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Essays on liquidity risk, credit market contagion, and corporate cash holdings

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ESSAYS ON LIQUIDITY RISK, CREDIT MARKET CONTAGION, AND CORPORATE CASH HOLDINGS

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To my family who sacrificed the most for this study

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ABSTRACT

This thesis consists of three chapters and investigates the issues related to liquidity risk, credit market contagion, and corporate cash holdings. The first chapter is coauthored work with Professor Jay Sa-Aadu and Associate Professor Ashish Tiwari and is titled 'Market Liquidity, Funding Liquidity, and Hedge Fund Performance.' The second chapter is sole-authored and is titled 'Credit Market Contagion and Liquidity Shocks.' The third chapter is coauthored with Steven Savoy and titled 'Ambiguity Aversion and Corporate Cash Holdings.'

The first chapter examines the interaction between hedge funds' performance and their market liquidity risk and funding liquidity risk. Using a 2-state Markov regime switching model we identify regimes with low and high market-wide liquidity. While funds with high market liquidity risk exposures earn a premium in the high liquidity regime, this premium vanishes in the low liquidity states. Moreover, funding liquidity risk, measured by the sensitivity of a hedge fund's return to the Treasury-Eurodollar (TED) spread, is an important determinant of fund performance. Hedge funds with high loadings on the TED spread underperform low-loading funds by about 0.49% (10.98%) annually in the high (low) liquidity regime, during 1994-2012.

The second chapter provides evidence on credit market contagion using CDS index data and identifies the channels through which contagion propagates in credit markets. The results show that funding liquidity and market liquidity are significant channels of contagion during periods with widening credit spreads and adverse liquidity shocks. These results provide support for the theoretical model proposed by Brunnermeier and Pedersen (2009) according to which negative liquidity spirals can lead

to contagion across various asset classes. Furthermore, during periods with tightening credit spreads and positive liquidity shocks, the results indicate that a prime broker index and a bank index are important channels contributing to co-movement in credit spreads. This suggests that financial intermediaries play an important role in spreading market rallies across credit markets.

The third chapter investigates the link between investors' ambiguity aversion and precautionary corporate cash holdings. Investors' ambiguity aversion is measured by the proportion of individual investors in a firm's investor base who are hypothesized to be more ambiguity averse compared to institutional investors. We show that the value of cash holdings is negatively associated with the extent of ambiguity aversion in a firm's shareholder base for firms that are financially constrained. Our results also show that financially constrained firms with a higher proportion of ambiguity averse investors hold less cash. These results provide support for models in which ambiguity averse investors dislike the cash holdings of firms, that are held for precautionary reasons to fund long term projects, given that the returns on long term projects are ambiguous.

PUBLIC ABSTRACT

In this dissertation I explore the controversial issues related to liquidity risk, credit market contagion, and corporate cash holdings. The economic crisis of 2008 provided a dramatic illustration of the importance of liquidity and the risk of contagion in the economy. Researchers and practitioners have been studying the recent crisis to better understand the implications of such risks to avoid similar events in the future.

In the first chapter, we examine the interaction between hedge funds' performance and their market liquidity risk and funding liquidity risk. In normal circumstances, investors earn a premium by having exposure to market liquidity. We show that this premium vanishes during low market liquidity periods. Our results also show that funding liquidity is an important factor in hedge fund performance.

The second chapter explores the issues around financial contagion in credit markets. The recent crisis of 2008 started in the sub-prime mortgage market and extended to the whole economy. I provide evidence on the existence of contagion in U.S. credit markets and determine the channels through which the contagion propagates. My results show that liquidity is an important channel for contagion in credit markets.

The third chapter examines the cash holdings held by U.S. corporations. Cash holdings of U.S. companies have grown enormously in the recent decades. We explain this phenomenon from the perspective of investors. Our results show that firms with high level of ambiguity averse investors, or retail investors, hold less cash. We attribute the difference to the relatively higher ambiguity aversion of retail investors compared to institutional investors.

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CHAPTER 1: MARKET LIQUIDITY, FUNDING LIQUIDITY, AND HEDGE FUND PERFORMANCE

1.1 Introduction

The financial crisis of 2008 provided a dramatic illustration of the importance of liquidity in financial markets. In addition to this recent episode, a number of other prior events including the October 1987 market crash, the 1998 Russian debt crisis, and the 2007 Quant (hedge fund) Crisis have underscored the role of liquidity, or lack thereof, in market downturns.[1] Furthermore, the potential for negative liquidity spirals and the contagious nature of (il)liquidity across asset classes, can both magnify and prolong the severity of financial crises. For example, Brunnermeier and Pedersen (2009) develop a model that rationalizes the link between an asset's *market liquidity* reflecting the ease with which it can be traded, and traders' *funding liquidity* which reflects the ease/cost of obtaining funding. An important implication of the model is that negative liquidity spirals can arise under certain conditions. Specifically, according to the model, adverse funding shocks can lead to portfolio liquidations that hurt asset values and market liquidity, leading to increased margin requirements which could further depress market liquidity.

Hedge funds represent an increasingly important group of investors that are exposed to both *market liquidity* risk stemming from the relatively illiquid nature of their portfolio holdings, and *funding liquidity* shocks due in large part to their reliance on leverage. As a result, in the wake of several high profile hedge fund failures in recent years there is increasing concern among regulators and market participants about the

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[1] Examples of academic studies that discuss some of these episodes include Roll (1988), Brunnermeier (2009), Khandani and Lo (2007), and Billio, Getmansky, and Pelizzon (2010).

potential systemic risk posed by hedge funds.[2] In this study we examine the relation between the liquidity risk exposure of hedge funds and their performance, with a particular focus on the interaction between the funds' market liquidity risk and funding liquidity risk.[3] A key result of the present study demonstrates that funding liquidity risk as measured by the sensitivity of a hedge fund's return to a measure of market-wide funding costs, is an important determinant of hedge fund performance. Furthermore, funding liquidity risk plays a critical role in the variation of hedge fund illiquidity premia across liquidity regimes.

Our paper builds on the recent literature that examines the effects of liquidity risk on the performance of hedge funds. The paper provides an explicit link between hedge fund performance and the state of liquidity in the economy that is related to a similar finding by Sadka (2010) who documents that funds with high market liquidity risk loadings, on average, outperform low-loading funds. However, this paper goes further in showing that the premium enjoyed by high market liquidity risk loading funds is state dependent. Specifically, the premium vanishes in low liquidity states because of the importance of liquidity spirals emanating from negative shocks to funding liquidity. The paper also extends the results documented by Khandani and Lo (2011) who provide evidence of time variation in hedge fund illiquidity premia during the period 1998-2006. In this context, we use a regime switching model to identify states with high and low market liquidity and find that having a high exposure to funding liquidity risk adversely

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[2] See, for example, GAO report number GAO-08-200 entitled *'Hedge Funds: Regulators and Market Participants Are Taking Steps to Strengthen Market Discipline, but Continued Attention Is Needed'* dated February 25, 2008.

[3] Drehmann and Nikolaou (2013) define funding liquidity risk as the possibility that over a particular horizon a financial intermediary will be unable to "settle obligations with immediacy."

impacts hedge fund performance. Importantly, the adverse impact of funding liquidity risk is particularly pronounced during the low market liquidity regime – a finding that is consistent with the Brunnermeier and Pedersen (2009) framework. Our results highlight the role of the interaction between market and funding liquidity in determining the dynamics of hedge fund liquidity premia. The results regarding the interaction between market and funding liquidity are broadly consistent with the findings of Aragon and Strahan (2012) who document that stocks held by Lehman Brothers' hedge fund clients experienced unexpectedly large declines in market liquidity after Lehman's bankruptcy in 2008. Our findings also complement those of Boyson, Stahel, and Stulz (2010) who find that shocks to asset liquidity and funding liquidity increase the probability of contagion across hedge fund styles.

The characteristic nature of hedge fund strategies makes them particularly susceptible to adverse shocks to aggregate market liquidity conditions. For example, relative value strategies require sufficient liquidity in the underlying asset markets for the strategy to profit from the (eventual) convergence in asset values. Fixed income arbitrage strategies exploit mispricing of fixed income securities; however such opportunities often tend to be concentrated in illiquid securities. Consequently, the performance of such strategies is sensitive to changes in liquidity conditions. Similarly, emerging market strategies target less mature markets which tend to be relatively illiquid. Event driven strategies are also sensitive to aggregate market liquidity as they typically rely on the ability to execute trades quickly, and in sufficient volume, in order to exploit opportunities surrounding corporate events. Hedge funds as a group also employ a relatively high degree of leverage. This renders them particularly vulnerable to changes in funding liquidity conditions, i.e., changes in the cost or ease with which they may obtain funding to support their positions.

In order to explore the link between liquidity risk and hedge fund performance, we first identify hedge funds' market liquidity exposure across different liquidity regimes using a sample of hedge funds from the Lipper TASS hedge fund database. A number of recent studies have emphasized the systematic nature of the risk posed by market-wide liquidity fluctuations (see, e.g., Chordia, Roll, and Subrahmanyam (2000)). Using various measures of market-wide liquidity, Pástor and Stambaugh (2003), Acharya and Pedersen (2005), and Sadka (2006) provide evidence that systematic liquidity risk is priced in the cross section of asset returns. Furthermore, Sadka (2010) shows that most hedge fund strategies exhibit significant exposure to a market-wide liquidity factor. Moreover, as discussed above, recent market episodes suggest that market liquidity conditions can change dramatically over time with adverse implications for asset values during periods of low liquidity. Accordingly, we use market-wide liquidity measures and a 2-state Markov regime switching model to identify periods with high and low liquidity. We identify market liquidity regimes using both the Pástor and Stambaugh (2003) liquidity measure as well as the Sadka (2006) permanent (variable) price impact liquidity measure. We show that while most hedge fund strategies exhibit positive loadings on the market liquidity factor in the *high liquidity* regime, they appear to decrease their liquidity exposure in the *low liquidity* regime.

One explanation for the variation in the market liquidity betas of hedge funds across the high and low liquidity regimes is that they are able to successfully time market-wide liquidity changes (see, for example, Cao, et al. (2013)). Another possibility is that binding funding constraints during periods of low liquidity lead to forced liquidations of assets, thereby lowering the funds' liquidity betas during such periods. To investigate this issue we follow Sadka (2010) who documents that funds with high market liquidity risk loadings outperform low-loading funds by about 6% per year on average during 1994-2008, based on the Fung and Hsieh (2004) 7-factor model. We use a similar research design to examine the performance of hedge funds across the two liquidity regimes during the period 1994-2012. Our analysis is based on the funds' alphas computed with respect to the Fung-Hsieh 8-factor model that incorporates an emerging markets factor in addition to the original seven factors included in the Fung-Hsieh (2004) model. We find that funds with high market liquidity risk loadings outperform low-loading funds by about 6.15% annually during the *high* liquidity regime. However, the performance difference between the high- and low-liquidity loading funds is -10.38% during the *low* liquidity regime. These results suggest that hedge funds may not be entirely successful in timing liquidity changes – particularly during periods of low liquidity.

Further analysis of the performance of the market liquidity sorted portfolios shows that their alphas and the average monthly returns display an upward trend across the liquidity beta-sorted deciles in the high liquidity regime. On the other hand, in the low liquidity regime, the performance of hedge funds monotonically declines as the funds' exposure to market liquidity increases. The latter result hints at the potential role played by funding liquidity during the low liquidity regime. In particular, it suggests that liquidity spirals originating via shocks to funding liquidity could potentially lead to a negative relation between hedge fund returns and market liquidity during crisis periods.

To investigate this issue we next explore the relation between hedge fund performance and funding liquidity. We employ the TED spread, i.e., the spread between the three-month LIBOR rate and the three-month U.S. Treasury bill rate, as a proxy measure of funding liquidity.[4] We measure a hedge fund's funding liquidity risk as the sensitivity of the fund's returns to the TED spread using a regression specification that incorporates the market index return in addition to the TED spread. Our results show that the hypothetical high-minus-low *funding liquidity* risk portfolio strategy earns an annualized 8-factor alpha of -0.49% in the high market liquidity regime during the period 1994-2012. Interestingly, the strategy's performance is negative even in the high market liquidity state, compared to a performance of 6.15% for a similar strategy based on *market liquidity* sorted portfolios as mentioned earlier. Furthermore, the strategy has an annualized alpha of -10.98% in the low liquidity regime. These results show that a high funding liquidity risk exposure is detrimental to hedge fund returns, especially during the low market liquidity state and there is no premium associated with funding liquidity risk in the high liquidity regime.

We further examine the role of the interaction between funding liquidity and market liquidity in determining the performance of hedge funds. We double-sort funds into quintiles based on their market liquidity and their funding liquidity exposures and examine the performance of the resulting 25 (5x5) fund portfolios. The results suggest that, in general, high funding liquidity exposure is detrimental to fund performance across

[4] The TED spread is a commonly used measure of funding liquidity in the literature (e.g., Boyson, Stahel, and Stulz (2010), and Teo (2011))).

all market liquidity quintiles. As expected, the adverse impact of a high funding liquidity exposure is particularly pronounced during the low market liquidity regime.

Finally, we examine whether share restrictions in the form of lockup periods allow hedge funds to manage the investor flow-related funding liquidity risk. Our results suggest that longer lockup periods are effective only in the high liquidity states in terms of their ability to mitigate the flow-induced funding liquidity risk. On the other hand, lockup period restrictions do not help improve fund performance in the low liquidity state.

Collectively, our results provide evidence of the role of funding liquidity risk in explaining the performance of hedge funds. The results are supportive of the Brunnermeier and Pedersen (2009) theoretical model that rationalizes the link between market liquidity and funding liquidity. Their model suggests that market liquidity and funding liquidity shocks could be mutually reinforcing which leads to liquidity spirals under certain conditions. We document that hedge fund returns are the highest (lowest) for the funds with high (low) market liquidity exposure and low (high) funding liquidity exposure. We also show that high exposure to market liquidity does not by itself guarantee that a hedge fund can successfully capture the associated liquidity premium. In particular, we document the poor performance of funds with high exposures to both market liquidity as well as funding liquidity. This result highlights the risks of being exposed to funding liquidity shocks. Funds that are sensitive to funding liquidity shocks are likely to engage in asset fire sales when faced with margin calls, for example, leading to their poor performance.

Our paper is related to a number of prior studies that examine the role of market liquidity in the context of hedge fund performance. Using estimated return autocorrelations as a measure of illiquidity, Khandani and Lo (2011) document average illiquidity premia ranging from 2.74% to 9.91% per year for various hedge funds and fixed income mutual funds. They also examine the time variation in the hedge fund illiquidity premia during the period 1998-2006 and find that funds with the most illiquid assets suffered the most during the second half of 1998 – a period that witnessed the Long-Term Capital Management (LTCM) crisis. However, during the subsequent "normal" periods the realized illiquidity premia increased. As noted above, Boyson, Stahel, and Shulz (2010) document that large, adverse shocks to market and funding liquidity increase the probability of contagion across hedge fund styles. Their study focuses on return co-movements in the left tails of the return distributions for various hedge fund styles. Reca, Sias, and Turtle (2014) also focus on the tails of the hedge fund return distributions and document that liquidity shock-induced contagion is not the primary factor driving the correlation across hedge fund styles. This suggests that hedge fund returns at the extreme tails may be driven by other factors, in addition to liquidity shocks.[5] By contrast, rather than focusing on the tails of hedge fund return distributions, in this study our objective is to analyze the impact of market and funding liquidity risk on hedge fund performance in different liquidity regimes that are endogenously determined.

[5] Reca, Sias, and Turtle (2014) conclude that the prior evidence of liquidity shock induced contagion (e.g., Boyson, Stahel, and Stulz (2010), and Dudley and Nimalendran (2011)) is largely explained by model misspcification and time-varying market volatility.

This framework allows us to explicitly focus on the dynamics of hedge fund illiquidity premia, and in particular on the interaction between market and funding liquidity.

The rest of the paper is organized as follows. Section 1.2 describes the data. Section 1.3 outlines the Markov regime switching model employed in the analyses. Section 1.4 documents the liquidity exposures of hedge fund strategies in different regimes. Section 1.5 analyzes the performance of liquidity risk-sorted portfolios in the high and low liquidity regimes. Section 1.6 provides further evidence on the impact of market liquidity and funding liquidity on hedge fund performance. Section 1.7 analyzes the impact of lockup restrictions on the performance of funding liquidity risk-sorted fund portfolios in the two liquidity regimes, while Section 1.8 concludes.

1.2 Data

This section describes the sample of hedge funds, the Fung and Hsieh factors, and the liquidity factors employed in the empirical analysis.

1.2.1 Hedge Fund Sample

Our sample of hedge funds is obtained from the Lipper TASS database. The original sample extends from January 1994 to May 2012. The Lipper TASS database includes hedge fund data from the following vendors: Cogendi, FinLab, FactSet (SPAR), PerTrac, and Zephyr.

It is well known that hedge fund data suffer from a number of biases. In order to address the backfilling bias we delete the first 24 observations of a fund. Another common bias in hedge fund data is the survivorship bias. To guard against this issue we restrict our sample to the post–1994 period during which “graveyard” funds are retained in the Lipper TASS database. We restrict our sample to funds with at least 24 months of consecutive return observations. Only funds that report their returns on a monthly basis and net of all fees are included and a currency code requirement of "USD" is imposed. All returns are expressed in excess of the risk-free rate. In addition, we unsmooth hedge fund returns following the procedure recommended by Getmansky, Lo, and Makarov (2004). We include hedge funds in the following investment styles: convertible arbitrage, dedicated short bias, emerging markets, equity market neutral, event driven, fixed income arbitrage, fund of funds, global macro, long/short equity hedge, managed futures, and multi strategy. The final sample includes 5,599 funds.

