of returns, we next add returns from CRSP to the dataset. Sufi's data includes 255 firms with access to credit lines. Because we extended the sample to 2010, more firms obtained access to credit lines. Therefore, our initial sample includes 270 firms. We use the Fama and MacBeth (1973) two stage method to determine if firms that make great use of their credit lines and those that do not use their credit lines have different returns in the cross section. Following Hahn and Lee (2009), we address the errors-in-variables problem by using the Brennan, Chordia and Subrahmanyam (1998), method of substituting risk-adjusted returns for simple returns as the dependent variable. First, we estimate the factor loadings on the Fama-French 3-factor model for the 60-month period of 1992-1996 using the following equation:

$$r_{jt} = \alpha_j + \beta_{1j} MRP_t + \beta_{2j} SMB_t + \beta_{3j} HML_t + \eta_t \tag{1}$$

The monthly factors are retrieved from the Kenneth French data library.[7] MRP is the market risk premium, SMB is the small stock premium, and HML is the value stock premium. The monthly return is denoted by r.

Next, we construct the risk-adjusted returns as described below:

$$r^*_{jt} = r_{jt} - r_{ft} - \hat{\beta}_{1j} MRP_t - \hat{\beta}_{2j} SMB_t - \hat{\beta}_{3j} HML_t \tag{2}$$

[7] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

The risk-adjusted return, r_{jt}^{*}, is the excess return (the monthly return, r_{jt}, minus the risk-free return, r_{ft}, the one month Treasury bill also from the French website), minus the factor loadings from the previous equation multiplied by the factors in the current sample. The risk-adjusted returns are calculated for the period 1997-2010. Finally, the risk-adjusted returns are combined with the accounting data by CUSIP to complete the dataset formation process. We also conduct our analysis using risk-adjusted returns from the 1-factor Capital Asset Pricing Model (CAPM).

Our main study variable is a dichotomous measure indicating whether or not a firm uses a high percentage of its credit lines. To avoid reliance on one definition of high and low users, three methods are computed[8]. LOC used ratio is defined as LOC Used/Total LOC. In other words, LOC used ratio is the ratio of drawn credit lines to total credit. Our first categorization of credit line usage is that high (low) LOC users are firms with LOC used ratio higher (lower) than the sample median (0.076). Therefore, the HiLOC indicator variable takes the value of 1 if a firm has a LOC Used ratio higher than the sample median. Since credit line data was retrieved from annual reports, this data series is computed annually. Our second categorization, HiLOC2, defines high (low) users as those firms in the top (bottom) 30% of the sample. The third categorization, HiLOC3, defines high (low) users as those firms in the top (bottom) 30% of credit line usage by year.

METHODOLOGY

Before commencing with our study concerning credit line usage, we revisit Sufi (2009) main results for two reasons. First, we endeavor to determine whether his central

[8] We thank Dr. Licheng Sun for this suggestion.

conclusion, that credit lines are more valuable to firms with high cash flow, remains intact after the addition of seven years of data. Second, we are interested to confirm whether treating high and low users separately provides additional explanatory power for a firm's liquidity choice, controlling for the variables in his model. To perform this analysis. the variables from his Table 3 are included. Equation (3) describes the model specification.

$$\left(\frac{Total\ LOC}{Total\ LOC+Cash}\right)_t =$$

$$\beta_0 + \beta_1 CashFlow_{t-1} + \beta_2 AssetTangibility_{t-1} + \beta_3 NonCash\ Assets_{t-1} +$$

$$\beta_4 NetWorth_{t-1} + \beta_5 MTB_{t-1} + \beta_6 CFVol_{t-1} + \beta_7 Not\ in\ S\&P\ Index_{t-1} + \beta_8 OTC_{t-1} +$$

$$\beta\ \ LAge_{t-1} + \ \eta_t$$

(3)

The dependent variable in all models is the percentage that credit lines, *Total LOC*, constitute of total liquidity, *Total LOC + Cash*. As in Sufi (2009), cash flow is calculated as $\frac{EBITDA}{Assets-Cash}$. Sufi finds that cash flow is positively related to the percentage that credit lines are used of total liquidity when the complete sample of firms (with and without access to credit lines) is utilized. However, this result is less robust for firms with access to credit lines. For firms with a credit line, he does not find a relationship between cash flow and credit lines as a percentage of liquidity for one of his two credit line measures. Theory suggests that this result may reflect the concept that cash flow is more important for more financially constrained firms (Almeida, Campello and Weisbach (2004)).

The remaining variables are expected to have the same relationship with credit lines as a percentage of total liquidity as in Sufi. *NonCash Assets*, calculated as

$Ln(\text{Assets} - \text{Cash})$, should have a positive relationship with the choice to use credit lines for liquidity. *NetWorth*, Market to book ratio (*MTB*), and Cash flow volatility (*CFVol*) are expected to be negatively related to credit lines as a percentage of total liquidity. *NetWorth* is calculated as $\frac{Assets-Cash-Liabilities}{Assets-Cash}$. *MTB* is calculated as $\frac{\text{Assets}-\text{BV of Equity}+\text{MV of Equity}-\text{Cash}}{Assets-Cash}$. *CFVol* is the standard deviation of the previous four annual changes in cash flow scaled by (Total Assets-Cash). We also include *AssetTangibility*, $\frac{Tangible\ Assets}{Total\ Assets}$, *LAge*, the natural logarithm of the number of years since IPO, and dummy variables indicating the firms' inclusion in the S&P 500, S&P 400, or S&P 600 Index and over the counter trading status. All data have annual periodicities. We estimate the equation using OLS. T-statistics are calculated with heteroskedasticity-consistent errors. Industry and year indicator variables are also included.

LOC usage and financial constraints

We next examine our hypothesis that credit line usage is related to a firm's level of financial constraint by using several established financial constraint measures. Following the literature, (Gilchrist and Himmelberg (1995), Fazzari, Hubbard and Petersen (1988), Whited (1992), Kashyap and Lamont (1994), Calomiris, Himmelberg and Wachtel (1995), Almeida, Campello and Weisbach (2004), Hahn and Lee (2009)) we measure financial constraints with a firm's bond rating, commercial paper status, dividend payment policy, and asset size.

To evaluate the different levels of financial constraint of high and low users of credit lines, we assign indicator variables to represent financial constraint according to each measure. The *BondRate* variable takes the value of 1 if a firm has a bond rating and 0 otherwise. *CommPaper* takes the value of 1 if a firm has a commercial paper rating and

0 otherwise. *HighDivPay* takes the value of 1 if a firm's dividend payout ratio is in the top 30% of the sample by year and 0 if the dividend payout is in the bottom 30% by year. *HighAssets* takes the value of 1 if a firm's assets in the top 30% of the sample by year and 0 if assets rank in the bottom 30% by year. We then compare the mean indicator variable values for high and low credit line users to determine if high and low users are subject to different level of financial constraints. We expect that high LOC users will be more constrained than low LOC users, resulting in lower means for high users. The financial constraint difference between high and low users, are then tested for statistical significance using a T-test for all four classification schemes.

LOC usage and the cross-section of returns

The next step in our analysis examines the relationship between credit line usage and the cross section of returns. If credit line usage reflects a firm's financially constrained status, then this should also be reflected in the cross section of returns. Since financially constrained firms have been associated with higher returns (Whited and Wu (2006), Livdan, Sapriza and Zhang (2009)) we expect that high users of credit lines will have higher returns than low users.

We investigate this expectation by regressing the risk-adjusted returns obtained from Equation (2) on lagged credit line and accounting variables. Due to our requirement that both CRSP and Compustat data are available, our cross-sectional returns analysis includes 181 firms. Hahn and Lee (2010) suggest that although size and book to market (BTM) are included in the procedure to create risk-adjusted returns, it is prudent to include them in the final regression to allow for the possibility that these important factors have some residual effect. Lagging the independent variables allows a causal relationship between the independent variables and the risk-adjusted return to be determined, and also controls for the endogeneity of the corporate liquidity decision. The regression takes the following specification:

$$r_{t+1}{}^{*} = \gamma_0 + \gamma_1 Size_t + \gamma_2 BTM_t + \gamma_3 LOCTotal_t + \gamma_4 Crisis_t + \gamma_5 HiLOC_t + \sum \gamma Industry_i + \eta_t \quad (4)$$

where *Size* is the natural logarithm of total assets, *BTM* is the book to market ratio calculated as $\frac{Book\ Value\ of\ the\ Firm}{Total\ Shares \times Share\ Price}$. Both firm size and book to market have been demonstrated to be related to cross-section of returns (Hahn and Lee 2010). The total number of credit lines, *LOCTotal*, is included in the regression to allow us to distinguish the effects of the total amount of credit lines from the effects of credit line usage. The *HiLOC* term is an indicator variable that takes the value of 1 if a firm has a *LOCUsedRatio*, $\frac{\text{LOC Used}}{\text{LOCTotal}}$, higher than the median and 0 otherwise. Ivashina and Scharfstein (2010) find that the downturn of the credit market financial crisis began in 2007. Accordingly, we use the *Crisis* indicator variable that takes the value of 1 if a firm-year observation is in 2007 or 2008 and 0 otherwise. Industry dummies are determined by the Fama French 12-industry SIC codes. The final term, η_t, is the residual.

For both 1- and 3-factor risk-adjusted returns, we utilize models for each of the three different definitions of high credit line users (higher than median, top 30%, top 30% by year), resulting in six separate models. The models are estimated using separate OLS regressions and heteroskedasticity-consistent errors. Industry dummy variables are also employed. We expect that the coefficient of the *HiLOC* measure, γ_5, to be positive, indicating that firms with high credit line drawdowns have higher returns in the cross section.

A robustness test

To evaluate if the relationship between credit line usage and the cross section of returns is actually reflects the firm's financial constraint or market cycles, we conduct similar analyses by adding different financial constraint and market cycle measures to the regression. Equation (5) specifies the model.

$$r_{t+1}^{*} = \gamma_0 + \gamma_1 Size_t + \gamma_2 BTM_t + \gamma_3 LOCTotal_t + \gamma_4 HiLOC_t + \gamma_5 Crisis_t + \gamma 6 Constraint\ or\ Markett + \gamma Industryi + \eta t \qquad (5)$$

If HiLOC is a robust financial constraint measure, its coefficient will remain positive and significant, even after other financial constraint measures are added to the model.

We also include two more financial constraint measures (*BondRate*, *CommPaper*) and two market performance measures (*Up* and *Up3*). *BondRate* and *CommPaper* are indicator variables that take the value of 1 if a firm has a bond rating or access commercial paper, respectively, and 0 otherwise. The market cycle measures are from the Chicago Fed National Activity Index (CFNAI)[9], which measure the rate of expansion of the economy. *Up* takes the value of 1 for months when the market expands at a rate that exceeds the historical trend growth rate and 0 otherwise. *UP3* takes the value of 1 when the 3-month moving average of the CFNAI exceeds the average and 0 otherwise. Since

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9 The Chicago Fed National Activity Index data was retrieved from http://www.chicagofed.org/webpages/research/data/cfnai/historical_data.cfm

firms with a bond rating (*BondRate*=1) or access to commercial paper (*CommPaper*=1) are not considered financially constrained, we expect a negative coefficient on these variables, signifying that constrained firms have higher returns in the cross section than unconstrained firms (Whited and Wu (2006), Livdan, Sapriza and Zhang (2009)).

LOC usage, investment and profitability

In addition to the relation between credit line usage and the cross section of returns, our hypothesis, that credit line usage reflects a firm's level of financial constraint, has predictions for corporate investment and profitability. If firms with greater use of credit lines are financially constrained, then these high LOC users are expected to engage in less corporate investment activities and be less profitable.

To examine this line of reasoning, we employ a methodology similar to that of Campello, Giambona, Graham and Harvey (2011) and hypothesize that high LOC users (i.e. firms with a high percentage of credit lines used) have lower levels of corporate investment than low LOC users. Since they are using credit lines for other purposes (i.e., address short term-financing needs probably due to low cash flows and limited access to capital markets), we conjecture that they will be unable to take advantage of the investment-increasing effects of LOCs' liquidity insurance function. To address this prediction we modify the base-line specification of Campello, Giambona, Graham and Harvey (2011) by including an indicator variable to account for high users of credit lines, as shown in Equation (6) below.

$$Investment_{t+1} = \gamma_0 + \gamma_1 Size_t + \gamma_2 Cash_t + \gamma_3 LOCTotal_t + \gamma_4 Cash * LOCTotal_t + \gamma_5 HiLOC_t + \eta \qquad (6)$$

Since high users of credit lines have little access to additional liquidity and are unable to exploit the liquidity insurance properties of credit lines, they are expected to invest less than low LOC users. Consequently, the *HiLOC* indicator variable should enter the regression with a negative coefficient. High users of credit lines have little access to additional liquidity and are unable to exploit the liquidity insurance properties of credit lines, resulting in less investment than low users. As in the previous analysis, we define high users with three different measures to ensure our results are not driven by a specific measure of high LOC usage. We also expect to confirm the result of Campello, Giambona, Graham and Harvey (2011), who find that credit lines increase the ability of firms to invest above what they could have done with cash alone. Specifically, we expect a positive coefficient on both the *LOCTotal* and the interaction of *LOCTotal* and *HiLOC*. As in Campello, Giambona, Graham and Harvey (2011), we examine three different types of corporate investment: capital expenditures (*Capex*), *R&D*, and employment (*Empl*). Industry dummies are also added to the specification to control for industry-specific variation in corporate investment.

Finally, we turn our focus to the profitability of high and low users of credit lines. To the extent that credit lines reflect whether firms are financially constrained, high LOC users will be less likely to engage in efficient corporate investment and therefore be less profitable. Hence, we expect high users of credit lines to have lower levels of profitability. To examine the impact of LOC usage on profitability, we regress three profitability measures (ROA, EBITDA scaled by total assets, and ROE) against LOCTotal, HiLOC, and control variables, as listed in Equation (7), below.

$$Profitability_{t+1} = \gamma_0 + \gamma_1 Size_t + \gamma_2 BTM + \gamma_3 LOCTotal_t + \gamma_4 HiLOC_t + \eta_t \quad (7)$$

In our analysis we use ROA, EBITDA scaled by total assets, and ROE as profitability measures. Our regression specification is constructed to control for known determinants of profitability. Joh (2003) finds that firm size, market to book, industry, and time can all impact firm profitability. Accordingly, we include the following control variables: *Size* (the natural logarithm of assets) and *BTM*, the book to market ratio. Industry dummy variables and year dummy variables are included to impose industry and year fixed effects.

RESULTS

Descriptive statistics

We first take a closer look at the sample by examining the descriptive statistics reported in Table 1 and defining additional variables used in this study. Panel A reports statistics for the entire 270-firm sample, while Panels B and C provide statistics for low and high users of credit lines, respectively. When the sample is split in this manner some immediate differences between the two types of firms are revealed. *LOCTotal* is the total amount of lines of credit, used and unused. *LOCUsed* is the fraction of used line of credit and the *LOCUsedRatio* is $\frac{LOCUsed}{LOCTotal}$. For the entire sample, in Panel A, the median firm used 11% of credit lines. But the differences between low and high users are striking. Low users (in Panel B) do not use their credit lines at all with 0% median *LOCRatioUsed*, while high users (in Panel C) use 47% of their credit line availability. This significant

LOC drawdown difference provides support for the supposition that the latter are using credit lines for different purposes.

It seems that firms with access to credit lines and low LOC drawdowns are more likely to use them as a hedging instrument against a liquidity shock (i.e., a safeguard against the inability to obtain financing when valuable opportunities arise) while firms with high LOC drawdowns use them to meet short term-financing needs probably

Table 1. Descriptive Statistics (Total and by LOC Usage)

This table provides summary statistics for the variables used in this study after merging with monthly return data from CRSP. Data are from 270 sample firms from 1996-2010 that have access to lines of credit. 1996-2003 data is from Amir Sufi's (2009) study. 2004-2010 data was hand collected for this study. Accounting data are from COMPUSTAT. Line of credit data are from Amir Sufi's website (1996-2003) and firm 10-K reports (2004-2010). Assets is the firm's total assets. MTB is the cash-adjusted book to market ratio, $\frac{Book\ Value\ of\ Equity + Market\ Value\ of\ Equity - Cash}{Non-Cash\ Total\ Assets}$. Cash is the amount of cash (stock). Employment is the number of employees. Capex is the annual firm capital expenditures in plant, property, and equipment. R&D is the annual expenditure on research and development. LOCTotal is the total amount of lines of credit, used and unused. LOCUsed is the amount of used line of credit. LOCUsedRatio is $\frac{LOCUsed}{LOCTotal}$. BookLeverage is book debt divided by total assets. Liquidity is liquid assets divided by total assets. N is the number of observations. Panel A presents statistics for the full sample set. Panel B presents statistics for the sample subset of firms with LOC usage less than the median (HiLOC=0). Panel C presents statistics for the sample subset of firms with LOC usage greater than the median (HiLOC=1).

Panel A: All Firms

Variable	*Median*	*Mean*	*Minimum*	*Maximum*	*Std Dev*	*N*
LOCTotal	52.66	287.39	0.100	14671.000	751.469	2418
LOCUsedRatio	0.11	0.26	0.000	1.000	0.310	2418
Assets	342.19	2823.50	0.246	227251.000	13702.591	2348
MTB	1.35	1.99	-0.640	89.589	2.950	2274
Cash	15.85	112.61	0.000	9782.000	438.872	2307
BookLeverage	0.48	0.51	0.020	28.045	0.837	2330
Liquidity	0.50	0.49	0.027	0.982	0.230	2279
Employment	2.20	14.00	0.000	366.000	37.509	2326
Capex	14.14	199.42	0.000	17633.000	1170.752	2340
R&D	2.43	56.88	0.000	5273.000	352.718	1393

Panel B: Low LOC users

Variable	*Median*	*Mean*	*Minimum*	*Maximum*	*Std Dev*	*N*
LOCTotal	45.90	295.13	0.100	7940.000	774.308	1209
LOCUsedRatio	0.00	0.01	0.000	0.111	0.025	1209
Assets	351.96	4012.82	0.246	227251.000	18429.477	1167
MTB (Cash Adj)	1.54	2.27	-0.035	34.083	2.767	1132
Cash	31.73	175.23	0.000	9782.000	588.371	1149
BookLeverage	0.38	0.48	0.020	28.045	1.167	1152
Liquidity	0.55	0.53	0.037	0.982	0.222	1147
Employment	2.30	17.74	0.007	366.000	45.848	1160
Capex	15.24	301.12	0.000	17538.000	1558.819	1162
R&D	2.96	83.08	0.000	5273.000	468.553	759

Panel C: High LOC users

Variable	*Median*	*Mean*	*Minimum*	*Maximum*	*Std Dev*	*N*
LOCTotal	65.00	279.65	0.100	14671.000	728.151	1209
LOCUsedRatio	0.47	0.51	0.112	1.000	0.259	1209
Assets	328.81	1648.28	2.021	164735.000	5920.839	1181
MTB (Cash Adj)	1.23	1.70	-0.640	89.589	3.096	1142
Cash	6.23	50.48	0.000	2765.196	180.666	1158
BookLeverage	0.53	0.55	0.060	2.685	0.232	1178
Liquidity	0.46	0.44	0.027	0.960	0.229	1132
Employment	2.04	10.27	0.000	295.000	26.245	1166
Capex	12.34	99.11	0.000	17633.000	553.794	1178
R&D	1.65	25.52	0.000	1900.000	94.233	634

because of low cash flows and limited access to capital markets. In fact, we observe that low credit line users have significantly higher levels of cash (175.2 versus 50.5) and liquidity (0.53 versus 0.44) than high credit line users. Furthermore, low LOC users are more than twice as large as the mean firm of high LOC users (mean assets of 4,013 for low users versus 1,648 for high users). Low usage firms also have a higher market to book ratio (MTB) than high LOC usage firms (2.27 versus 1.70) and lower levels of book leverage (0.48 versus 0.55).

Corporate investment follows a similar pattern. Low users have higher levels of investment in employment (*Empl*), capital expenditures (*Capex*) and research and development (*R&D*). All together, these univariate results appear to be consistent with our hypothesis that credit line usage mirror's a firm's level of financial constraint. Like financially constrained firms, high users of credit lines are smaller, have fewer growth opportunities, and less liquidity than their low user counterparts. They also engage in less corporate investment activities than firms that have access to credit lines, but use them less.

We now examine credit line usage by industry, using the Fama French 12 industry SIC codes from Kenneth French's website, and report the results in Table 2. These results indicate that there is a large variation in total credit lines across industries. Business Equipment has the lowest mean number of credit lines (89.53) and Telephone and TV has the largest (1662.03). Similarly, the mean percentage of LOCs used also varies by industry from a low of 20% for Business Equipment to a high of 44% for Energy. It is interesting to note that Energy, one of the industries that has the fewest credit lines, also uses them the most. The results of this table suggest that industry differences are

Table 2 LOC Usage by Industry

This table provides mean LOC usage by industry for sample firms. Data are from 270 sample firms from 1996-2010 that have access to lines of credit. 1996-2003 data is from Amir Sufi's (2009) study. 2004-2010 data was hand collected for this study. Accounting data are from COMPUSTAT. Industry categories are calculated using the Fama French 12 industry SIC codes. Line of credit data are from Amir Sufi's website (1996-2003) and firm 10-K reports (2004-2010). *LOCTotal* is the total amount of lines of credit, used and unused. *LOCUsedRatio* is $\frac{LOCUsed}{LOCTotal}$. N is the number of observations.

Industry	*Mean LOCTotal*	*Mean LOCUsedRatio*	*N*
Non-Durables	120.49	0.33	183
Durables	659.55	0.21	67
Manufacturing	296.47	0.21	482
Energy	93.56	0.44	82
Chemicals	305.93	0.30	39
Business Equipment	89.53	0.20	339
Telephone and TV	1662.03	0.31	82
Utilities	356.42	0.34	65
Shops	278.39	0.24	452
Health	345.14	0.25	234
Other	177.52	0.32	393

important in determining credit line usage. We therefore control for industry effects in our empirical analyses.

Determinants of liquidity choice

A key result of Sufi (2009) is that cash flow is a main determinant of a firm's choice between cash and credit lines in corporate liquidity management. He argues that high cash flow firms are more able to use credit lines due to the restrictive covenants. However his results, based on the sample that only includes firms with access to credit lines, provide mixed support. Our results in Table 3 mirror this mixed finding on the importance of cash flow. To aid in comparison, we report models 1 through 4 using only years included in Sufi's analysis (1997-2003) as well as models 5 through 8 using entire sample (1997-2010). In Model 1, consistent with his results, cash flow is not significantly associated with the choice to use credit lines for liquidity. When we add the HiLOC indicator as an additional independent variable in Model 2, we find that LOC usage is important in a firm's liquidity decisions.

High users are more likely to choose credit lines than cash. The coefficient of HiLOC is 0.21 and significant at the 1% level. To further explore this result, we then add an interacted term of HiLOC*CashFlow and find that CashFlow and LOC usage has a positive influence on the liquidity choice. The interacted variable in Model 2 is also significant at the 1% level, with a coefficient of 0.29. These results also hold for the entire extended sample from 1996-2010.

Recent research suggests that a firm's LOC hedging may influence its liquidity choices (Berrospide, Meisenzahl and Sullivan (2012)). To examine this assertion, we collect information from the firms' 10-K reports about whether or not the credit lines are hedged. We follow the procedure set forth in Berrospide, Meisenzahl and Sullivan (2012) to determine firms with hedged credit lines. Specifically, we download 10-K reports for the 1996-2010 time period for each firm that has access to credit lines and then use a search engine to find the words "interest rate agreement," "interest rate agreements," "interest rate exchange agreement," "interest rate exchange agreements," "interest rate hedge," "interest rate hedges," "interest rate swap," or "interest rate swaps" within 1500 characters of words indicating credit line usage, "credit facility," "credit facilities," "credit line," "credit lines," "line of credit," "lines of credit," "loan facility," "loan facilities," "revolving facility," "term loan," and "term loans." We then read the portions of the annual reports to examine if the firm explicitly states that it is hedging its revolving debt.

The binary variable *hedge* captures the results of this data collection process, which takes the value of 1 if a firm hedges its credit lines and 0 otherwise. In Models (4) and (8) we add the *hedge* variable to the specification to assess how hedging influences firms' liquidity choices. For both models, the HiLOC variable is robust to adding the *hedge* indicator variable. During 1996-2003, hedging does not influence liquidity choice. However, for the entire sample, 1996-2010, the evidence shows that firms with hedged LOCs choose credit lines rather than cash for liquidity. While these findings support previous literature in that hedging has an impact on corporate liquidity, the LOC usage remains highly significant even after controlling for hedging behavior. Additionally, caution must be taken when interpreting these results concerning hedging, as the sample contained only 23 firms that reported hedging their credit lines.