Table 1.1 reports summary statistics for the sample described above. Panel A reports statistics (number of funds, average monthly return, standard deviation, skewness, and excess kurtosis) for all sample hedge funds. The figures within a category are equally weighted averages of the statistics across the funds. The cross-sectional average monthly excess return and the average standard deviation are 29 basis points and 4.26%, respectively. As may be seen, the sample funds have negatively skewed returns and thick tails in the return distributions.

Panel B reports the statistics by investment style. The Dedicated short bias category exhibits the lowest performance among all strategies, at -25 basis points. The average monthly performance of the Fund of Funds strategy is 10 basis points, which is low compared to other investment styles. The multiple fee structure in this category contributes to its low performance. Most of the investment styles display negative skewness. The fixed income arbitrage strategy exhibits the highest kurtosis, which is largely influenced by the Russian debt crisis in 1998 – an episode that famously led to the collapse of the fund, Long Term Capital Management (LTCM).

1.2.2 Fung and Hsieh Factors

The Fung and Hsieh (2004) seven-factor model is widely used in the literature modeling hedge fund performance. The domestic equity factors used in the model are the excess return on the CRSP value-weighted index and the Fama-French size factor. The fixed-income factors are the change in the term spread (the difference between the 10-year Treasury constant maturity yield and Treasury bill yield) and the change in the credit spread (Moody's Baa yield minus 10-year Treasury constant maturity yield). The model also includes three factors designed to mimic trend following strategies employed by certain hedge funds that trade in bond (PTFSBD), commodity (PTFSCOM), and currency (PTFSFX) markets. Recently, Fung and Hsieh have added an eighth factor to the model, namely, the emerging market factor (MSCI emerging market index). We compute fund alphas based on the 8-factor model with the above factors.

Table 1.2 (Panels A to D) displays the summary statistics for the Fung and Hsieh factors. Most notably, the trend-following factors have the highest standard deviations with negative average returns, which confirms the riskiness of these strategies. The credit spread factor has the highest kurtosis which indicates the widening in credit spreads during crises periods.

1.2.3 Liquidity Factors

Liquidity is an important factor affecting asset prices. However, there are several dimensions to liquidity and it is not easily captured by a single measure. There has been several liquidity proxies proposed in the literature. In this study we employ three liquidity measures: the Pástor and Stambaugh (2003) liquidity factor, the Sadka (2006) permanent-variable measure, and the 3-month TED spread.[6]

The Pástor and Stambaugh (2003) and Sadka (2006)[7] liquidity factors are measures of *market liquidity* which is typically defined as the ability to trade large quantities quickly, at low cost, and without moving the price. On the other hand, the TED spread is a measure of *funding liquidity* which essentially reflects the ability to borrow against a security. The TED spread is calculated as 3-month US LIBOR minus 3-month Treasury yield. Since this is a measure of illiquidity, to be consistent with the other two measures, we add a negative sign to make it a liquidity measure for which a positive shock represents an enhancement to (funding) liquidity.

There is no consensus on how liquidity should be measured. The three measures mentioned above measure different aspects of liquidity. As noted, while the TED spread is a measure of funding liquidity, the Pástor and Stambaugh (2003) and the Sadka (2006) measures reflect market liquidity. However, the Pástor and Stambaugh (2003) and Sadka (2006) measures capture different facets of market liquidity. The Pástor and Stambaugh (2003) measure focuses on an aspect of market liquidity associated with temporary price reversals induced by order flow. By contrast, Sadka's (2006) measure is related to permanent price movements induced by the information content of a trade.

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[6] For examples of other liquidity measures employed in the literature, see Amihud (2002), Acharya and Pedersen (2005), and Getmansky, Lo, and Makarov (2004). Kruttli, Patton, and Ramadorai (2013) construct a measure based on the illiquidity of hedge fund portfolios and show that it has predictive ability for asset returns.

[7] We thank Lubos Pástor and Ronnie Sadka for making the liquidity factors available.

Panel E of Table 1.2 exhibits the summary statistics for the three liquidity measures. All three measures display negative skewness and high excess kurtosis, which is more pronounced for the TED spread. It is of interest to examine the interactions among the factors discussed above. In Table 1.3, we display the pairwise correlations among the factors used in this study. The correlations of the three liquidity factors with the other factors are low in general. The only notable correlation is between the various liquidity factors and the credit spread: -0.27, -0.45, and -0.36 for the Pástor Stambaugh (2003) measure, the TED Spread, and the Sadka (2006) measure, respectively. This shows that credit conditions worsen during periods of low liquidity. Also note that although both the Pástor and Stambaugh (2003) and the Sadka (2006) liquidity factors are measures of market liquidity, the correlation between the two measures is quite low at 0.08. This confirms that these factors measure different aspects of market liquidity.

1.3 Methodology

The purpose of this paper is to study the relationship between the liquidity exposure of hedge funds and their performance. However, hedge funds often employ dynamic strategies which they adjust depending on the state of the economy and trade a variety of financial securities with non-linear payoffs, including equity and fixed income derivatives. On the other hand, liquidity is a factor which has state-dependent impact on funds' performance. While hedge funds enhance their returns when liquidity is abundant, their performance suffers with negative liquidity shocks. Sadka (2010) shows that hedge funds that significantly load on market liquidity risk outperform low-loading funds by 6% per year, on average. Focusing on the nine months of the recent financial crisis

(September-November 1998, August-October 2007, and September-November 2008), he also shows that the performance of this strategy is negative during the crisis period.

In this study, we employ a 2-state Markov regime switching model[8] to endogenously identify the different liquidity regimes. The regimes are identified based on the liquidity factors. Our simple regime switching model for the liquidity factor is given below:

$$L_t = \mu_{S_t} + \varepsilon_t \tag{1.1}$$

$$\varepsilon_t \sim \mathrm{N}\left(0, \sigma_{S_t}^2\right),$$

where L_t is the liquidity factor, and S_t is a 2-state Markov chain with transition matrix, Π_s:

$$\Pi_s = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix},$$

where p_{ij} denotes probability of transitioning from state *i* to state *j*. Note that the model has two key regime-specific parameters; the mean, μ_{S_t}, and the variance, $\sigma_{S_t}^2$.

We determine the high and low liquidity regimes based on a particular liquidity factor by estimating the model using maximum likelihood. The model provides us with a time series of filtered probabilities for each state. For each month in the sample period, the estimated filtered probabilities for the two states add up to one. The state with the highest filtered probability is identified as the state of the economy for that month. Accordingly, based on the 2-state model, the state with filtered probability higher than 50% in a given month is identified as the state of the economy for that particular month.

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[8] Markov regime switching models are widely used in the literature, e.g., Hamilton (1989, 1990), Ang and Bekaert (2002), Bekaert and Harvey (1995), Guidolin and Timmermann (2008), and Gray (1996).

Table 1.4 displays the estimation results of the 2-state Markov regime switching model based on the Pástor and Stambaugh (2003) liquidity measure and the Sadka (2006) liquidity measure. Panel A exhibits the mean estimate of the liquidity factors for the high and low liquidity regimes. Panel B displays the expected duration for the high and low liquidity regimes. Panel C reports the transition matrices. Note that regardless of the liquidity measure employed, the high liquidity regime is more persistent and has a longer duration compared to the low liquidity regime. We also note that the low liquidity regime identified by the model based on both the Pástor and Stambaugh (2003) liquidity measure and the Sadka (2006) liquidity measure includes the three recent liquidity crises considered in Sadka (2010).

1.4 Market Liquidity Exposures of Hedge Fund Strategies in Different Regimes

In this section, we examine the market liquidity risk exposures and the performance of different hedge fund categories across different liquidity regimes. We start our analyses by sorting hedge funds into 11 portfolios corresponding to the investment styles listed in Section 1.2.1. We then identify the regimes based on estimates of the 2-state Markov model.[9] For each of the two regimes we regress the investment style portfolio excess returns on the eight Fung and Hsieh factors and the Pástor and Stambaugh (2003) liquidity factor as shown in the model below:

$$R_t^P - r_{f,t} = \alpha_s^P + \sum_{k=1}^{9} \beta_{k,s}^P F_{k,t} + \varepsilon_t^P, \qquad s = H, L \tag{1.2}$$

[9] In this section we identify liquidity regimes based on the Pástor and Stambaugh (2003) liquidity factor.

where R_t^P is the investment style portfolio return and $r_{f,t}$ is the risk free rate at time t. The subscript s denotes the high and low liquidity regimes. In the above specification, we incorporate 9 factors. These include the eight Fung and Hsieh factors discussed above and the Pástor and Stambaugh (2003) liquidity factor.

In a similar context, Sadka (2010) reports positive and significant loadings on his liquidity factor for most investment style portfolios without considering the effect of different liquidity regimes. As we noted in Section 1.3, hedge funds' liquidity exposure behaves differently in different states of the economy. Therefore, we examine the changes in hedge funds' liquidity exposure in high and low liquidity regimes identified by the 2-state Markov regime switching model.

Table 1.5 reports the regression results. As Sadka (2010) noted, market liquidity loading varies across investment styles. In the high liquidity regime, only the Dedicated Short Bias strategy has negative market liquidity loading, all other investment styles have positive loadings. However, in the low liquidity regime most investment styles have negative market liquidity loadings. Importantly, note that the market liquidity exposure of the investment style portfolios is lower in the low liquidity regime for all investment styles.[10] Although some of the results are statistically insignificant, they are directionally consistent. The reduction in market liquidity loading in the low liquidity regime might stem from one of two scenarios: either hedge funds successfully lower their liquidity

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[10] As a robustness test, we repeat the results in Table 1.5 by employing Sadka's (2006) liquidity factor in the regression specified in Equation (1.2) as well as in the identification of the liquidity regimes. We find that 7 of the 12 investment style portfolios exhibit lower liquidity exposure in the low liquidity regime versus the high liquidity regime. The 7 investment styles include the convertible arbitrage, emerging markets, equity market neutral, event driven, fixed income arbitrage, global macro, and long/short equity hedge strategies.

exposures during liquidity crises as suggested by the findings of Cao, et al. (2013), or alternatively, they are forced to liquidate their holdings involuntarily to meet funding requirements during such periods. Note that nine out of eleven hedge fund strategies exhibit a lower alpha in Table 1.5 during the low liquidity regime (the two exceptions being the Emerging Markets and the Long/Short Equity Hedge categories). This result hints at the possibility that hedge funds are at best only partially successful in attempting to time their market liquidity exposure. While their market liquidity exposure is indeed lower in the low liquidity regime, their performance is also generally lower in the low liquidity regime. To further investigate this issue we analyze the performance of liquidity beta-sorted portfolios in the high and low liquidity regimes in the next section.

1.5 Compensation for Market Liquidity Risk in High and Low Liquidity Regimes

After documenting the market liquidity exposure of investment style portfolios across different liquidity regimes in the previous section, we now focus on the pricing of market liquidity risk using liquidity sorted portfolios. We first estimate the market liquidity loading of each hedge fund by regressing the fund returns on the market excess return and the liquidity factor during the prior 24-month period:

$$R_t^i - r_{f,t} = \alpha_t^i + \beta_m^i R_t^m + \beta_L^i L_t + \varepsilon_t^i, \tag{1.3}$$

where R_t^i is a fund's return in month t, $r_{f,t}$ is the risk free rate, R_t^m is the market excess return, and L_t is Sadka's (2006) liquidity factor for month t.

The first set of estimates is obtained using the data for the two-year period prior to January 1996. We only include funds with at least 18 months of non-missing observations. We then sort hedge funds into 10 portfolios based on their estimated market liquidity exposures, β_L^i, from the two factor regression described above with equal number of funds in each decile. We implement this process on a rolling basis each month from January 1996 to May 2012. Funds are kept in the deciles for one month. Following this procedure we obtain a time series of portfolio returns for each of the ten market liquidity deciles.

The purpose of this exercise is to compare the performance of the high market liquidity loading portfolio to the low market liquidity loading portfolio for different states of the economy, namely for the high and low liquidity regimes. To do this we follow a strategy that takes a long position in the high market liquidity decile portfolio and a short position in the low market liquidity decile portfolio. The performance of the strategy is evaluated using the Fung-Hsieh 8–factor model described below:

$$R_t^D - r_{f,t} = \alpha_s^D + \sum_{k=1}^{8} \beta_{k,s}^D F_{k,t} + \varepsilon_t^D \,,\; s = H, L\,, \tag{1.4}$$

where R_t^D is the liquidity decile portfolio return and $r_{f,t}$ is the risk free rate during month time t. The subscript s denotes the high and low liquidity regimes. In the above specification, we incorporate the 8 Fung-Hsieh factors described previously in Section 1.2.2. However, two of the Fung and Hsieh factors, namely, the change in the term spread and the change in the credit spread, are non-traded factors. We replace these two factors by the returns to tradable portfolios so that the intercept or the alpha of the model represented by Equation (1.4) can be interpreted as an excess return. As a proxy for the term spread we use the return difference between Barclay's 7-10 year Treasury Index and the one-month Treasury bill rate. Similarly, we employ the return difference between

Barclay's 7-10 year Corporate Baa Index and the Barclay's 7-10 year Treasury Index as a proxy for the credit spread.

Sadka (2010) documents that, on average, the high liquidity-loading funds outperform low liquidity-loading funds by about 6% annually. However, as noted earlier, hedge funds' performance might suffer during the low liquidity states. In this section we analyze the performance of the high-minus-low liquidity strategy in different states of the economy. For this part of the analysis we identify liquidity regimes using the 2-state Markov model estimated based on the liquidity measure. Table 1.6 displays the results. Panel A of the table reports the performance statistics (the Fung-Hsieh eight factor alpha and the average monthly excess return) of the decile portfolios and the high-minus-low liquidity strategy for the entire sample during the period January 1994 to May 2012. The high-minus-low liquidity beta strategy earns an annualized alpha of 4.09% and average annualized excess return equal to 3.66%.[11] Panel B of Table 1.6 exhibits the results for the high liquidity regime in which the Fung-Hsieh alpha and the average monthly excess return for the high-minus-low portfolio are 6.15% and 5.50%, respectively. However, as shown in panel C of the table, in the low liquidity regime the high-minus-low portfolio performance measures are much lower: annualized alpha of -10.38% and annualized excess return equal to -4.79%.[12] Furthermore, comparing the alphas reported in Panels B

[11] The 6% alpha reported by Sadka (2010) is calculated for the period 1994 to 2008 using the Fung and Hsieh (2004) 7-factor model. In our analyses that cover the period 1994 to 2012 we employ the Fung and Hsieh eight-factor model that includes the emerging market factor in addition to the original Fung and Hsieh (2004) 7 factors.

[12] Most performance measures in the low liquidity regime are statistically insignificant due to the small number of observations in this regime.

and C, we can see that with the exception of the lowest liquidity beta decile portfolio, the estimated alphas are consistently lower in the low liquidity state.[13]

The above results are graphically displayed in Figure 1.1. The figure plots the performance statistics for the liquidity beta-sorted decile portfolios for the whole sample (Panel A) as well as for the high liquidity regime (Panel B) and the low liquidity regime (Panel C). Note that in Panels A and B, the fund alphas and the average monthly excess returns increase monotonically across the market liquidity beta deciles. However, this is not the case in the low liquidity regime as shown in Panel C of the figure. In the low liquidity regime, the performance of hedge funds monotonically declines as the funds' exposure to market liquidity increases.

These results show that the liquidity premium is nonexistent in the low liquidity state. While hedge funds enjoy favorable performance when market liquidity is abundant, their performance suffers when market liquidity dries up. This is consistent with the view that the profitability of many hedge fund strategies seeking to exploit mispricing of securities is sensitive to market liquidity conditions. In periods of low liquidity, asset prices may fail to converge to fundamental values leading to the poor performance of many convergence/arbitrage trading strategies.

In section 1.4, we documented that the hedge funds reduce their market liquidity exposure in the low liquidity regime. The evidence presented in Table 1.6 confirms that the performance of liquidity beta-sorted hedge fund portfolios is significantly lower during the low liquidity state. This suggests that the reduction in hedge funds' market

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[13] The lowest liquidity beta decile portfolio (Portfolio 1) has strongly negative liquidity exposures in both the high liquidity state (liquidity beta = -4.08), and the low liquidity state (liquidity beta = -2.42).

liquidity exposure during periods of liquidity crises is not due to successful liquidity timing, but rather due to involuntary liquidation of assets, possibly in order to meet funding requirements. Such forced liquidations could potentially explain the significantly lower performance in the low liquidity states. Collectively, these results help extend the earlier findings of Cao, et al. (2013) and provide a more nuanced view of the liquidity timing ability of hedge funds. In particular, our results suggest that hedge funds are not entirely successful in timing liquidity changes – particularly during periods of low liquidity.

Furthermore, our results also strongly hint at the potential role played by funding liquidity during the low liquidity regime. In particular, they suggest that liquidity spirals originating via shocks to funding liquidity could potentially lead to a negative relation between hedge fund returns and market liquidity during crisis periods. We investigate the role of funding liquidity in more detail in the next section.

1.6 Market Liquidity and Funding Liquidity

The liquidity measure employed in the previous section is a measure of *market liquidity* which is the ability to trade large quantities quickly, at low cost, and with low price impact. A different aspect of liquidity is *funding liquidity* which reflects the ease with which a fund may obtain funding by borrowing against a security. As we have shown in the earlier sections, hedge funds with high exposure to market liquidity outperform low-loading-funds during the high liquidity regime. In this section we analyze the performance of the high-minus-low liquidity beta strategy in the context of funding liquidity exposure. As mentioned earlier, we employ the TED spread as a proxy for funding liquidity. We estimate the funding liquidity exposures in a framework in which hedge fund returns are regressed on the market excess return and the funding liquidity measure, the TED spread. Subsequently, we form the funding liquidity decile portfolios following the same procedure employed in Section 1.4.

Table 1.7 reports the eight-factor Fung and Hsieh alpha and the average monthly excess returns for the funding liquidity deciles, as well as for the high-minus-low funding liquidity beta portfolio. Panel A displays the results for the whole sample. Panels B and C of the table report the results for the high and low liquidity regimes, respectively. In order to enable a direct comparison with the results documented in Table 1.6, we determine the regimes using the Sadka (2006) liquidity measure. For the entire sample, over the period January 1994 to May 2012, the high-minus-low liquidity beta strategy earns an annualized alpha of -1.49% with an average annual excess return equal to -0.66%. Note that in contrast to the results reported in Table 1.6 for *market liquidity* beta sorted portfolios, the performance of the high-minus-low strategy based on *funding liquidity* beta sorted portfolios is negative. It is evident that the funds with high exposure to funding liquidity underperform funds with low funding liquidity exposure. This result highlights the importance of funding liquidity risk exposure in the performance of hedge funds especially when the state of liquidity in the economy is already low.

In panels B and C of Table 1.7 we report the results for the two liquidity regimes. In the high liquidity state, the strategy's annualized Fung and Hsieh alpha and the annual average excess returns are -0.49% and 0.01%, respectively. However, in the low liquidity state the results are dramatic: an annualized alpha of -10.98% and annualized average excess return of -3.82%. These results show that while funding liquidity exposure hurts hedge fund performance in general, its impact is severe in the low liquidity regime. One of the reasons for this poor performance is the fact that hedge funds typically employ high leverage which magnified the impact of the recent crises on their performance. When combined with high exposure to funding liquidity, highly levered hedge funds suffered when they faced margin calls in periods of low liquidity.

Note that unlike the results related to market liquidity beta sorted strategy presented in Table 1.6, the performance of the high-minus-low funding liquidity strategy, measured as the eight factor alpha, reported in Table 1.7 is negative in both liquidity regimes. Clearly, there is no risk premium associated with funding liquidity risk. This is perhaps not surprising given that funding liquidity risk, in contrast to market liquidity risk, is not considered to be a systematic (non-diversifiable) risk.

Next, we graphically display the results reported in Table 1.7. Figure 1.2 depicts the Fung and Hsieh alphas and the average excess returns across the funding liquidity deciles. Panel A of the figure shows that hedge funds' performance slightly declines as their funding liquidity exposure increases, for the entire sample period. On the other hand, the performance trends depicted in Panel B are approximately flat. This suggests that funding liquidity exposure does not significantly impact hedge fund performance in the high liquidity regime. However, as seen in Panel C, hedge funds with high finding liquidity exposure significantly underperform the funds that have low exposure to funding liquidity risk.

Since funding liquidity conditions and market liquidity measures are positively correlated, it would be useful to isolate the impact of funding liquidity risk that is orthogonal to market liquidity.[14] To this end, we project the TED spread on the market liquidity measure (i.e., the Sadka (2006) liquidity factor) and use the orthogonal component to compute the funding liquidity betas and form liquidity beta sorted portfolios. We display the performance of the new liquidity decile portfolios in Table 1.8. Note that the performance of the high-minus-low liquidity strategy is negative across the board for both performance measures. Therefore, our results are robust to the use of the orthogonal component of the TED spread as a measure of funding liquidity.

1.6.1 Liquidity Spirals

In the model considered by Brunnermeier and Pedersen (2009), under certain conditions market liquidity and funding liquidity are mutually reinforcing which creates liquidity spirals. In the model an adverse shock to speculators' funding liquidity forces them to lower their leverage and reduce the liquidity they provide to the market, which in turn leads to diminished overall market liquidity. When funding liquidity shocks are severe, the decrease in market liquidity makes funding conditions even more restrictive, which leads to a liquidity spiral. We investigate the implications of their model in this section.

In Tables 1.6 and 1.7, we documented the average excess returns of hedge funds and the fund alphas for each liquidity decile portfolio based on market liquidity and funding liquidity exposure, respectively. We now jointly consider the two liquidity scenarios and display the fund alphas in a two-way matrix in Table 1.9. The table shows

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[14] The Pearson correlation coefficient between the Sadka (2006) liquidity factor and the TED spread is 0.40.

the fund alphas for a total of 25 (5x5) portfolios. Note that we divide the sample of hedge funds into quintiles (rather than deciles) based on both the market and funding liquidity betas, in order to obtain a sufficient number of hedge funds in each portfolio. Panel A (B) displays the results for the high (low) liquidity regime. Along with the performance of each of the 25 portfolios, the performance of the high-minus-low liquidity beta strategy is also reported.

It is clear from Panel A that in the high liquidity regime, the fund alphas are generally the highest for funds with a high market liquidity exposure. On the other hand, the lowest alpha is recorded by funds with low market liquidity exposure and high funding liquidity exposure.[15] Also note that the performance of the high-minus-low *market liquidity* strategy is positive across each of the funding liquidity quintiles, ranging from 4.58% to 9.13% per year. However, the performance of the high-minus-low *funding liquidity* strategy is negative in three of the five market liquidity quintiles as shown in Table 1.9, ranging from -3.38% to 2.08% per year. This shows that while having high exposure to market liquidity helps hedge funds in the high liquidity regime, exposure to funding liquidity hurts hedge fund performance.

Panel B of Table 1.9 displays the results for the low liquidity regime. First, note that most of the alphas of the 25 portfolios are negative and generally lower compared to their corresponding alphas in the high liquidity regime. The performance of the high-minus-low *funding liquidity* strategy is strikingly lower in the low liquidity regime with the worst performance at -11.63% per year. Further, in contrast to Panel A, the market

[15] In unreported results we confirm that a similar pattern holds for monthly excess returns of hedge fund portfolios.

liquidity strategies also perform poorly in the low liquidity regime. The performance of the high-minus-low *market liquidity* strategy is negative in four of the five funding liquidity quintiles, ranging from -4.31% to 0.94% per year. This shows that funding liquidity risk is the primary driver of hedge fund performance in the low liquidity state.

Next, we graphically display the fund alphas for the high and low liquidity regimes in Figures 1.3 and 1.4, respectively. Figure 1.3 shows that in the high liquidity regime, funds with high exposure to market liquidity have higher alphas. Moreover, funds with high exposure to funding liquidity and low exposure to the market liquidity perform poorly in the high liquidity regime. On the other hand, Figure 1.4 shows that in the low liquidity regime, funds with low exposure to funding liquidity perform better regardless of the level of market liquidity exposure. Similarly, the funds with high exposure to funding liquidity perform poorly regardless of the level of market liquidity exposure.

Figures 1.3 and 1.4 demonstrate that hedge fund performance varies significantly across different quintiles of market and funding liquidity which shows that market liquidity and funding liquidity impact hedge fund performance differently. Under certain market conditions, reflected in the low liquidity regime, the two liquidity characteristics mutually reinforce each other. Note that in Figure 1.4, the worst performance is obtained when exposure to funding liquidity and market liquidity is the highest. These results provide support for a key prediction of the Brunnermeier and Pedersen (2009) model.

1.6.2 Discussion

Our results regarding the significance of funding liquidity risk exposure, and the mutually reinforcing impact of funding liquidity risk and market liquidity risk in the low liquidity regime, have important implications for understanding the dynamics of hedge fund performance. In contrast to mutual funds, most hedge fund strategies invest in relatively illiquid assets and employ significant leverage. This makes them particularly vulnerable to adverse shocks to funding liquidity conditions as evidenced by the above results that highlight the key role played by funding liquidity risk exposure. These results also have broader implication in the context of the evolving market environment. During the past decade, non-traditional intermediaries like hedge funds and proprietary trading desks of banks have come to play an increasingly prominent role – as liquidity suppliers and counterparties in transactions in several markets. In recent years hedge funds have also become important participants in several less developed financial markets. In contrast to traditional market makers or banking intermediaries that face mandatory capital requirements, hedge funds are largely unregulated. Further, as highlighted by the events of August 2007 when a number of hedge funds employing quantitative strategies suffered substantial losses, return correlations across hedge funds have increased markedly in recent years.[16] Our results suggest that a better understanding of the funding liquidity risk exposure of hedge funds is particularly relevant for a broader assessment of the robustness of the evolving market ecosystem.

1.7 Impact of Lockup Restrictions on Fund Performance across Liquidity Regimes

In order to cope with funding problems related to investor fund flows, many hedge funds adopt share restrictions which limit the liquidity of fund investors. These restrictions may be in the form of a lockup provision specifying a minimum lockup

[16] See Khandani and Lo (2007) for a fuller discussion of these issues.

period during which no redemptions are allowed, or a redemption notice period specifying a minimum notice that the investor is required to provide before redeeming shares. Funds with share restrictions are likely less funding restricted than otherwise similar funds. A number of recent studies suggest that such share restrictions have a significant impact on the ability of hedge funds to manage their liquidity risk. For example, Aragon (2007) shows that funds with lockup restrictions outperform funds without such restrictions by 4-7% annually suggesting that share restrictions enable funds to efficiently manage illiquid assets. Teo (2011) examines the performance of liquid hedge funds that grant favorable redemption terms (i.e., redemptions at monthly, or more frequent intervals) to investors and finds that high net inflow funds outperform low net inflow funds by 4.79% per year. Furthermore, he documents that within the group of liquid hedge funds the return impact of fund flows is stronger when market liquidity is low and when funding liquidity is tight.

Given the aforementioned results in the literature, it is of interest to examine how the presence or absence of share restrictions affects the funding liquidity risk and performance of hedge funds in the high as well as the low liquidity regimes. Accordingly, in this section we analyze the impact of lockup period restrictions on the performance of funding liquidity sorted decile portfolios in the two regimes. Following Teo (2011), we define liquid hedge funds as funds with favorable redemption terms, i.e., funds that allow monthly or more frequent redemptions.[17] Similarly, we define illiquid hedge funds as funds with lockup periods that are longer than one month. Tables 1.10 and 1.11 report the

[17] Liquid funds are identified using the 'lockup period' variable in the Lipper TASS database with values equal to 0 or 1. This results in 75.6% of the funds in our sample being classified as 'liquid' funds.

performance of the funding liquidity sorted decile portfolios for the liquid and illiquid hedge funds, respectively. Portfolio performance is reported in the form of monthly excess returns as well as 8-factor alphas.

First consider the performance figures for the respective fund decile portfolios in the high liquidity state reported in Panel B of the respective tables. It can be seen that in the high liquidity state the performance of the decile portfolios of liquid hedge funds (Panel B, Table 1.10) is lower compared to the illiquid hedge funds' portfolios (Panel B of Table 1.11) in nine out of ten cases. Furthermore, in the case of illiquid funds the high-minus-low funding liquidity risk portfolio strategy has a positive alpha equal to 1.82% per year. By contrast, in the case of liquid funds the high-minus-low funding liquidity risk portfolio strategy has an annualized alpha of -1.18%. These results suggest that having protection against investor flow-related funding liquidity risk in the form of redemption gates helps hedge funds improve their performance in the high liquidity state.

On the other hand, as seen in Panel C of Tables 1.10 and 1.11, in the low liquidity state there are no significant performance differences between the liquid and illiquid funds in most decile portfolios. Furthermore, the performance of the high-minus-low funding liquidity risk portfolio strategy is actually lower for illiquid funds, with an annualized alpha of -13.00% vs. -10.27% for liquid funds. This shows that imposing longer lockup periods does not improve fund performance in the low liquidity state, because the impact of funding liquidity risk in the low liquidity state is far greater. These results contribute to the recent literature by documenting the effectiveness of share restrictions in different liquidity states. In particular, our results suggest that longer lockup periods are effective only in the high liquidity states in terms of their ability to mitigate the flow-induced funding liquidity risk.

1.8 Concluding Remarks

This paper provides evidence on the relation between the liquidity risk exposure of hedge funds and their performance. The analysis focuses in particular on the interaction between the funds' market liquidity risk and their funding liquidity risk. A key result of the paper is that funding liquidity risk as measured by the sensitivity of a hedge fund's return to a measure of market-wide funding costs, is an important determinant of fund performance. Furthermore, funding liquidity risk is a critical determinant of the variation in hedge fund illiquidity premia across liquidity regimes.

The paper's results help shed further light on earlier findings regarding a market liquidity premium in hedge fund returns. We extend the literature in two ways. First, we analyze hedge funds' market liquidity exposure in high and low liquidity regimes identified using a 2-state Markov regime switching model. We document that while funds with high market liquidity exposure enjoy a premium over low-loading funds in the high liquidity regime, this premium vanishes in the low liquidity regime. Second, we examine the impact of both market liquidity and funding liquidity on hedge fund performance. We show that hedge fund returns are the highest (lowest) for the funds with high (low) market liquidity exposure and low (high) funding liquidity exposure. We also show that, over the liquidity grid, market liquidity and funding liquidity interact with each other, potentially leading to liquidity spirals, especially in the low liquidity regime. These results provide empirical evidence in support of the Brunnermeier and Pedersen's (2009) theoretical model which rationalizes the link between market liquidity and funding liquidity.

Given the critical importance of funding liquidity for hedge funds demonstrated in this paper, investors clearly need to pay attention to the funding liquidity risk exposure of funds. In order to identify the funding liquidity risk exposure an investor would need to track a hedge fund's leverage and the quality of assets held in its portfolio. However, this is not an easy task given the absence of reporting requirements for hedge funds. The framework adopted in this paper provides a convenient way to analyze a fund's funding liquidity exposure from an investment management perspective.

Table 1.1: Summary Statistics for Monthly Excess Hedge Fund Returns

Panel A reports statistics (average monthly return, standard deviation, skewness, and excess kurtosis) for all sample hedge funds, and Panel B reports statistics by category. The figures within a category are equally weighted averages of the statistics across the funds in the category. The sample includes funds in the Lipper TASS database with at least 24 months of consecutive return data. Only funds that report their returns on a monthly basis and net of all fees are included and a currency code of "USD" is imposed. The sample period is January 1994 to May 2012.

Category	Funds	Mean	St. Dev.	Skewness	Kurtosis
Panel A: Full Sample					
All Funds	5599	0.29	4.26	-0.36	3.51
Panel B: By Hedge Fund Category					
Directional Funds					
Dedicated Short Bias	34	-0.25	6.11	0.28	3.08
Emerging Markets	444	0.42	7.00	-0.36	3.67
Global Macro	223	0.33	4.03	0.10	2.50
Managed Futures	412	0.43	5.19	0.20	2.23
Non-Directional Funds					
Convertible Arbitrage	136	0.23	3.50	-0.68	7.05
Equity Market Neutral	202	0.26	2.55	-0.15	3.05
Fixed Income Arbitrage	151	0.24	3.01	-1.02	9.97
Semi-Directional Funds					
Event Driven	421	0.37	3.56	-0.49	4.55
Long/Short Equity Hedge	1529	0.43	5.21	-0.09	2.35
Multi Strategy	320	0.36	4.02	-0.44	4.56
Fund of Funds					
Fund of Funds	1727	0.10	3.06	-0.70	3.70

Table 1.2: Summary Statistics for Factors

The table lists the Fung and Hsieh hedge fund factors and the liquidity factors employed in this paper and reports average monthly returns, standard deviation, skewness, and excess kurtosis of the factors. The factors are described in the text. The sample period for all factors is January 1994 to May 2012.

Factor	Description	Mean	St. Dev.	Skewness	Kurtosis
	Panel A: Domestic Equity Factors				
MKTXS	Excess return of CRSP value-weighted index	0.49	4.64	-0.68	0.93
SMB	Fama-French size factor	0.20	3.56	0.87	7.98
	Panel B: Fixed Income Factors				
D10YR	Change in the 10YR Treasury yield	-0.02	0.24	-0.17	1.56
DSPRD	Change in Moody's Baa yield minus 10YR Treasury yield	0.01	0.20	1.22	15.23
	Panel C: Trend Following Factors				
PTFSBD	Primitive trend follower strategy bond	-1.15	15.55	1.39	2.53
PTFSFX	Primitive trend follower strategy currency	-0.20	19.68	1.34	2.53
PTFSCOM	Primitive trend follower strategy commodity	-0.53	13.69	1.16	2.28
	Panel D: Global Factors				
EM	MSCI emerging markets	0.70	7.28	-0.49	1.57
	Panel E: Liquidity Factors				
Pastor-Stambaugh	Pastor-Stambaugh (2003) liquidity measure	-2.94	7.46	-1.00	2.71
Sadka	Sadka (2006) permanent-variable liquidity measure	0.04	0.59	-0.92	6.23
TED Spread	-(3 month US LIBOR - 3 month Treasury yield)	-0.48	0.40	-3.03	13.03

Table 1.3: Correlations

The table reports the Pearson correlations of the Fung and Hsieh factors and the Pástor-Stambaugh (2003) (PS) liquidity measure, the TED spread, and the Sadka (2006) liquidity measure as described in Table 1.2. P-values are reported in square brackets. The sample period for all factors is January 1994 to May 2012.