Table 3. Determinants of Liquidity Choice

This model is based on Table 3 from Sufi (2009). The dependent variable is the percentage that credit lines constitute of total liquidity. Following Sufi (2009), *CashFlow* is calculated as $\frac{EBITDA}{Assets-Cash}$. *AssetTangibility* is $\frac{Tangible\ Assets}{Total\ Assets}$. *NonCashAssets* is calculated as Ln(Assets − Cash). *NetWorth* is calculated as $\frac{Assets-Cash-Liabilities}{Assets-Cash}$. *MTB* is the cash-adjusted book to market ratio, $\frac{Book\ Value\ of\ Equity+Market\ Value\ of\ Equity-Cash}{Non-Cash\ Total\ Assets}$. *CFVol*, cashflow volatility, is the standard deviation of the previous four annual changes in cash flow scaled by (Total Assets-Cash). *LAge* is the natural logarithm of the number of years since IPO. Dummy variables indicating the firms' inclusion in an S&P Index and over the counter trading status are also included. *HiLOC* takes the value of 1 if a firm has a LOCusedRatio higher than the median and 0 otherwise. *Hedge* takes the value of 1 if a firm reported that is hedging its LOCs and 0 otherwise. **, * are statistically significant at the 1% and 5% level, respectively.

Panel A	*Dep. Var: Total Line/(Total Line + Cash)*							
	Sufi Sample (1996-2003)				*Full Sample (1996-2010)*			
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
Intercept	0.84**	0.70**	0.70**	0.71**	0.73**	0.66**	0.68**	0.66**
	(8.78)	(8.02)	(8.21)	(8.19)	(8.72)	(10.10)	(10.46)	(9.48)
CashFlow	0.02	0.06	-0.03	-0.06	0.00	0.04	-0.02	-0.02
	(0.32)	(1.26)	(-0.57)	(-1.01)	(0.08)	(0.76)	(-0.32)	(-0.39)
AssetTangibility	0.02	-0.00	-0.00	-0.00	0.02	-0.01	-0.02	-0.01
	(0.38)	(-0.02)	(-0.07)	(-0.04)	(0.23)	(-0.15)	(-0.26)	(-0.20)
NonCashAssets	0.02	0.02*	0.02*	0.02**	0.02*	0.02*	0.02*	0.02*
	(1.79)	(2.50)	(2.53)	(2.68)	(2.45)	(2.62)	(2.45)	(2.35)
NetWorth	-0.21**	-0.11*	-0.10*	-0.11*	-0.07**	-0.06**	-0.06**	-0.05**
	(-3.83)	(-2.23)	(-2.00)	(-2.43)	(-4.42)	(-8.33)	(-7.09)	(-3.17)
MTB(Cash Adj)	-0.02	-0.02**	-0.02**	-0.02**	-0.02*	-0.02**	-0.02**	-0.02**
	(-1.95)	(-4.45)	(-4.59)	(-4.64)	(-2.73)	(-6.01)	(-5.90)	(-5.93)

CFVol	-0.52**	-0.33**	-0.34**	-0.35**	-0.11	-0.05	-0.09	-0.08
	(-3.85)	(-2.69)	(-3.16)	(-3.44)	(-1.28)	(-0.65)	(-1.02)	(-0.75)
Not In S&P Index	0.02	-0.01	-0.01	-0.00	0.03	-0.01	-0.00	0.00
	(0.46)	(-0.37)	(-0.29)	(-0.14)	(0.78)	(-0.19)	(-0.07)	(0.08)
OTC	0.02	-0.00	0.00	-0.00	0.04	0.03	0.03	0.03
	(0.54)	(-0.00)	(0.06)	(-0.03)	(0.96)	(0.70)	(0.76)	(0.78)
LAge	-0.01	-0.01	-0.01	-0.01	0.00	0.01	0.00	0.01
	(-0.92)	(-0.90)	(-0.97)	(-0.98)	(0.04)	(0.55)	(0.43)	(0.51)
HiLOC		0.21**	0.18**	0.17**		0.20**	0.17**	0.17**
		(9.53)	(7.56)	(7.04)		(10.84)	(8.27)	(8.03)
*HiLOC*CashFlow*			0.29**	0.31**			0.28**	0.27**
			(3.45)	(3.60)			(3.91)	(3.59)
Hedge				0.01				0.08**
				(0.40)				(2.77)
Industry Dummies	yes	yes	yes	yes	yes	yes	yes	yes
Year Dummies	yes	yes	yes	yes	yes	yes	yes	yes
Observations	1289	1121	1121	1098	2178	1997	1997	1951
R-squared	0.2304	0.3807	0.3925	0.4022	0.1826	0.3152	0.3256	0.3302

In all, the results in Table 3 are consistent with our suggestion that there are important differences between high and low users of credit lines. We would expect that cash flow would be very important in the liquidity choice of high users of credit lines. Since we suspect high users are financially constrained, it makes sense that firms with relatively better cash flow would be able to use the credit lines. Cash flow-related covenants would influence lower cash flow firms to use cash instead of credit lines. However, for the unconstrained low LOC users, cash flow covenants would have less influence on their choices. They intend to use the credit lines as liquidity insurance, rather than to meet investment or working capital needs.

LOCs and financial constraints

We next address our main contention, that corporate financial constraints influence bank credit line usage. Table 4 reports the mean values of commonly used financial constraint measures for high and low LOC users. Bond rating, commercial paper, high dividends and high assets are reported in panels A, B, C, and D, respectively. In panel A, we find that high users of credit lines are significantly less likely to have a bond rating than low users of credit lines. Similarly, Panel B reports that high users are also less likely to have access to commercial paper than low users. Jointly these results are statistically significant at the 1% level advocating that high users are more financially constrained than low users. Panel D shows that high users have fewer assets than low users, although the difference is not statistically significant. Only Panel C seems to provide some evidence that high users are not constrained, although the result is not

Table 4. T-Tests For Different Financial Constraints

This table provides the statistical significance of the difference of the sample means of study variables for firms that are high LOC users (HiLOC=1) versus those that are not high LOC users (HiLOC=0). Data are from sample firms from 1997-2010 that have access to lines of credit. 1997-2003 data is from Amir Sufi's (2009) study. 2004-2010 data was hand collected for this study. Annual accounting data are from COMPUSTAT. The following four criteria are used for financial constraint: bond rating, commercial paper rating, dividend payout, and assets. HiLOC takes the value of 1 if a firm has a LOCusedRatio higher than the median and 0 otherwise. Differences are calculated with four different measures of financial constraint. Bond rate takes the value of 1 if the firm has a bond rating and 0 otherwise. Comm paper takes the value of 1 if a firm has a commercial paper rating and 0 otherwise. High DivPay takes the value of 1 if a firm's dividend payout ratio is in the top 30% of the sample by year and 0 if the dividend payout is in the bottom 30% by year. High Assets takes the value of 1 if a firm's assets in the top 30% of the sample by year and 0 if assets rank in the bottom 30% by year. Constrained firms are those with bond rating = 0, Comm Paper = 0, High DivPay=0, High Assets = 0; **, **, * are statistically significant at the 1%, 5%, and 10% level, respectively.

	Measure of Financial Constraint							
	A.Has Bond rating		*B:Has Comm Paper*		*C:High DivPay*		*D:High Assets*	
	N	*Mean*	*N*	*Mean*	*N*	*Mean*	*N*	*Mean*
Low LOC Users	835	0.3413	835	0.1341	209	0.5072	480	0.5313
High LOC Users	828	0.2826	828	0.0713	131	0.5344	488	0.4816
Difference		0.0587***		0.0629***		-0.0272		0.0497
T-stat		(2.59)		(4.25)		(-0.49)		(1.55)

significant and there are very few observations included in the analysis since our sample does not contain very many firms that pay dividends. Overall, Table 4 provides evidence suggesting that high users are more financially constrained than low users of credit lines.

LOC usage and cross-section of returns

We now turn to examine the relation between credit line usage and the cross section of stock returns using equation (4). Results from regressing risk-adjusted returns against the *HiLOC* and total credit lines (*LOCTotal*), including controls for firm characteristics and an indicator variable for the financial crisis, are reported in Table 5. Panels A and B report regression results using 1- and the 3-factor risk-adjusted returns, respectively. Each panel also includes three models: one for each definition of high users for a total of six models in the entire table. The central result is the positive and statistically significant coefficients of *HiLOC*, *HiLOC2* and *HiLOC3* variables in all regressions. All three *HiLOC* measures are positive and significant in both A and B Panels. In Panel A with 1-factor risk adjusted returns, *HiLOC*, *HiLOC2*, and *HiLOC3* have coefficients of 0.47, 0.40, and 0.52, respectively. *HiLOC* and *HiLOC3* are significant at the 1% level, while *HiLOC2* is significant at the 5% level. In Panel B with3-factor risk-adjusted returns, we also find that HiLOC is positive and statistically significant. Consistent with Whited and Wu (2006), who find that constrained firms have higher returns in the cross section, these results provide support for our assertion that firms that use a high percentage of their credit lines are financially constrained.

In contrast, *LOCTotal* does not influence returns in most models in Panels A and B. Coefficients are not significantly different from zero for the *HiLOC* and *HiLOC3* models, but are marginally negative in the models using *HiLOC2*. The results for *LOCTotal* indicate that the amount credit lines per se do not reveal whether a firm is financially constrained.

The *Crisis* indicator variable is not significantly related to returns in the 1-factor models, but is positively related to returns in the 3-factor models. This probably reflects the higher weight given to the market return factor in the 1-factor models, when determining risk-adjusted returns. Any variation in returns due to the crisis may already be compensated for during the process of creating the risk-adjusted returns. Jointly, the results of Table 5 suggest that firms with greater LOC usage are more financially constrained than firms with lower LOC usage.

It is possible that the previous results reflect missing variables. Hence, to address this issue we include in the analysis financial constraint variables to assess the importance of *HiLOC*, *HiLOC2* and *HiLOC3* variables. Specifically, we regress 3-factor risk-adjusted returns on the same variables listed in the previous section, but we add a constraint or market indicator variable as well. The complete specification is explained by Equation (7). If the *HiLOC* variable is significantly positive, controlling for other financial constraint measures, then we can conclude that the usage of credit lines is important on its own and not merely substituting for other financial constraint measures. We also include indicator variables for bond rating and commercial paper, as they were significant in Table 4.

Table 5. Risk-Adjusted Return vs. Total LOC Percent of Liquidity

This table provides OLS regression results of monthly risk-adjusted returns, r*, on size, and book to market ratio, and LOC variables. Data are from sample firms from 1997-2010 that have access to lines of credit. 1997-2003 data is from Amir Sufi's (2009) study. 2004-2010 data was hand collected for this study. Accounting data are from COMPUSTAT. Line of credit data are from Amir Sufi's website (1997-2003) and firm 10-K reports (2004-2010). Risk adjusted returns were calculated using the Fama-MacBeth method with the Fama-French 1- and 3-Factor market model as the baseline as indicated and CRSP return data. Size is the natural logarithm of the firm's otal assets. BTM is the book to market ratio, $\frac{\text{Book Value of the Firm}}{\text{Total Shares} \times \text{Share Price}}$. LOCTotal is the natural logarithm of the total amount of lines of credit, used and unused. HiLOC, HiLOC2, and HiLOC3 are dummy variables for 3 different methods of defining high LOCs users. HiLOC takes the value of 1 if a firm has a LOCusedRatio higher than the median and 0 otherwise. HiLOC2 takes the value of 1 if a firm's LOCUsedRatio is in the top 30% of the sample and 0 if LOCUsedRatio is in the bottom 30%. HiLOC3 takes the value of 1 if a firm's LOCUsedRatio is in the top 30% for each year and 0 if LOCUsedRatio is in the bottom 30% for each year. Industry dummies are calculated using the Fama French 12 industry SIC codes. Crisis is a dummy variable that takes the value of 1 if a observation is in 2007 or 2008 and takes the value of 0 otherwise. T-statistics are calculated with heteroskedasticity-consistent errors. ***, **, * are statistically significant at the 1%, 5%, and 10% level, respectively.

	A: 1-Factor Model			*B: 3-Factor Model*		
Parameter	*HiLOC*	*HiLOC2*	*HiLOC3*	*HiLOC*	*HiLOC2*	*HiLOC3*
Intercept	-8.15***	-9.68***	-9.65***	-9.10***	-11.00***	-10.85***
	(-15.61)	(-15.39)	(-15.05)	(-14.62)	(-14.87)	(-14.45)
Size	0.92***	1.30***	1.16***	1.09***	1.54***	1.41***
	(10.53)	(11.22)	(10.46)	(9.70)	(10.99)	(10.30)
BTM	1.11***	1.17***	1.11***	1.03***	1.09***	1.02***
	(5.20)	(5.18)	(4.93)	(4.55)	(4.54)	(4.24)
LOCTotal	0.04	-0.15*	-0.01	0.01	-0.25**	-0.11
	(0.66)	(-1.85)	(-0.10)	(0.15)	(-2.32)	(-1.09)
Crisis	-0.03	0.12	-0.03	0.67***	0.79***	0.61**
	(-0.17)	(0.50)	(-0.12)	(2.65)	(2.59)	(2.02)
HiLOC	0.47***			0.45**		
	(3.23)			(2.53)		
HiLOC2		0.40**			0.42*	
		(1.97)			(1.72)	
HiLOC3			0.52***			0.53**
			(2.69)			(2.22)
Industry Dummies	yes	yes	yes	yes	yes	yes
Observations	18995	13657	13507	18995	13657	13507
Adj R-Squared	0.0521	0.0625	0.0619	0.0394	0.0493	0.0484

Table 6 reports these regression results. Although less statistically robust than in Table 5, the *HiLOC* indicator variable still is significantly positively related to returns. The *HiLOC* coefficients are 0.32 and 0.33 for the *BondRate* and *CommPaper* models, respectively. As expected, the coefficients of *BondRate* and *CommPaper* measures of financial constraint are negative and highly significant at the 1% level. Firms with a bond rating or credit rating are not financially constrained and consistent with previous studies (Whited and Wu (2006), Livdan, Sapriza and Zhang (2009)) are associated with lower returns in the cross section.

We also control for market movements using indicator variables based on the CFNAI measures. Once again, *HiLOC* is positive in each model, with a coefficient of 0.45 and 5% level of significance. However, we do not find any relationship between the market expansion/contraction and returns in the cross section. This is likely due to the fact that risk-adjusted returns control for market movements. In all, we find evidence suggesting that controlling for other financial constraint measures and market movements, investors demand higher returns in the cross section for holding stock in firms that use a high percentage of their credit lines. This result provides further evidence suggesting that these high LOC users are financially constrained.

Influence of credit line usage on investment and profitability

We next examine two additional areas that may reveal differences between high and low users of credit lines: corporate investment and profitability. If, as we propose, high users of credit lines are financially constrained, we would expect high users to

Table 6. Risk-Adjusted Returns by Financial Constraint Measures

This table provides OLS regression results of risk-adjusted returns, r*, on size, book to market ratio, LOC variables and financial constraint variables. Data are from sample firms from 1997-2010 that have access to lines of credit. 1997-2003 data is from Amir Sufi's (2009) study. 2004-2010 data was hand collected for this study. Accounting data are from COMPUSTAT. Line of credit data are from Amir Sufi's website (1997-2003) and firm 10-K reports (2004-2010). Risk adjusted returns were calculated using the Fama-MacBeth method with the Fama-French 3-Factor market model and CRSP return data. Size is the natural logarithm of the firm's total assets. BTM is the book to market ratio, $\frac{Book\ Value\ of\ the\ Firm}{Total\ Shares \times Share\ Price}$. LOCTotal is the natural logarithm of the total amount of lines of credit, used and unused. HiLOC takes the value of 1 if t a firm is has a LOCUsedRatio higher than the median and 0 otherwise. Crisis is a dummy variable that takes the value of 1 if a observation is in 2007 or 2008 and takes the value of 0 otherwise. BondRate takes the value of 1 if a firm has a bond rating and 0 otherwise. CommPaper takes the value of 1 if a firm has a commercial paper rating and 0 otherwise. High DivPay takes the value of 1 if a firm's dividend payout ratio is in the top 30% of the sample by year and 0 if the dividend payout is in the bottom 30% by year. High Assets takes the value of 1 if a firm's assets in the top 30% of the sample by year and 0 if assets rank in the bottom 30% by year. Constrained firms are those with bond rating = 0, CommPaper = 0, High DivPay=0, HighAssets = 0; Up takes the values of 1 for months when the market is expanding at a rate greater than average (Chicago Fed National Activity Index (CFNAI) greater than 0) and 0 otherwise. Up3 takes the values of 1 for months when the 3-month moving average of the CFNAI is greater than 0 and 0 otherwise. Industry dummies are calculated using the Fama French 12 industry SIC codes. T-statistics are calculated with heteroskedasticity-consistent errors. ***, **, * are statistically significant at the 1%, 5%, and 10% level, respectively.

Parameter	*BondRate*	*CommPaper*	*Up*	*Up3*
Intercept	-10.76***	-9.67***	-9.11***	-9.17***
	(-15.44)	(-14.85)	(-14.20)	(-14.24)
Size	1.46***	1.17***	1.09***	1.09***
	(11.65)	(10.15)	(9.72)	(9.77)
BTM	1.03***	1.03***	1.03***	1.03***
	(4.60)	(4.55)	(4.52)	(4.53)
LOCTotal	0.06	0.06	0.01	0.01
	(0.66)	(0.72)	(0.15)	(0.14)
HiLOC	0.32*	0.33*	0.45**	0.45**
	(1.81)	(1.83)	(2.53)	(2.50)
Crisis	0.52**	0.67***	0.68**	0.72***
	(2.04)	(2.63)	(2.57)	(2.68)
BondRate	-2.77***			
	(-11.99)			
CommPaper		-2.11***		
		(-10.66)		
Up			0.02	
			(0.10)	

Parameter	*BondRate*	*CommPaper*	*Up*	*Up3*
Up3				0.10
				(0.55)
Industry Dummies	yes	yes	yes	yes
Observations	18995	18995	18995	18995
Adj R-Squared	0.0457	0.0414	0.0393	0.0393

engage in less investment and have lower levels of accounting profitability than low LOC (unconstrained) firms.

Table 7 reports the OLS regression results of corporate investment (*Capex*, *R&D*, and Employment) on the LOC usage variables as described in Equation (5), based on the Campello, Giambona, Graham and Harvey (2011) regression specification. Panels A, B and C show results when high users of credit lines are defined as greater than the median of the sample, top 30% of the sample, and top 30% by year, respectively. This stratification allows stronger conclusions to be drawn from the regression results, as there are larger differences between high and low users of credit lines.

First, we examine the main hypothesis, that high users of credit lines will have lower levels of investment because they are not able to benefit from the liquidity insurance property of credit lines. In Panel A, the negative coefficients of *HiLOC* for *Capex* and *Empl* (-152.04 and -4.51, respectively) are significant at the 1% level. We obtain nearly identical results in Panels B and C; the coefficients of *HiLOC2* and *HiLOC3* for Capex and Employment expenditures are negative and significant at the 1% level in all cases. These results provide support for our conjecture that high LOC users, as financially constrained firms, are less likely to deploy lines of credit for investment purposes. Although Campello, Graham and Harvey (2010) examine firms only during the financial crisis, our results consistent with theirs show that investment is reduced for financially constrained firms. However, the results for R&D are quite different from the results of Capex and Employment. In all panels, there is no statistically significant relationship between credit line usage and investment in R&D. This result indicates that risky corporate investment is most often funded by cash.

Looking next at the coefficient of *LOCTotal*, we find that lines of credit are positively related to both *Capex* and employment investment. Regardless of the model used, the coefficient of *LOCTotal* is positive and significant at the 1% level in all cases. Consistent with Campello, Giambona, Graham and Harvey (2011) we find strong evidence that credit lines allow firms to increase their level of investment above the level they could have achieved with cash alone. In Panels A, B, and C, the coefficients of the interacted variable *Cash*LOCTotal* are positive and significant at the 1% level for *Capex* with t-statistics of 4.34, 4.77, and 4.72, respectively. Again, in line with Campello, Giambona, Graham and Harvey (2011) credit lines do not appear to boost corporate investment in *R&D* or employment. *Cash* is significantly and positively related to both R&D and employment expenditures for all three definitions of high credit line users. However, the coefficient of the interacted variable (*Cash*LOCTotal*) is not significantly different from zero for R&D expenditures and is negative for employment expenditures. While the results of Table 7 indicate that LOC's are positively associated with corporate investment, high LOC users invest considerably less in capital expenditures and employment that low LOC users. This evidence provides additional support for our conjecture that high LOC users, as financially constrained firms, are more likely to use their lines of credit for non-investment purposes. Hence, firms with high LOC drawdowns are also expected to be less profitable.

The next area of our investigation centers on the effect of high LOC usage on profitability. As discussed so far, since high LOC users are unable to take advantage the liquidity insurance function of credit lines and less able to invest efficiently in capex and

Table 7. Determinants of Investment Spending

This table provides OLS regression results based on the Campello, Giambona, Graham, and Harvey (2009) specification. Data are from sample firms from 1997-2010 that have access to lines of credit. 1997-2003 data is from Amir Sufi's (2009) study. 2004-2010 data was hand collected for this study. Annual accounting data are from COMPUSTAT. Line of credit data are from Amir Sufi's website (1997-2003) and firm 10-K reports (2004-2010). Dependent variables are Capex, R&D, and Employment in separate models. Capex is the annual firm capital expenditures in plant, property, and equipment. R&D is the annual expenditure on Research and Development. Employees are the number of employees. Size is the natural logarithm of the firm's total assets. Cash is the annual amount of cash (stock). LOCTotal is the total amount of lines of credit, used and unused. HiLOC, HiLOC2, and HiLOC3 are dummy variables for 3 different methods of defining high LOCs users. HiLOC takes the value of 1 if a firm is has a LOCusedRatio higher than the median and 0 otherwise. HiLOC2 takes the value of 1 if a firm's LOCUsedRatio is in the top 30% of the sample and 0 if LOCUsedRatio is in the bottom 30%. HiLOC3 takes the value of 1 if the firm's LOCUsedRatio is in the top 30% for each year and 0 if LOCUsedRatio is in the bottom 30% for each year. Industry dummies are calculated using the Fama French 12 industry SIC codes. T-statistics are calculated with heteroskedasticity-consistent errors. ***, **, * are statistically significant at the 1%, 5%, and 10% level, respectively.

	A: HiLOC			*B: HiLOC2*			*C: HiLOC3*		
Parameter	*Capex*	*R&D*	*Empl*	*Capex*	*R&D*	*Empl*	*Capex*	*R&D*	*Empl*
Intercept	262.56**	-54.99	-8.25**	312.73**	-84.31	-1.24	316.21**	-87.16	-1.46
	(2.30)	(-1.31)	(-2.00)	(2.31)	(-1.58)	(-0.30)	(2.32)	(-1.57)	(-0.34)
Size	-45.52*	12.98	2.94***	-60.11*	22.90*	0.64	-62.48*	24.32*	0.55
	(-1.65)	(1.34)	(3.15)	(-1.88)	(1.82)	(0.74)	(-1.92)	(1.91)	(0.61)
Cash	-0.31	0.83***	0.02**	-0.34	0.90***	0.01**	-0.34	0.88***	0.01**
	(-1.39)	(4.94)	(2.58)	(-1.40)	(6.46)	(2.13)	(-1.39)	(6.05)	(2.12)
LOCTotal	1.34***	-0.20***	0.03***	1.57***	-0.29***	0.06***	1.57***	-0.30***	0.06***
	(6.27)	(-4.11)	(4.63)	(4.43)	(-4.65)	(5.47)	(4.48)	(-4.73)	(5.43)
*Cash*LOCTotal*	0.00***	0.00	-0.00*	0.00***	0.00	-0.00***	0.00***	0.00	-0.00***
	(4.34)	(0.72)	(-1.96)	(4.77)	(0.65)	(-2.81)	(4.72)	(0.81)	(-2.80)
HiLOC	-152.04***	2.20	-4.51***						
	(-5.23)	(0.17)	(-4.18)						

	A: HiLOC			*B: HiLOC2*			*C: HiLOC3*		
Parameter	*Capex*	*R&D*	*Empl*	*Capex*	*R&D*	*Empl*	*Capex*	*R&D*	*Empl*
HiLOC2				-131.55***	2.45	-4.71***			
				(-4.45)	(0.14)	(-3.64)			
HiLOC3							-132.16***	4.69	-5.07***
							(-4.51)	(0.30)	(-3.97)
Year Dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry Dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	1402	826	1389	1004	588	993	988	584	978
Adj R-Squared	0.8099	0.7264	0.5567	0.7782	0.7530	0.5477	0.7817	0.7483	0.5510

employment, we expect them to be less profitable than firms that do not extensively use their credit lines.

To examine this final prediction, we regress ROA, EBITDA scaled by total assets, and ROE, our three profitability measures, against *LOCTotal*, the *HiLOC* measures, controlling for other effects, as listed in Equation (6). The results, reported in Table 8, once again show strong support for our hypothesis. When profitability is measured by ROA in Panels A, B, and C the coefficient of the *HiLOC* indicator variable is negative and significant at the 1% level (t-statistics of -2.74, -3.56, and -3.66, respectively). With EBITDA as the profitability measure, the coefficient of the *HiLOC* variable is not statistically different from 0 in Panel A. However, when there is a stronger delineation between high and low users, as in Panels B and C, the coefficients are negative and significant at the 5% level. The coefficients for *HiLOC* in the ROE models are also negative and significant in all cases. Additionally, the coefficient on the *LOCTotal* is positive and significant at the 1% level in all models, showing that firms that have access to credit lines are associated with higher profitability. The results of Table 8 provide final support for our hypothesis that the degree of credit line usage does reflect financial constraint. High LOC users have lower accounting performance than low users.