	PTFSBD	PTFSFX	PTFSCOM	SMB	MKT-RF	MSCI	ΔTERM	ΔCREDIT	PS	TED
PTFSFX	0.26									
	[0.00]									
PTFSCOM	0.21	0.39								
	[0.00]	[0.00]								
SMB	-0.09	-0.02	-0.06							
	[0.18]	[0.75]	[0.39]							
MKT-RF	-0.26	-0.20	-0.18	0.24						
	[0.00]	[0.00]	[0.01]	[0.00]						
MSCI	-0.25	-0.18	-0.16	0.30	0.78					
	[0.00]	[0.01]	[0.02]	[0.00]	[0.00]					
ΔTERM	-0.19	-0.19	-0.12	0.09	0.10	0.11				
	[0.00]	[0.00]	[0.07]	[0.18]	[0.13]	[0.11]				
ΔCREDIT	0.19	0.28	0.19	-0.21	-0.30	-0.30	-0.52			
	[0.01]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]			
PS	-0.06	-0.12	-0.06	0.02	0.21	0.15	0.23	-0.27		
	[0.37]	[0.07]	[0.41]	[0.73]	[0.00]	[0.03]	[0.00]	[0.00]		
TED	-0.13	-0.19	-0.20	0.08	0.22	0.22	0.12	-0.45	0.24	
	[0.05]	[0.01]	[0.00]	[0.21]	[0.00]	[0.00]	[0.08]	[0.00]	[0.00]	
Sadka	-0.03	-0.11	-0.08	0.08	0.13	0.16	0.08	-0.36	0.08	0.39
	[0.67]	[0.10]	[0.27]	[0.25]	[0.06]	[0.02]	[0.26]	[0.00]	[0.22]	[0.00]

Table 1.4: Estimation Results from the 2-State Markov Regime Switching Model

The table exhibits the estimation results from the 2-state Markov regime switching model. Regimes are identified using the Pástor and Stambaugh (2003) (PS) liquidity measure or the Sadka (2006) liquidity measure. Panel A reports the estimated means of the respective liquidity measures in the high and the low liquidity states. The associated p-values are reported in square brackets. Panel B reports the expected duration of each state in months. Panel C reports the estimated transition probabilities.

Panel A: Mean

State	**PS**	**Sadka**
High Liquidity State	-0.02	0.0005
	[0.00]	[0.01]
Low Liquidity State	-0.21	0.0016
	[0.00]	[0.19]

Panel B: Expected Duration (months)

State	**PS**	**Sadka**
High Liquidity State	26.35	27.14
Low Liquidity State	1.32	8.01

Panel C: Transition Probabilities

State	**PS**		**Sadka**	
	High LS	Low LS	High LS	Low LS
High Liquidity State	0.96	0.04	0.96	0.04
Low Liquidity State	0.76	0.24	0.12	0.88

Table 1.5: Time Series Regressions of Hedge Fund Returns for Different Investment Styles over High and Low Liquidity Regimes

The table reports the results of time-series regressions of hedge fund portfolios on the Fung & Hsieh factors and the Pástor-Stambaugh (2003) (PS) liquidity factor (as described in Table 1.2) for high and low liquidity regimes. Liquidity regimes are identified by the PS liquidity factor. Hedge funds are sorted monthly into 11 equally weighted portfolios according to investment style. T-statistics are reported in square brackets. The sample of hedge funds is described in Table 1.1. The sample period is January 1994 to May 2012.

PrimaryCategory	State	Intercept	PTFSBD	PTFSFX	PTFSCOM	SMB	MKT-RF	MSCI	ΔTERM	ΔCREDIT	PS	Adjusted R2
Convertible Arbitrage	High Liquidity	0.0030	-0.0081	-0.0047	-0.0184	0.0029	0.0569	0.1514	-1.3975	-2.7616	0.0368	0.35
	State	[2.03]	[-0.82]	[-0.58]	[-1.66]	[0.07]	[1.24]	[4.78]	[-1.78]	[-2.57]	[1.41]	
	Low Liquidity	-0.1451	-0.1405	-0.0409	-0.0280	-0.3256	-0.6425	-0.0248	-12.8937	-15.6344	-0.5957	0.76
	State	[-1.95]	[-1.87]	[-0.84]	[-0.4]	[-1.13]	[-1.85]	[-0.22]	[-2.11]	[-3.46]	[-1.91]	
Dedicated Short Bias	High Liquidity	-0.0008	0.0012	0.0002	-0.0002	-0.4217	-0.4528	-0.0285	0.1804	-0.5569	-0.0344	0.47
	State	[-0.38]	[0.09]	[0.02]	[-0.01]	[-6.74]	[-6.84]	[-0.62]	[0.16]	[-0.36]	[-0.91]	
	Low Liquidity	-0.1610	-0.1819	0.1228	-0.2446	-0.2484	-0.9845	-0.5576	-19.1820	-18.5413	-0.6552	0.22
	State	[-0.81]	[-0.91]	[0.94]	[-1.3]	[-0.32]	[-1.06]	[-1.81]	[-1.18]	[-1.53]	[-0.79]	
Emerging Markets	High Liquidity	0.0041	-0.0124	0.0054	-0.0108	-0.0765	-0.1675	0.6924	-0.8300	-1.1566	0.0760	0.80
	State	[2.61]	[-1.2]	[0.63]	[-0.91]	[-1.67]	[-3.45]	[20.62]	[-1]	[-1.02]	[2.76]	
	Low Liquidity	0.0152	0.0040	-0.0748	0.1595	-0.1149	0.0660	0.5321	3.1190	-2.1632	0.0643	0.90
	State	[0.24]	[0.06]	[-1.79]	[2.64]	[-0.46]	[0.22]	[5.37]	[0.6]	[-0.56]	[0.24]	
Equity Market	High Liquidity	0.0041	-0.0143	0.0075	-0.0096	0.0921	0.0550	-0.0041	-0.0987	-0.7518	0.0148	0.11
Neutral	State	[3.79]	[-2.03]	[1.29]	[-1.19]	[2.94]	[1.66]	[-0.18]	[-0.17]	[-0.97]	[0.79]	
	Low Liquidity	-0.0266	-0.0240	0.0124	0.0087	0.0928	-0.1896	0.0340	-2.0660	-3.3368	-0.1153	0.20
	State	[-0.86]	[-0.77]	[0.61]	[0.3]	[0.77]	[-1.31]	[0.71]	[-0.81]	[-1.77]	[-0.89]	
Event Driven	High Liquidity	0.0042	-0.0149	0.0026	-0.0074	0.0966	0.1185	0.1055	-0.5182	-2.5541	0.0437	0.71
	State	[5.79]	[-3.08]	[0.65]	[-1.35]	[4.52]	[5.24]	[6.74]	[-1.34]	[-4.81]	[3.41]	
	Low Liquidity	-0.0563	-0.0312	-0.0127	0.0161	0.0123	-0.2008	0.0493	-1.6640	-7.2870	-0.2590	0.74
	State	[-1.33]	[-0.73]	[-0.46]	[0.4]	[0.07]	[-1.01]	[0.75]	[-0.48]	[-2.82]	[-1.45]	
Fixed Income	High Liquidity	0.0034	-0.0062	-0.0069	-0.0074	0.0206	-0.0156	0.0576	-1.1492	-1.8451	0.0074	0.16
Arbitrage	State	[3.69]	[-1.03]	[-1.39]	[-1.07]	[0.77]	[-0.55]	[2.95]	[-2.38]	[-2.79]	[0.46]	
	Low Liquidity	-0.0070	-0.0702	0.0009	0.0177	0.0955	0.0525	-0.0867	-2.1791	-5.7164	-0.0265	0.60
	State	[-0.14]	[-1.36]	[0.03]	[0.37]	[0.48]	[0.22]	[-1.09]	[-0.52]	[-1.83]	[-0.12]	

Table 1.5: Time Series Regressions of Hedge Fund Returns for Different Investment Styles over High and Low Liquidity Regimes (Continued)

PrimaryCategory	State	Intercept	PTFSBD	PTFSFX	PTFSCOM	SMB	MKT-RF	MSCI	ΔTERM	ΔCREDIT	PS	Adj R^2
Fund of Funds	High Liquidity	0.0024	-0.0021	0.0127	0.0130	0.0613	0.0185	0.1687	-0.9798	-2.2423	0.0444	0.56
	State	[2.61]	[-0.35]	[2.56]	[1.9]	[2.31]	[0.66]	[8.68]	[-2.04]	[-3.4]	[2.78]	
	Low Liquidity	-0.0372	0.0105	-0.0501	0.1095	-0.1322	-0.3281	0.2281	-0.6102	-4.5303	-0.1731	0.75
	State	[-0.83]	[0.23]	[-1.71]	[2.59]	[-0.76]	[-1.57]	[3.29]	[-0.17]	[-1.67]	[-0.92]	
Global Macro	High Liquidity	0.0041	-0.0116	0.0319	0.0116	0.0133	0.0205	0.1148	-1.7971	-1.9871	0.0409	0.34
	State	[3.64]	[-1.56]	[5.19]	[1.37]	[0.41]	[0.59]	[4.77]	[-3.01]	[-2.43]	[2.07]	
	Low Liquidity	-0.0491	-0.0145	-0.0461	0.1083	-0.0832	-0.2704	0.0536	-1.7035	-2.5748	-0.2169	0.18
	State	[-1.12]	[-0.33]	[-1.6]	[2.61]	[-0.49]	[-1.32]	[0.79]	[-0.47]	[-0.96]	[-1.18]	
Long/Short Equity	High Liquidity	0.0058	-0.0016	0.0036	0.0053	0.2753	0.2486	0.1475	-0.3254	-0.7796	0.0632	0.73
Hedge	State	[5.22]	[-0.23]	[0.6]	[0.64]	[8.56]	[7.3]	[6.26]	[-0.56]	[-0.97]	[3.26]	
	Low Liquidity	0.0091	0.0301	-0.0633	0.1065	-0.0971	0.0228	0.3343	1.8112	0.6079	0.0243	0.51
	State	[0.1]	[0.34]	[-1.1]	[1.28]	[-0.28]	[0.06]	[2.44]	[0.25]	[0.11]	[0.07]	
Managed Futures	High Liquidity	0.0056	0.0291	0.0348	0.0579	-0.0019	-0.0413	0.0853	-2.0490	-1.7179	0.0321	0.25
	State	[3.17]	[2.51]	[3.64]	[4.39]	[-0.04]	[-0.76]	[2.27]	[-2.21]	[-1.35]	[1.04]	
	Low Liquidity	-0.0493	0.0785	0.0127	0.0836	-0.1117	-0.6488	0.2023	-2.3278	-4.2727	-0.2316	0.78
	State	[-0.98]	[1.54]	[0.38]	[1.75]	[-0.57]	[-2.75]	[2.58]	[-0.56]	[-1.39]	[-1.09]	
Multi-Strategy	High Liquidity	0.0043	-0.0091	0.0027	0.0047	0.0406	0.0993	0.1165	-0.8239	-1.9453	0.0491	0.67
	State	[6.06]	[-1.95]	[0.71]	[0.88]	[1.96]	[4.53]	[7.68]	[-2.19]	[-3.78]	[3.94]	
	Low Liquidity	-0.0665	-0.0383	-0.0471	0.0812	-0.2509	-0.3004	0.0676	-5.4165	-6.0783	-0.2916	0.64
	State	[-1.56]	[-0.89]	[-1.69]	[2.01]	[-1.52]	[-1.51]	[1.02]	[-1.55]	[-2.34]	[-1.63]	

Table 1.6: Performance of Market Liquidity Beta Sorted Portfolios

Hedge funds are sorted into 10 equally weighted portfolios each month according to historical liquidity betas. The liquidity beta is calculated by a regression of monthly hedge fund returns on the market portfolio and the liquidity factor (Sadka (2006)), using the 24 months prior to portfolio formation. Portfolio formation starts January 1996 and only funds with at least 18 months of returns over the two year period are included. The table reports the average monthly excess returns (in percent) of the decile portfolios and the high-minus-low portfolio. Fund alphas are calculated using the eight Fung & Hsieh factors, where credit and term factors are replaced by tradable portfolios. T-statistics are reported in square brackets. The portfolio returns cover the period January 1996 to May 2012. Panel A displays the results for the whole sample. Panel B and C report the results for the high and low liquidity regimes, respectively. Liquidity regimes are identified by the Sadka (2006) liquidity measure.

Panel A: All Observations

	Liquidity Beta Deciles										Monthly	Annual
	1	2	3	4	5	6	7	8	9	10	10-1	
Avg Monthly Return	0.33	0.29	0.32	0.34	0.32	0.36	0.33	0.46	0.44	0.63	0.30	3.66
	[0.52]	[0.67]	[0.97]	[1.12]	[1.21]	[1.34]	[1.15]	[1.28]	[1.10]	[0.97]	[0.33]	
Alpha	0.01	0.05	0.14	0.17	0.16	0.22	0.16	0.28	0.24	0.35	0.33	4.09
	[0.09]	[0.53]	[1.78]	[2.29]	[2.31]	[3.16]	[2.19]	[2.87]	[2.45]	[2.23]	[1.66]	

Panel B: High Liquidity State

	Liquidity Beta Deciles										Monthly	Annual
	1	2	3	4	5	6	7	8	9	10	10-1	
Avg Monthly Return	0.29	0.32	0.35	0.38	0.38	0.42	0.41	0.59	0.53	0.73	0.45	5.50
	[0.44]	[0.73]	[1.02]	[1.26]	[1.42]	[1.54]	[1.40]	[1.56]	[1.28]	[1.13]	[0.48]	
Alpha	0.00	0.09	0.16	0.22	0.23	0.28	0.25	0.42	0.33	0.50	0.50	6.15
	[-0.03]	[0.92]	[2.10]	[3.11]	[3.50]	[4.65]	[3.72]	[4.21]	[3.55]	[3.15]	[2.31]	

Table 1.6: Performance of Market Liquidity Beta Sorted Portfolios (Continued)

Panel C: Low Liquidity State

	Liquidity Beta Deciles										Monthly	Annual
	1	2	3	4	5	6	7	8	9	10	10-1	
Avg Monthly Return	0.53	0.14	0.20	0.12	0.03	0.07	-0.06	-0.14	0.04	0.13	-0.41	-4.79
	[1.01]	[0.35]	[0.68]	[0.42]	[0.11]	[0.26]	[-0.25]	[-0.49]	[0.11]	[0.19]	[-0.48]	
Alpha	0.32	-0.04	0.03	-0.11	-0.15	-0.11	-0.25	-0.35	-0.20	-0.59	-0.91	-10.38
	[0.76]	[-0.14]	[0.11]	[-0.44]	[-0.65]	[-0.45]	[-0.99]	[-1.33]	[-0.67]	[-1.23]	[-1.65]	

Table 1.7: Performance of Funding Liquidity Beta Sorted Portfolios

Hedge funds are sorted into 10 equally weighted portfolios each month according to historical liquidity betas. The liquidity beta is calculated by a regression of monthly hedge fund returns on the market portfolio and the liquidity factor (TED spread), using the 24 months prior to portfolio formation. Portfolio formation starts January 1996 and only funds with at least 18 months of returns over the two year period are included. The table reports the average monthly excess returns (in percent) of the decile portfolios and the high-minus-low portfolio. Fund alphas are calculated using the eight Fung & Hsieh factors, where credit and term factors are replaced by tradable portfolios. T-statistics are reported in square brackets. The portfolio returns cover the period January 1996 to May 2012. Panel A displays the results for the whole sample. Panel B and C report the results for the high and low liquidity regimes, respectively. Liquidity regimes are identified by the Sadka (2006) liquidity measure.

Panel A: All Observations

	Liquidity Beta Deciles										Monthly	Annual
	1	2	3	4	5	6	7	8	9	10	10-1	
Avg Monthly Return	0.48	0.42	0.36	0.34	0.38	0.32	0.32	0.37	0.42	0.42	-0.05	-0.66
	[0.76]	[1.07]	[1.13]	[1.20]	[1.36]	[1.14]	[1.09]	[1.06]	[1.00]	[0.62]	[-0.06]	
Alpha	0.20	0.21	0.19	0.16	0.22	0.16	0.15	0.17	0.23	0.08	-0.12	-1.49
	[1.30]	[2.34]	[2.89]	[2.35]	[3.03]	[2.24]	[2.04]	[2.00]	[2.12]	[0.52]	[-0.61]	

Panel B: High Liquidity State

	Liquidity Beta Deciles										Monthly	Annual
	1	2	3	4	5	6	7	8	9	10	10-1	
Avg Monthly Return	0.49	0.46	0.43	0.40	0.45	0.39	0.38	0.44	0.48	0.49	0.00	0.01
	[0.76]	[1.15]	[1.32]	[1.40]	[1.58]	[1.36]	[1.24]	[1.25]	[1.14]	[0.71]	[0.00]	
Alpha	0.22	0.24	0.27	0.22	0.30	0.24	0.22	0.26	0.32	0.18	-0.04	-0.49
	[1.36]	[2.82]	[4.12]	[3.30]	[4.53]	[3.78]	[3.23]	[3.22]	[2.98]	[1.22]	[-0.20]	

Table 1.7: Performance of Funding Liquidity Beta Sorted Portfolios (Continued)

Panel C: Low Liquidity State

	Liquidity Beta Deciles										Monthly	Annual
	1	2	3	4	5	6	7	8	9	10	10-1	
Avg Monthly Return	0.42	0.22	0.05	0.06	0.03	0.00	0.06	0.01	0.09	0.10	-0.32	-3.82
	[0.79]	[0.65]	[0.16]	[0.21]	[0.13]	[0.01]	[0.24]	[0.04]	[0.24]	[0.15]	[-0.39]	
Alpha	0.37	0.18	-0.14	-0.15	-0.14	-0.27	-0.13	-0.26	-0.27	-0.59	-0.96	-10.98
	[0.83]	[0.73]	[-0.67]	[-0.66]	[-0.52]	[-1.01]	[-0.49]	[-0.88]	[-0.79]	[-1.25]	[-1.89]	

Table 1.8: Performance of Funding Liquidity Beta Sorted Portfolios Identified Using the Orthogonal component of the TED spread

Hedge funds are sorted into 10 equally weighted portfolios each month according to historical liquidity betas. The liquidity beta is calculated by a regression of monthly hedge fund returns on the market portfolio and the orthogonal component of the TED spread when projected onto the Sadka measure, using the 24 months prior to portfolio formation. Portfolio formation starts January 1996 and only funds with at least 18 months of returns over the two year period are included. The table reports the average monthly excess returns (in percent) of the decile portfolios and the high-minus-low portfolio. Fund alphas are calculated using the eight Fung & Hsieh factors, where credit and term factors are replaced by tradable portfolios. T-statistics are reported in square brackets. The portfolio returns cover the period January 1996 to May 2012. Panel A displays the results for the whole sample. Panel B and C report the results for the high and low liquidity regimes, respectively. Liquidity regimes are identified by the Sadka (2006) liquidity measure.

Panel A: All Observations

	Liquidity Beta Deciles										Monthly	Annual
	1	2	3	4	5	6	7	8	9	10	10-1	
Avg Monthly Return	0.62	0.44	0.35	0.34	0.29	0.26	0.36	0.36	0.37	0.42	-0.20	-2.34
	[1.01]	[1.12]	[1.11]	[1.2]	[1.07]	[0.91]	[1.21]	[1.03]	[0.89]	[0.62]	[-0.21]	
Alpha	0.32	0.23	0.18	0.19	0.13	0.09	0.20	0.20	0.18	0.07	-0.25	-2.93
	[2.03]	[2.69]	[2.48]	[2.81]	[1.97]	[1.18]	[2.7]	[2.37]	[1.69]	[0.47]	[-1.2]	

Panel B: High Liquidity State

	Liquidity Beta Deciles										Monthly	Annual
	1	2	3	4	5	6	7	8	9	10	10-1	
Avg Monthly Return	0.68	0.50	0.44	0.41	0.36	0.32	0.41	0.43	0.42	0.44	-0.23	-2.74
	[1.07]	[1.24]	[1.35]	[1.43]	[1.29]	[1.1]	[1.36]	[1.2]	[0.98]	[0.64]	[-0.24]	
Alpha	0.37	0.29	0.26	0.28	0.21	0.16	0.25	0.28	0.23	0.13	-0.25	-2.94
	[2.44]	[3.62]	[3.79]	[4.48]	[3.52]	[2.36]	[3.91]	[3.67]	[2.23]	[0.81]	[-1.2]	

Table 1.8: Performance of Funding Liquidity Beta Sorted Portfolios Identified Using the Orthogonal component of the TED spread (Continued)

Panel C: Low Liquidity State

	Liquidity Beta Deciles										Monthly	Annual
	1	2	3	4	5	6	7	8	9	10	10-1	
Avg Monthly Return	0.34	0.15	-0.05	0.01	-0.02	-0.04	0.11	0.02	0.18	0.31	-0.03	-0.39
	[0.64]	[0.42]	[-0.18]	[0.04]	[-0.09]	[-0.14]	[0.43]	[0.07]	[0.46]	[0.51]	[-0.04]	
Alpha	0.17	0.05	-0.18	-0.17	-0.23	-0.25	-0.13	-0.23	-0.16	-0.29	-0.46	-5.33
	[0.37]	[0.18]	[-0.87]	[-0.7]	[-0.92]	[-0.93]	[-0.5]	[-0.81]	[-0.51]	[-0.58]	[-0.87]	

Table 1.9: Market Liquidity Beta and Funding Liquidity Beta Sorted Portfolios

Hedge funds are sorted into 25 (5 by 5) equally weighted portfolios each month according to historical market and funding liquidity betas. The market liquidity beta (funding liquidity beta) is calculated by a regression of monthly hedge fund returns on the market portfolio and the liquidity factor, Sadka (2006) liquidity measure (TED spread), using the 24 months prior to portfolio formation. Portfolio formation starts January 1996 and only funds with at least 18 months of returns over the two year period are included. The table reports the fund alphas (in percent) of the quintile portfolios and the high-minus-low portfolio. Fund alphas are calculated using the eight Fung & Hsieh factors, where credit and term factors are replaced by tradable portfolios. T-statistics are reported in square brackets. The portfolio returns cover the period January 1996 to May 2012. Panel A and B report the results for the high and low liquidity regimes, respectively. Liquidity regimes are identified by the Sadka (2006) liquidity measure.

Panel A: Fund Alphas in High Liquidity State

		Funding Liquidity Beta Quintiles					Monthly	Annual
		1	2	3	4	5	5-1	
Market Liquidity Beta Quintiles	1	0.04	0.16	0.14	-0.02	-0.24	-0.29	-3.38
		[0.31]	[1.31]	[0.93]	[-0.17]	[-1.08]	[-1.07]	
	2	0.20	0.20	0.18	0.17	-0.01	-0.21	-2.54
		[1.79]	[3.42]	[2.68]	[1.70]	[-0.08]	[-1.05]	
	3	0.19	0.27	0.24	0.23	0.36	0.17	2.08
		[1.70]	[4.29]	[3.59]	[3.06]	[2.07]	[0.84]	
	4	0.51	0.31	0.34	0.30	0.40	-0.11	-1.33
		[1.85]	[3.90]	[5.12]	[4.38]	[3.03]	[-0.37]	
	5	0.48	0.53	0.54	0.41	0.49	0.01	0.07
		[2.11]	[3.70]	[4.56]	[3.53]	[2.85]	[0.02]	
Monthly	5-1	0.44	0.37	0.40	0.43	0.73		
		[1.62]	[1.99]	[2.05]	[2.39]	[2.59]		
Annual		5.40	4.58	4.89	5.34	9.13		

Panel B: Fund Alphas in Low Liquidity State

		Funding Liquidity Beta Quintiles					Monthly	Annual
		1	2	3	4	5	5-1	
Market Liquidity Beta Quintiles	1	0.33	0.23	0.23	0.10	-0.39	-0.72	-8.29
		[0.82]	[0.68]	[0.59]	[0.25]	[-0.64]	[-0.99]	
	2	0.38	-0.24	-0.14	-0.16	-0.18	-0.55	-6.42
		[1.33]	[-1.13]	[-0.51]	[-0.50]	[-0.37]	[-0.99]	
	3	0.34	-0.01	-0.24	-0.27	-0.35	-0.69	-7.96
		[1.11]	[-0.06]	[-0.99]	[-1.05]	[-0.81]	[-1.30]	
	4	0.05	-0.26	-0.36	-0.25	-0.27	-0.31	-3.70
		[0.11]	[-0.97]	[-1.51]	[-0.94]	[-0.74]	[-0.58]	
	5	0.40	-0.14	0.06	-0.19	-0.62	-1.03	-11.63
		[0.71]	[-0.47]	[0.19]	[-0.52]	[-1.38]	[-1.41]	
Monthly	5-1	0.08	-0.37	-0.17	-0.28	-0.23		
		[0.63]	[0.84]	[0.78]	[0.82]	[0.96]		
Annual		0.94	-4.31	-2.03	-3.31	-2.71		

Table 1.10: Performance of Funding Liquidity Beta Sorted Portfolios of Liquid Hedge Funds

Liquid hedge funds that offer monthly or better redemption periods are sorted into 10 equally weighted portfolios each month according to historical liquidity betas. The liquidity beta is calculated by a regression of monthly hedge fund returns on the market portfolio and the liquidity factor (TED spread), using the 24 months prior to portfolio formation. Portfolio formation starts January 1996 and only funds with at least 18 months of returns over the two year period are included. The table reports the average monthly excess returns (in percent) of the decile portfolios and the high-minus-low portfolio. Fund alphas are calculated using the eight Fung & Hsieh factors, where credit and term factors are replaced by tradable portfolios. T-statistics are reported in square brackets. The portfolio returns cover the period January 1996 to May 2012. Panel A displays the results for the whole sample. Panel B and C report the results for the high and low liquidity regimes, respectively. Liquidity regimes are identified by the Sadka (2006) liquidity measure.

Panel A: All Observations

	Liquidity Beta Deciles										Monthly	Annual
	1	2	3	4	5	6	7	8	9	10	10-1	
Avg Monthly Return	0.46	0.33	0.36	0.30	0.36	0.29	0.29	0.33	0.42	0.36	-0.10	-1.21
	[0.65]	[0.77]	[1.03]	[0.98]	[1.15]	[0.94]	[0.87]	[0.87]	[0.90]	[0.47]	[-0.09]	
Alpha	0.20	0.14	0.19	0.14	0.20	0.14	0.12	0.15	0.23	0.02	-0.17	-2.05
	[1.14]	[1.60]	[2.82]	[1.90]	[2.68]	[1.92]	[1.51]	[1.63]	[2.08]	[0.14]	[-0.78]	

Panel B: High Liquidity State

	Liquidity Beta Deciles										Monthly	Annual
	1	2	3	4	5	6	7	8	9	10	10-1	
Avg Monthly Return	0.46	0.36	0.42	0.37	0.44	0.36	0.34	0.40	0.49	0.41	-0.06	-0.67
	[0.64]	[0.83]	[1.18]	[1.17]	[1.37]	[1.13]	[1.02]	[1.03]	[1.04]	[0.53]	[-0.05]	
Alpha	0.21	0.17	0.27	0.20	0.29	0.21	0.19	0.23	0.31	0.11	-0.10	-1.18
	[1.20]	[2.01]	[3.93]	[2.85]	[4.13]	[3.31]	[2.62]	[2.77]	[2.86]	[0.70]	[-0.43]	

Table 1.10: Performance of Funding Liquidity Beta Sorted Portfolios of Liquid Hedge Funds (Continued)

Panel C: Low Liquidity State

	Liquidity Beta Deciles										Monthly	Annual
	1	2	3	4	5	6	7	8	9	10	10-1	
Avg Monthly Return	0.43	0.19	0.06	0.01	-0.03	-0.02	0.02	-0.02	0.08	0.11	-0.32	-3.76
	[0.72]	[0.49]	[0.18]	[0.03]	[-0.10]	[-0.09]	[0.06]	[-0.05]	[0.20]	[0.16]	[-0.34]	
Alpha	0.42	0.16	-0.08	-0.18	-0.18	-0.25	-0.20	-0.24	-0.21	-0.48	-0.90	-10.27
	[0.88]	[0.65]	[-0.39]	[-0.76]	[-0.69]	[-0.97]	[-0.72]	[-0.82]	[-0.67]	[-1.06]	[-1.68]	

Table 1.11: Performance of Funding Liquidity Beta Sorted Portfolios of Illiquid Hedge Funds

Illiquid hedge funds that offer longer than monthly redemption periods are sorted into 10 equally weighted portfolios each month according to historical liquidity betas. The liquidity beta is calculated by a regression of monthly hedge fund returns on the market portfolio and the liquidity factor (TED spread), using the 24 months prior to portfolio formation. Portfolio formation starts January 1996 and only funds with at least 18 months of returns over the two year period are included. The table reports the average monthly excess returns (in percent) of the decile portfolios and the high-minus-low portfolio. Fund alphas are calculated using the eight Fung & Hsieh factors, where credit and term factors are replaced by tradable portfolios. T-statistics are reported in square brackets. The portfolio returns cover the period January 1996 to May 2012. Panel A displays the results for the whole sample. Panel B and C report the results for the high and low liquidity regimes, respectively. Liquidity regimes are identified by the Sadka (2006) liquidity measure.

Panel A: All Observations

	Liquidity Beta Deciles										Monthly	Annual
	1	2	3	4	5	6	7	8	9	10	10-1	
Avg Monthly Return	0.63	0.71	0.42	0.50	0.49	0.35	0.53	0.48	0.52	0.67	0.04	0.48
	[0.53]	[0.84]	[0.60]	[0.82]	[0.80]	[0.57]	[0.84]	[0.61]	[0.61]	[0.49]	[0.02]	
Alpha	0.30	0.47	0.22	0.33	0.30	0.15	0.34	0.27	0.30	0.33	0.03	0.33
	[2.14]	[3.74]	[2.22]	[3.55]	[3.55]	[1.76]	[3.59]	[2.49]	[2.41]	[1.83]	[0.14]	

Panel B: High Liquidity State

	Liquidity Beta Deciles										Monthly	Annual
	1	2	3	4	5	6	7	8	9	10	10-1	
Avg Monthly Return	0.68	0.77	0.50	0.59	0.52	0.39	0.60	0.56	0.63	0.80	0.12	1.44
	[0.56]	[0.89]	[0.70]	[0.95]	[0.84]	[0.63]	[0.95]	[0.69]	[0.74]	[0.58]	[0.06]	
Alpha	0.34	0.51	0.28	0.42	0.34	0.20	0.40	0.35	0.42	0.49	0.15	1.82
	[2.13]	[3.77]	[2.71]	[4.46]	[3.97]	[2.32]	[4.41]	[3.20]	[3.55]	[3.01]	[0.76]	

Table 1.11: Performance of Funding Liquidity Beta Sorted Portfolios of Illiquid Hedge Funds (Continued)

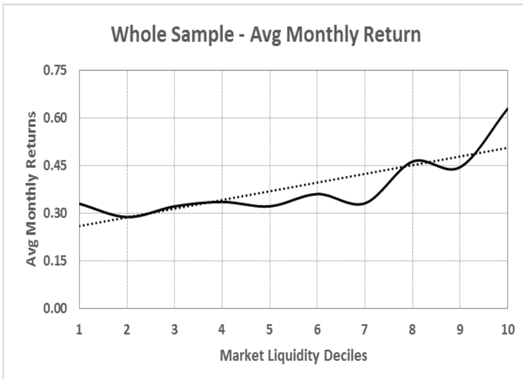
Panel C: Low Liquidity State

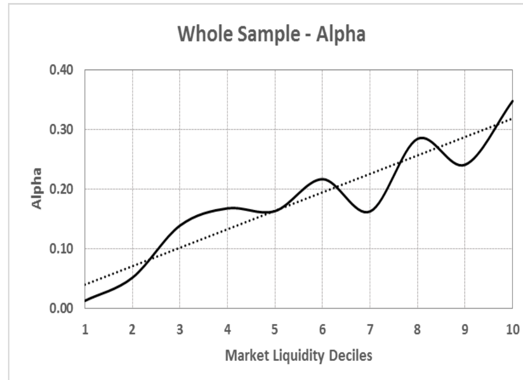
	Liquidity Beta Deciles										Monthly	Annual
	1	2	3	4	5	6	7	8	9	10	10-1	
Avg Monthly Return	0.40	0.45	0.07	0.06	0.34	0.14	0.19	0.12	0.02	0.06	-0.34	-3.99
	[0.36]	[0.58]	[0.10]	[0.11]	[0.58]	[0.25]	[0.31]	[0.17]	[0.02]	[0.04]	[-0.19]	
Alpha	0.11	0.40	-0.23	-0.27	0.05	-0.16	-0.13	-0.19	-0.35	-1.04	-1.15	-13.00
	[0.28]	[1.22]	[-0.84]	[-0.87]	[0.19]	[-0.60]	[-0.43]	[-0.59]	[-0.79]	[-1.64]	[-1.79]	

Figure 1.1: Fund Alphas and Average Monthly Excess Returns for Market Liquidity-Sorted Portfolios

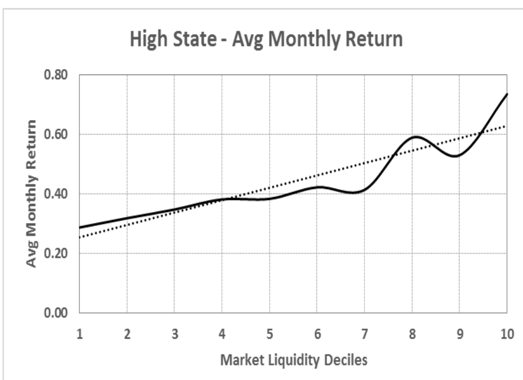
The figure exhibits the fund alphas and the average monthly excess return for the liquidity deciles described in Table 1.6, based on the Sadka (2006) liquidity measure. Panel A displays the results for the whole sample. Panel B and C report the results for the high and low liquidity regimes, respectively.