CONCLUSION

The study of credit line drawdowns is in its early stages. Unlike previous studies, we address the important question why firms with access to credit lines have different drawdowns. We hypothesize that high LOC users are more financially constrained than

Table 8. Determinants of Profitability

This table provides OLS regression results based on the Campello, Giambona, Graham, and Harvey (2009) specification. Data are from sample firms from 1997-2010 that have access to lines of credit. 1997-2003 data is from Amir Sufi's (2009) study. 2004-2010 data was hand collected for this study. Dependent variables are ROA, EBITDA/Assets and ROE. Annual accounting data are from COMPUSTAT. Line of credit data are from Amir Sufi's website (1997-2003) and firm 10-K reports (2004-2010). Size is the natural logarithm of the firm's total assets. BTM is the book to market ratio, $\frac{Book\ Value\ of\ the\ Firm}{Total\ Shares \times Share\ Price}$. LOCTotal is the natural logarithm of the total amount of lines of credit, used and unused. HiLOC, HiLOC2, and HiLOC3 are dummy variables for 3 different methods of defining high LOCs users. HiLOC takes the value of 1 if a firm has a LOCUsedRatio higher than the median and 0 otherwise. HiLOC2 takes the value of 1 if a firm's LOCUsedRatio is in the top 30% of the sample and 0 if LOCUsedRatio is in the bottom 30%. HiLOC3 takes the value of 1 if a firm's LOCUsedRatio is in the top 30% for each year and 0 if LOCUsedRatio is in the bottom 30% for each year. Industry dummies are calculated using the Fama French 12 industry SIC codes. T-statistics are calculated with heteroskedasticity-consistent errors. ***, **, * are statistically significant at the 1%, 5%, and 10% level, respectively.

	A: HiLOC			*B: HiLOC2*			*C:HiLOC3*		
Parameter	*ROA*	*EBITDA/Assets*	*ROE*	*ROA*	*EBITDA/Assets*	*ROE*	*ROA*	*EBITDA/Assets*	*ROE*
Intercept	-0.00	0.09***	1.28	0.03	0.12***	13.74	0.02	0.11***	9.48
	(-0.16)	(3.63)	(0.13)	(0.88)	(4.06)	(1.27)	(0.72)	(3.62)	(0.82)
Size	-0.01	-0.01	-1.81	-0.01*	-0.01**	-3.57*	-0.01*	-0.01**	-3.08
	(-1.25)	(-1.47)	(-1.09)	(-1.66)	(-2.14)	(-1.65)	(-1.88)	(-2.17)	(-1.44)
BTM	-0.02**	-0.03**	-12.25**	-0.02**	-0.02*	-12.77**	-0.02**	-0.02*	-12.64**
	(-2.13)	(-2.07)	(-2.26)	(-1.99)	(-1.92)	(-2.38)	(-1.98)	(-1.90)	(-2.35)
LOCTotal	0.02***	0.02***	7.77**	0.02***	0.02***	9.64**	0.02***	0.02***	9.51**
	(3.51)	(4.67)	(2.40)	(2.96)	(4.16)	(1.99)	(3.30)	(4.42)	(2.17)
HiLOC	-0.02***	-0.01	-14.00*						
	(-2.74)	(-1.55)	(-1.75)						
HiLOC2				-0.04***	-0.02**	-20.29**			
				(-3.56)	(-2.01)	(-1.98)			

	A: HiLOC			B: HiLOC2			C:HiLOC3		
Parameter	*ROA*	*EBITDA/Assets*	*ROE*	*ROA*	*EBITDA/Assets*	*ROE*	*ROA*	*EBITDA/Assets*	*ROE*
HiLOC3							-0.04***	-0.02**	-21.31**
							(-3.66)	(-2.27)	(-2.00)
Year Dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry Dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	1414	1413	1398	1014	1014	999	998	997	982
Adj R-Squared	0.0722	0.1225	0.0249	0.0770	0.1325	0.0291	0.0732	0.1308	0.0302

low users. Consequently, we also conjecture that high LOC user firms will be associated with higher stock returns. Finally, because the liquidity insurance properties of credit lines are only available to firms with low LOC drawdowns they are expected to lose the ability to employ credit lines for liquidity insurance purposes leading to lower investment and profitability.

We address these issues and find strong evidence in support of our first conjecture that firms with LOW usage are more financially constrained than firms with low LOC usage. High LOC users are smaller and less liquid than low LOC users. High users are also less likely to have a bond rating and access to commercial paper. We also examine the influence of credit line usage in the cross section of returns, using different methods of calculating risk-adjusted returns and for three alternative methods of defining high LOCs users, and find them to be associated with higher stock returns than low LOC users. This pattern persists even after controlling for other financial constraint measures and the state of macroeconomic conditions. Finally, we find that high LOC users relative to low LOC users have lower investment in capital expenditures and profitability than low LOC users. Overall, our evidence suggests that credit line usage, and not just access to lines of credit, is a more effective way to identify whether a firm is financially constrained.

CHAPTER II

CREDIT LINE USAGE DURING THE 2008 FINANCIAL CRISIS

INTRODUCTION

The theoretical literature suggests lines of credit (LOCs) enable firms to smooth cash flows thereby allowing firms to invest during times of limited credit availability (Campbell (1978), Hawkins (1982), Shockley and Thakor (1997), Holmstrom and Tirole (1998), DeMarzo and Fishman (2007)). This literature suggests that LOCs provide liquidity insurance that helps firms maintain value-enhancing corporate investment when other forms of liquidity are limited.

However, recent empirical studies have called into question the effectiveness of LOCs as liquidity insurance. Sufi (2009) provides early evidence that cash flow influences LOC usage. He finds that low cash flow firms are less likely to use LOCs than firms with higher cash flows. Since then, the literature has uncovered limitations of LOC usage due to the economic environment (Ivashina and Scharfstein (2010), Berrospide, Meisenzahl and Sullivan (2012)) and due to a firm's financial health (Jimenez, Lopez and Saurina (2009), Campello, Graham and Harvey (2010)). Additionally, Lins, Servaes and Tufano (2010) suggest that LOCs are more difficult to use during periods of limited credit availability. Jimenez, Lopez and Saurina (2009) and Acharya, Almeida, Ippolito and Perez (2012) argue that bank monitoring may also limit LOC usage. These empirical studies suggest that there are limits to the deployment of credit lines that may hinder their liquidity insurance effectiveness.

This disagreement between the theoretical predictions and recent empirical research on the LOCs suggests that additional study is warranted. On one hand, theory states that LOCs may be activated to maintain steady cash flows. This cash flow smoothing should enable firms to invest during credit-restricted periods. On the other hand, empirical studies indicate that firms may have difficulty activating LOCs when the economic environment is unfavorable. To address this gap between the theoretical and empirical literature, we examine the question: How do firms use LOCs during the 2008 financial crisis? Specifically, we examine credit line usage and corporate investment in Capex, employment, and R&D to determine if LOCs aid firms in avoiding investment declines during times of reduced credit availability when compared to the earlier period of credit stability. In addressing this question we provide evidence that LOCs may be limited in their ability to provide liquidity insurance in unfavorable economic conditions.

The ability to test this theoretical prediction has been limited due to the scarce availability of credit line data and the short duration of previous credit-constrained periods. However, the recent global financial turmoil provides an ideal exogenous event that enables us to perform a direct investigation to learn how firms use credit lines in a crisis. When the housing bubble burst in 2007, falling housing values undermined the subprime mortgage markets and associated securitized financial products crashed. Credit market unrest peaked in the aftermath of the delisting of Lehman Brothers in September 2008. However, even as the U.S. federal government intervened to inject solvency in select institutions, credit markets remained tight, making this challenging environment for corporate liquidity management an ideal laboratory for our study.

We conduct our empirical analysis with a unique dataset of integrated credit line and financial data. We manually collect information on credit line drawdowns from firm 10-Ks from 2004 to 2010 and combine it with the credit line usage data from Amir Sufi's website for a total dataset of credit line usage from 1996-2010. We then combine the credit line data with financial information from Compustat. Since literature suggests liquidity hedging may increase credit line usage (Disatnik, Duchin and Schmidt (2009), Berrospide, Meisenzahl and Sullivan (2012)) we also hand-collect information from 10-Ks about whether or not each firm hedges its revolving debt. In all, we have credit line, hedging, and financial data on 300 firms from 1996-2010.

We empirically test the theoretical prediction that credit lines provide liquidity insurance by examining the influence of LOC access and LOC usage on corporate investment in periods before and during the recent financial crisis. We first examine LOC access and find that firms are equally likely to have access to LOCs in both the pre-crisis and crisis periods. We then assess the impact of LOCs on corporate investment by regressing Capex, employment, and R&D on firm financial variables. We find it is only in combination with cash that LOCs increase the ability of a firm to invest in Capex and employment. The LOC variable on its own is not statistically significant in our model.

Next, we look at LOC usage, rather than LOC access, by using a measure of LOCs drawn down in our analysis. We find that among firms with access to LOCs, those whose usage is greater than the median (an indicator of constraint) invest less in Capex and employment. Additionally, our analysis of these high LOC users shows that LOCs do not impact their investment differently during the crisis when compared with the period of normal credit availability prior to the crisis. The largest contributor to the decrease in investment is the financial crisis itself, and the crisis effect is not mitigated by LOC usage. In all, contrary to theoretical predictions, we find strong evidence that firms are not using LOCs to invest during the crisis period. Our findings suggest that LOCs may not be able to provide effective liquidity insurance that allows value-enhancing investment to continue during severe credit market conditions.

This study makes contributions to several strands of literature. We add to the risk management literature with our finding that credit line hedging positively influences LOC drawdowns and negatively influences corporate investment. However, our main contributions are to the liquidity management and investment literatures. By investigating LOC usage during the financial crisis, we are able to provide information concerning liquidity management and investment in distressed economic times, when liquidity should be most valuable. We confirm that credit lines do improve the ability of a firm to invest above the amount that could have occurred with cash alone. We also provide solid evidence that credit line usage is consistent across pre-crisis and crisis periods - a finding suggesting that LOCs are not more extensively used during a financial crisis than during other periods of greater credit availability. In all, our results add to the recent literature questioning the effectiveness of LOCs' theoretical role of liquidity insurance and suggest that firms should not depend solely on LOCs to maintain investment during a crisis.

LITERATURE REVIEW

Credit lines are a significant source of corporate liquidity. In the Holmstrom and Tirole (1998) theoretical model, LOCs are one of the four ways firms are able to satisfy liquidity requirements[10]. By using LOCs, firms contract with financial institutions to ensure access to additional liquidity without going through the time and vetting process involved with obtaining other forms of financing. Although both cash and LOCs may allow firms to engage in corporate investment without going to capital markets, LOCs have three properties that firms may find more valuable than cash: corporate governance, tax advantages, and liquidity insurance. Yun (2009) investigates whether the use of LOCs influences corporate governance. He finds that managers are less likely to use LOCs than cash to misappropriate shareholders' wealth. He also reports that firms exhibiting poor corporate governance have more LOCs than cash in order to reduce the chance that managers will squander firm cash. Demiroglu and James (2011) state that LOCs have another advantage over cash in that interest payments are tax deductable, whereas interest earned from cash holdings is taxed. Unlike these studies that focus on LOCs from the corporate governance and tax advantages perspective, this paper examines the liquidity insurance property of LOCs. Theoretical literature is unified in its assertion that LOCs enable firms to have access to liquidity on-demand (Campbell (1978), Hawkins (1982), Shockley and Thakor (1997), Holmstrom and Tirole (1998), DeMarzo and Fishman (2007)). The "just in time" liquidity that LOCs provide is often called liquidity insurance because it potentially provides access to liquidity when funding may otherwise be difficult or costly to obtain.

However, recent empirical studies have raised some doubt about the ability of LOCs to adequately provide liquidity insurance. Sufi (2009) is the first in-depth empirical study on LOCs. His main finding is that LOCs are employed mostly by firms with

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[10]Issuing debt or equity, buying other firms' debt or equity, and buying government securities are the other three.

significant positive cash flows. Furthermore, he finds that low cash flow firms tend to choose cash, rather than credit lines to satisfy liquidity requirements because bank lines of credit often include loan covenants that restrict firms' investment activities if cash flow requirements are not met. Overall, his findings suggest that there may be limits to the effectiveness of LOCs in providing liquidity insurance. In an international study utilizing survey data, Lins, Servaes and Tufano (2010) find evidence suggesting that firms are more likely to use LOCs during periods of economic growth. In fact, they find that firms prefer to use cash for meeting liquidity needs during times of economic turmoil. The greater reliance on cash during economic crises seems to be consistent with the view that LOC users suffer a reduction in bank financing due to a market-wide credit supply contraction without being able to tap external (bond) financing (Adrian, Colla and Shin (2012)).

Further evidence that LOCs may provide limited liquidity insurance is implied by studies examining the monitoring power of banks. Jimenez, Lopez and Saurina (2009) find a negative relationship between a firm's age and amount of total LOCs the firm reports. This result is particularly strong for firms that use LOCs extensively. Jimenez, Lopez and Saurina (2009) suggest that over time, banks may reduce firms' access to LOCs. Likewise, Acharya, Almeida, Ippolito and Perez (2012) find that banks use covenants to affect firm behavior, e.g., imposing restrictions on cash outlays for dividends or investment. By limiting firms' usage of funds from credit lines, the covenants may effectively reduce the LOCs' liquidity insurance properties. Taken together, these studies illustrate several limitations on LOCs' ability to provide liquidity insurance[11]. Hence, further study is required mainly for three reasons. First, most of these studies examine the liquidity insurance properties of credit lines during relatively calm or normal economic environments. This might be an explanation why previous studies find the liquidity insurance properties of credit lines are limited. Instead, in line with the theoretical suggestion (Campbell (1978), Hawkins (1982), Shockley and Thakor (1997), Holmstrom and Tirole (1998), DeMarzo and Fishman (2007)) that LOC usage is expected to provide liquidity insurance during periods of limited credit availability, we examine LOC usage around the recent financial crisis, a rare and economically important event of tight credit conditions, to assess the liquidity insurance properties of credit lines. Since empirical studies suggest that the liquidity insurance properties of credit lines may be limited during normal times, we expect the LOC usage to be amplified during periods of credit crisis. If true, such a result would imply that credit lines are most likely to be effective for liquidity insurance, precisely when firms need them the most. That is, if LOCs are acquired to protect firms against tight credit market conditions, they should hedge firms from the adversity of limited credit availability. Consequently, firms will be able to use credit lines to maintain corporate investment during the 2008 financial crisis.

Second, while some recent literature investigates credit line usage during the recent financial crisis they rely on survey data due to the difficulty in obtaining drawdown information for LOCs. The survey-based analysis of Campello, Graham and Harvey (2010) shows that financially constrained firms planned to use more LOCs and cash during the 2008 financial crisis than firms that were more financially healthy. Using

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[11] Demiroglu and James (2011)'s review article summarizes the possible reasons for limitations on LOC's ability to provide liquidity insurance as loan characteristics (financial covenants, material adverse change clauses, borrowing base, and performance pricing) and external factors such as the financial health of the lending institution and rollover risk.

a different survey, Campello, Giambona, Graham and Harvey (2011) report that LOCs may help firms with high levels of liquidity to engage in corporate investment during the crisis. However, drawing inferences about the impact of LOCs on investment from survey-based data may be subject to some limitations that data from financial reports avoids. For example, in Campello, Graham and Harvey (2010), managers provide information about their projected investment plans during the financial crisis. However, it is unclear whether the proposed investment happened as planned. Furthermore, Pan and Statman (2012) argue that managers answer questions differently whether they are asked before or after an event. Unlike survey data, the dataset employed in this study provides a unique portrayal of firms' LOC usage that allows us to determine the effectiveness of LOCs in practice during a period of limited credit availability.

Third, most previous studies have not taken into account the fact that risk management may influence a firm's ability to activate the liquidity insurance properties of LOCs. Some firms choose to use derivatives such as interest rate swaps to reduce variability of the cash flows. Disatnik, Duchin and Schmidt (2009) investigate the effects of this cash flow hedging prior to the financial crisis and find that cash flow hedging diminishes a firm's need for cash. They argue that since firms that engage in cash flow hedging need less cash, these hedging firms often choose credit lines to satisfy their liquidity requirements. Thus, cash flow hedging through the use of derivatives such as interest rate swaps may offer firms an alternative method to smooth cash flows than using LOCs. Berrospide, Meisenzahl and Sullivan (2012) examine LOC usage during the crisis, focusing on three possible explanations for LOC drawdowns: interest rate risk, loan covenants, and hedging of the credit lines. They find evidence suggesting that during the crisis, firms that hedge their LOCs are more likely to draw down their credit lines more heavily than firms that do not engage in hedging. That is, LOC usage is likely to be greater if firms hedge credit lines. Hence, liquidity insurance properties of LOCs could be more pronounced. In fact, the interest rate hedging documented by Berrospide, Meisenzahl and Sullivan (2012) may be an effort of firms to escape the limits to liquidity insurance, particularly cash flow-based covenants. Both Disatnik, Duchin and Schmidt (2009) and Berrospide, Meisenzahl and Sullivan (2012) focus on the impact of interest rates and interest rate hedging on LOC usage, which has been ignored in much of the previous literature. This omission may be another reason that the literature has been unable to verify the liquidity insurance properties of LOCs. In our study, we account for hedging to shed light on how interest rate hedging affects the use of LOCs and a firm's ability to use LOCs for investment. Hedging should have a positive impact on investment or at least allow firms to avoid the adverse effects of tight credit conditions on investment levels.

The study that is most closely related to ours is Ivashina and Scharfstein (2010)'s analysis of how the 2008 financial crisis influenced the credit supply. Their investigation centers on both LOC usage and investment from the perspective of the lending institutions. They are primarily concerned with understanding how panic-driven aggregate credit line drawdowns affected the ability of banks to continue making other types of loans. Since they do not have data on credit line drawdowns, they augment their supply-side analysis with a small sample of credit line drawdowns from 24 firms during five months in 2008. These drawdowns were reported in the news and therefore thought to represent surprise or unexpected drawdowns. They find that unanticipated drawdowns increased significantly during the crisis, while cash levels increased, suggesting that firms were hoarding cash rather than using LOCs as liquidity insurance to maintain investment. We build on this study by taking a more in-depth look at all credit line drawdowns (rather than surprise drawdowns) over 15 years. We examine how access to credit lines and credit line drawdowns before and during the financial crisis influence corporate investment, and whether the credit lines enable firms to avoid decreases in investment as the theoretical literature suggests. Our demand-focused test of the theoretical prediction that LOCs provide liquidity insurance complements Ivashina and Scharfstein (2010)'s predominantly supply-side paper, and contributes to the literature by enhancing our understanding of the role of LOCs in the financial crisis.

DATA

Our dataset consists of a random sample of 300 firms from Compustat spanning the period from 1996 to 2010. These firms represent 6.5% of firms that had at least four consecutive years of financial data between 1996 and 2003, as used in Sufi's study. LOC usage for 2004 to 2010 was collected from the 10-Ks using the procedure documented in Sufi (2009). Specifically, 10-Ks were downloaded from the U.S. Securities and Exchange Commission's EDGAR website.[12] We then read the 10-K looking for notes that reported the amount of total credit lines, used and unused. Only committed credit lines with banking institutions were recorded. Letters of credit and credit lines engaged for the sole purpose of supporting a commercial paper program were excluded. LOC drawdown information from 1996 to 2003 was retrieved from Sufi's website[13].

[12] http://www.sec.gov/edgar/searchedgar/webusers.htm
[13] http://faculty.chicagobooth.edu/amir.sufi/data.html

Firms that engage in LOC hedging may be able to mitigate the effect of restrictive covenants, thereby maintaining the liquidity insurance properties of their LOCs. Therefore, we collected hedging data for each of the 300 firms by reading the 10-Ks to account for possible LOC hedging effects in our experiments. Following Berrospide, Meisenzahl and Sullivan (2012), we employed a search engine to look for the hedging terms ("interest rate agreement," "interest rate agreements," "interest rate exchange agreement," "interest rate exchange agreements," "interest rate hedge," "interest rate hedges," "interest rate swap," "interest rate swaps") within 1500 characters of LOC terms ("credit facility," "credit facilities," "credit line," "credit lines," "line of credit," "lines of credit," "loan facility," "loan facilities," "revolving facility," "term loan," "term loans")[14]. We then read the documents to determine if the firm stated that the LOCs were hedged. We found evidence that some firms were required to hedge their LOCs as a condition having access to the credit lines. Other firms were voluntarily hedging their LOCs. Many firms did not report whether or not hedging was required. However, our investigation shows that few sample firms engage in this practice of hedging their LOCs. Specifically, we were able to identify only 23 firms that hedged LOCs for any time during the 1996-2010 period. Only 19 firms hedged their LOCs for more than one year.

Finally, the credit line drawdowns and hedging information are combined with Compustat financial variables for a final sample of 300 firms over 15 years. Table 9 provides descriptive statistics for the sample. Panel A reports statistics for the entire sample, while Panel B breaks down the sample into periods that are unaffected by the credit crisis (1996-2006) and those affected by the financial crisis (2007-2010). We refer

[14] Although we do not report hedging of term loans, we follow Berrospide et al (2012) practice of including the search term to be conservative.

to these two periods as pre-crisis and crisis, respectively. The crisis period includes 2007, since Ivashina and Scharfstein (2010) find that the impact of the credit crisis on bank lending began to be felt in 2007.

For the 1996-2010 period, Panel A shows that most sample firms utilized LOCs. Our sample firms had access to credit lines in 68% of the firm-year observations. The median sample firm had cash flow of 0.111. These values are similar to those reported in Disatnik, Duchin and Schmidt (2009), who state that 71.2% of their firms have access to LOCs with a sample median cash flow of 0.106. In Panel B we divide the sample into pre-crisis (1996-2006) and crisis (2007-2010) time periods to see if the crisis had any impact on access to credit lines. We see that access to LOCs increased from 66.9% before the crisis to 73.7% during the crisis, a statistically significant change. Mean total LOCs also increased from 263.6 to 385.4. These results are in line with Ivashina and Scharfstein (2010)'s finding that firms increased credit lines after the delisting of Lehman Brothers in an attempt to secure future credit. Firms during the crisis period also had more cash and corporate investment (Capex, R&D, and employment) than firm-year observations in the pre-crisis period. Median cash levels increased threefold (10.3 to 32.9), which is in line with the evidence of Ivashina and Scharfstein (2010) indicating that firms tend to hoard cash during the recent financial crisis. However, not surprisingly, during the crisis period firms experienced a reduction in liquidity (current assets/total assets) of 5.5% over the pre-crisis firms. Before the crisis, firms also had a lower cash-adjusted net worth ($\frac{Assets-Cash-Liabilities}{Assets-Cash}$) than pre-crisis firms (-0.530 versus 0.338). Adrian, Colla and Shin (2012) show that during the recent financial crisis, bank lending to firms declined substantially: loan issuance dropped 75%, and the probability of obtaining a loan fell by

14%. Given the economic environment of reduced lending, as well as the deteriorating financial positions and increasing cash positions during the crisis, the increases in investment seem to be driven by cash, at least at a univariate level of analysis.

We next examine sample firm characteristics by industry during the pre-crisis and crisis periods to see if most firms increased their credit lines during the crisis, or if the phenomenon was driven by a few key industries. In Table 10, we find that the tendency of firms to increase credit lines during the crisis is indeed prevalent. All industries, except for Non-durables and Chemicals, increased firms' access to credit lines after 2006. Non-durables' LOC access remained constant at 81% and Chemical experienced a decrease in percentage of firms with LOC access from 75.6% to 63.6%. In fact, several industries (Durables, Energy, Telephone and TV, Utilities) had 100% of firm-year observations with LOCs in the crisis period, although this observation is tempered by the fact that there are fewer observations in the crisis period. There is great variation in the amount of corporate investment and cash across different industries, which requires us to control for industry effects in our multivariate analysis. However, most industries saw a significant increase in cash during the crisis period which suggests that the cash-hoarding behavior was widespread and not confined to a few industries.

Table 9. Descriptive Statistics (Total and by Crisis Period)

This table provides summary statistics for the variables used in this study. Panel A reports the entire sample of 300 firms. Panel B reports the data divided into pre-crisis and crisis periods. *LOCTotal* is the total amount of lines of credit, used and unused for firms with access to LOCs. *LOCUsedRatio* is $\frac{LOCUsed}{LOCTotal}$. *LineYes* is an indicator variable that takes the value of 1 if the firm-year observation has access to LOCs and 0 otherwise. *Cash* is the amount of cash (stock). *Capex* is the annual firm capital expenditures in plant, property, and equipment. *R&D* is the annual expenditure on research and development. *Employment* is the number of employees. *ROA* is $\frac{net\ income}{Assets}$. *CashFlow* is calculated as $\frac{EBITDA}{Assets-Cash}$. *Liquidity* is liquid assets divided by total assets. *MTB* is the cash-adjusted book to market ratio, $\frac{BookValueofEquity+MarketValueofEquity-Cash}{Non-CashTotalAssets}$. *NetWorth* is calculated as $\frac{Assets-Cash-Liabilities}{Assets-Cash}$. *AssetTangibility* is $\frac{TangibleAssets}{TotalAssets}$. N is the number of observations.

Panel A: Entire sample period

Variable	*N*	*Mean*	*Median*	*Std Dev*	*Minimum*	*Maximum*
LOCTotal	2348	285.824	50.100	753.034	0.100	14671.000
LOCUsedRatio	2348	0.262	0.115	0.311	0.000	1.000
LineYes	3451	0.680	1.000	0.466	0.000	1.000
Cash	3451	103.948	12.667	432.548	0.000	9782.000
Capex	3431	145.918	8.413	973.630	0.000	17633.000
R&D	2206	63.362	3.397	352.888	0.000	5273.000
Employment	3348	10.489	1.151	32.784	0.000	366.000
ROA	3448	-0.127	0.026	1.083	-44.500	1.798
CashFlow	3401	-0.113	0.111	1.503	-38.500	3.513
Liquidity	3361	0.540	0.558	0.247	0.027	1.000
MTB	3275	3.420	1.472	11.291	-89.615	276.328
NetWorth	3396	0.192	0.465	5.240	-255.125	0.998
AssetTangibility	3406	0.290	0.223	0.231	0.000	0.961

Panel B: Pre-crisis and crisis periods

	1996-2006			2007-2010			
Variable	*N*	*Mean*	*Median*	*N*	*Mean*	*Median*	*Delta Mean*
LOCTotal	1920	263.624	46.781	428	385.415	112.850	121.791***
LOCUsedRatio	1920	0.270	0.140	428	0.224	0.010	-0.046***
LineYes	2870	0.669	1.000	581	0.737	1.000	0.068***
Cash	2870	77.403	10.307	581	235.073	32.877	157.670***
Capex	2853	125.673	7.669	578	245.847	16.182	120.174*
R&D	1814	52.153	3.404	392	115.233	3.331	63.080**
Employment	2785	9.675	1.051	563	14.513	2.086	4.838***
ROA	2867	-0.120	0.026	581	-0.162	0.027	-0.042
CashFlow	2826	-0.102	0.112	575	-0.164	0.107	-0.062
Liquidity	2795	0.546	0.565	566	0.514	0.525	-0.03***
MTB	2720	3.439	1.530	555	3.327	1.294	-0.11
NetWorth	2826	0.338	0.474	570	-0.530	0.402	-0.868*
AssetTangibility	2830	0.291	0.224	576	0.286	0.211	-0.005

Table 10. LOC Access and Investment by Industry and Crisis Period

This table provides mean LOC access and investment information by industry and crisis time period. *LineYes* is an indicator variable that takes the value of 1 if the firm-year observation has access to LOCs and 0 otherwise. *Cash* is the amount of cash (stock). *Capex* is the annual firm capital expenditures in plant, property, and equipment. *R&D* is the annual expenditure on research and development. *Employment* is the number of employees. N is the number of observations.

	Pre-Crisis (1996 - 2006)						Crisis (2007 - 2010)					
Industry	*LineYes*	*Cash*	*Capex*	*R&D*	*Employment*	*N*	*LineYes*	*Cash*	*Capex*	*R&D*	*Employment*	*N*
Non-Durables	0.810	27.222	22.712	5.381	4.176	200	0.810	47.531	10.609	4.831	2.584	21
Durables	0.731	156.607	219.988	298.731	33.939	78	1.000	669.200	261.267	527.933	50.778	9
Manufacturing	0.834	32.294	44.627	28.452	6.794	452	0.853	137.539	59.838	36.751	7.331	102
Energy	0.970	23.448	60.838	.	0.640	67	1.000	75.137	184.964	.	0.716	11
Chemicals	0.756	39.691	24.551	62.106	1.636	41	0.636	38.128	20.101	55.652	1.486	11
Bus. Equip.	0.441	117.883	33.720	84.697	1.804	621	0.522	377.107	82.086	276.871	4.196	113
Telephone/TV	0.747	257.140	1918.496	41.958	34.626	83	1.000	1246.340	3955.716	2.806	46.343	18
Utilities	0.942	53.077	155.683	.	2.546	52	1.000	118.424	523.536	.	2.626	13
Shops	0.829	95.459	131.477	0.622	22.547	420	0.907	193.401	214.793	2.857	32.204	108
Health	0.480	51.927	78.438	42.358	11.109	383	0.519	168.962	122.988	100.745	15.219	79
Other	0.658	62.165	82.480	3.867	6.853	473	0.708	140.206	117.182	0.658	11.747	96

Table 11 sheds light on the differences between firms with and without credit lines. Data for the entire period, pre-crisis period, and crisis period are reported in Panels A, B and C, respectively. Evidence in Panel A suggests that firms with credit lines are more financially healthy than firms that do not have LOCs. Firms with access to credit lines have more investment in Capex (199.423 versus 31.160) and employment (13.998 versus 2.502) than firms that do not. However, firms with LOCs do not have more investment in R&D than firms without access to credit lines. It seems that LOCs do not enable firms to boost growth opportunities, i.e., engage in risk-seeking R&D investment. This observation is supported by the fact that firms with LOCs have MTB of 1.987, while firms without credit lines have a much higher MTB of 6.677. Firms with LOCs also have higher ROA, cash flow, net worth, and asset tangibility than firms without credit lines. Somewhat surprisingly, there is no significant difference between the levels of cash in firms with and without LOCs. Perhaps firms perceive that there are limits to the liquidity insurance that LOCs provide and therefore maintain robust levels of cash even when they have access to credit lines. These differences, as shown in Panels B and C, are generally consistent across both pre-crisis and crisis time periods. The difference between cash flow of firms with and without LOCs is 0.618 in the pre-crisis period and is even larger during the crisis at 1.088. Although firms with credit lines are more financially robust than firms without credit lines, the univariate results do not provide any indication that LOCs yield more protection against investment reductions during the crisis period than in the pre-crisis period.

Table 11. Descriptive Statistics Firms With and Without LOCs

This table provides summary statistics for the variables used in this study for firms with and without access to LOCs. Panel A reports the entire sample period 1996-2000. Panels B and C report pre-crisis and crisis time periods, respectively. *LOCTotal* is the total amount of lines of credit, used and unused. *LOCUsedRatio* is $\frac{LOCUsed}{LOCTotal}$. *LineYes* is an indicator variable that takes the value of 1 if the firm-year observation has access to LOCs and 0 otherwise. *Cash* is the amount of cash (stock). *Capex* is the annual firm capital expenditures in plant, property, and equipment. *R&D* is the annual expenditure on research and development. *Employment* is the number of employees. *ROA* is $\frac{net\ income}{Assets}$. *CashFlow* is calculated as $\frac{EBITDA}{Assets-Cash}$. *Liquidity* is liquid assets divided by total assets. *MTB* is the cash-adjusted book to market ratio, $\frac{BookValueofEquity+MarketValueofEquity-Cash}{Non-CashTotalAssets}$. *NetWorth* is calculated as $\frac{Assets-Cash-Liabilities}{Assets-Cash}$. *AssetTangibility* is $\frac{TangibleAssets}{TotalAssets}$. N is the number of observations.

Panel A: 1996-2010

	Without LOCs			*With LOCs*			
Variable	*N*	*Mean*	*Median*	*N*	*Mean*	*Median*	*Δ Mean*
LOCTotal	1103	0.000	0.000	2348	285.824	50.100	285.824***
LOCUsedRatio		.	.	2348	0.262	0.115	0.262***
LineYes	1103	0.000	0.000	2348	1.000	1.000	1.000***
Cash	1103	89.688	8.776	2348	110.647	15.063	20.959
Capex	1091	31.160	1.507	2340	199.423	14.142	168.263***
R&D	813	74.463	4.787	1393	56.884	2.429	-17.579
Employment	1022	2.502	0.210	2326	13.998	2.204	11.496***
ROA	1100	-0.384	-0.056	2348	-0.007	0.037	0.377***
CashFlow	1095	-0.577	0.009	2306	0.108	0.131	0.685***
Liquidity	1082	0.658	0.706	2279	0.485	0.495	-0.173***
MTB	1001	6.677	2.199	2274	1.987	1.354	-4.690***
NetWorth	1093	-0.239	0.533	2303	0.396	0.444	0.635**
AssetTangibility	1099	0.217	0.137	2307	0.325	0.273	0.108***

Panel B: Pre-Crisis (1996-2006)

	Without LOCs			*With LOCs*			
Variable	*N*	*Mean*	*Median*	*N*	*Mean*	*Median*	*Δ Mean*
LOCTotal	950	0.000	0.000	1920	263.624	46.781	263.624***
LOCUsedRatio	.	.	.	1920	0.270	0.140	0.270***
LineYes	950	0.000	0.000	1920	1.000	1.000	1.000***
Cash	950	78.582	7.945	1920	76.820	12.457	-1.762
Capex	940	30.276	1.572	1913	172.548	12.753	142.272***
R&D	690	67.775	4.701	1124	42.563	2.420	-25.212*
Employment	878	2.498	0.214	1907	12.980	2.000	10.482***
ROA	947	-0.345	-0.054	1920	-0.009	0.038	0.336***
CashFlow	943	-0.514	0.017	1883	0.104	0.131	0.618***
Liquidity	932	0.661	0.707	1863	0.488	0.498	-0.173***
MTB	854	6.447	2.253	1866	2.063	1.393	-4.384***
NetWorth	944	0.216	0.551	1882	0.399	0.450	0.183
AssetTangibility	947	0.221	0.142	1883	0.327	0.276	0.106***

Panel C: Crisis (2007-2010)

	Without LOCs			*With LOCs*			
Variable	*N*	*Mean*	*Median*	*N*	*Mean*	*Median*	*Δ Mean*
LOCTotal	134	0.000	0.000	428.000	385.415	112.850	0.000
LOCUsedRatio	0	.	.	428.000	0.224	0.010	0.000
LineYes	153	0.000	0.000	428.000	1.000	1.000	0.000
Cash	153	158.651	17.915	428.000	262.393	39.492	103.742*
Capex	151	36.659	0.797	427.000	319.823	25.202	283.164***
R&D	123	111.978	5.078	269.000	116.722	2.486	4.744
Employment	144	2.524	0.174	419.000	18.633	3.100	16.109***
ROA	153	-0.624	-0.070	428.000	0.003	0.035	0.627***
CashFlow	152	-0.964	-0.077	423.000	0.124	0.126	1.088***
Liquidity	150	0.639	0.702	416.000	0.470	0.477	-0.169***
MTB	147	8.012	1.891	408.000	1.639	1.242	-6.373***
NetWorth	149	-3.121	0.395	421.000	0.386	0.405	3.500*
AssetTangibility	152	0.196	0.095	424.000	0.319	0.251	0.123***

In addition to LOC access, we also examine LOC usage during the financial crisis. Figure 1 shows that among firms that have access to LOCs, the amount of total lines of credit increased almost consistently throughout our study period. The finding of increased LOC liquidity is similar to previous literature that documents that firms have been holding more cash (Bates, Kahle and Stulz (2009), Duchin (2010)). However, Figure 2 demonstrates that LOC usage has been decreasing. The mean annual LOCUsedRatio (calculated as LOCUsed/LOCTotal) has a downward trend over the 1996-2010 study period. Notable exceptions to the decreasing trend are increases during the 2000 dot com market crash and 2008 credit crisis, which likely reflect the cash hoarding behavior previously documented (Ivashina and Scharfstein (2010)). The average amount of LOCs has increased, but the usage has decreased during the crisis, which may be another indication that firms are unable to utilize their credit lines during the crisis. It would be reasonable to expect that firms would increase drawdowns in an effort to overcome the adverse credit conditions. Hence, this reduction in drawdowns may be evidence of increased bank monitoring as suggested by Jimenez, Lopez and Saurina (2009) and Acharya, Almeida, Ippolito and Perez (2012).

METHODOLOGY

As discussed earlier, theory predicts that credit lines should allow firms to minimize disruption to investment in the event of a tightening of the credit markets (Campbell (1978), Hawkins (1982), Shockley and Thakor (1997), Holmstrom and Tirole (1998), DeMarzo and Fishman (2007)). However, empirical evidence suggests that bank

Figure 1. Total LOC by Year

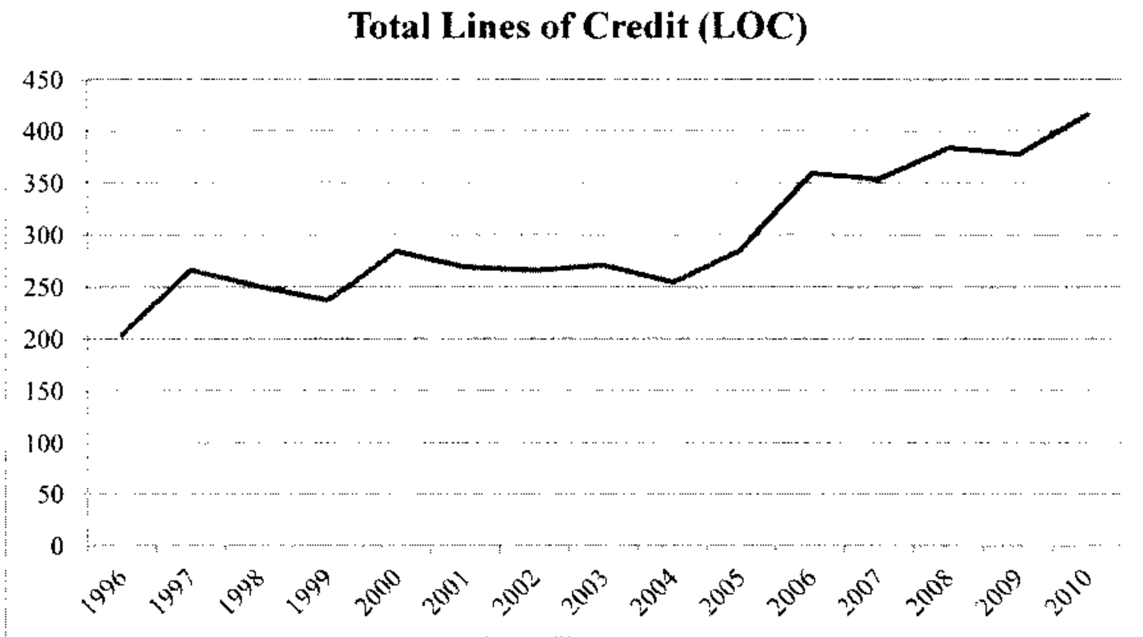
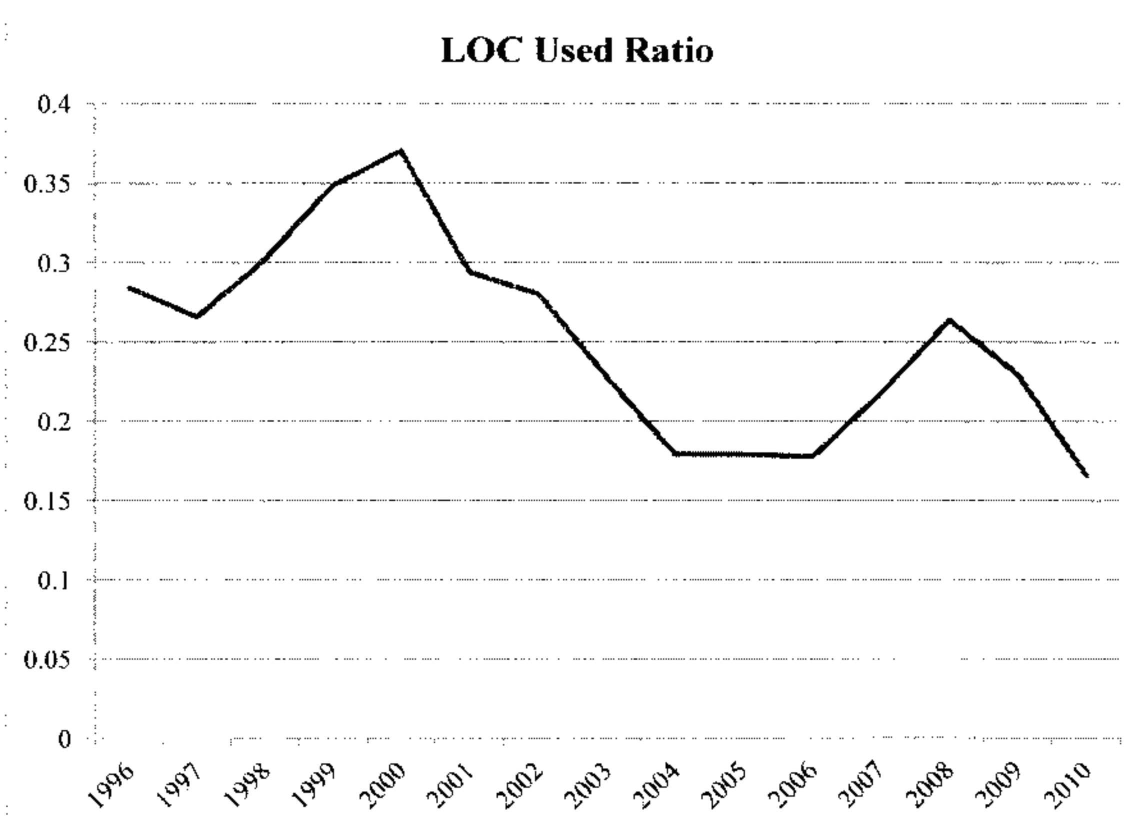


Figure 2. LOCUsedRatio (LOCUsed/LOCTotal) by Year



monitoring may make LOCs more difficult to activate during a credit crisis (Lins, Servaes and Tufano (2010), Jimenez, Lopez and Saurina (2009) and Acharya, Almeida, Ippolito and Perez (2012)). We investigate both LOC access and LOC drawdowns during the global financial crisis in an effort to resolve the differences between the theoretical and empirical predictions concerning the role of credit lines during the 2008 financial crisis. To determine whether LOCs allow firms to mitigate the impact of limited credit availability on investment, our investigation involves two stages. We first examine the effect of access to LOCs on firm investment. Then we examine how credit lines are used during the financial crisis period.

Access to LOCs

We now proceed with the first objective of understanding how access to credit lines impacts firm investment. Our main study variable for this investigation is an indicator variable, *LineYes*, that takes the value 1 if a firm has credit lines and 0 otherwise. To gain a better comprehension of the characteristics that influence access to LOCs, we first perform a logistic regression, specified in Equation (8).

$$LineYes_{t+1} = \beta_0 + \beta_1 CreditCrunch_t + \beta_2 CashFlow_t + \beta_3 AssetTangibility_t + \beta_4 NonCash\ Assets_t + \beta_5 NetWorth_t + \beta_6 MTB_t + \beta_7 CFVol_t + \beta_8 Not\ in\ S\&P\ Index_t + \beta_9 OTC_t + \beta\ \ LAge_t + \sum industry + \eta_t \quad (8)$$

CreditCrunch is an indicator variable that takes the value of 1 if the observation is in years 2007 through 2010 and 0 otherwise. This variable allows us to determine if firms are more or less likely to have access to LOCs during the financial crisis. Since severe limitations of credit availability happen infrequently, the recent financial crisis is an ideal opportunity to find answers to this empirical question. Our variables follow the definitions in previous literature, particularly Sufi (2009)'s seminal paper and are included because they have been previously shown to impact credit line usage. *CashFlow* is measured by EBITDA scaled by assets minus cash. *AssetTangibility* is tangible assets scaled by total assets. *NonCashAssets* is the natural logarithm of assets minus cash. We expect *CashFlow*, *AssetTangibility*, and *NonCashAssets* to positively influence LOC access because these variables indicate positive financial health. Firms with higher cash flow, asset tangibility, and assets are more likely to be approved for bank lines of credit. Similarly, net worth, market to book ratio, cash flow volatility, and age are included as measures that may influence a firm's financing costs. *NetWorth* is calculated as $\frac{Assets - Cash - Liabilities}{Assets - Cash}$. Cash-adjusted market to book ratio, *MTB*, is calculated as $\frac{Book\ Value\ of\ Equity + Market\ Value\ of\ Equity - Cash}{Non\text{-}Cash\ Total\ Assets}$. Cashflow volatility, *CFVol*, is represented by the standard deviation of the four previous annual changes in cash flow divided by assets minus cash. *LAge* is the natural logarithm of the number of years since the firm's IPO. We also include several indicator variables to control for equity market characteristics. *Not in S&P Index* takes the value of 1 if the firm is not included in the S&P 500, S&P 400, or S&P 600, and 0 otherwise. *OTC* takes the value of 1 if the firm is traded over the counter and 0 otherwise. We also include industry dummies for the Fama French 12-industry categories from Kenneth French's website.

Next, we examine our main question: whether or not LOCs allow a firm to continue investment during a financial crisis. We conduct this phase of the study using

OLS regressions, with heteroskedasticity-consistent standard errors. The regression specification follows in Equation (9) with the main variable of interest being the interaction of the *CreditCrunch* and the *LineYes* indicator variables. To the extent that LOCs assist firms to mitigate the impact of limited credit availability on investment, we expect a positive coefficient, demonstrating that firms with access to credit lines are more likely to invest during a financial crisis.

$$Investment_{t+1} = \gamma_0 + \gamma_1 Size_t + \gamma_2 Cash_t + \gamma_3 LineYes_t + \gamma_4 Cash * LineYes_t + \gamma_5 CreditCrunch_t + \gamma_6 CreditCrunch * LineYes_t + \gamma_7 Hedge_t + \sum industry + \eta_t \quad (9)$$

We are interested in a firm's ability to invest in three types of corporate investment: capital expenditures, research and development (R&D), and employment. Accordingly, the *Investment* variable of Equation (9) takes the value of capital expenditures. R&D, and employment in separate models. This regression specification controls for firm size and cash. *Size* is the natural logarithm of the firm's total assets. *Cash* is the annual amount of cash. The main variable of interest in this regression is the interaction of the *CreditCrunch* and the *LineYes* indicator variables. We expect a positive coefficient, demonstrating that firms with access to credit lines are more able to invest during a financial crisis. We also include the *Hedge* indicator variable that takes the value of 1 if the firm hedges its credit lines and 0 otherwise, as Berrospide, Meisenzahl and Sullivan (2012) find that hedging influences LOC usage.

Similarly, we examine annual changes by substituting changes in investment for the dependent variable. Since investment levels may be fairly consistent over time, changes in investment may allow us to more accurately assess changes in investment policy. Once again, we expect that the interaction of *CreditCrunch* and *LineYes* will be positively related to changes in investment in these models.

LOC drawdowns

We now move on to the next objective of our study that examines LOC drawdowns, rather than access. Our hand-collected data allows us the unique opportunity to discern LOC usage during a financial crisis. As with the access investigation, we begin with a logistic regression analysis to examine the determinants of LOC usage. Since our focus is on LOC usage, we only include firms that have access to credit lines in this section of the study. The logistic regression is specified in Equation (10).

$$\begin{aligned} HiLOC_{t+1} = \; & \beta_0 + \beta_1 CreditCrunch_t + \beta_2 CashFlow_t + \beta_3 AssetTangibility_t \\ & + \beta_4 NonCash\ Assets_t + \beta_5 NetWorth_t + \beta_6 MTB_t + \beta_7 CFVol_t \\ & + \beta_8 Not\ in\ S\&P\ Index_t + \beta_9 OTC_t + \beta_{10} LAge_t + \beta_{11} Hedge_t \\ & + \beta_{12} BondRate_t + \beta_{13} CommPaper_t + \sum industry + \eta_t \end{aligned} \tag{10}$$

HiLOC is an indicator variable that takes the value of 1 if the firm has a LOCUsedRatio (LOCUsed/LOC Total) greater than the median and 0 otherwise. Previous literature suggests that firms exercised LOCs more extensively during the financial crisis (Ivashina and Scharfstein (2010)). Accordingly, a positive relationship between *CreditCrunch* and

HiLOC may be expected. However, the empirical literature also finds that covenants may prohibit firms from using their credit lines in hard financial times, which would indicate a negative relationship between *CreditCrunch* and *HiLOC* (Sufi (2009)). Since the literature provides indications of both a positive and negative coefficient on *CreditCrunch,* the prediction of the coefficient is an empirical matter that will be resolved by the analysis. We also regress the *HiLOC* dummy on other variables previously shown to have an impact on liquidity decisions. *Hedge* is an indicator variable that takes the value of 1 if the firm hedges its LOC (either voluntarily or by mandate), and 0 otherwise. *BondRate* and *CommPaper* are indicator variables that take the value of 1 if the firm has a bond rating or access to commercial paper, respectively. Since previous literature indicates that high LOC users may be financially constrained, we expect a negative coefficient on *CashFlow, NetWorth, MTB, BondRate, and CommPaper.*

We then examine the effect of LOC usage, rather than access to LOCs, on corporate investment during the financial crisis. In contrast to the specification in Equation (9), where we examine the effect of having credit lines on investment, the following models allow us to determine whether or not the liquidity insurance benefits of LOCs are dependent on the degree of LOC usage. Again, we investigate three measures of investment: capital expenditures, research and development, and employment in the specification listed in Equation (11).

$$Investment_{t+1} = \gamma_0 + \gamma_1 Size_t + \gamma_2 Cash_t + \gamma_3 HiLOC_t + \gamma_4 Cash * HiLOC_t + \gamma_5 CreditCrunch_t + \gamma_6 CreditCrunch * HiLOC_t + \gamma_7 Hedge_t + \sum industry + \eta_t \quad (11)$$

Since bank financing is limited during the credit crisis, we expect less investment during the crisis than in more healthy economic environments. Consequently, we anticipate a negative coefficient on both *CreditCrunch* and *HiLOC* indicator variables. We also expect that the more financially constrained high LOC users will have a small amount of additional credit line liquidity to utilize. Since they have exhausted a significant portion of their LOCs, the remaining LOC credit will have little, if any impact on investment.