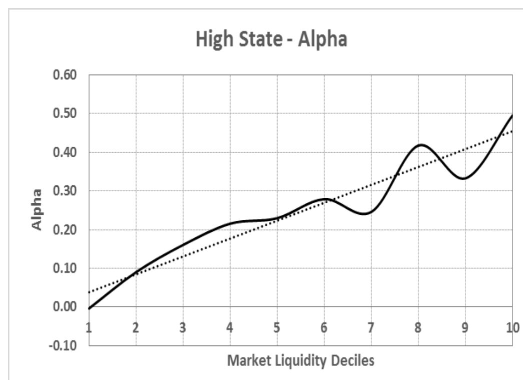
Panel A:



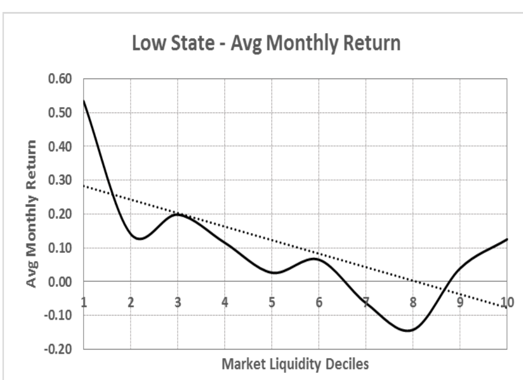


Panel B:





Panel C:



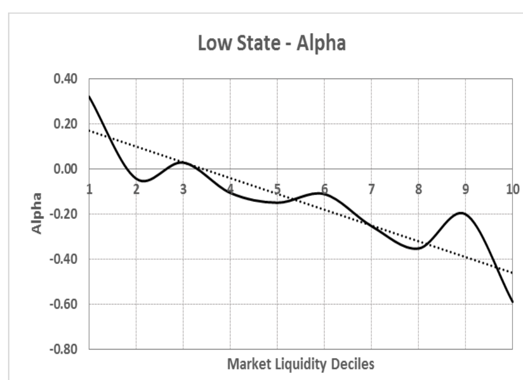
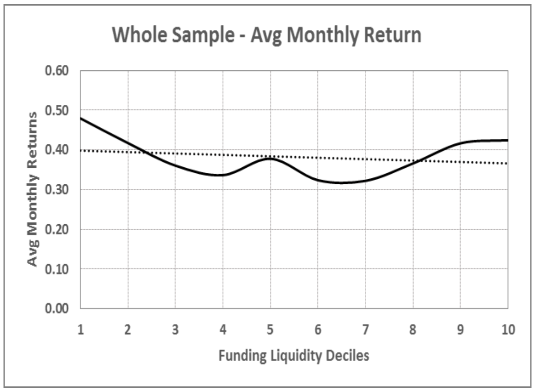
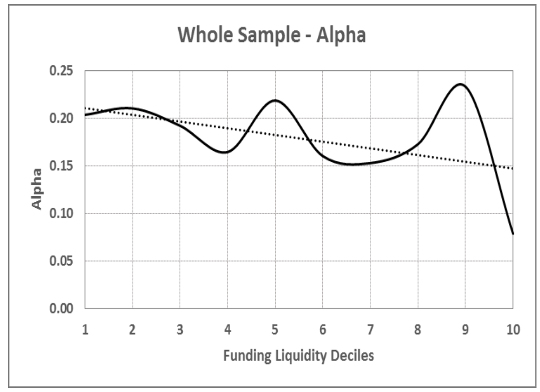


Figure 1.2: Fund Alphas and Average Monthly Excess Returns for Funding Liquidity-Sorted Portfolios

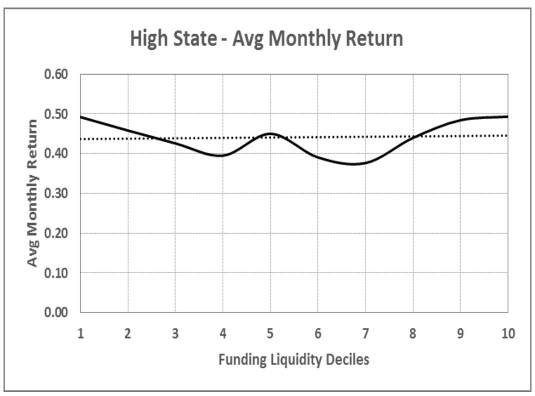
The figure exhibits the fund alphas and the average monthly excess return for the funding liquidity deciles described in Table 1.7, based on the TED spread. Panel A displays the results for the whole sample. Panel B and C report the results for the high and low liquidity regimes, respectively.

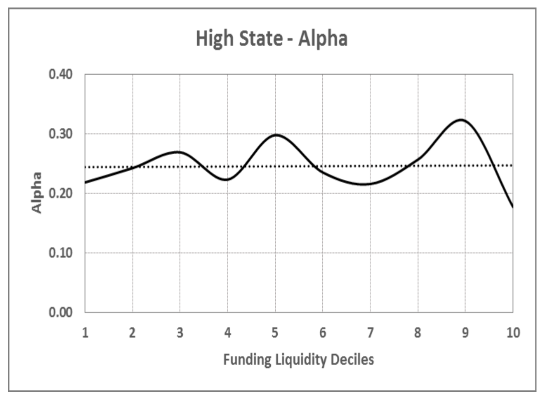
Panel A:



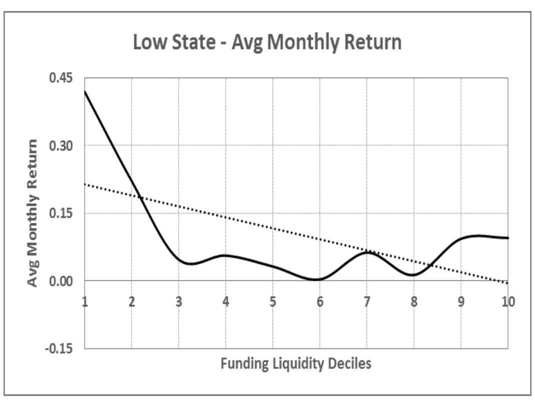


Panel B:





Panel C:



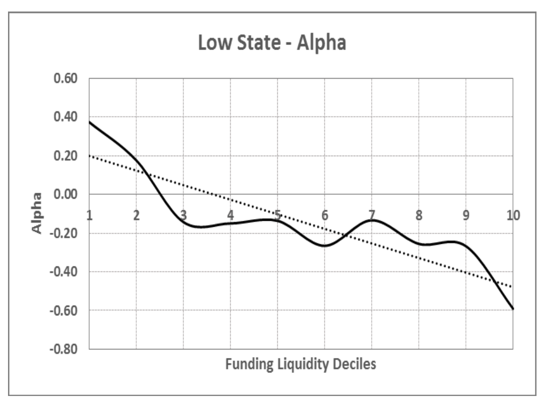


Figure 1.3: Fund Alphas for Market and Funding Liquidity-Sorted Portfolios (High Liquidity Regime)

The figure exhibits the fund alphas for the market and funding liquidity sorted quintile portfolios for the high liquidity regime.

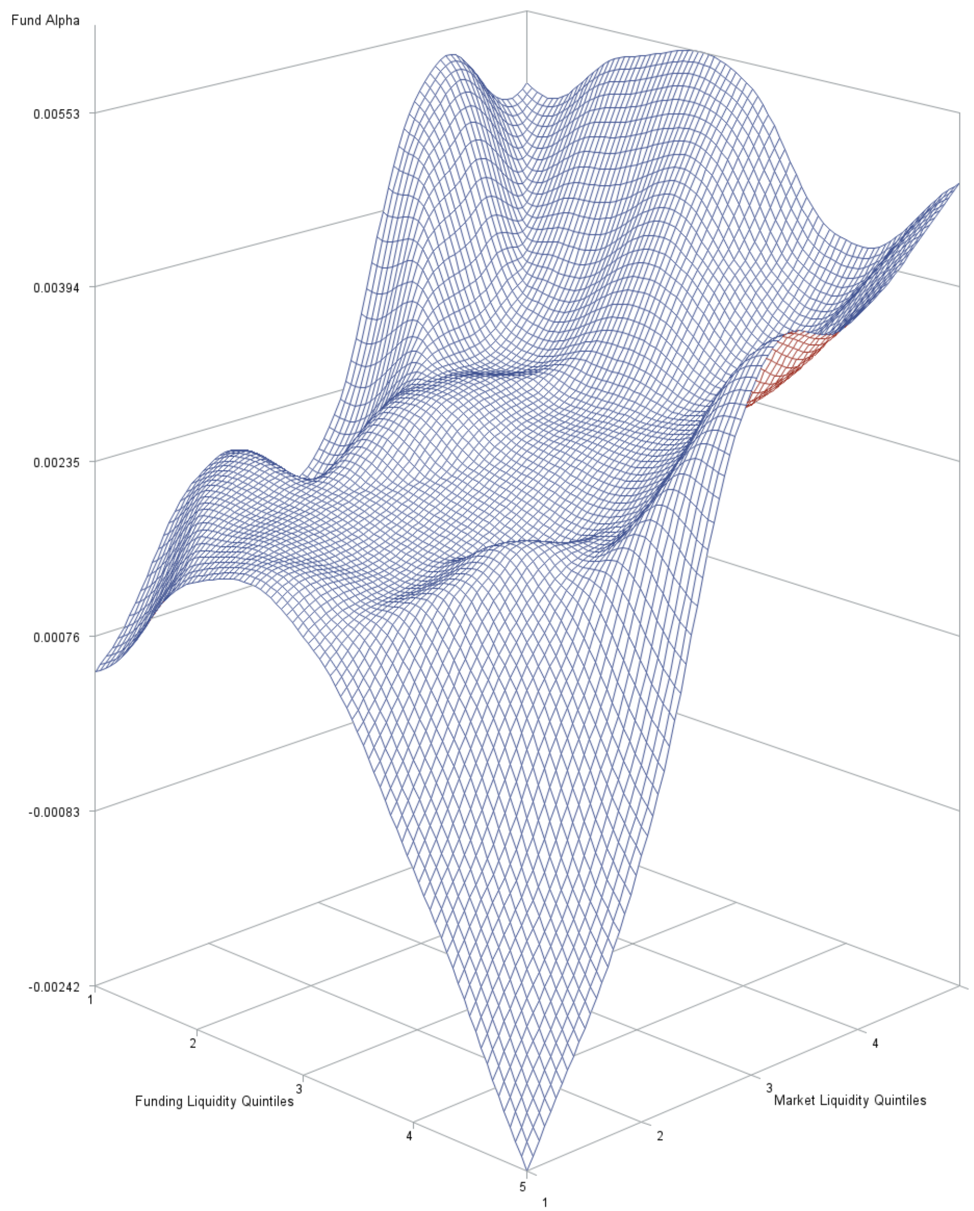
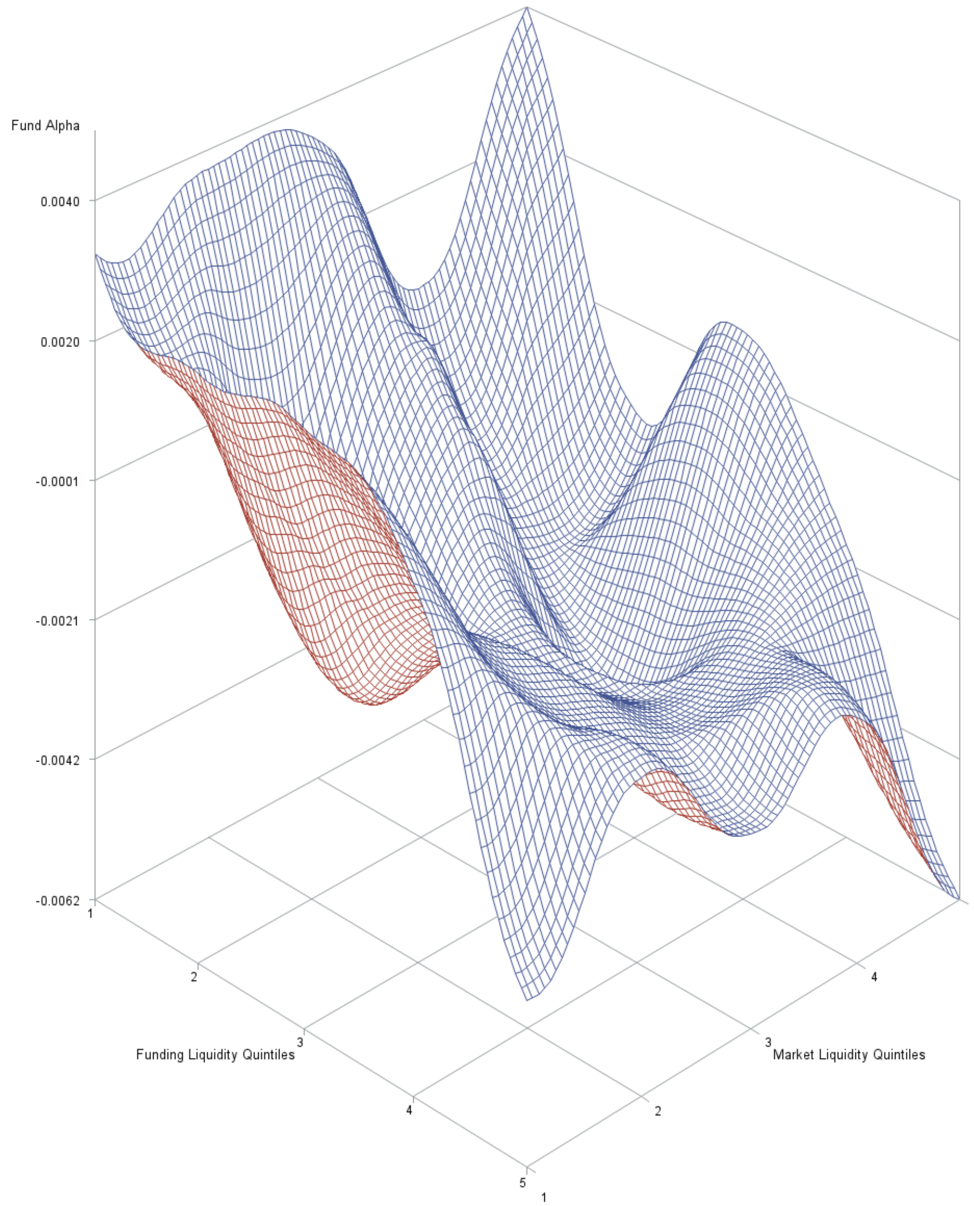


Figure 1.4: Fund alphas for Market and Funding Liquidity-Sorted Portfolios (Low Liquidity Regime)

The figure exhibits the fund alphas for the market and funding liquidity sorted quintile portfolios for the low liquidity regime.



CHAPTER 2: CREDIT MARKET CONTAGION AND LIQUIDITY SHOCKS

2.1 Introduction

The consensus about the sub-prime mortgage crisis among investment professionals in 2007 was that the crisis would be contained and not spread to other financial markets. Portfolio managers considered the worsening credit conditions in the sub-prime mortgage market as a local event which would not have an effect on other mortgage markets such as prime mortgages. However, the credit problems in the sub-prime mortgage market eventually ended up spreading into other credit markets such as alt-A mortgages, prime mortgages, asset-backed commercial paper, mortgage-backed securities (MBS), asset-backed securities (ABS), commercial mortgage-backed securities (CMBS), corporate high yield bonds, corporate investment grade bonds, and leveraged loans. While the credit markets experienced adverse conditions during this period, many other financial markets remained intact. For instance, the S&P 500 index still traded around the 1400 level in May, 2008. Nevertheless, as the market experienced more severe shocks, the tide of contagion that started in the credit markets ended up spreading over to other financial markets, including stock and commodity markets. During this time, the hope was that the crisis would not spread to other sectors in real economy. Yet, the crises did eventually spread to the other sectors, and the U.S. markets faced the worst recession since the Great Depression.

During the spread of the crisis from the sub-prime market to the other sectors in the U.S. economy, contagion played an important role in propagating the shocks from one market to another.[18] Therefore, it is crucial to understand the nature of contagion in financial markets. Several studies in finance literature examine the roots and consequences of contagion, including Brunnermeier and Pedersen (2005, 2009), Allen and Gale (2000, 2004), Longstaff (2010), Kodres and Pritsker (2002), Kyle and Xiong (2001), and Bae, Karolyi, and Stulz (2003). The literature proposes at least three channels of financial contagion. First, under the *risk premium channel*, faced with a negative shock in one market, investors require a higher risk premium in order to invest in other markets, therefore affecting the returns in other markets. Second, the *information channel* suggests that shocks are transmitted when uninformed (noise) traders think that the prices in other markets following a shock reflect informed traders' information about fundamentals, consequently changing the prices in that market. Third, through the *liquidity channel*, investors who suffer losses in one market experience funding liquidity problems. This can potentially lead to liquidity spirals in market liquidity causing significant changes in asset prices across all markets.

The recent experience suggests that through various channels, contagion was one of the main drivers of the crisis in 2007-2008. Although the sub-prime mortgage market is a relatively smaller market in the U.S. financial system, through contagion channels the shocks in the sub-prime mortgage market were propagated to other financial markets, resulting in a major recession. However, before we experienced the worsening in other financial markets and the real sectors, the crisis spread first in the credit markets following the shock in the sub-prime mortgage market. Therefore, it is important to

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[18] Following Bekaert, Harvey, and Ng (2005), I define contagion as correlation over and above that expected from economic fundamentals.

understand this early stage of contagion in which the shocks first propagated in the credit markets, such as MBS, ABS, CMBS, corporate credit, and leveraged loans, in order to take regulative actions and develop market mechanisms to prevent a broader recession in the future.

In this study, I examine the contagion in credit markets using various credit default swap (CDS) indices including CDX IG, CDX HY, ABX.HE AAA, ABX.HE BBB, CMBX AAA, CMBX BBB, and LCDX.[19] These indices are superior to other cash based indices in reflecting the credit conditions in the related credit markets because they provide clean measures of credit/default risk. In addition, only institutions (i.e., informed traders) are allowed to trade these CDS indices. Therefore, one would expect these data to be less noisy. I use weekly data on CDS indices listed above for a more precise analysis of contagion in credit markets. Specifically, I show that large adverse shocks to market and funding liquidity increase the likelihood of contagion during periods with widening credit spreads. I also show that financial intermediaries such as prime brokers and banks are instrumental in spreading the co-movements in credit spreads during periods with tightening credit spreads.

Bekaert, Harvey, and Ng's (2005) definition of contagion as correlation over and above that expected from economic fundamentals, suggests that any clustering we observe across CDS indices after filtering for economic factors is contagion. Since the spreads on CDS indices are autocorrelated and exposed to various economic factors, I

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[19] The indices correspond to credit default swaps in corporate investment grade, corporate high yield, asset-backed securities, commercial mortgage backed securities, and leveraged loan markets, respectively.

filter the raw data using AR(1) models combined with the following factors: three Fama and French (1993) factors, spot rate, slope of the yield curve, default premium, swap rate, and the VIX index. I use the residuals from these models as filtered spreads which should reduce the possibility of clustering in CDS index spreads due to common economic factors and autocorrelation.

I begin my analysis by showing the existence of contagion in credit markets by employing a semi-parametric (quantile regression) and a parametric (logit) model, following Boyson, Stahel, and Stulz (2010). The quantile regression model estimates the conditional probability that a random variable is below or above a quantile given that another random variable is in the same threshold. This method does not require any distributional assumptions and allows for heteroskedasticity. Using the quantile regression approach, I show that for quantiles on both sides of the distribution of the filtered CDS index spread data, the conditional probability that a CDS index spread exceeds the same threshold as the equally weighted average of other CDS indices is significantly higher than the benchmark probability which assumes no dependence between the two variables. This result shows that not only during periods of high CDS spreads, but also for tighter CDS spreads, there is evidence of clustering among CDS indices. This finding provides strong evidence for contagion/dependence among credit markets instruments in both the worsening and improving credit markets.