RESULTS

We now report the results on the effectiveness of LOCs to mitigate the impact of limited credit availability on investment during the financial crisis. Recall that theory predicts that LOCs act as liquidity insurance, enabling firms to invest when external liquidity may be difficult to acquire. The financial crisis provides an ideal exogenous event to examine this prediction. We first ascertain which firm characteristics contribute to a firm's ability to obtain LOCs. We then examine the relation between corporate investment and LOCs to see if lines of credit are able to fulfill their liquidity insurance function during this financial crisis.

Determinants of access to LOCs

We begin our multivariate analysis by investigating the factors that allow a firm to have LOCs. That is, what characteristics contribute to the likelihood of a firm having access to credit lines. To accomplish this aim, we utilize logistic regression where the indicator variable, *LineYes*, is regressed on credit environment, firm characteristics, and firm financial health. These results are presented in Table 12. Our main result is that the coefficient of *CreditCrunch* is not significant. This means that firms are equally likely to have LOCs before and during the financial crisis. The finding that the crisis did not influence firms' access to LOCs is somewhat surprising. We would expect that firms would seek access to additional credit lines during a period of credit market instability, resulting in a positive relationship between *CreditCrunch* and *LineYes*. Our results suggest that banks may have been reluctant to supply additional LOCs during the crisis. Likewise, the absence of a negative relationship between *CreditCrunch* and *LineYes* is consistent with Berrospide, Meisenzahl and Sullivan (2012)'s finding that LOCs were rarely canceled during the crisis. On the supply side of LOCs, this result suggests that financial institutions do not reduce the availability of LOCs during economic downturns, a finding consistent with Ivashina and Scharfstein (2010). Since the credit environment does not significantly influence whether or not firms have LOCs, it is possible that LOCs may be able to provide a source of liquidity during credit-constrained periods of time, as the theoretical literature predicts. However, this is preliminary evidence. We need to examine the firms' investments to fully test the hypothesis that the liquidity insurance

Table 12. Determinants of Having Credit Line (1996-2010)

This table reports results of logistic regression of *LineYes* on independent variables. *LineYes* is an indicator variable that takes the value of 1 if the firm-year observation has access to LOCs and 0 otherwise. *CreditCrunch* is an indicator variable that takes the value of 1 if the observation is in years 2007-2010 and 0 otherwise. *CashFlow* is calculated as $\frac{EBITDA}{Assets-Cash}$. *AssetTangibility* is $\frac{TangibleAssets}{TotalAssets}$. *NonCashAssets* is calculated as Ln(Assets – Cash). *NetWorth* is calculated as $\frac{Assets-Cash-Liabilities}{Assets-Cash}$. *MTB* is the cash-adjusted book to market ratio, $\frac{BookValueofEquity+MarketValueofEquity-Cash}{Non-CashTotalAssets}$. *CFVol*, cashflow volatility, is the standard deviation of the previous four annual changes in cash flow scaled by (Total Assets-Cash). *LAge* is the natural logarithm of the number of years since IPO. *Not in S&P Index* takes the value of 1 if the firm is not included in the S&P 500, S&P 400, or S&P 600, and 0 otherwise. *OTC* takes the value of 1 if the firm is traded over the counter and 0 otherwise Industry dummies are calculated using the Fama French 12 industry SIC codes.

	Logistic Regression: Probability LineYes=1		
Parameter	*Estimate*	*Wald Chi-Square*	*Pr > ChiSq*
Intercept	-0.6752	4.9671	0.0258
CreditCrunch	-0.1881	2.1147	0.1459
CashFlow	0.7295	19.1987	<.0001
AssetTangibility	0.4315	3.0495	0.0808
NonCashAssets	0.2664	67.0854	<.0001
NetWorth	-0.1634	23.2740	<.0001
MTB	-0.0530	11.2942	0.0008
CFVol	-0.3029	2.2516	0.1335
Not In S&P Index	0.0958	0.4854	0.4860
OTC	-0.1686	1.4089	0.2352
LAge	0.1659	10.4201	0.0012
Industry Dummies		yes	
Observations		3101	
Likelihood Ratio		893.5210	<.0001
Score		775.3498	<.0001
Wald		530.1712	<.0001

property of LOCs enables firms to mitigate the impact of limited credit availability on investment.

Not surprisingly, we also find that firms with a higher level of financial health are more likely to have LOCs. *CashFlow*, *AssetTangibility*, *NonCashAssets*, and *LAge* are all positively related to *LineYes*. We also find that firms with a higher net worth and MTB are less likely to have LOCs. This may stem from the fact that these firms are more marketable and may have access to other types financing, such as issuing equity and term loans. The coefficients of *CFVol, Not In S&P Index, and OTC* are insignificant, suggesting that stock market factors may be unrelated to LOC access. But our main takeaway from Table 12 is that firms have access to LOCs in both the pre-crisis and crisis periods.

Investment and access to LOCs

Having examined the determinant characteristics of firms possessing access to LOCs, we now move on to assess the impact of LOC access on corporate investment during a crisis. Table 13 reports these results. The evidence shows that firms with LOCs invest less in Capex than firms that do not. The negative coefficient of the *LineYes* indicator variable for both Capex and Employment models suggests that LOCs do not assist firms in funding their corporate investment. On the contrary, firms with LOCs tend to invest less or direct LOCs into other corporate needs rather than retain or enhance their growth options. Since there is no statistically significant relationship between *LineYes* and R&D investment, it seems that these firms may have exhausted their growth options. However, the *Cash* and the *Cash*LineYes* variables enter the regressions with positive and significant coefficients suggesting that firms rely on internally generated cash flows to finance their investments and that LOCs for these firms (i.e., cash-rich firms with LOCs) exert a positive influence on investment, especially on Capex and Employment. This finding is consistent with both Sufi (2009) and Campello, Giambona, Graham and Harvey (2011). Interestingly, the LOC variables have an insignificant association with R&D spending indicating that growth seeking investments are not dependent on access to credit lines. On the contrary, the positive and significant influence *Cash* is exerting on R&D suggests that this type of investment is funded by internally-generated cash flows.

The negative *CreditCrunch* coefficient indicates that the financial crisis, as expected, had a contractionary influence on corporate investment. The coefficient of the interaction term, *CreditCrunch*LineYes*, is also negative (although significant only at the 10% level). This result suggests that firms with LOCs not only failed to reverse the decreasing investment trend during the crisis period, but may have experienced an even greater investment deterioration than firms without LOCs, especially Capex. This finding is consistent with the suggestion of Lins, Servaes and Tufano (2010) that LOCs may be difficult to deploy during economic upheavals. Hence, the theoretical prediction that lines of credit provide liquidity insurance that helps firms maintain value-enhancing corporate investment when other forms of liquidity are limited (Campbell (1978), Hawkins (1982), Shockley and Thakor (1997), Holmstrom and Tirole (1998), DeMarzo and Fishman (2007)) fails to gain support in the data. Our results thus far seem to be more in line with the recent empirical literature, which casts doubts on the effectiveness of LOCs as liquidity insurance. Having examined the impact of LOC access on the level of corporate

Table 13. Influence of LOC Access on Corporate Investment (1996-2010)

This table provides OLS regression results based on the Campello, Giambona, Graham, and Harvey (2011) specification. Dependent variables are Capex, R&D, and Employment in separate models. *Capex* is the annual firm capital expenditures in plant, property, and equipment. *R&D* is the annual expenditure on Research and Development. *Empl* is the number of employees. *Size* is the natural logarithm of the firm's total assets. *Cash* is the annual amount of cash (stock). *LineYes* is an indicator variable that takes the value of 1 if the firm-year observation has access to LOCs and 0 otherwise. *CreditCrunch* is an indicator variable that takes the value of 1 if the observation is in years 2007-2010 and 0 otherwise. *Hedge* takes the value of 1 if the firm reported hedging its LOCs and 0 otherwise. Industry dummies are calculated using the Fama French 12 industry SIC codes. T-statistics are calculated with heteroskedasticity-consistent errors. ***, **, * are statistically significant at the 1%, 5%, and 10% level, respectively.

	Dependent Variable					
Parameter	$Capex_{t+1}$		$R\&D_{t+1}$		$Empl_{t+1}$	
Intercept	-285.10***	-295.93***	-27.44*	-32.67**	-20.58***	-20.79***
	(-5.13)	(-5.26)	(-1.88)	(-2.01)	(-10.90)	(-10.97)
Size	74.00***	74.24***	6.54	6.68	5.69***	5.70***
	(5.95)	(5.96)	(1.12)	(1.14)	(13.56)	(13.57)
Cash	0.06*	0.06*	0.65***	0.65***	0.00	0.00
	(1.82)	(1.74)	(3.65)	(3.65)	(0.19)	(0.14)
LineYes	-78.73***	-65.00***	-28.20	-21.45	-1.93**	-1.66*
	(-4.37)	(-3.36)	(-1.34)	(-1.10)	(-2.23)	(-1.80)
*Cash*LineYes*	1.13***	1.14***	0.13	0.13	0.03***	0.03***
	(4.83)	(4.86)	(0.68)	(0.71)	(4.45)	(4.47)
CreditCrunch	-91.81	21.61	-38.35**	6.78	-3.59**	-1.40
	(-1.63)	(1.01)	(-2.17)	(0.17)	(-2.04)	(-0.90)
*CreditCrunch*LineYes*		-150.63*		-64.87		-2.91
		(-1.92)		(-1.45)		(-1.06)
Hedge	-313.76***	-310.14***	-38.86*	-36.18	-3.80	-3.74
	(-2.63)	(-2.59)	(-1.73)	(-1.64)	(-0.83)	(-0.82)
Industry Dummies	yes	yes	yes	yes	yes	yes
Observations	3131	3131	2022	2022	3093	3093
Adj R-Squared	0.3549	0.3551	0.6875	0.6881	0.3545	0.3544

investment, we now turn our attention to the influence access to credit lines has on changes in investment.

Investment changes and access to LOCs

In this section we report new regression results with specifications that are similar to the previous analysis. However in these regressions, the dependent variables are *changes* in Capex, R&D, and employment investment. Table 14 reports these results. Since firms may maintain the same level of investment year after year, this specification allows to us to see how LOC access affects changes in investment policy. As in the previous analysis in Table 12, we find a negative coefficient on *LineYes* in the Capex model. This result suggests that firms with access to LOCs reduced spending in capital expenditures. When the *CreditCrunch*LineYes* variable enters the model with a negative coefficient, *LineYes* becomes insignificant, indicating that the reduction in Capex investment occurs during the crisis period. Likewise, the *CreditCrunch*LineYes* variable is negative and significant for the Employment model, which suggests that LOCs do not allow firms to maintain their workforces during a poor economic climate. Hence, we find further evidence that LOCs are not able to be successfully deployed for investment during the financial crisis. On the contrary, firms with LOCs reduced both Capex and Employment investment. The coefficient on the *Hedge* indicator variable is insignificant for Capex and Employment, but negative in the R&D model which again suggests that LOC hedging does not assist firms in increasing investment. Jointly the evidence in Tables 13 and 14 suggest that simply having access to LOCs does not provide insurance

Table 14. Influence of LOC Access on Changes in Investment (1996-2010)

This table provides OLS regression results based on the Campello, Giambona, Graham, and Harvey (2011) specification. Dependent variables are annual changes in Capex, R&D, and Employment in separate models. *Capex* is the annual firm capital expenditures in plant, property, and equipment. *R&D* is the annual expenditure on Research and Development. *Empl* is the number of employees. *Size* is the natural logarithm of the firm's total assets. *Cash* is the annual amount of cash (stock). *LineYes* is an indicator variable that takes the value of 1 if the firm-year observation has access to LOCs and 0 otherwise. *CreditCrunch* is an indicator variable that takes the value of 1 if the observation is in years 2007-2010 and 0 otherwise. *Hedge* takes the value of 1 if the firm reported hedging its LOCs and 0 otherwise. Industry dummies are calculated using the Fama French 12 industry SIC codes. T-statistics are calculated with heteroskedasticity-consistent errors. ***, **, * are statistically significant at the 1%, 5%, and 10% level, respectively.

	Dependent Variable					
Parameter	$\Delta Capex_{t+1}$		$\Delta R\&D_{t+1}$		$\Delta Empl_{t+1}$	
Intercept	-19.86	-24.12	-15.00**	-14.46**	0.10	0.05
	(-1.34)	(-1.54)	(-2.33)	(-2.21)	(0.32)	(0.14)
Size	6.48*	6.58*	4.12**	4.11**	0.05	0.05
	(1.88)	(1.90)	(2.27)	(2.25)	(0.73)	(0.75)
Cash	-0.10*	-0.10*	0.03	0.03	0.00	0.00
	(-1.65)	(-1.70)	(0.71)	(0.71)	(1.12)	(1.09)
LineYes	-10.77*	-5.39	-3.27	-3.96	0.01	0.08
	(-1.79)	(-0.99)	(-0.65)	(-0.84)	(0.08)	(0.74)
*Cash*LineYes*	0.11	0.11*	-0.04	-0.04	-0.00	-0.00
	(1.64)	(1.71)	(-0.65)	(-0.65)	(-0.53)	(-0.48)
CreditCrunch	-33.87***	10.44	-5.82	-10.34	-0.66***	-0.11
	(-3.01)	(1.15)	(-0.88)	(-1.14)	(-3.00)	(-1.08)
*CreditCrunch*LineYes*		-58.84***		6.50		-0.73**
		(-3.06)		(0.51)		(-2.32)
Hedge	-14.54	-13.08	-5.90*	-6.17**	1.01	1.03
	(-0.45)	(-0.41)	(-1.86)	(-1.98)	(1.07)	(1.08)
Industry Dummies	yes	yes	yes	yes	yes	yes
Observations	3122	3122	1995	1995	3036	3036
Adj R-Squared	0.0238	0.0248	0.0335	0.0332	0.0070	0.0072

against decreases in investment during both normal credit market conditions and the recent financial crisis, an extremely tight credit market environment[15]. This surprising result is in contrast to the theoretical predictions suggesting LOCs provide liquidity insurance to help firms smooth investment when credit is scarce or costly (Campbell (1978), Hawkins (1982), Shockley and Thakor (1997), Holmstrom and Tirole (1998), DeMarzo and Fishman (2007)). We investigate this matter further by looking at LOC usage rather than simple access in the following sections.

Investment and LOC usage

We next draw our attention to the effect that LOC usage has on corporate investment. The literature largely focuses on the advantages and consequences of having access to credit lines. LOC usage, or drawdowns, has been all but ignored. The theoretical literature implies that LOCs allow firms to protect themselves from investment declines. LOCs provide access to additional liquidity that helps firms to smooth cash flows and maintain investment. However, we expect that firms that draw down their credit lines extensively (high LOC users) will have limited unused credit to boost investment. Therefore, it is likely that LOCs will possess effective liquidity insurance properties only for firms which do not extensively draw down their credit lines (low LOC users).

Before we look at the effect of LOCs on investment, we first examine the characteristics that influence LOC usage in an effort to understand what drives some firms to use LOCs more extensively than others. Firms that have access to credit lines

[15] Results consistent with Tables 13 and 14 were obtained when Operating Expenses (Selling, General, and Administrative and Cost of Goods Sold) were substituted for the dependent variable. Results are available upon request.

may choose to employ them in either an aggressive or conservative manner. Firms that maintain aggressive liquidity policies are more likely to use a high percentage of available credit lines. As a result these high LOC users may be unable to employ LOCs to invest when credit markets tighten. On the other hand, firms that adopt more conservative liquidity policies, reserving unused LOCs for future investment, may be better situated to continue value-enhancing investment during a financial crisis. To examine how LOC usage is linked to corporate investment, we use an indicator variable, *HiLOC*, which takes the value of 1 when a firm uses a higher than median percentage of its LOCs and 0 otherwise.

Table 15 reports the determinants of LOC usage, using logistic regression of *HiLOC* on firm characteristics. The evidence shows that firms are less likely to use a high amount of their LOCs during the crisis than before the crisis. This may be due to bank monitoring as suggested by Jimenez, Lopez and Saurina (2009) and Acharya, Almeida, Ippolito and Perez (2012). We also find that high LOC users have lower cash flow, net worth and market to book. They also have less access to equity markets, as seen by the positive coefficients on the *Not in S&P Index* and *OTC* indicator variables. High LOC users are less likely to have a bond rating or access to commercial paper. Consistent with previous literature, the results in Table 15 suggest that high LOC users may be financially constrained. We also find a positive coefficient on the *Hedge* dummy, indicating that firms that hedge their credit lines tend to use the LOCs more. This finding is consistent with Disatnik, Duchin and Schmidt (2009) and Berrospide, Meisenzahl and Sullivan (2012). In sum, we find evidence that high LOC users are financially constrained with

Table 15. Determinants of High LOC Usage (1996-2010)

This table reports results of logistic regression of *HiLOC* on independent variables. *HiLOC* takes the value of 1 if the firm has a LOCUsedRatio higher than the median and 0 otherwise. *CreditCrunch* is an indicator variable that takes the value of 1 if the observation is in years 2007-2010 and 0 otherwise. *CashFlow* is calculated as $\frac{EBITDA}{Assets-Cash}$. *AssetTangibility* is $\frac{TangibleAssets}{TotalAssets}$. *NonCashAssets* is calculated as Ln(Assets – Cash). *NetWorth* is calculated as $\frac{Assets-Cash-Liabilities}{Assets-Cash}$. *MTB* is the cash-adjusted book to market ratio, $\frac{BookValueofEquity+MarketValueofEquity-Cash}{Non-CashTotalAssets}$. *CFVol*, cashflow volatility, is the standard deviation of the previous four annual changes in cash flow scaled by (Total Assets-Cash). *LAge* is the natural logarithm of the number of years since IPO. *Hedge* takes the value of 1 if the firm reported hedging its LOCs and 0 otherwise. *Not in S&P Index* takes the value of 1 if the firm is not included in the S&P 500, S&P 400, or S&P 600, and 0 otherwise. *OTC* takes the value of 1 if the firm is traded over the counter and 0 otherwise. Indicator variables indicating if the firm has a bond rating and access commercial paper are also included.

Logistic Regression: Probability HiLOC=1			
Parameter	*Estimate*	*Wald Chi-Square*	*Pr > ChiSq*
Intercept	0.9849	7.7035	0.0055
CreditCrunch	-0.2215	3.3147	0.0687
CashFlow	-1.0208	13.9921	0.0002
AssetTangibility	0.5796	5.8647	0.0154
NonCashAssets	0.0002	0.0000	0.9960
NetWorth	-0.3070	9.2398	0.0024
MTB	-0.1185	15.6167	<.0001
CFVol	-3.8394	25.3792	<.0001
Not In S&P Index	0.3401	7.4435	0.0064
OTC	0.3885	5.9369	0.0148
LAge	-0.1838	14.3757	0.0001
Hedge	0.8335	8.5580	0.0034
BondRate	-0.2712	3.5990	0.0578
CommPaper	-0.9583	19.1048	<.0001
Industry Dummies		yes	
Observations		2189	
Likelihood Ratio		279.9746	<.0001
Score		240.4340	<.0001
Wald		217.9914	<.0001

limited access to external funding. As such, these high LOC users may actually be impacted less by the financial crisis than low LOC users, since they likely had less involvement in credit markets.

Next, we regress three measure of investment (Capex, R&D, and Employment) on LOC and control variables to determine if LOC usage has an effect on a firm's ability to successfully utilize the liquidity insurance qualities of credit lines. Table 16 reports the results. We expect that if LOCs do provide liquidity insurance during the crisis, then the effect would only reveal itself with low LOC users. The negative and highly significant coefficients on *HiLOC* indicate high LOC users invest less in Capex and employment than low LOC users. However, the coefficient on *CreditCrunch*HiLOC* is not significantly different from zero for Capex, R&D and employment models. Hence, the financially constrained High LOC users invest less than low LOC users, regardless of the credit environment. It seems that LOCs do not allow high users to invest more before or during the crisis. We also find that the coefficients of *LOCTotal* and *Cash*LOC Total* are positive and significant at the 1% level for Capex. This result shows that LOCs in association with cash do help firms invest. It also provides support for the Campello, Giambona, Graham and Harvey (2011) assertion that the combination of credit lines and cash help increase investment. In all, our results show that credit lines may help low LOC users invest, but they do not provide any special assistance or protection during the crisis.

Table 16. Influence of High LOC Usage on Corporate Investment (1996-2010)

This table provides OLS regression results based on the Campello, Giambona, Graham, and Harvey (2011) specification. Dependent variables are Capex, R&D, and Employment in separate models. *Capex* is the annual firm capital expenditures in plant, property, and equipment. *R&D* is the annual expenditure on Research and Development. *Empl* is the number of employees. *Size* is the natural logarithm of the firm's total assets. *Cash* is the annual amount of cash (stock). *CreditCrunch* is an indicator variable that takes the value of 1 if the observation is in years 2007-2010 and 0 otherwise. LOCTotal is the total amount of lines of credit, used and unused. *HiLOC* takes the value of 1 if the firm has a LOCUsedRatio higher than the median and 0 otherwise. *Hedge* takes the value of 1 if the firm reported hedging its LOCs and 0 otherwise. Industry dummies are calculated using the Fama French 12 industry SIC codes. T-statistics are calculated with heteroskedasticity-consistent errors. ***, **, * are statistically significant at the 1%, 5%, and 10% level, respectively.

	Dependent Variable								
Parameter	$Capex_{t+1}$			$R\&D_{t+1}$			$Empl_{t+1}$		
Intercept	219.53***	218.89***	206.02***	-3.23	-4.49	-4.83	-6.29**	-6.30**	-6.44**
	(3.40)	(3.39)	(3.24)	(-0.13)	(-0.18)	(-0.20)	(-2.39)	(-2.39)	(-2.44)
Size	-18.38	-18.35	-15.32	-4.54	-4.54	-4.32	2.37***	2.37***	2.41***
	(-1.22)	(-1.22)	(-1.02)	(-0.75)	(-0.75)	(-0.71)	(4.08)	(4.09)	(4.15)
Cash	-0.35	-0.35	-0.36	0.64***	0.64***	0.63***	0.02***	0.02***	0.02***
	(-1.49)	(-1.49)	(-1.53)	(3.77)	(3.77)	(3.76)	(2.73)	(2.74)	(2.72)
LOCTotal	0.84***	0.84***	0.84***	0.03	0.03	0.03	0.03***	0.03***	0.03***
	(6.39)	(6.39)	(6.40)	(1.43)	(1.45)	(1.47)	(7.53)	(7.51)	(7.50)
*Cash*LOCTotal*	0.00***	0.00***	0.00***	0.00	0.00	0.00	0.00*	-0.00*	-0.00*
	(3.65)	(3.65)	(3.66)	(1.38)	(1.38)	(1.38)	(-1.87)	(-1.87)	(-1.87)
CreditCrunch	-62.17	-58.53	-52.08	-54.26***	-46.10*	-45.00	-3.25*	-3.15	-3.07
	(-1.21)	(-0.68)	(-0.60)	(-2.71)	(-1.67)	(-1.62)	(-1.71)	(-1.00)	(-0.98)
HiLOC	-194.50***	-193.43***	-186.96***	1.79	4.34	4.76	-4.92***	-4.89***	-4.81***
	(-5.97)	(-5.55)	(-5.49)	(0.20)	(0.50)	(0.55)	(-5.32)	(-4.78)	(-4.70)
*CreditCrunch*HiLOC*		-8.02	-8.44		-18.51	-18.97		-0.24	-0.25
		(-0.08)	(-0.08)		(-0.49)	(-0.50)		(-0.06)	(-0.07)
Hedge			-307.25***			-28.33			-3.41
			(-3.22)			(-1.12)			(-1.37)
Industry Dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	2150	2150	2150	1287	1287	1287	2134	2134	2134
Adj R-Squared	0.6887	0.6886	0.6902	0.6791	0.6789	0.6789	0.5755	0.5753	0.5753

Table 17. Influence of High LOC Usage on Changes in Corporate Investment (1996-2010)

This table provides OLS regression results based on the Campello, Giambona, Graham, and Harvey (2011) specification. Dependent variables are annual changes in Capex, R&D, and Employment in separate models. *Capex* is the annual firm capital expenditures in plant, property, and equipment. *R&D* is the annual expenditure on Research and Development. *Empl* is the number of employees. *Size* is the natural logarithm of the firm's total assets. *Cash* is the annual amount of cash (stock). *CreditCrunch* is an indicator variable that takes the value of 1 if the observation is in years 2007-2010 and 0 otherwise. LOCTotal is the total amount of lines of credit, used and unused. *HiLOC* takes the value of 1 if the firm has a LOCusedRatio higher than the median and 0 otherwise. *Hedge* takes the value of 1 if the firm reported hedging its LOCs and 0 otherwise. Industry dummies are calculated using the Fama French 12 industry SIC codes. T-statistics are calculated with heteroskedasticity-consistent errors. ***, **, * are statistically significant at the 1%, 5%, and 10% level, respectively.

	Dependent Variable								
Parameter	$\Delta Capex_{t+1}$			$\Delta R\&D_{t+1}$			$\Delta Empl_{t+1}$		
Intercept	0.03	2.32	1.81	-19.77	-19.53	-19.57	0.18	0.24	0.29
	(0.00)	(0.09)	(0.07)	(-1.38)	(-1.37)	(-1.37)	(0.46)	(0.61)	(0.70)
Size	2.38	2.27	2.38	5.13	5.13	5.16	0.09	0.09	0.08
	(0.49)	(0.47)	(0.50)	(1.29)	(1.29)	(1.29)	(1.28)	(1.23)	(1.09)
Cash	0.06	0.06	0.06	-0.04	-0.04	-0.04	0.00	0.00	0.00
	(1.12)	(1.13)	(1.12)	(-0.35)	(-0.35)	(-0.35)	(1.05)	(1.07)	(1.11)
LOCTotal	0.01	0.01	0.01	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.26)	(0.25)	(0.25)	(-0.19)	(-0.20)	(-0.20)	(-0.46)	(-0.48)	(-0.46)
*Cash*LOCTotal*	-0.00	-0.00	-0.00	0.00	0.00	0.00	-0.00	-0.00	-0.00
	(-1.53)	(-1.52)	(-1.52)	(0.40)	(0.40)	(0.40)	(-1.23)	(-1.21)	(-1.23)
CreditCrunch	-48.94***	-61.90***	-61.65***	-4.36	-5.88	-5.70	-0.88***	-1.23***	-1.25***
	(-3.52)	(-2.66)	(-2.69)	(-0.55)	(-0.64)	(-0.61)	(-3.06)	(-2.82)	(-2.89)
HiLOC	-22.09	-25.90	-25.65*	-6.79*	-7.27*	-7.21*	-0.32	-0.42	-0.45
	(-1.57)	(-1.61)	(-1.65)	(-1.75)	(-1.81)	(-1.82)	(-1.29)	(-1.48)	(-1.60)
*CreditCrunch*HiLOC*		28.58	28.55		3.48	3.42		0.78	0.79
		(1.13)	(1.13)		(0.72)	(0.70)		(1.52)	(1.54)
Hedge			-11.40			-4.69			1.08
			(-0.35)			(-0.90)			(1.10)
Industry Dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	2146	2146	2146	1269	1269	1269	2127	2127	2127
Adj R-Squared	0.0205	0.0204	0.0200	0.0126	0.0119	0.0112	0.0084	0.0085	0.0092

For changes in investment, we find that the credit crisis was the single most important factor on firms' decreased investment in capital expenditures and employment. Table 17 shows that the coefficient of *CreditCrunch* is negative and significant at the 1% level in both capital investment and employment models. However, the *CreditCrunch*HiLOC* term is not significant in any of the models. These results may be explained by the fact that high LOC users do not have access to external funding in good *and* bad times. They have limited access to both equity and bond financing and are less likely to have bond ratings or commercial paper programs. Therefore, it seems that the financial crisis did not represent a change in credit environment for high LOC users.

CONCLUSION

In this paper we examine whether credit lines possess liquidity insurance properties that allow firms to invest during periods of limited credit availability. The financial crisis that peaked in 2008 is an exogenous event, providing an opportunity to assess the impact of lines of credit on corporate investment during a period of severe economic instability. With a unique dataset that includes bank lines of credit, LOC drawdowns, and hedging data, we examine the relation between credit line usage and corporate investment (Capex, employment, and R&D). Our results provide strong evidence that LOCs on their own do not enhance a firm's ability to maintain its investment during a crisis. This finding calls into question the theoretical view that LOCs provide liquidity insurance that assist firms invest during harsh economic times and tight credit conditions (Campbell (1978), Hawkins (1982), Shockley and Thakor (1997), Holmstrom and Tirole (1998), DeMarzo and Fishman (2007)). However, we do find that

LOCs enable firms to engage in more corporate investment than they would be able to with cash alone. Interestingly, this interactive effect is observed across both pre-crisis and crisis periods.

Our findings tend to contradict the predictions of theoretical literature that credit lines assist firms to avoid decreases in investment during credit-constrained economic environments. Our empirical evidence is more consistent with studies suggesting that bank monitoring limits the ability of firms to deploy credit lines. In all, our research suggests that LOCs have not provided effective liquidity insurance during the 2008 financial crisis.

CHAPTER III

DID THE 2008 FINANCIAL CRISIS IMPACT INTEGRATION BETWEEN THE REAL ESTATE AND STOCK MARKETS?

INTRODUCTION

Previous studies illustrate that Real Estate Investment Trusts (REITs) are important because they allow investors to diversify into real estate (Goetzmann and Ibbotson (1990)). Specifically, studies find that REITs may be able to help investors smooth market cycles. Glascock, Michayluk and Neuhauser (2004) examine the reaction of equity REITs (EREITs) and the stock market in the days surrounding the October 1997 crash. They document that after the market crash, REIT prices declined less than non-REIT stocks. They also find that the bid-ask spreads of non-REIT stocks increased after the crash, whereas REIT bid-ask spreads decreased. They conclude that REITs are good defensive stocks. However, the October 1997 crash was largely caused by automated stock market program trading. But what happens when market turmoil is related to real estate? Are REITs still good defensive stocks? To address these questions, we examine the interaction among the returns of the stock market proxy (CRSP Value-Weighted Index) and returns from the equity REIT (EREIT) and mortgage REIT (MREIT) indices produced by FTSE/NAREIT. In addition to securitized REITs, we also examine estimated daily FTSE/NAREIT PurePlay transaction-based indices at the aggregate return level and by geographic/property type[16]. These analyses provide additional insight since they may more accurately reflect the values of the underlying commercial property.

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[16] This analysis is made possible by the creation of new daily transaction-based commercial real estate indices created by David Geltner and Brad Case, who we thank for their early release for this study.

Market integration is framed in the literature in two main ways. Some studies define market integration as the degree to which systematic risk is equally priced in each market (Liu, Hartzell, Greig and Grissom (1990), Bekaert and Harvey (1995), Chen and Knez (1995), and Ling and Naranjo (1999)). According to this definition, if the real estate market and the stock market are integrated, then only stock market systematic risk (and not real estate market systematic risk) is priced in both the real estate and stock markets (Liu, Hartzell, Greig and Grissom (1990)). The second definition of integration is the degree to which the market returns move together. Studies that examine market integration using the co-movement definition include Karolyi and Stulz (1996), Glascock, Lu and So (2000), Bekaert, Hodrick and Zhang (2009), and Simon and Ng (2009). Although clearly related, the two definitions lead to different empirical methodologies. The present study uses the second definition of market integration. By examining the relationship between stock market returns and commercial real estate market returns before and after the 2008 financial crisis, we are able to assess how the crisis affected the markets' degree of integration.

Previous studies show that return spillovers between the stock market and REITs are unidirectional - the stock market influences EREIT returns, but EREIT returns do not influence the stock market returns (Subrahmanyam (2007)). Accordingly, we expect that prior to the 2008 financial crash both MREITs and EREITs will have little or no influence on the stock market. However, because issues relating to real estate (sub-prime mortgage loans) are widely blamed for precipitating the financial crisis, we expect that the both MREIT and EREIT returns will influence the stock market returns after the crisis. The intuition behind this argument is demonstrated by making a comparison to international diversification. Buying international stocks may help reduce reliance on the U.S. stock market, especially during times of crisis. It may smooth returns for investors desiring less volatility (Goetzmann and Ibbotson (1990)). In such cases, buying European stock indices may be recommended to increase diversification. However, when the source of the uncertainty in the U.S. stock market can be traced to uncertainty surrounding the solvency of several European nations, then the diversification effects of buying the European index may be limited. Subrahmanyam (2007) suggests that one reason REITs are adept at smoothing portfolio returns is that during market downturns, investors tend to move their money to the real estate market in search of more stability. If investors seek safe markets in times of crisis, then investors may not have fled to the real estate market after the 2008 crisis, thereby reducing the balancing nature of the real estate investment and increasing the level of integration.

Consistent with previous research, we find that the stock market influences REITs prior to the 2008 crisis, and we find no evidence that MREITs or EREITs influence the greater stock market returns. Using Granger-causality, vector autoregression (VAR) and state space models, we find that after the 2008 crisis the relationship changed; the relationship is no longer unidirectional. Instead, MREIT and EREIT returns influence stock market returns in addition to the stock market returns influencing REIT returns. Our results are robust to alternate dates specified for the financial crisis. We also find that estimated transaction-based REIT returns influence stock market returns and that some geographic/property type (pure play) indices may be less integrated with the stock market, particularly after a crisis.

Although this study uses the co-movement definition of market integration, our results support recent studies that find evidence of increased systematic risk in REITs. Chatrath, Liang and McIntosh (2000) suggest that REITs have larger betas during economic downturns than during times of market expansion. Accordingly, it is not surprising that recent evidence from the 2008 financial crisis shows that REIT systematic risk is unusually high ((Devaney (2012), Devos, Ong, Spieler and Tsang (2012)). In fact, Devos, Ong, Spieler and Tsang (2012) report that average REIT betas increased from 0.65 before the crisis to 1.58 after the crisis. Our finding of increased integration between the real estate and stock markets is consistent with this increased level of systematic risk.

We add to the real estate and portfolio management literature in three main ways. This is the first study to find evidence of REIT returns influencing stock market returns. Previous studies have maintained that even in the wake of market turmoil, REITs have little or no influence on the greater stock market. Additionally, we find that spillovers from REITs to the stock market were not limited to securitized REITs – we found the same result in estimated transaction-based REIT indices. Returns derived from the underlying value of real estate have been found to have low correlation with stocks and be more comparable to physical real estate investments, so this finding is more surprising (Ling and Naranjo (1999)). Finally, the results from our study suggest that while REITs have historically been a good tool for diversification, they should be seen as only one component of an overall diversification strategy. REITs may not always provide adequate diversification for every portfolio. When there are ties between a stock market downturn and real estate, an investor may find that aggregate REIT indices do not offer as much diversification protection as with an unrelated market decline. However, some of the regional/property type investments still offered diversification benefits after the crisis, suggesting that it is possible to use REITs to protect a portfolio even with a real estate-related market crash.

LITERATURE REVIEW

Although much of the research of market integration involves the linkages with and among foreign markets, many studies document the relationship between stock market returns and real estate returns (Gyourko and Keim (1992), Ling and Naranjo (1999), Clayton and MacKinnon (2003), and Peng and Schulz (Forthcoming)). The literature examining the level of integration between the real estate and stock markets primarily seeks to assess the efficacy of real estate as a diversifying investment for financial portfolios. Goetzmann and Ibbotson (1990) find that real estate can augment a portfolio by making the portfolio less sensitive to market swings. Real estate may have a smoothing effect on portfolio returns that some investors find desirable. In contrast, Liow and Yang (2005) find that in Asia, the linkages between securitized real estate and the stock market are so strong that using securitized real estate is ineffective for diversification. The conflicting results may be caused by the differing time periods. Ling and Naranjo (1999) and Clayton and MacKinnon (2001) find that over time, this relationship changes. The level of integration of the stock market and the real estate market is not static. One reason for the change in integration level over time may be that investors view real estate as a substitute investment for stocks. Several studies suggest that during times of stock market uncertainty, investors shift funds from the stock market as a whole to real estate investments. (Case, Quigley and Shiller (2005), and Subrahmanyam (2007)).

A number of other studies look at the performance of REITs relative to the stock market in times of crisis. Glascock, Michayluk and Neuhauser (2004) examine the performance of REITs and non-REITs following the 1997 stock market crash. They find that REITs are good defensive stocks because REIT returns fell less than returns of non-REIT stocks after the market fell. However, it may be a mistake to assume their results are applicable to the most recent market decline. The 1997 crash was much different from the 2008 financial crisis. Due to their reliance on leverage, REITs may have been hit particularly hard by the crisis (Horrigan, Case, Geltner and Pollakowski (2009)), which may impact the flow of funds from the stock market to real estate securities.

Simon and Ng (2009) also analyze the level of integration between the stock market and REITs during the 2007 downturn. They find increased correlations between the S&P 500 and REITs. Their mixed-copula analysis also concludes that levels of tail dependencies increased. However, since the tail dependence coefficients are lower than those reported for foreign stocks, the authors conclude that REITs remain more suitable for protection from severe market declines than foreign stocks. Our study takes an approach similar to the Subrahmanyam (2007) analysis of return integration and differs from Simon and Ng (2009) in several important ways. First, we employ vector autoregressive (VAR) and state space models to examine the lead-lag relationships between the stock market and REITs, rather than the mixed-copula approach, since our focus is on the co-movement of returns. Second, our study covers a longer time period, including over two years of data following the collapse of Lehman Brothers. Finally, we investigate the integration of the geographic/property type indices in addition to MREITs and EREITs.

DATA

To examine the level of integration between the stock market and the real estate market, we use several proxies. We utilize the CRSP Value-Weighted index (CRSPVW) to represent the entire stock market. The FTSE/NAREIT indices are used for the securitized mortgage REITs (MREITs) and equity REITs (EREITs). CRSPVW was collected from the CRSP database, and the REIT indices (MREITs and EREITs) were collected from the Global Financial Database. In addition to the market proxy and the securitized real estate indices, we also examine the integration levels between the stock market and the real estate market by analyzing the FTSE/NAREIT PurePlay indices[17]. These daily indices report de-levered estimated returns by geographic area and property type. They are created by using regressions of stock market price movements and detailed characteristics of the property holdings to determine the price movements in the underlying commercial property. This approach may offer a more timely assessment of real estate property values than either transaction- or appraisal-based methods. Details about the formation of the indices are available in Horrigan, Case, Geltner and Pollakowski (2009).

For this study, we use the following total return FTSE/NAREIT PurePlay indices: PUREP is the total return index for the U.S., including all property types. APTE, APTM, and APTS are apartment property type returns for east, midwest, and south regions,

[17] We thank David Geltner, Brad Case and National Association of Real Estate Investment Trusts (NAREIT) for access to this dataset.

respectively[18]. INDE, INDM. and INDSW are industrial property type returns for the east, midwest, and southwest regions. FTSE/NAREIT combined the south and west regions for this property type. Office property returns are reported for the midwest, south, and west regions by OFCM, OFCS, and OFCW, respectively. The retail property types are reported with RETM, RETS, and RETW for the midwest, south and west regions, respectively[19].

Since the daily PurePlay indices have not been used in previous empirical studies, we next compare them to more established indices. The Moody's/REAL commercial property index (CPPI) is the leading transaction-based REIT index[20]. Like the PurePlay indices, the CPPI is also available by region and property type. The CPPI includes all four property types covered by the PurePlay indices, but it only includes three regions: East, South, and West. Figures 3 through 6 display index values over time for corresponding property types and regions, where indices comparable to the sample PurePlay indices exist. The values of the CPPI indices are plotted quarterly and the PurePlay values are daily. To ensure comparability, the CPPI values were standardized to PurePlay data series start date by dividing all index values by their level as of March 2006.

[18] The west region apartment index was omitted from this study due to it high correlation with CRSPVW, after conducting variance inflation factor (VIF) tests.
[19] Similar to the apartment index for the west region, the office and retail property types for the east region were excluded from this study due to high VIFs.
[20] The Moody's/REAL CPPI data was retrieved from http://web.mit.edu/cre/research/credl/rca.html.

Figure 3. FTSE NAREIT PurePlay and Moody's/REAL CPPI Regional Apartment Sector Index Values

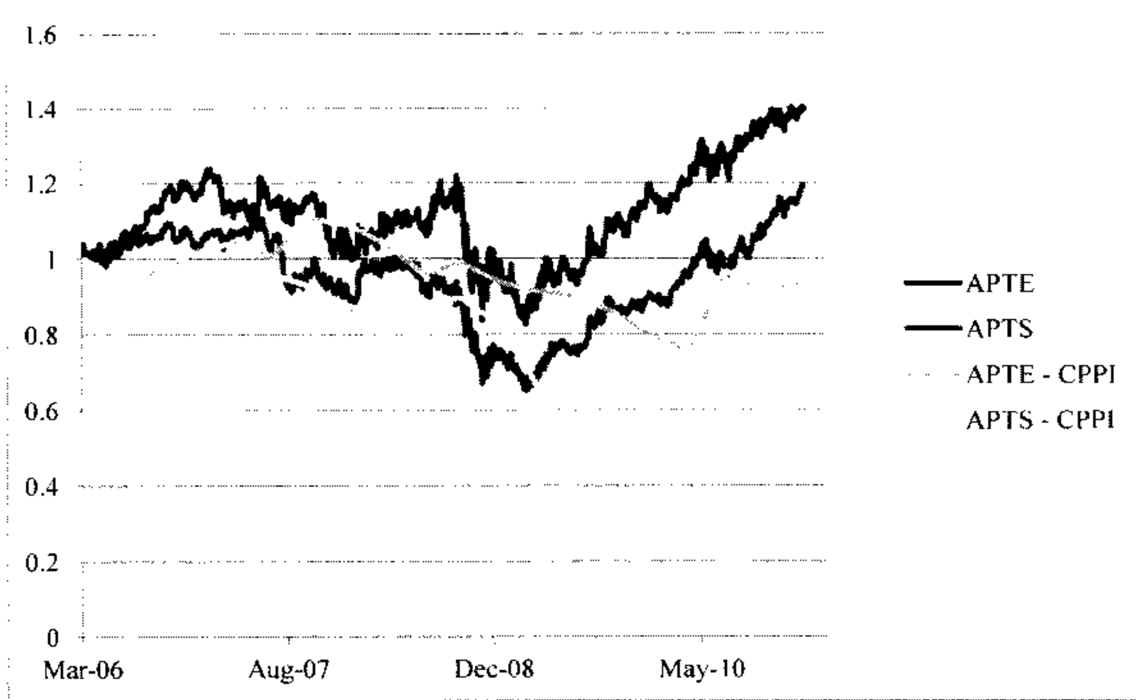
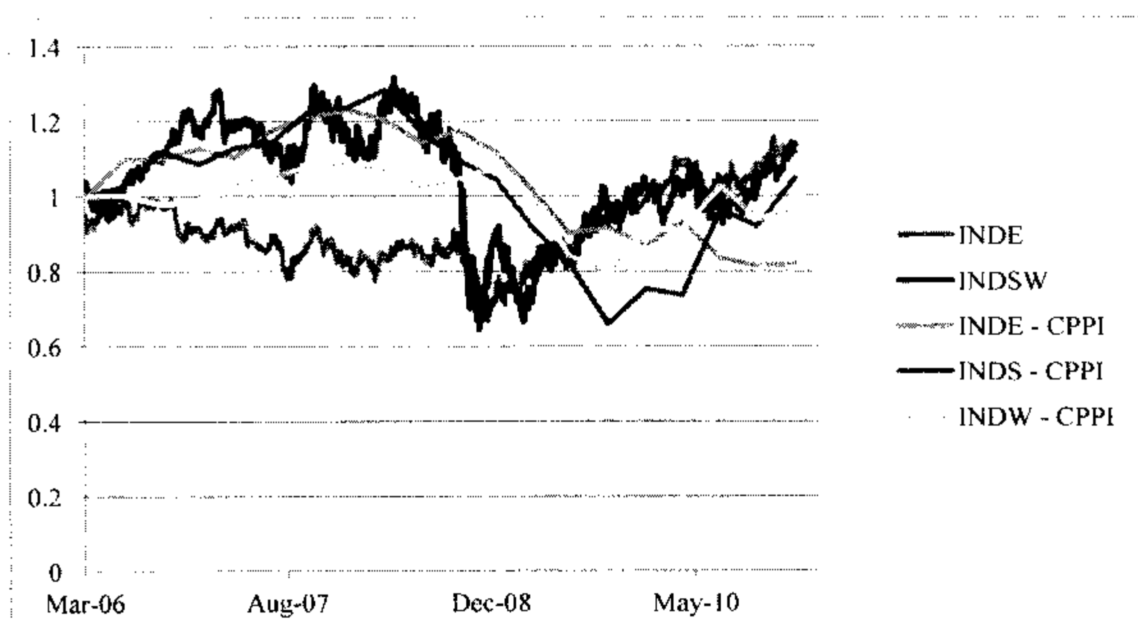


Figure 4. FTSE NAREIT PurePlay and Moody's/REAL CPPI Regional Industrial Sector Index Values



The index comparison for the Apartment sector is reported in Figure 3. The East and South regions for both PurePlay and CPPI are included. The PurePlay Midwest region is omitted because a CPPI Midwest region does not exist. Prior to the 2008 crisis, the indices seem to agree in movement direction and timing. Both PurePlay and CPPI indices for the East Region have higher index values than those for the South region. However, the PurePlay indices start their recovery sooner than the CPPI indices. Both the East and South PurePlay indices start to increase in early 2009. The CPPI indices do not start to recover until nearly a year later. This may due to the securities market information discovery process. This finding is consistent with Horrigan, Case, Geltner and Pollakowski (2009) who argue that since market information is used to determine PurePlay index values, the PurePlay indices are expected to lead indices based on the private market.

The Industrial sector indices are reported in Figure 4. Note that the South and West regions are combined in the PurePlay indices, so there are only two PurePlay series, but three CPPI series for East, South, and West regions. As with the Apartment sector, the Industrial sector indices generally move together until the financial crisis. The PurePlay indices then begin their recovery well before the CPPI indices.

The Office and Retail sector indices are plotted in Figures 5 and 6, respectively. Once again, the PurePlay and CPPI track well with each other before the 2008 financial crisis. The Office sector, Figure 5, shows that even after the crisis, both sets of indices

Figure 5. FTSE NAREIT PurePlay and Moody's/REAL CPPI Regional Office Sector Index Values

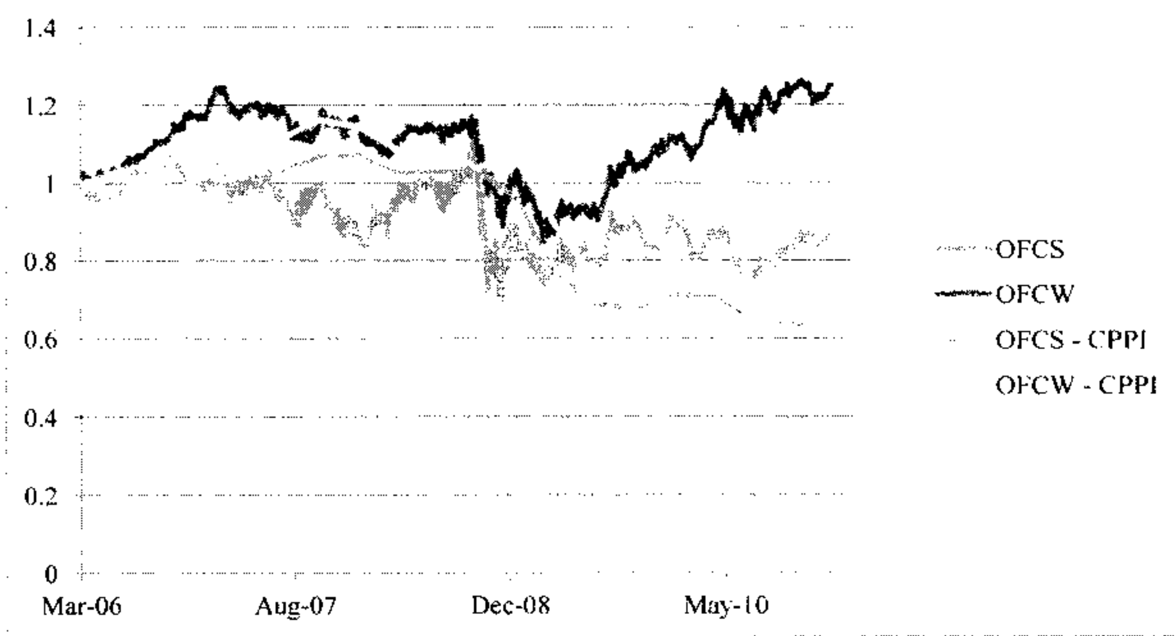
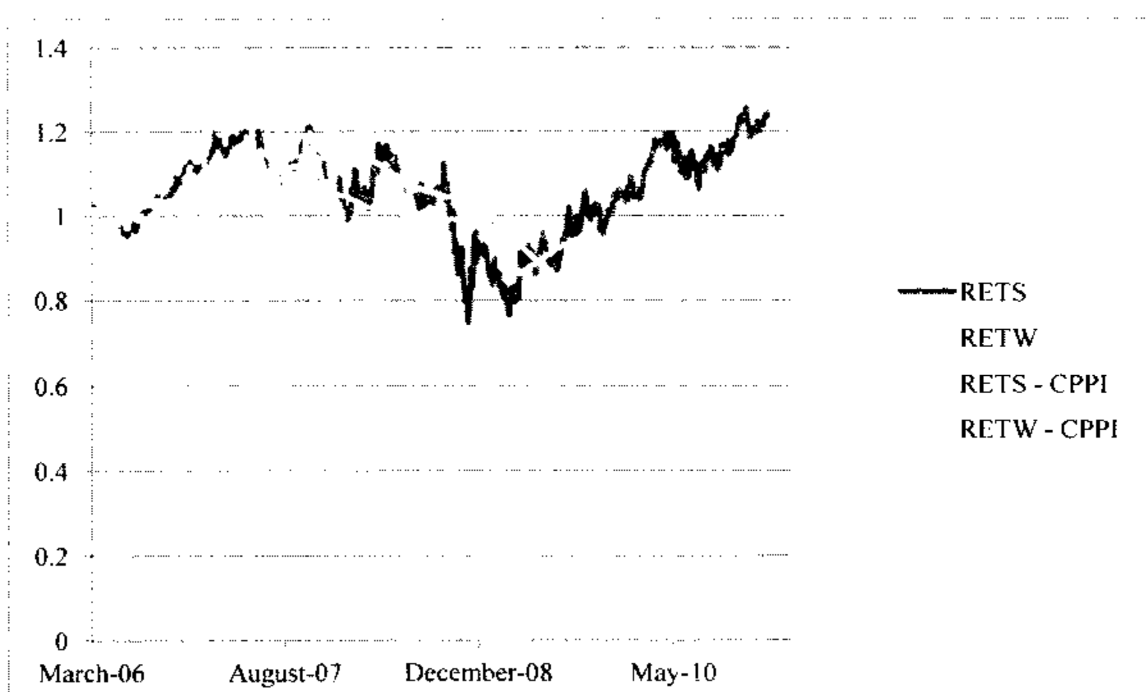


Figure 6. FTSE NAREIT PurePlay and Moody's/REAL CPPI Regional Retail Sector Index Values



agree. Although the PurePlay West region index increases throughout the sample period, the PurePlay West. CPPI South, and CPPI West region indices stay relatively flat. We see more of a disagreement for the Retail sector in Figure 6. Both the South and West PurePlay regions show significant signs of recovery, while the CPPI indices do not. However, Figures 3 through 6 show that overall, the PurePlay and CPPI indices are in general agreement, prior to the 2008 financial crisis, and the PurePlay indices lead the CPPI indices in the years following the crisis.