In addition to the semi-parametric quantile regression approach, I employ a parametric model, namely a logit model, to provide evidence of clustering among CDS indices. In the logit model, the dependent variable is an indicator variable which takes the value one if a CDS index has a value in the bottom decile, and zero otherwise. The explanatory variable in the model, COUNT, is the number of *other* CDS indices which have values in the bottom decile in the same week. I repeat this exercise also for the top decile of the data in order to show that the clustering exists in both tails of the distribution. The results show positive and significant coefficients on the variable COUNT, which indicate that the clustering in other CDS indices increase the probability of clustering for a given CDS index. Therefore, both quantile regression and logit model approaches show that the clustering in CDS indices is not due to autocorrelation in CDS index data or to economic factors. This suggests that the evidence of clustering I document is due to contagion in credit markets.

Next, I investigate the channels through which the contagion propagated in credit markets. Among the three contagion channels mentioned, information and risk-premium channels are reflected in the economic factors used in the filtering process. The eight economic factors I employ already include the contagion effects which would be transmitted through information and risk-premium channels. Therefore, in this study I investigate the liquidity channel through which shocks to market and funding liquidity increase the probability of contagion. For this purpose, I determine the contagion channel variables for which an extreme realization is associated with extreme changes in market or funding liquidity. The contagion channel variables employed in this study includes the TED spread, REPO rate, returns to banks and prime brokers, the Amihud (2002) illiquidity factor, and the Hu, Pan, and Wang (2013) NOISE factor. Following Boyson, Stahel, and Stulz (2010), I employ a multinomial logistic model to examine if extreme shocks to the contagion channel variables are associated with credit market contagion. In the logistic model, the dependent variable, OCCUR, is a measure of the degree of contagion among CDS indices. The main explanatory variable in the model which models extreme shocks for each of the contagion channel variables is an indicator variable set to one when the corresponding channel variable experience a large shock and zero otherwise. I repeat the analyses for both sides of the distribution of CDS index spreads given that contagion/dependence among CDS indices exists for both worsening and improving credit conditions. The results show that when CDS index spreads widen, the funding liquidity measures, TED spread and REPO rate, and the market liquidity measures Amihud (2002) and NOISE are linked to both high and low levels of contagion intensity across CDS indices. Therefore, both market and funding liquidity contribute to the contagion in worsening credit conditions. This result is consistent with Brunnermeier and Pedersen (2009) who suggest that market liquidity and funding liquidity shocks could be mutually reinforcing which leads to liquidity spirals, therefore leading to contagion across various asset classes during periods with widening credit spreads.

On the other hand, while the results show that the funding and market liquidity factors are not significant channels for contagion in improving credit market conditions, the prime broker index and a bank index are significant contagion channels. This result suggests that the intermediaries such as prime brokers and banks play an important role in spreading a market rally across various credit markets.

Collectively, the results presented in this study provide evidence of contagion in credit markets in both worsening and improving credit markets and show the channels through which contagion is propagated in credit markets.

The rest of the paper is organized as follows. Section 2.2 summarizes the methodology we employ to evaluate financial contagion. Section 2.3 describes the data.

Section 2.4 outlines the quantile regression and the logit model to show the existence of contagion in credit markets. Section 2.5 examines the channels through which contagion spread across CDS indices, while Section 2.6 concludes.

2.2 Measuring Financial Contagion

In this study, I follow the methodology by Bae, Karolyi, and Stulz (2003) in evaluating financial contagion which captures the coincidence of extreme return shocks. They determine the extent of contagion, its determinants and economic significance by employing a multinomial logistic model.

Prior studies mostly attempts to investigate financial contagion by examining if asset markets move more closely in turbulent times. These studies focus on correlation changes among asset markets over time in order to determine financial contagion. However, Baig and Goldfajn (1999) and Forbes and Rigobon (2001) point out to the statistical difficulties involved in testing changes in correlations across tranquil and turbulent periods. These studies show that, after taking into account the fact that correlation estimates are biased, there is no strong evidence the asset returns are correlated during financial crises. Furthermore, King, Sentana, and Wadhwani (1995) and Karolyi and Stulz (1996) show that even correlations across asset returns change over time, it is challenging to explain such changes.

In investigating the changes in correlations across asset markets, prior literature on financial contagion presumes that the extreme events around financial crises lead to irrational behavior and panic among investors. In return, investors ignore economic fundamentals as financial markets deteriorate. Therefore, the large negative returns are expected to be contagious rather than small negative returns. However, examining correlation changes in financial contagion research would be misleading given that correlations assign equal weights across the return distribution, including large and small returns and undermine the effects of large negative shocks.

Bae, Karolyi, and Stulz (2003) abandon the correlation framework and instead examine the large positive and negative return days. In other words, they measure the joint occurrences of large returns by developing an econometric model of the joint occurrences of large returns (exceedances) using multinomial logistic model, instead of computing correlations. An advantage of multinomial logistic models is that they enable us to condition on attributes and characteristics of joint occurrences using control variables. Consequently, contagion is defined as the fraction of exceedance events that is not explained by the covariates.

2.3 CDX Index Data

The CDS indices employed in this study include the CDX Investment Grade (IG), CDX High Yield (HY), ABX.HE AAA, ABX.HE BBB, CMBX AAA, CMBX BBB, and LCDX indices maintained by the Markit Group Ltd. Market quotations of these indices are not widely available. Fortunately, I was given access to a proprietary dataset by an asset management firm. The dataset includes daily quotations for CDS indices (formed from the on-the-run series) from June 2007 to April 2014. In my analysis I use weekly spread changes (Wednesday to Wednesday) for the corresponding on-the-run CDS index. All CDS indices used in this study are of 5 year maturity.

A CDS index is a standardized credit derivative used to hedge credit/default risk on a basket of credit entities. Many investors prefer to express a credit view on a group of entities. CDS indices of credit derivatives fulfill this preference and provide liquidity on the underlying baskets. Every six months CDS indices get revised and a new series of CDS index is created with updated constituents twice a year. The new index becomes the "on the run" index series, which is typically the most liquid of all existing index series. All CDS indices are over-the-counter products.

CDX IG and HY indices are CDS indices on corporate credit that started trading in 2003 and 2004, respectively. While CDX IG consists of 125 investment grade corporate credits, CDX HY consists of 100 high yield corporate names in North America.

ABX.HE index is a credit default swap index referencing a basket of 20 subprime mortgage-backed securities (MBS). ABX indices include five separate indices based on portfolios of sub-prime home equity (HE) collateralized debt obligations (CDO) with initial credit ratings of AAA, AA, A, BBB, and BBB-. ABX indices help market participants assess the performance of subprime residential MBS. The first ABX.HE index was launched in January 2006. In this study, I employ the ABX.HE AAA and ABX.HE BBB indices to represent two different risk appetites of investors. Since only the prices on ABX indices were available in the dataset instead of the spreads, I include a negative sign in the ABX index data to make sure they are directionally consistent with other CDS index data.

CMBX index is a CDS index referencing a basket of 25 commercial mortgage-backed securities (CMBS). This index provides insight into the performance of the CMBS market. The first CMBX index was launched in March 2006. Similar to ABX.HE indices, among the various CMBX indices available with different credit ratings, I employ the CMBX AAA and CMBX BBB indices in this study.

Finally, LCDX index consists of 100 reference entities, referencing first lien leveraged loans CDS. Normally a bank loan is considered secured debt; however the names that usually trade in the leveraged loan market are lower quality credits. Thus, LCDX index is mostly traded by investors who seek exposure to high yield debt. First LCDX index was launched in May 2007.

The CDS indices provide clean measures of credit/default risk for various credit markets. They are liquid and standardized products that allow investors to accurately gauge market sentiment around credit markets. In order to ensure the CDS index data used in this study are stationary, I use the first differences of weekly spreads for all seven indices in place of the spreads themselves.

2.4 Tests for Contagion in Credit Markets

2.4.1 Filtering the CDX Index Data

Following Bekaert, Harvey, and Ng (2005)'s definition of contagion, i.e., correlation over and above that expected from economic fundamentals, I filter the CDS index spread changes for major economic factor that would affect CDS spreads. These economic factors include three Fama and French (1993) factors (MKTRF, SMB, and HML), weekly changes in spot rate (5-year constant maturity treasury yield), weekly changes in slope of the yield curve (10-year constant maturity treasury yield – 3-month constant maturity treasury yield), weekly changes in default premium (Moody's yield difference on seasoned corporate bonds, i.e., BBB – AAA), weekly changes in 5-year swap rate, and weekly changes in the VIX index.[20] I control for common risk factors given above by regressing CDS index spread changes on these factors to make sure I do not attribute the correlations that are related to these common factors to contagion correlations. In addition, many studies in CDS literature show that CDS spreads are autocorrelated.[21] Therefore, I include the first lag of CDS index spread changes in each model to control for autocorrelation. The complete filtering model is given below:

$$\Delta S_t^i = \alpha^i + \Delta S_{t-1}^i + \sum_{k=1}^{8} \beta_k^i F_{k,t} + \varepsilon_t^i \qquad (2.5)$$

where ΔS_t^i is the weekly spread change for CDS index i at time t and $F_{k,t}$ is the weekly change in factor k. In this specification, I incorporate 8 factors as defined above.

I subsequently use the residuals from these models in my analyses as filtered spreads. Panel A of Table 2.1 exhibits the summary statistics (median, standard deviation, skewness, and excess kurtosis) for the filtered spreads. Note that filtered CDS index spreads differ significantly in the level of standard deviation. Moreover, while two of the indices (CDX IG and CMBX BBB) exhibit negative skewness, other indices have positive skewness. Finally, excess kurtosis is relatively high for most indices. Panel B presents the Pearson correlations for filtered CDS index spreads. While the correlations for the *filtered* spreads are positive ranging from 0.01 to 0.53, they are significantly lower than the correlations among *raw* CDS index spreads reported in Panel B of Table 2.2 ranging from 0.09 to 0.75.

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[20] Prior studies that employ these common factors to explain credit spreads include Turnbull (2005), Breitenfellner and Wagner (2012), Tang and Yan (2013), Zhang, Zhou, and Zhu (2009), and Galil et al. (2014).

[21] See Doshi et al. (2013) and Cont and Kan (2011).

2.4.2 Contagion Tests by Quantile Regression

Following Boyson, Stahel, and Stulz (2010), I employ two methods to show the existence of contagion among CDS indices, a semi-parametric approach (quantile regressions), and a parametric approach (a logit model).

In this section, I present the results from the quantile regression approach[22] which visually shows the existence of contagion using the co-movement box suggested by Cappiello, Gerard, and Manganelli (2005). This approach is robust to departures from normality and allows heteroscedasticity.

Quantile regressions estimate the conditional probability that a variable falls below a given threshold (quantile) when another random variable is also below the same quantile. Following this approach, I estimate the probability that a CDX index has a filtered spread above (below) a specified quantile given that average of other CDS indices is also above that quantile for right tail clustering (left tail clustering). I graph the conditional probabilities on a unit square co-movement box where the conditional probabilities are plotted against quantiles.

In case of *independence* of the two variables of interest (the specified CDS index and the average of other CDS indices), the conditional probability for the 10th decile can be easily calculated by the joint probability of the two events divided by the scaling factor: 0.10*0.10/0.10=0.10. Similarly, the conditional probability for the 90th decile can be calculated as 0.10*0.10/(1-0.90)=0.10. Such conditional probabilities associated with the case of independence are plotted in the co-movement box as the no dependence

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[22] Other studies that employ the quantile regression approach include Adrian and Brunnermeier (2009), Engle and Manganelli (2004), and Koenker and Bassett (1978).

benchmark which is a two-piece 45-degree line shown on Figure 2.1. Conditional probabilities depicted above the no dependence benchmark are evidence of positive conditional co-movement between the specified CDS index and the average of other CDS indices.

The conditional probabilities can easily be calculated for each CDS index using simple OLS regressions of quantile co-exceedance variables on a constant. The dependent variable in the regression is an indicator co-exceedance variable which is the product of two indicator variables, one for the specified CDS index and one for the average of other CDS indices for each quantile.

Figure 2.1 presents the co-movement box estimated using the filtered weekly data on seven CDS indices employed in this study. Conditional probabilities above the no dependence benchmark indicate positive dependence and values below the benchmark indicate negative dependence among CDS indices. The results show that all CDS indices exhibit positive dependence for quantiles both above and below median. Therefore, the co-movement box illustrates symmetry in CDS index data in terms of clustering on both right and left tails of the CDS spread distribution. This gives us a chance to examine the channels of this contagion during periods with both widening and tightening credit spreads.

2.4.3 Contagion Tests by a Logit Model

This section explores the existence of contagion in CDS indices using logit models which have been used extensively in the contagion literature including studies by Boyson, Stahel, and Stulz (2010), Bae, Karolyi, and Stulz (2003), and Eichengreen, Rose, and Wyplosz (1996). The logit models employed in this study estimate the likeliness of a given CDS index has an extreme observation when other indices also have extreme values.

The results from the quantile regression analyses in the previous section show that contagion exits in both tails of the filtered CDS index spread distribution. Therefore, I employ logit models for both tails as well. The dependent variable in the model is an indicator variable set to one if a given CDS index has a filtered spread in the 90th percentile of the spread distribution (10th percentile) during a period with widening (tightening) credit spreads. Figure 2.1 shows that clustering in CDS indices exits in all quantiles, therefore the analyses would also hold for other quantiles as well.

The main explanatory variable in the logit model is COUNT which is equal to the number of other CDS indices that have values in the 90th percentile (10th percentile) during a period with widening (tightening) credit spreads. A positive and significant coefficient estimate on the variable COUNT indicates an increase in the probability of having an extreme value in the CDS index in question when other indices also have extreme values. In other words, extreme values of the specified index cluster with the extreme values of other indices.

Table 2.3 exhibits the results from the logit models. During business contractions[23] (Panel A), the coefficients on COUNT are always positive and significant at 1% significance level. During business expansions (Panel B), coefficients on COUNT are positive and significant at 1% significance level for six out of seven indices, except for the ABX BBB index. These results, consistent with co-movement box in Figure 2.1,

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[23] Note that credit spreads widen (tighten) during business contractions (expansions).

provide strong evidence that filtered CDS index spreads exhibit clustering. Remember that this clustering exists despite the fact that the spread data is filtered for common economic factors and first degree autocorrelation. Therefore, following Bekaert, Harvey, and Ng (2005)'s definition of contagion as correlation over and above that expected from economic fundamentals, this observed clustering can be referred as contagion.

2.5 Channels of Credit Market Contagion

In this section, I investigate the channels that explain the contagion I document in the previous section. The contagion literature suggests at least three channels of contagion: the risk-premium channel, the information channel, and the liquidity channel. During the filtering process described in Section 2.4.1, the common economic factors already include contagion effects transmitted through the information and risk-premium channels. Therefore, in this section I investigate the liquidity channel through which shocks to market and funding liquidity increase the probability of contagion in credit markets.

Brunnermeier and Pedersen (2009) provide a theoretical model which suggests that under certain conditions market liquidity and funding liquidity are mutually reinforcing, potentially leading to liquidity spirals. They show that an adverse shock to speculators' funding liquidity, either through increased margins or a decline in the value of assets they hold, forces them to lower their leverage in a time of crisis and reduce the prices and the liquidity they provide to the market, which in turn results in diminished overall market liquidity. Concurrently, the value of speculators' holdings will decline leading to margin calls at a higher margin rate which results in more delevering in a bear market, which leads to a self-reinforcing liquidity spiral.

The seminal work of Brunnermeier and Pedersen (2009) implies that liquidity has commonality across securities,[24] since severe liquidity reductions occur simultaneously across asset classes in which distressed institutions are marginal investors. This commonality across securities caused by liquidity shocks is an important channel of contagion. Given that majority of the products in credit markets (especially in structured credit) are traded by institutions such as banks, insurance companies, mutual funds, hedge funds, and investment companies which have great exposure to liquidity shocks, credit markets are not immune to contagion triggered through the liquidity channel. Note that according to Brunnermeier and Pedersen (2009), liquidity induced contagion is a contraction event. However, given the symmetry of clustering presented in the previous section, I test the liquidity channel for both tails of the CDS index spread distribution to see if their implication holds.

Next, to test the liquidity channel of contagion I identify the contagion channel variables for which an extreme realization is associated with extreme changes in market or funding liquidity. The contagion channels variables employed in this study include the TED spread, i.e., the spread between the three-month LIBOR rate and the three-month U.S. Treasury bill rate, as a proxy measure of funding liquidity; REPO rate, i.e., the difference between overnight repurchase rate and 3-month treasury, as another proxy measure of funding liquidity; returns to banks and prime brokers, i.e., the bank index employed here is the KBW Bank Index (BANK) available on Bloomberg and the prime broker index (PBI) is a stock price index of eleven prime broker firms; Amihud (2002)

[24] Other academic work that document commonality through liquidity include Chordia, Sarkar, and Subrahmanyam (2005) and Acharya, Schaefer, and Zhang (2008).

(il)liquidity factor, and Hu, Pan, and Wang (2013) NOISE factor. Amihud (2002) and Hu, Pan, and Wang (2013) measures are stock and fixed income based measures of market liquidity, respectively. The details for these contagion channel variables and their relation to liquidity are presented in Table 2.4.

To remove autocorrelation, I filter each of the contagion channel variables via an AR(1) model. Summary statistics (median, standard deviation, skewness, and excess kurtosis) for the filtered channel variables are exhibited on Panel A of Table 2.5. The TED spread, Amihud (2002), and NOISE exhibit high excess kurtosis, hinting heavy tails for these variables. Panel B of the table presents the Pearson correlations among the contagion channel variables. Note that as expected, the correlation between the prime broker index and the bank index is positive and significant, 0.56. Also, the correlation between the TED spread and NOISE is positive and significant, 0.31, as they are both measures of illiquidity. On the other hand, the correlations of the TED spread with the prime broker index and the bank index are both negative and significant, -0.31 and -0.20, respectively.