We conduct our analysis with daily continuously compounded returns (log returns) for 571 trading days before and 571 trading days after the delisting of Lehman Brothers. The actual delisting date, September 17, 2008 was omitted. The pre-crisis period is June 12, 2006 through September 16, 2008. The during-crisis period is September 18, 2008 through December 31, 2010.

Table 18 reports summary statistics for the study variables. CRSPVW daily returns increased in the during-crisis period from 0.00005 to 0.00024. MREIT, EREIT, and the aggregate PUREP returns also increased in the crisis period. However, more than half of the regional property type pure play returns decreased in the during-crisis period, providing a preliminary finding that they may be less integrated with the stock market than MREITs or EREITs. The standard deviations of all returns increased after the crisis, demonstrating the increased market volatility after the collapse of Lehman Brothers.

Correlations between CRSPVW and all real estate indices increased after the

Table 18. Descriptive Statistics of Returns

This table presents descriptive statistics for the daily log returns for stock market and real estate indices. CRSP Value-Weighted index (CRSPVW) represents the entire stock market. The FTSE/NAREIT indices represent securitized mortgage REITs (MREITs) and equity REITS (EREITs). Real estate FTSE/NAREIT PurePlay indices include: PUREP, the total estimated transaction commercial real estate return index for the U.S.,including all property types. APTE, APTM, and APTS are apartment property type returns for east, midwest, and south regions, respectively. INDE, INDM, and INDSW are industrial property type returns for the east, midwest, and southwest regions. FTSE/NAREIT combined the south and west regions for this property type. Office property type returns are reported for the midwest, south, and west regions by OFCM, OFCS, and OFCW, respectively. The retail property types are reported with RETM, RETS, and RETW for the midwest, south and west regions, respectively. The pre-crisis period is June 12, 2006, through September 16, 2008. The during-crisis period is September 18, 2008, through December 31, 2010. There are 571 trading day observations each in the pre- and during-crisis periods.

	Pre-2008 Crisis				*During-2008 Crisis*			
Variable	*Mean*	*Std Dev*	*Minimum*	*Maximum*	*Mean*	*Std Dev*	*Minimum*	*Maximum*
CRSPVW	0.00005	0.01061	(0.04674)	0.03882	0.00024	0.02054	(0.09405)	0.10875
MREIT	(0.00181)	0.02428	(0.19274)	0.13694	0.00028	0.02879	(0.14923)	0.21970
EREIT	(0.00023)	0.01840	(0.09109)	0.08117	(0.00010)	0.03985	(0.20588)	0.16366
PUREP	0.00016	0.00935	(0.04059)	0.04145	0.00019	0.01628	(0.07813)	0.05722
APTE	0.00018	0.01136	(0.04923)	0.05433	0.00032	0.01792	(0.07413)	0.07524
INDE	(0.00013)	0.01036	(0.05789)	0.05083	0.00030	0.01485	(0.05272)	0.05437
APTM	0.00053	0.00822	(0.04393)	0.03984	(0.00035)	0.01396	(0.09214)	0.05410
INDM	(0.00018)	0.01669	(0.08338)	0.05530	(0.00164)	0.01949	(0.24078)	0.08892
OFCM	(0.00029)	0.00936	(0.03206)	0.03716	0.00095	0.01441	(0.04990)	0.06358
RETM	0.00010	0.00772	(0.03174)	0.02632	0.00002	0.01403	(0.07512)	0.05393
APTS	(0.00024)	0.00918	(0.03289)	0.04757	0.00045	0.01480	(0.06991)	0.08092
OFCS	0.00019	0.01431	(0.06791)	0.05917	(0.00032)	0.02519	(0.17145)	0.11116
RETS	0.00014	0.01102	(0.04596)	0.05249	0.00023	0.01727	(0.08031)	0.07855
INDSW	0.00018	0.01517	(0.06506)	0.06391	(0.00004)	0.02386	(0.09407)	0.08269
OFCW	0.00017	0.00692	(0.02767)	0.02516	0.00015	0.01342	(0.08051)	0.05932
RETW	(0.00000)	0.01273	(0.04705)	0.05796	(0.00026)	0.02222	(0.09471)	0.08331

Table 19. Pearson Correlations

This table presents Pearson correlations for the daily log returns for stock market and real estate indices. CRSP Value-Weighted index (CRSPVW) represents the entire stock market. The FTSE/NAREIT indices represent securitized mortgage REITs (MREITs) and equity REITS (EREITs). Real estate FTSE/NAREIT PurePlay indices include: PUREP, the total estimated transaction commercial real estate return index for the U.S., including all property types. APTE, APTM, and APTS are apartment property type returns for east, midwest, and south regions, respectively. INDE, INDM, and INDSW are industrial property type returns for the east, midwest, and southwest regions. FTSE/NAREIT combined the south and west regions for this property type. Office property type returns are reported for the midwest, south, and west regions by OFCM, OFCS, and OFCW, respectively. The retail property types are reported with RETM, RETS, and RETW for the midwest, south and west regions, respectively. The pre-crisis period is June 12, 2006, through September 16, 2008. The during-crisis period is September 18, 2008, through December 31, 2010. There are 571 trading day observations each in the pre- and during-crisis periods. Correlations with a 5% level of significance are reported in bold.

Panel A

	Pre-2008 Crisis														
	CRSPVW	*MREIT*	*EREIT*	*PUREP*	*APTE*	*INDE*	*APTM*	*INDM*	*OFCM*	*RETM*	*APTS*	*OFCS*	*RETS*	*INDSW*	*OFCW*
MREIT	**0.659**														
EREIT	**0.793**	**0.734**													
PUREP	**0.778**	**0.696**	**0.989**												
APTE	**0.662**	**0.580**	**0.874**	**0.891**											
INDE	**0.334**	**0.331**	**0.397**	**0.391**	**0.304**										
APTM	**-0.082**	-0.081	**-0.149**	**-0.143**	**-0.205**	-0.072									
INDM	**0.251**	**0.172**	**0.372**	**0.372**	**0.338**	**-0.189**	-0.025								
OFCM	**0.175**	**0.173**	**0.159**	**0.157**	**0.163**	**0.141**	**-0.148**	**-0.351**							
RETM	**0.713**	**0.613**	**0.827**	**0.836**	**0.731**	**0.387**	**-0.107**	**0.227**	**0.229**						
APTS	**0.653**	**0.611**	**0.827**	**0.830**	**0.655**	**0.349**	**-0.259**	**0.290**	**0.179**	**0.727**					
OFCS	**0.637**	**0.599**	**0.795**	**0.808**	**0.711**	**0.381**	-0.014	**0.254**	-0.044	**0.689**	**0.652**				
RETS	**0.685**	**0.611**	**0.896**	**0.893**	**0.782**	**0.343**	**-0.111**	**0.380**	0.064	**0.668**	**0.720**	**0.740**			
INDSW	**0.727**	**0.659**	**0.917**	**0.921**	**0.816**	**0.371**	**-0.159**	**0.196**	**0.179**	**0.782**	**0.760**	**0.739**	**0.804**		
OFCW	**0.696**	**0.618**	**0.875**	**0.891**	**0.751**	**0.332**	**-0.122**	**0.314**	**0.170**	**0.753**	**0.735**	**0.679**	**0.767**	**0.814**	
RETW	**0.589**	**0.571**	**0.827**	**0.820**	**0.725**	**0.293**	**-0.146**	**0.391**	**0.101**	**0.649**	**0.651**	**0.574**	**0.694**	**0.740**	**0.724**

Panel B

	During-2008 Crisis														
	CRSPVW	*MREIT*	*EREIT*	*PUREP*	*APTE*	*INDE*	*APTM*	*INDM*	*OFCM*	*RETM*	*APTS*	*OFCS*	*RETS*	*INDSW*	*OFCW*
MREIT	**0.754**														
EREIT	**0.839**	**0.855**													
PUREP	**0.847**	**0.833**	**0.985**												
APTE	**0.796**	**0.812**	**0.943**	**0.949**											
INDE	**0.540**	**0.394**	**0.537**	**0.570**	**0.512**										
APTM	**-0.388**	**-0.525**	**-0.576**	**-0.544**	**-0.578**	**-0.222**									
INDM	0.073	0.022	0.015	0.040	0.010	**-0.211**	0.049								
OFCM	**0.359**	**0.293**	**0.356**	**0.365**	**0.334**	**0.325**	**-0.213**	**-0.323**							
RETM	**0.760**	**0.687**	**0.856**	**0.872**	**0.823**	**0.577**	**-0.404**	0.016	**0.316**						
APTS	**0.754**	**0.788**	**0.909**	**0.928**	**0.854**	**0.525**	**-0.566**	0.040	**0.358**	**0.805**					
OFCS	**0.728**	**0.787**	**0.889**	**0.880**	**0.861**	**0.451**	**-0.491**	0.079	**0.150**	**0.777**	**0.827**				
RETS	**0.759**	**0.770**	**0.896**	**0.911**	**0.868**	**0.507**	**-0.511**	-0.012	**0.364**	**0.729**	**0.844**	**0.765**			
INDSW	**0.800**	**0.775**	**0.934**	**0.945**	**0.887**	**0.538**	**-0.478**	-0.065	**0.357**	**0.834**	**0.868**	**0.821**	**0.860**		
OFCW	**0.815**	**0.770**	**0.931**	**0.950**	**0.878**	**0.569**	**-0.500**	0.022	**0.357**	**0.853**	**0.871**	**0.824**	**0.842**	**0.889**	
RETW	**0.653**	**0.639**	**0.807**	**0.838**	**0.774**	**0.456**	**-0.412**	0.125	**0.304**	**0.716**	**0.765**	**0.668**	**0.719**	**0.784**	**0.805**

2008 crisis, except for the midwest industrial property type[21]. The increased correlations in most returns, reported in Table 2, agree with the Simon and Ng (2009) finding of higher correlations between the returns of the S&P500 and REITs after the 2007 downturn.

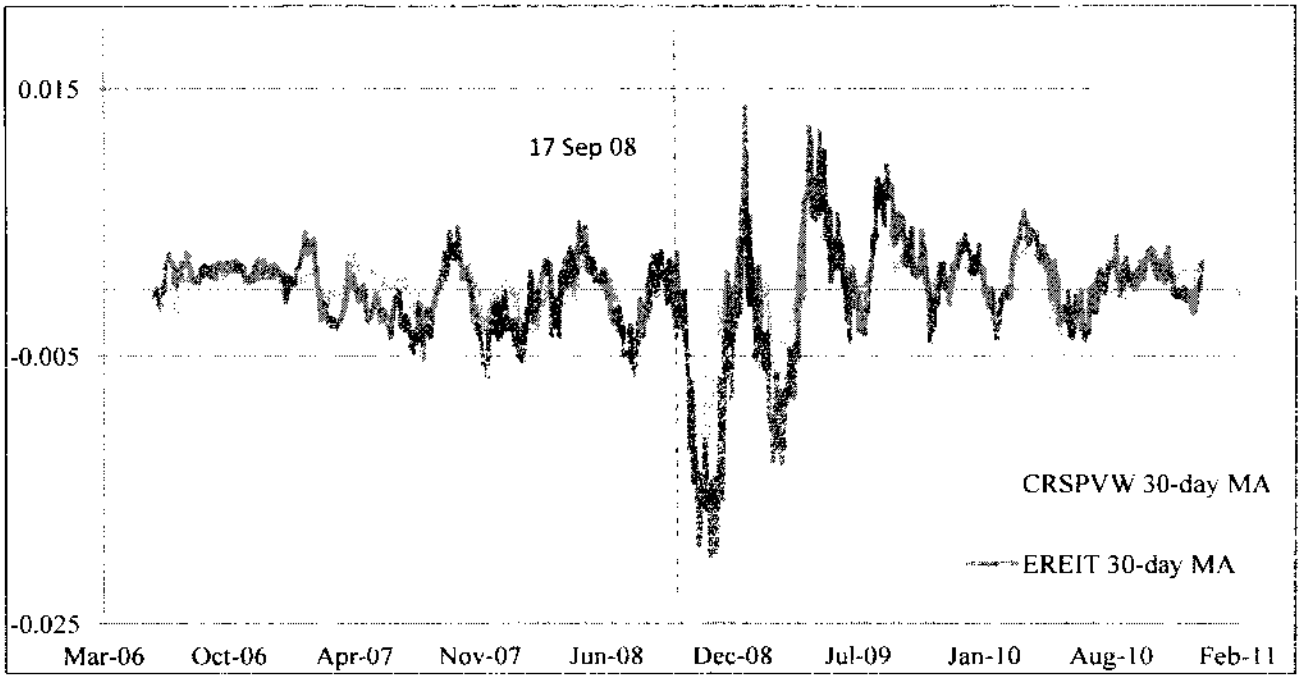
A more visual examination of the relationship between stock market and REIT returns is presented in Figure 7. We chart the 30-day moving average log return for both CRSPVW and EREIT to examine the comovement over time. Although the two series clearly move together, it appears that the stock market returns tend to lead REIT returns. After the 2008 crisis, this trend reverses. The EREIT returns clearly lead CRSPVW returns for most of the during-crisis period. This result provides additional preliminary evidence that real estate returns may influence stock market returns after the financial crisis.

METHODOLOGY/RESULTS

To study the level of integration between the real estate and stock markets, we employ three main empirical analyses. First, we examine Granger-causality tests to determine if the market returns are Granger-caused by the other sample market returns. Next, we perform vector autoregressions (VARs) to estimate the specific relationships between CRSPVW and the REIT indices. Finally, we utilize state space modeling to provide additional information about the linkages between stock market and real estate

[21] The Midwest industrial index decreased from 0.251 (statistically significant at the 5% level) to an insignificant 0.073.

Figure 7. EREIT and CRSPVW Returns 30- Day Moving Average



market returns. Each of the three tests is performed on the pre-crisis and during-crisis samples so that we are able to examine any changes in the integration level before and after the delisting of Lehman Brothers.

Granger-causality and vector autoregession (VAR)

Like Subrahmanyam (2007), we employ vector autoregression (VAR) and Granger-causality to test the level of integration among MREITs, EREITs, and the stock market because we are interested in market co-movement. Prior to running either test, we perform Dickey-Fuller unit root tests and confirm that all returns are stationary. Table 20 reports the results of the Granger-causality tests. Chi-square statistics and p-values show the probability of rejecting the null hypothesis that the Group 1 variable is not Granger-caused by the other variables. Due to the high level of correlation between EREIT and PUREP, the tests are completed in separate panels. Panel A tests relationships between CRSPVW, MREIT, and EREIT, while Panel B tests CRSPVW and PUREP.

We find that prior to the 2008 crisis, the tests fail to reject the hypothesis that CRSPVW is not Granger-caused by MREIT and EREIT in Panel A and PUREP in Panel B. We interpret this finding as a lack of evidence of market integration. After the crisis, the tests show that the stock market returns are Granger-caused by MREITs, EREITs, and PUREP, significant at the 1% level. The Granger-causality tests support the hypothesis of increased integration of real estate and stock markets after the 2008 crisis.

Table 20. Granger-causality Tests

This table reports the results of Granger-causality tests for daily log returns for stock market and real estate indices. CRSP Value-Weighted index (CRSPVW) represents the entire stock market. The FTSE/NAREIT indices represent securitized mortgage REITs (MREITs) and equity REITS (EREITs). Real estate FTSE/NAREIT PurePlay index, PUREP, is the total estimated transaction commercial real estate return index for the U.S., including all property types. The pre-crisis period is June 12, 2006, through September 16, 2008. The during-crisis period is September 18, 2008, through December 31, 2010. There are 571 trading day observations each in the pre- and during-crisis periods.

Panel A

Granger-Causality Wald Test				
	Pre-2008 Crisis		*During-2008 Crisis*	
Group 1 Variable	*Chi-Square*	*Pr > ChiSq*	*Chi-Square*	*Pr > ChiSq*
CRSPVW	1.91	0.3854	20.34	0.0024
MREIT	6.46	0.0395	26.35	0.0002
EREIT	4.11	0.1279	16.23	0.0126

Panel B

Granger-Causality Wald Test				
	Pre-2008 Crisis		*During-2008 Crisis*	
Group 1 Variable	*Chi-Square*	*Pr > ChiSq*	*Chi-Square*	*Pr > ChiSq*
CRSPVW	4.36	0.2256	20.45	0.0001
PUREP	14.88	0.0019	15.91	0.0012

Table 21. Vector Autoregressions (VAR)

This table reports the results of vector autoregressions (VAR) using daily log returns for stock market and real estate indices. CRSP Value-Weighted index (CRSPVW) represents the entire stock market. The FTSE/NAREIT indices represent securitized mortgage REITs (MREITs) and equity REITS (EREITs). Real estate FTSE/NAREIT PurePlay index, PUREP, is the total estimated transaction commercial real estate return index for the U.S., including all property types. The pre-crisis period is June 12, 2006, through September 16, 2008. The during-crisis period is September 18, 2008, through December 31, 2010. There are 571 trading day observations each in the pre- and during-crisis periods. ** and * denote statistical significance at the 1% and 5% level, respectively. T-values are in parentheses.

Panel A

	Pre-2008 crisis			*During-2008 crisis*		
	CRSPVW	*MREIT*	*EREIT*	*CRSPVW*	*MREIT*	*EREIT*
Constant	0.00005	-0.00170	-0.00031	0.00019	-0.00001	-0.00026
	(0.12)	(-1.67)	(-0.40)	(0.22)	(-0.01)	(-0.17)
CRSPVW(t-1)	-0.17101*	-0.36531*	-0.16497	-0.09816	0.10059	0.04981
	(-2.46)	(-2.28)	(-1.37)	(-1.18)	(0.93)	(0.32)
MREIT(t-1)	-0.02773	0.03205	-0.05778	0.03593	-0.07500	0.00838
	(-1.02)	(0.51)	(-1.22)	(0.56)	(-0.90)	(0.07)
EREIT(t-1)	0.05837	0.05169	-0.00603	0.00188	-0.18964**	-0.28641**
	(1.30)	(0.50)	(-0.08)	(0.04)	(-2.81)	(-2.89)
CRSPVW(t-2)				-0.24344**	-0.16191	-0.25790
				(-2.96)	(-1.52)	(-1.65)
MREIT(t-2)				-0.06810	-0.15876	-0.21731
				(-1.06)	(-1.90)	(-1.77)
EREIT(t-2)				0.14402**	0.12202	0.16634
				(2.70)	(1.76)	(1.64)
CRSPVW(t-3)				0.30141**	0.33778**	0.40539**
				(3.93)	(3.39)	(2.78)
MREIT(t-3)				-0.08084	-0.15531*	-0.09893
				(-1.41)	(-2.08)	(-0.91)
EREIT(t-3)				-0.05914	-0.04831	-0.10111
				(-1.17)	(-0.73)	(-1.05)

Panel B

	Pre-2008 Crisis		*During-2008 Crisis*	
	CRSPVW	*PUREP*	*CRSPVW*	*PUREP*
Constant	0.00009	0.00021	0.00083	0.00065
	(0.21)	(0.54)	(0.18)	(0.28)
CRSPVW(t-1)	-0.21210**	-0.12682*	0.08127	0.06348
	(-3.18)	(-2.17)	(-1.46)	(-0.36)
PUREP(t-1)	0.09849	-0.01659	0.10435	0.08151*
	(1.30)	(-0.25)	(0.90)	(-2.34)
CRSPVW(t-2)	-0.07499	-0.06386	0.08073**	0.06306*
	(-1.11)	(-1.08)	(-3.44)	(-2.29)
PUREP(t-2)	0.02920	-0.03174	0.10720**	0.08374
	(0.38)	(-0.48)	(2.78)	(1.44)
CRSPVW(t-3)	-0.11526	-0.18762**	0.07762**	0.06063**
	(-1.72)	(-3.20)	(3.97)	(2.98)
PUREP(t-3)	0.12885	0.15610*	0.10024**	0.07830*
	(1.70)	(2.34)	(-2.73)	(-2.04)

Next. we examine the VAR model estimation in Table 21. The number of lags used in each model was determined by electing the smallest Akaike Information Criterion (AIC). Panel A once again reports results from models with CRSPVW, MREIT, and EREIT as dependent variables. CRSPVW and PUREP are the dependent variables in Panel B. The pre-crisis model is VAR(1) and the during-crisis model was determined to be VAR(3). Looking at the pre-crisis period, we find that MREIT and EREIT lags do not influence stock market returns. Only one of the lagged values of itself influences CRSPVW. The market returns (CRSPVW) do influence MREIT, significant at the 5% level. EREIT is not influenced by either CRSPVW or MREIT. During-2008 crisis, the links between stock market returns and real estate returns increase. EREIT influences CRSPVW with a 2-day lag, significant at the 1% level. EREIT also influences MREIT with a 1-day lag, significant at the 1% level. Finally, CRSPVW influences MREIT and EREIT with a 3-day lag, again significant at the 1% level.

In Panel B, we examine the relationship between stock market returns and the aggregate pure play return index, PUREP. As in Panel A, the only significant predictor of CRSPVW in the pre-crisis time period is one lag of itself, significant at the 1% level. In the during-crisis period, 2 and 3 lags of PUREP influence CRSPVW at the 1% level. These results provide additional evidence of increases in the linkages between the stock and real estate markets.

State space models

We next examine the data using state space models (Akaike (1976)), which are useful in analyzing the relationships among stationary time series data. The state space models incorporate variables and autocorrelations that are helpful in predicting future variables, but omit those that are not significantly explanatory, often resulting in a parsimonious model. Because the model considers all autocorrelations jointly, it may also result in more accurate estimates than models like VAR which estimate each dependent variable separately (Aoki and Havenner (1989)). The significant variables and autocorrelations are called the state vector, which is selected using the VAR model with the lowest AIC and then performing canonical correlation analysis to determine which variables are explanatory and hence belong in the state vector. After the state vector is identified, the transition matrix that maps the state space vector to its forecast is estimated using approximate maximum likelihood and a Kalman filter recursive algorithm. See Harvey and Peters (1990) for a detailed description of state space models.

Panel A shows the results of the state space model for CRSPVW, MREIT, and EREIT. In the pre-crisis period, the stock market returns (CRSPVW) are only significantly influenced by 1 lag of itself. MREIT is also influenced by 1 lag of CRSPVW, significant at the 5% level. There is no relationship between EREIT and CRSPVW or MREIT in the pre-crisis period. In the during-2008 crisis period, the stock market returns are influenced by EREIT at 1- and 2-day lags, significant at the 1% level. There is a contemporaneous relationship between CRSPVW and MREIT, suggesting that the stock market and the real estate market may move together. 1-day lags of CRSPVW and EREIT are also significant at the 5% and 1% level, respectively. EREIT is strongly (1% level) influenced by CRSPVW for 1- and 2-day lags, whereas there was no relationship before the crisis.

Table 22. State Space Models

This table reports the results of state space models using daily log returns for stock market and real estate indices. CRSP Value-Weighted index (CRSPVW) represents the entire stock market. The FTSE/NAREIT indices represent securitized mortgage REITs (MREITs) and equity REITS (EREITs). Real estate FTSE/NAREIT PurePlay index, PUREP, is the total estimated transaction commercial real estate return index for the U.S., including all property types. The pre-crisis period is June 12, 2006, through September 16, 2008. The during-crisis period is September 18, 2008, through December 31, 2010. There are 571 trading day observations each in the pre- and during-crisis periods. ** and * denote statistical significance at the 1% and 5% level, respectively. T-values are in parentheses.

Panel A

	Pre-2008 Crisis			*During-2008 Crisis*		
	CRSPVW	*MREIT*	*EREIT*	*CRSPVW*	*MREIT*	*EREIT*
CRSPVW(t)					1.19665**	
					(7.87)	
CRSPVW(t-1)	-0.17087*	-0.36601*	-0.16679	-1.48056**	0.15540*	-0.92841**
	(-2.52)	(-2.35)	(-1.43)	(-7.35)	(2.23)	(-2.62)
MREIT(t-1)	-0.02767	0.03175	-0.05859		-0.13074*	
	(-1.03)	(0.52)	(-1.26)		(-2.56)	
EREIT(t-1)	0.05814	0.05280	-0.00310	0.51391**	-0.14967**	-0.28556
	(1.34)	(0.53)	(-0.04)	(4.09)	(-3.53)	(-1.41)
CRSPVW(t-2)				-0.39507**		-0.52469**
				(-5.59)		(-4.56)
MREIT(t-2)				-0.01949		-0.09271
				(-0.40)		(-1.21)
EREIT(t-2)				0.24146**		0.18248*
				(4.97)		(2.40)

Panel B

	Pre-2008 Crisis		*During-2008 Crisis*	
	CRSPVW	*PUREP*	*CRSPVW*	*PUREP*
CRSPVW(t)				0.57347**
				(6.99)
CRSPVW(t-1)	-0.20451**		-0.57722**	0.01909
	(-3.11)		(-3.96)	(0.55)
PUREP(t-1)	0.10404	0.20765		-0.21315**
	(1.40)	(0.86)		(-5.11)
CRSPVW(t-2)			-0.41114**	
			(-5.41)	
PUREP(t-2)		0.56081*	0.36758**	
		(2.38)	(4.29)	
CRSPVW(t-3)		-0.02594		
		(-0.42)		
PUREP(t-3)		0.05629		
		(1.11)		

Panel B results are very similar to Panel A. CRSPVW and PUREP are not related prior to the crisis. However, after the delisting of Lehman Brothers, 2 lags of PUREP influence CRSPVW at the 1% level, and PUREP is contemporaneously related to CRSPVW. The state space results support and confirm the VAR results that the linkages between the stock market and real estate market have increased. Taken together, Tables 22 and 23 provide strong evidence that the stock market and real estate market have become more integrated since the 2008 crisis.

ROBUSTNESS CHECKS

We now perform several analyses to ensure that our results are robust to alternative specifications. First, we examine an alternate definition of the start of the crisis. We then examine additional pure play indices to see if geographic and property type indices have different results from the aggregate returns used in our main analysis. Finally, we utilize an alternate market proxy, the Russell 2000 small cap index.

Beginning date of the financial crisis

Simon and Ng (2009) investigate the level of integration between the stock market and real estate surrounding the real estate market downturn. To ensure our results are not sensitive to the crisis date, we repeat our analyses using their January 31, 2007, downturn date. In accordance with the previous analysis, we use 571 trading day observations before and after the downturn, resulting in a pre-downturn period from October 22, 2004, to January 31, 2007, and a during-downturn period of February 1,

Table 23. Granger-causality Tests and Vector Autoregressions (Pre- and During-2007 Downturn)

This table reports the results of Granger-causality tests and vector autoregressions using daily log returns for stock market and real estate indices. CRSP Value-Weighted index (CRSPVW) represents the entire stock market. The FTSE/NAREIT indices represent securitized mortgage REITs (MREITs) and equity REITS (EREITs). Real estate FTSE/NAREIT PurePlay index, PUREP, is the total estimated transaction commercial real estate return index for the U.S., including all property types. The pre-downturn period is from October 22, 2004, to January 31, 2007, and the during-downturn period is from February 1, 2007 to May 8, 2009. There are 571 trading day observations each in the pre- and during-crisis periods. ** and * denote statistical significance at the 1% and 5% level, respectively. T-values are in parentheses.

Panel A

Granger-Causality Wald Test				
	Pre-2007 Downturn		*During-2007 Downturn*	
Group 1 Variable	*Chi-Square*	*Pr > ChiSq*	*Chi-Square*	*Pr > ChiSq*
CRSPVW	0.02	0.9901	20.62	0.0021
MREIT	1.08	0.5813	19.25	0.0038
EREIT	0.84	0.6578	13.91	0.0307

Panel B

	Pre-2007 Downturn			*During-2007 Downturn*		
	CRSPVW	*MREIT*	*EREIT*	*CRSPVW*	*MREIT*	*EREIT*
Constant	0.00061*	-0.00021	0.00068	-0.00067	-0.0027	-0.00249
	(2.18)	(-0.45)	(1.70)	(-0.79)	(-1.82)	(-1.53)
CRSPVW(t-1)	0.0091	0.03843	0.07413	-0.25783**	-0.19122	-0.19169
	(0.15)	(0.37)	(0.84)	(-3.20)	(-1.36)	(-1.24)
MREIT(t-1)	-0.00277	0.11508	0.00006	0.02247	-0.01799	0.02322
	(-0.06)	(1.56)	(0.00)	(0.56)	(-0.26)	(0.30)
EREIT(t-1)	0.00677	-0.08522	0.05762	0.06682	-0.10721	-0.21507*
	(0.14)	(-1.04)	(0.82)	(1.43)	(-1.31)	(-2.38)
CRSPVW(t-2)				-0.31599**	-0.30585*	-0.40194*
				(-3.90)	(-2.16)	(-2.58)
MREIT(t-2)				-0.01686	-0.05743	-0.06401
				(-0.42)	(-0.82)	(-0.83)
EREIT(t-2)				0.15649**	0.15763	0.13177
				(3.25)	(1.87)	(1.42)
CRSPVW(t-3)				0.23131**	0.20853	0.2332
				(2.99)	(1.54)	(1.57)
MREIT(t-3)				-0.0473	-0.10794	-0.06683
				(-1.19)	(-1.55)	(-0.87)
EREIT(t-3)				-0.02876	-0.01789	-0.04302
				(-0.62)	(-0.22)	(-0.48)

2007 to May 8, 2009. Since the estimated transactional (pure play) daily data are not available until March 2006, we conduct this test only on MREITs and EREITs.

Granger-causality tests, reported in Panel A of Table 23, confirm our previous results. Prior to the 2007 downturn, CRSPVW is not Granger-caused by either EREIT or MREIT. In fact, EREIT and MREIT are not Granger-caused by CRSPVW either. The VAR results in Panel B echo those from Granger-causality. Before the 2007 real estate downturn, there are no significant market linkages between the stock market and the real estate market. During-downturn, CRSPVW is influenced by EREIT with a 2-day lag, in addition to lags of itself, significant at the 1% level. MREIT and EREIT are both influenced by CRSPVW with a 2-day lag at a 5% level of significance.

In both Granger-causality and VAR, using an earlier downturn date shows less market integration prior to the 2007 downturn. However, both methods show that the stock market and real estate market are significantly linked after the downturn. The results demonstrate that our previous analyses are not sensitive to the definition of the start of the crisis/downturn and provide strong evidence that the real estate market and stock market are more integrated since the recent financial market turmoil.

Geographic/property type variation

Our analysis with stock market integration used an aggregate estimated transaction-based index (PUREP) as a proxy for commercial real estate returns. We found that PUREP did influence CRSPVW and that integration between the real estate market and the stock market increased following the collapse of Lehman Brothers. We

Table 24. Granger-causality Tests by Geographic/Property Type

This table presents Granger-causality tests for the daily log returns for stock market and real estate indices. CRSP Value-Weighted index (CRSPVW) represents the entire stock market. Real estate FTSE/NAREIT PurePlay indices include are estimated transaction commercial real estate return index for the U.S. APTE, APTM, and APTS are apartment property returns for east, midwest, and south regions, respectively. INDE, INDM, and INDSW are industrial property returns for the east, midwest, and southwest regions. FTSE/NAREIT combined the south and west regions for this property type. Office property returns are reported for the midwest, south, and west regions by OFCM, OFCS, and OFCW, respectively. The retail property types are reported with RETM, RETS, and RETW for the midwest, south and west regions, respectively. The pre-crisis period is June 12, 2006 through September 16, 2008. The during-crisis period is September 18, 2008 through December 31, 2010. There are 571 trading day observations each in the pre- and during-crisis periods.

Granger-Causality Wald Test				
	Pre-2008 Crisis		*During-2008 Crisis*	
Group 1 Variable	*Chi-Square*	*Pr > ChiSq*	*Chi-Square*	*Pr > ChiSq*
CRSPVW	10.84	0.5429	199.57	<.0001
APTE	35.34	0.0004	197.52	<.0001
INDE	19.22	0.0834	108.20	0.0001
APTM	8.48	0.7465	174.45	<.0001
INDM	17.77	0.1228	123.39	<.0001
OFCM	10.68	0.5566	166.77	<.0001
RETM	15.48	0.2161	204.15	<.0001
APTS	12.96	0.3719	190.36	<.0001
OFCS	27.92	0.0057	193.79	<.0001
RETS	16.07	0.1879	172.75	<.0001
INDSW	21.11	0.0489	183.12	<.0001
OFCW	11.47	0.4889	175.00	<.0001
RETW	11.45	0.4905	124.20	<.0001

now explore that result to see if the increased integration is stronger or weaker in certain geographic/property type sectors.

Table 24 shows results from Granger-causality tests. The p-value reports the probability of rejecting the null hypothesis that the Group 1 variable is not Granger-caused by the remaining variables. In the pre-crisis period, the test fails to reject the null hypothesis for CRSPVW with a p-value of 0.543. Three of the four geographic/property type segments are Granger-caused by the other variables (APTE, OFCS, and INDSW), but most show evidence of the same level of independence as CRSPVW. After the 2008 crisis, all markets are Granger-caused (1% significance) by the others indicating another striking increase in integration.

Table 25 provides the results of VAR analyses of the relationship between the geographic/property type segments and the stock market. Panel A shows the results for before the 2008 crisis from a VAR(1) model. CRSPVW is influenced by its own lagged value, significant at the 5% level. Real estate returns exhibit varying levels of integration with each other, but a weak relationship with the stock market as a whole. The during-crisis model is VAR(5) and is reported in Panel B. For the sake of brevity, we only report during-2008 crisis significant (5% level) influences of the stock market returns. Once again, we confirm the finding that market integration has increased since the 2008 crisis. Almost all of the real estate geographic/property type returns now influence stock market returns, whereas prior to the crisis, none of them did.

Table 25. Vector autoregressions (VAR) by Geographic/Property Type

This table presents vector autoregression (VAR) results for the daily log returns for stock market and real estate indices. CRSP Value-Weighted index (CRSPVW) represents the entire stock market. Real estate FTSE/NAREIT PurePlay indices include estimated transaction commercial real estate return index for the U.S. APTE, APTM, and APTS are apartment property returns for east, midwest, and south regions, respectively. INDE, INDM, and INDSW are industrial property returns for the east, midwest, and southwest regions. FTSE/NAREIT combined the south and west regions for this property type. Office property returns are reported for the midwest, south, and west regions by OFCM, OFCS, and OFCW, respectively. The retail property types are reported with RETM, RETS, and RETW for the midwest, south and west regions, respectively. The pre-crisis period is June 12, 2006, through September 16, 2008. The during-crisis period is September 18, 2008, through December 31, 2010. Due to space considerations, Panel B only reports significant estimates for the CRSPVW model. There are 571 trading day observations each in the pre- and during-crisis periods. ** and * denote statistical significance at the 1% and 5% level, respectively. T-values are in parentheses.

Panel A

	Pre-2008 Crisis												
	CRSPVW	*APTE*	*INDE*	*APTM*	*INDM*	*OFCM*	*RETM*	*APTS*	*OFCS*	*RETS*	*INDSW*	*OFCW*	*RETW*
Constant	0.00005	0.00014	-0.00024	0.00057	-0.00004	-0.00026	0.00010	-0.00025	0.00007	0.00008	0.00012	0.00013	-0.00001
	(0.12)	(0.29)	(-0.54)	(1.65)	(-0.06)	(-0.67)	(0.30)	(-0.65)	(0.11)	(0.17)	(0.18)	(0.44)	(-0.02)
CRSPVW(t-1)	-0.14739*	-0.09528	-0.07052	-0.00268	0.06294	-0.07055	-0.06335	-0.06421	-0.15979	-0.15782*	-0.18550	-0.02086	-0.00215
	(-2.19)	(-1.34)	(-1.07)	(-0.05)	(0.59)	(-1.18)	(-1.30)	(-1.09)	(-1.81)	(-2.26)	(-1.94)	(-0.47)	(-0.03)
APTE(t-1)	0.13928	0.28761**	0.18237*	-0.03707	-0.02684	0.15926*	0.15633**	0.18302*	0.28523**	0.14038	0.21181	0.08259	0.15682
	(1.69)	(3.30)	(2.26)	(-0.57)	(-0.21)	(2.17)	(2.62)	(2.55)	(2.63)	(1.64)	(1.81)	(1.53)	(1.57)
INDE(t-1)	-0.03249	-0.09022	0.02562	0.04170	0.04948	0.02551	0.00765	-0.03416	-0.00255	-0.05061	-0.07780	-0.02293	-0.03436
	(-0.62)	(-1.64)	(0.50)	(1.02)	(0.60)	(0.55)	(0.20)	(-0.75)	(-0.04)	(-0.94)	(-1.05)	(-0.67)	(-0.54)
APTM(t-1)	0.00445	0.04617	0.06848	-0.06560	-0.09553	0.04530	0.01156	0.01691	0.03584	0.03435	0.01754	0.03479	-0.01156
	(0.08)	(0.74)	(1.18)	(-1.42)	(-1.02)	(0.86)	(0.27)	(0.33)	(0.46)	(0.56)	(0.21)	(0.90)	(-0.16)
INDM(t-1)	0.00622	-0.08474*	-0.02415	0.01560	0.11920*	0.03351	-0.01670	-0.04325	-0.10162*	-0.05892	-0.06217	-0.02819	0.00549
	(0.16)	(-2.10)	(-0.65)	(0.52)	(1.98)	(0.99)	(-0.61)	(-1.30)	(-2.03)	(-1.49)	(-1.15)	(-1.13)	(0.12)
OFCM(t-1)	0.03325	-0.07364	-0.03329	0.02276	0.00018	-0.00746	-0.02416	-0.05753	-0.16087*	-0.05443	-0.10485	-0.04425	-0.06784
	(0.57)	(-1.19)	(-0.58)	(0.49)	(0.00)	(-0.14)	(-0.57)	(-1.12)	(-2.08)	(-0.89)	(-1.26)	(-1.15)	(-0.95)

RETM(t-1)	-0.05639	0.01146	-0.00324	0.07463	0.14568	-0.10069	-0.08347	0.06497	-0.04680	0.00768	0.08544	-0.01252	0.00312
	(-0.51)	(0.10)	(-0.03)	(0.86)	(0.84)	(-1.03)	(-1.05)	(0.68)	(-0.32)	(0.07)	(0.55)	(-0.17)	(0.02)
APTS(t-1)	-0.12102	0.06553	-0.11925	0.00902	0.00362	0.06038	-0.06510	0.04766	-0.11647	-0.04255	-0.10046	-0.05383	-0.07621
	(-1.36)	(0.70)	(-1.37)	(0.13)	(0.03)	(0.76)	(-1.01)	(0.61)	(-0.99)	(-0.46)	(-0.79)	(-0.92)	(-0.71)
OFCS(t-1)	0.02816	-0.07843	0.03670	0.03796	-0.12615	0.03937	0.00048	-0.06145	-0.13256	0.04441	-0.01891	-0.03754	-0.07779
	(0.50)	(-1.32)	(0.67)	(0.86)	(-1.42)	(0.79)	(0.01)	(-1.25)	(-1 79)	(0.76)	(-0.24)	(-1.02)	(-1.14)
RETS(t-1)	-0.01486	-0.04863	-0.13380	-0.00320	-0.12806	-0.02627	-0.00846	0.00074	-0.00812	-0.07770	-0.04626	-0.02785	0.02551
	(-0.17)	(-0.54)	(-1.61)	(-0.05)	(-0.96)	(-0.35)	(-0.14)	(0.01)	(-0.07)	(-0.88)	(-0.38)	(-0.50)	(0.25)
INDSW(t-1)	0.01604	-0.00050	-0.05826	-0.10858	0.32625**	-0.02965	-0.01260	-0.00243	-0.07677	-0.01585	0.02651	0.04705	0.06511
	(0.22)	(-0.01)	(-0.80)	(-1.88)	(2.80)	(-0.45)	(-0.24)	(-0.04)	(-0.79)	(-0.21)	(0.25)	(0.97)	(0.73)
OFCW(t-1)	-0.12340	-0.26955*	0.12909	0.01728	-0.46078*	-0.03974	-0.13328	-0.17509	-0.06657	-0.10927	-0.33767	-0.12613	-0.27621
	(-0.96)	(-1.99)	(1.03)	(0.17)	(-2.28)	(-0.35)	(-1.44)	(-1.57)	(-0.40)	(-0.82)	(-1.86)	(-1.50)	(-1.78)
RETW(t-1)	0.05903	-0.04341	0.00399	0.02276	-0.04709	-0.05325	0.01247	0.01059	0.02714	0.06454	0.04350	0.03985	0.05782
	(0.99)	(-0.69)	(0.07)	(0.49)	(-0.50)	(-1.01)	(0.29)	(0.20)	(0.35)	(1.04)	(0.51)	(1 02)	(0.80)

Panel B

During-2008 Crisis (Significant estimates for CRSPVW only)	
	CRSPVW
INDM(t-1)	0.16789**
	(3.08)
OFCM(t-1)	0.15310*
	(2.01)
RETW(t-1)	-0.14773*
	(-2.10)
CRSPVW(t-2)	-0.23520**
	(-2.82)
APTE(t-2)	0.39486**
	(2.67)
INDE(t-2)	-0.15562*
	(-2.07)
APTS(t-2)	-0.43250**
	(-2.86)
RETW(t-2)	0.18721**
	(2.59)
CRSPVW(t-3)	0.27783**
	(3.26)
APTE(t-3)	-0.30173*
	(-2.05)
INDE(t-3)	0.19636**
	(2.64)
APTM(t-3)	-0.21463**
	(-2.61)
OFCM(t-4)	0.20574**
	(2.79)
RETM(t-4)	-0.54044**
	(-4.17)
OFCM(t-5)	-0.22676**
	(-3.14)
OFCS(t-5)	-0.30989**
	(-3.93)

Unlike the analysis with MREIT, EREIT, and PUREP, there are a few exceptions to the high level of integration seen after the financial crisis. Although the results are not shown, INDSW does not influence the stock market, even after the crisis. CRSPVW does influence INDSW with lags of 2 and 3 days. Similarly, APTS influences CRSPVW at 2 lags, but the finding is not reciprocal. CRSPVW does not influence APTS. These geographic/property type segments demonstrate lower levels of integration than the other indices. Having exposure to these new, more specific property types and regions of real estate may allow an investor a better opportunity to diversify his portfolio than aggregate indices.

Market proxy index

Our main goal is to explore the relationship between the real estate market and the stock market as a whole. To that end, the majority of our study employs the CRSP value-weighted index as proxy for the stock market. However, previous literature suggests that REITs may perform more like small cap stocks than other securities (Glascock, Lu and So (2000)). Therefore, it is interesting to investigate whether the relationship between small cap stocks and the real estate market also changes after the financial crisis.

Table 26. Granger-Causality Tests and Vector Autoregressions (Pre- And During-2008 Crisis)

This table reports the results of Granger-causality tests and vector autoregressions using daily log returns for stock market and real estate indices. Russell 2000 index (Russell2000) represents the market of small cap stocks. The FTSE/NAREIT indices represent securitized mortgage REITs (MREITs) and equity REITS (EREITs). The pre-crisis period is June 12, 2006, through September 16, 2008. The during-crisis period is September 18, 2008, through December 31, 2010.There are 571 trading day observations each in the pre- and during-crisis periods. ** and * denote statistical significance at the 1% and 5% level, respectively. T-values are in parentheses.

Panel A

Granger-Causality Wald Test				
	Pre-2008 Crisis		*During-2008 Crisis*	
Group 1 Variable	*Chi-Square*	*Pr > ChiSq*	*Chi-Square*	*Pr > ChiSq*
Russell2000	1.29	0.5259	7.86	0.0970
MREIT	2.74	0.2535	15.33	0.0041
EREIT	2.26	0.3224	13.90	0.0076

Panel B

	Pre-2008 Crisis			*During-2008 Crisis*		
	Russell 2000	*MREIT*	*EREIT*	*Russell 2000*	*MREIT*	*EREIT*
Constant	0.00001	-0.00175	-0.00035	0.00000	-0.00003	-0.00029
	(0.01)	(-1.71)	(-0.45)	(0.00)	(-0.03)	(-0.18)
Russell2000(t-1)	-0.12053	-0.16151	-0.01840	0.03710	0.11684	0.17504
	(-1.60)	(-1.23)	(-0.19)	(0.42)	(1.24)	(1.28)
MREIT(t-1)	-0.03963	0.02277	-0.06755	0.03483	-0.07354	-0.00964
	(-1.09)	(0.36)	(-1.42)	(0.44)	(-0.89)	(-0.08)
EREIT(t-1)	0.04458	-0.00602	-0.06097	-0.10738	-0.21218**	-0.35711**
	(0.72)	(-0.06)	(-0.75)	(-1.56)	(-2.92)	(-3.38)
Russell2000(t-2)				-0.19788*	-0.16761	-0.29874*
				(-2.31)	(-1.85)	(-2.26)
MREIT(t-2)				-0.06519	-0.18347*	-0.26348*
				(-0.93)	(-2.47)	(-2.44)
EREIT(t-2)				0.13101*	0.14864*	0.22191*
				(1.97)	(2.11)	(2.17)

We employ the Russell 2000 small cap index (Russell2000) to represent the market of small cap firms and perform Granger causality tests and VARs with Russell2000, MREIT and EREIT. Table 26 reports the results of Granger causality tests in Panel A and VAR in Panel B. First examining the Granger causality tests in Panel A, we find that prior to the 2008 crisis there is no evidence that Russell2000, MREIT, or EREIT returns Granger cause the others. After the crisis, we find that MREIT and EREIT both Granger cause the group containing the other two variables. However, Russell2000 does not Granger cause the others. This result is not unexpected, given our previous finding that more focused real estate indices are less integrated with the market as a whole. Similarly, it appears that after the 2008 crisis, the Russell2000 is less integrated with the real estate market than is the CRSP value weighted index.

These results are confirmed in the VAR analysis in Panel B. In the Pre-2008 crisis period, there are no statistically significant relationships among the real estate and small cap market returns. After the crisis, EREIT returns influence Russell2000 returns with a two-day lag, significant at the 5% level. EREIT returns also influence MREIT returns with one- and two-day lags at 1% significance and 5% significance, respectively. EREIT returns are significantly related at the 5% level to 2-day lags of both Russell2000 and MREIT returns. The results in Table 26 provide further evidence supporting the notion that the real estate and stock markets have become more integrated since the 2008 financial crisis.

CONCLUSION

By examining the return linkages between the stock market and the real estate market, we investigate the effect the 2008 financial crisis had on the level of integration between these two markets. Although there is little evidence of integration prior to the crisis, we find strong levels of integration following the de-listing of Lehman Brothers. The results are robust to alternate methodologies (Granger-causality, VAR, state space) as well as alternate dates for the pre- and during- crisis periods and are consistent with recent findings of increases in REITs' systematic risk following the financial crisis. However, we do find that some focused regional/property type indices were less integrated with the stock market than the aggregate return indices. These pure play indices may provide a level of diversification, even when the stock market and real estate markets are integrated.

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Outstanding Doctoral Student in Finance, 2010-2011
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University Graduate Fellowship, 2010-2011
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PUBLICATIONS

Luchtenberg, Kimberly F., and Michael J. Seiler, "The Effect of Exogenous Information Signal Strength on Herding" Forthcoming in *The Review of Behavioral Finance.*

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