Following Boyson, Stahel, and Stulz (2010), I employ a multinomial logistic model to examine if extreme shocks to contagion channel variables are associated with credit market contagion. The dependent variable, OCCUR, which measures the intensity of contagion, takes the value *zero* in a given week if zero or one CDS indices have an extreme value during a given week (base case, no contagion), *one* if two or three CDS indices have an extreme value during a given week (LOW contagion case), and *two* if four or more CDS indices have an extreme value in a given week (HIGH contagion case). A weekly data is classified as an extreme value in business contractions (expansions) if it falls in the 90th (10th) percentile of the spread distribution. The multinomial logistic model simultaneously estimates the parameters in the model for HIGH and LOW contagion cases of OCCUR relative to the base case.

The key independent variable in the regressions which model extreme shocks for each of the contagion channel variables is an indicator variable set to one when the corresponding channel variable is in its lowest (highest) *liquidity quartile*[25] during business contractions (expansions), and zero otherwise. The regressions also include the continuous contagion channel variables winsorized at the 25th percentile[26] of a low liquidity indication to avoid double counting extreme realizations.

I repeat the analyses for both sides of the distribution of CDS index spreads given that contagion/dependence among CDS indices exists for both worsening and improving credit markets. A positive and significant coefficient on a channel indicator variable indicates that the liquidity shock associated with the channel variable increases the probability of contagion relative to the base case.

Table 2.6 presents the results from the multinomial logistic model during periods with widening credit spreads. The results suggest that the funding liquidity measures, TED spread and REPO rate, and the market liquidity measures Amihud (2002) and NOISE are linked to both HIGH and LOW levels of contagion intensity across CDS indices. Therefore, both market and funding liquidity contribute to contagion during

[25] Note that while the lowest liquidity quartile for the contagion channel variables the TED spread, REPO rate, Amihud (2002), and NOISE is their 75th percentile, it corresponds to the 25th percentile for the channel variables prime broker index and bank index.

[26] The quartile realizations are used in the analyses instead of decile realizations to avoid quasi-complete separation problem in estimating the multinomial logistic regressions.

business contractions. This result is consistent with Brunnermeier and Pedersen (2009) who suggest that market liquidity and funding liquidity shocks could be mutually reinforcing which leads to liquidity spirals, causing significant changes in asset prices across all markets, therefore leading to contagion across various asset classes during business contractions.

Another important variable during periods with widening credit spreads is the bank index which is only statistically significant at low levels of contagion. This result shows that an adverse shock to banks during business contractions can cause low level contagion among credit markets.

In order to measure the economic significance of these results, for each multinomial logistic regression, I set the winsorized continuous contagion channel variable to its time series mean and calculate the probability of contagion for LOW and HIGH contagion cases separately, depending on whether the contagion channel indicator variable is either zero or one, i.e., no liquidity shock or with liquidity shock cases. Following this procedure, I calculate the change in the probability of contagion in presence of a liquidity shock vs. no liquidity shock for both LOW and HIGH contagion cases. The economic significance of the contagion channel variables that are statistically significant is striking. An adverse shock to the funding liquidity proxy, TED spread increases the probability of HIGH (LOW) contagion from 4.3% to 15.6% (from 10.1% to 27.2%) compared to the no shock case. Similarly, an adverse shock to the other funding liquidity proxy, REPO rate increases the probability of LOW contagion from 28.2% to 78.2%. A negative shock to the market liquidity proxy, Amihud (2002), increases the probability of HIGH (LOW) contagion from 3.7% to 12.0% (from 10.4% to 23.6%).

Similarly for the other market liquidity proxy, NOISE, an adverse shock increases the probability of HIGH (LOW) contagion from 5.4% to 19.0% (from 14.4% to 36.7%). Finally, a negative shock to the bank index increases the probability of LOW contagion from 9.6% to 34.8%. These analyses show that the results I document in this section are not only statistically significant but also economically significant.

Table 2.7 presents the results from the multinomial logistic model during periods with tightening credit spreads. Note that the funding and market liquidity factors (Ted, Amihud (2002), and NOISE) are not significant channels for contagion during business expansions. However, the prime broker index is a significant LOW contagion channel and the bank index is a significant HIGH contagion channel. These results suggest that the intermediaries such as prime brokers and banks play an important role in spreading a market rally across various credit markets.

For the periods with tightening credit spreads, I repeat the economic significance analyses. A positive shock to the bank index increases the probability of HIGH contagion from 1.8% to 10.5%. On the other hand, a favorable shock to the prime broker index increases the probability of LOW contagion from 15.5% to 40.8%. Once again, the statistically significant results for business expansions are also economically significant.

2.6 Concluding Remarks

Starting in the sub-prime mortgage market, the recent financial crises systematically spread to credit markets, other financial markets, and finally to the real sectors, causing one of the worst recessions in history. Given the relatively small size of the sub-prime mortgage market, finance professionals did not anticipate the much larger scale market downturn. However, through channels of contagion, adverse shocks in the sub-prime mortgage market spread to other markets, starting initially in the credit markets. In this study, I analyze the contagion in credit markets where the shocks in the sub-prime mortgage market were propagated and magnified.

Bekaert, Harvey, and Ng (2005) define contagion as correlation over and above that expected from economic fundamentals. This definition suggests that any clustering across CDS indices, which are proxies for credit markets, after filtering for economic factors, must be due to contagion. I employ a semi-parametric (quantile regression) and a parametric (logit model) approach to show the existence of contagion in credit markets using the filtered CDS index spreads. The evidence supports existence of contagion/dependence in both business expansions and contractions.

Many prior studies treat contagion as only a contraction event. Brunnermeier and Pedersen (2009) show that negative liquidity shocks lead to a self-reinforcing liquidity spiral which causes contagion during business contractions. The results documented in this paper, produced by a multinomial logistic regression, suggest that during periods with widening credit spreads, both funding liquidity and market liquidity are significant contagion channels. This result supports Brunnermeier and Pedersen (2009)'s theoretical model. On the other hand, the prime broker index and the bank index are significant contagion channels during periods with tightening credit spreads. This finding indicates that financial intermediaries play an important role in spreading market rallies across credit markets during business expansions.

Table 2.1: Summary Statistics for Filtered Weekly Data on CDS Indices

Panel A reports the summary statistics (median, standard deviation, skewness, and excess kurtosis) for seven CDS indices. The indices include the corporate indices CDX Investment Grade (IG) and CDX High Yield (HY), the structured credit indices ABX AAA, ABX BBB, CMBX AAA, and CMBX BBB, and the loan index LCDX. Weekly data includes the sample period from 6/8/2007 to 4/25/2014. Panel B reports the Pearson correlations at various significance levels, *** for 1%, ** for 5%, and * for 10% significance.

	CDS Indices						
	CDX_IG	CDX_HY	ABX_AAA	ABX_BBB	CMBX_AAA	CMBX_BBB	LCDX
	Panel A: Summary Statistics						
Median	-0.04	-1.07	-0.10	-0.10	-0.48	0.90	-0.52
Standard Deviation	7.45	30.15	1.67	0.91	34.84	141.87	35.49
Skewness	-0.99	0.34	0.77	3.05	2.07	-1.01	1.39
Excess Kurtosis	7.81	3.97	7.22	29.29	25.42	13.96	14.36
	Panel B: Correlations						
CDX_IG	1.00	0.53***	0.31***	0.11**	0.43***	0.2***	0.35***
CDX_HY		1.00	0.19***	0.01	0.31***	0.14***	0.46***
ABX_AAA			1.00	0.32***	0.38***	0.41***	0.13**
ABX_BBB				1.00	0.01	0.09	0.04
CMBX_AAA					1.00	0.49***	0.35***
CMBX_BBB						1.00	0.22***
LCDX							1.00

Table 2.2: Summary Statistics for Raw Weekly Data on CDS Indices

Panel A reports the summary statistics (median, standard deviation, skewness, and excess kurtosis) for seven CDS indices. The indices include the corporate indices CDX Investment Grade (IG) and CDX High Yield (HY), the structured credit indices ABX AAA, ABX BBB, CMBX AAA, and CMBX BBB, and the loan index LCDX. Weekly data includes the sample period from 6/8/2007 to 4/25/2014. Panel B reports the Pearson correlations at various significance levels; *** for 1%, ** for 5%, and * for 10% significance.

	CDS Indices						
	CDX_IG	CDX_HY	ABX_AAA	ABX_BBB	CMBX_AAA	CMBX_BBB	LCDX
Panel A: Summary Statistics							
Median	-0.30	-1.10	-0.04	0.00	-0.54	14.63	-0.24
Standard Deviation	9.99	45.11	1.85	0.99	41.48	161.20	46.33
Skewness	0.23	0.62	0.96	4.49	2.68	-0.61	1.16
Excess Kurtosis	5.49	3.36	6.65	28.58	31.07	12.81	8.50
Panel B: Simple Correlations							
CDX_IG	1.00	0.75***	0.49***	0.14***	0.58***	0.37***	0.61***
CDX_HY		1.00	0.41***	0.09	0.52***	0.33***	0.71***
ABX_AAA			1.00	0.35***	0.5***	0.48***	0.34***
ABX_BBB				1.00	0.06	0.11**	0.09*
CMBX_AAA					1.00	0.55***	0.55***
CMBX_BBB						1.00	0.34***
LCDX							1.00

Table 2.3: Contagion Tests Using Filtered CDS Index Data

The table reports the results from logit regressions which separately model the event of an extreme value in each CDS index. A weekly data is classified as an extreme value if it falls in the 10% of the spread distribution in the tail on either side. The explanatory variable, COUNT, is the number of other CDS indices that also have extreme values for a given week. The t-statistics are given in parentheses. Coefficients with ***, **, and * are statistically significant at the 1%, 5%, and 10% levels, respectively. Panel A reports the results for the right hand side of the CDS spread distribution (90th percentile). Panel B reports the results for the left hand side of the spread distribution (10th percentile). The number of observations is 360. The pseudo R^2 is the scaled coefficient of determination suggested by Nagelkerne (1991).

Panel A: Logit Model Results for 90th Percentile							
	CDX_IG	CDX_HY	ABX_AAA	ABX_BBB	CMBX_AAA	CMBX_BBB	LCDX
Constant	-3.24***	-3.19***	-3.12***	-2.49***	-3.33***	-3.01***	-3.06***
	(-11.36)	(-11.41)	(-11.53)	(-11.61)	(-11.10)	(-11.61)	(-11.47)
Count	0.97***	0.94***	0.88***	0.36***	1.04***	0.97***	0.84***
	(6.75)	(6.64)	(6.54)	(3.15)	(6.76)	(6.19)	(6.21)
Pseudo R^2	0.30	0.29	0.27	0.05	0.32	0.23	0.24
Panel B: Logit Model Results for 10th Percentile							
	CDX_IG	CDX_HY	ABX_AAA	ABX_BBB	CMBX_AAA	CMBX_BBB	LCDX
Constant	-3.25***	-2.9***	-2.84***	-2.31***	-2.92***	-2.93***	-3.22***
	(-11.02)	(-11.28)	(-11.30)	(-11.15)	(-11.29)	(-11.24)	(-11.08)
Count	1.05***	0.75***	0.7***	0.17	0.77***	0.78***	1.01***
	(6.29)	(5.26)	(5.01)	(1.20)	(5.39)	(5.39)	(6.34)
Pseudo R^2	0.26	0.15	0.14	0.01	0.16	0.16	0.25

Table 2.4: Contagion Channel Variables

This table presents details on the contagion channel variables introduced in Section 2.5.

Variable	Details	Reference Literature
TED Spread: Change in Treasury-Eurodollar spread calculated as the difference between 3-month LIBOR and 3-month treasury yield. Available on Bloomberg.	TED spread is a measure of funding liquidity. An increase in spreads implies higher borrowing costs, hence a decrease in liquidity.	Boyson et al. (2010), Teo (2011), Gupta and Subrahmanyam (2000), Campbell and Taksler (2003), Taylor and Williams (2009)
REPO: Change in the difference between overnight repurchase rate and 3-month treasury, available on Bloomberg.	REPO rates reflect actual daily funding costs experienced by banks and investors.	Kambhu (2006), Adrian and Fleming (2005), Boyson et al. (2010)
BANK: Weekly change in the Keefe, Bruyette and Wooks bank index from Bloomberg.	Higher bank returns indicate improved liquidity.	Chan et al. (2006), Boyson et al. (2010)
PBI: Weekly change in the equally weighted stock price index of prime brokers including Morgan Stanley, Goldman Sachs, UBS AG, Bank of America Mellon, Credit Suisse, Bear Sterns, Bank of America, Deutsch Bank, Citigroup, Merrill Lynch, and Lehman Brothers, adjusted for mergers and including bankruptcy returns. Data available on CRSP.	Higher prime broker returns indicate improved liquidity. Prime brokers are counterparties to CDS contracts. Shocks to prime brokers are reflected in CDS spreads.	Boyson et al. (2010)
Amihud: A stock based market (il)liquidity measure suggested by Amihud (2002) derived from stock price data from CRSP.	Higher values of Amihud measure are associated with a decrease in market liquidity.	Amihud (2002), Acharya and Pedersen (2005), Boyson et al. (2010)
NOISE: A fixed-income base market liquidity measure suggested by Hu, Pan, and Wang (2013). Available from Jun Pan of MIT, Sloan School of Management.	Higher values of NOISE measure are associated with an increase in market liquidity.	Hu, Pan, and Wang (2013)

Table 2.5: Summary Statistics for Filtered Contagion Channel Variables

Panel A reports the summary statistics (median, standard deviation, skewness, and excess kurtosis) for six contagion channel variables. The variables include the corporate the TED spread, REPO rate minus 3-month treasury (REPO), a prime broker index (PBI), a bank index (BANK), Amihud (2002) market liquidity measure, and Hu et al. (2013) market liquidity measure (Noise). Weekly data includes the sample period from 6/8/2007 to 4/25/2014. Panel B reports the Pearson correlations at various significance levels, *** for 1%, ** for 5%, and * for 10% significance.

	Contagion Channel Variables					
	TED	REPO	PBI	BANK	Amihud	NOISE
Panel A: Summary Statistics						
Median	-0.12	0.00	0.25	1.20	-0.11	-0.03
Standard Deviation	18.94	0.23	2.43	11.41	7.59	0.64
Skewness	0.68	0.33	-1.09	-0.76	2.94	1.33
Excess Kurtosis	48.99	32.89	4.50	2.26	50.29	9.11
Panel B: Correlations						
TED	1.00	0.27***	-0.31***	-0.20***	0.07	0.31***
REPO		1.00	0.03	0.03	-0.02	0.15***
PBI			1.00	0.56***	0.00	-0.21***
BANK				1.00	-0.05	-0.05
AMIHUD					1.00	0.05
NOISE						1.00

Table 2.6: Credit Market Contagion in Business Contractions, Contemporaneous Contagion Channel Variables

The table reports the results from multinomial logistic regressions which model the co-occurrence of extreme values in CDS indices. The dependent variable, OCCUR, takes the value zero if zero or one CDS indices have an extreme value during a given week (base case, no contagion), one if two or three CDS indices have an extreme value during a given week (low contagion case), and two if four or more CDS indices have an extreme value in a given week (high contagion case). A weekly data observation is classified as an extreme value during periods with widening credit spreads, if it falls in the 10% of the spread distribution in the right tail. The regressions include the continuous contagion channel variables (winsorized at the 25th percentile of a low liquidity indication) and indicator variables corresponding to contemporaneous negative quartile realizations of the contagion channel variables. Reported below, the contagion channel variables include the TED spread, REPO rate minus 3 month Treasury (REPO), a prime broker index (PBI), a bank index (BANK), Amihud (2002) market liquidity measure, and Hu et al. (2013) market liquidity measure (Noise). The t-statistics are given in parentheses. Coefficients with ***, **, and * are statistically significant at the 1%, 5%, and 10% levels, respectively. The pseudo R^2 is the scaled coefficient of determination suggested by Nagelkerne (1991).

Dependent Variable: OCCUR						
	Channel Variable= TEDSPRD	Channel Variable= REPO	Channel Variable= PBI	Channel Variable= BANK	Channel Variable= Amihud	Channel Variable= NOISE
Constant (LOW)	-2.53***	-1.33***	-1.93***	-2.38***	-2.26***	-2.06***
	(-10.39)	(-4.41)	(-8.48)	(-8.77)	(-10.05)	(-8.35)
Constant (HIGH)	-3.34***	-2.53***	-3.08***	-2.81***	-3.3***	-3.12***
	(-9.50)	(-5.06)	(-8.01)	(-8.57)	(-9.43)	(-8.27)
Winsorized Continuous Channel Variables						
Cont. Chan. Winsorized $variable_t$ (LOW)	-0.08***	0.96	-0.22	0.02	-0.13***	-0.97**
	(-4.44)	(1.13)	(-1.37)	(0.65)	(-2.68)	(-2.14)
Cont. Chan. Winsorized $variable_t$ (HIGH)	-0.07***	0.90	-0.07	-0.04	-0.15***	-1.54***
	(-2.92)	(0.71)	(-0.31)	(-0.93)	(-3.08)	(-2.95)
Indicator Variables						
$Indicator_t$ (LOW)	0.99**	1.02***	0.20	1.29***	0.81**	0.94**
	(2.49)	(2.83)	(0.44)	(2.63)	(2.14)	(2.16)
$Indicator_t$ (HIGH)	1.29**	0.40	1.00	0.31	1.18**	1.26**
	(2.46)	(0.72)	(1.49)	(0.47)	(2.18)	(2.02)
Pseudo R^2	0.13	0.05	0.04	0.05	0.09	0.06

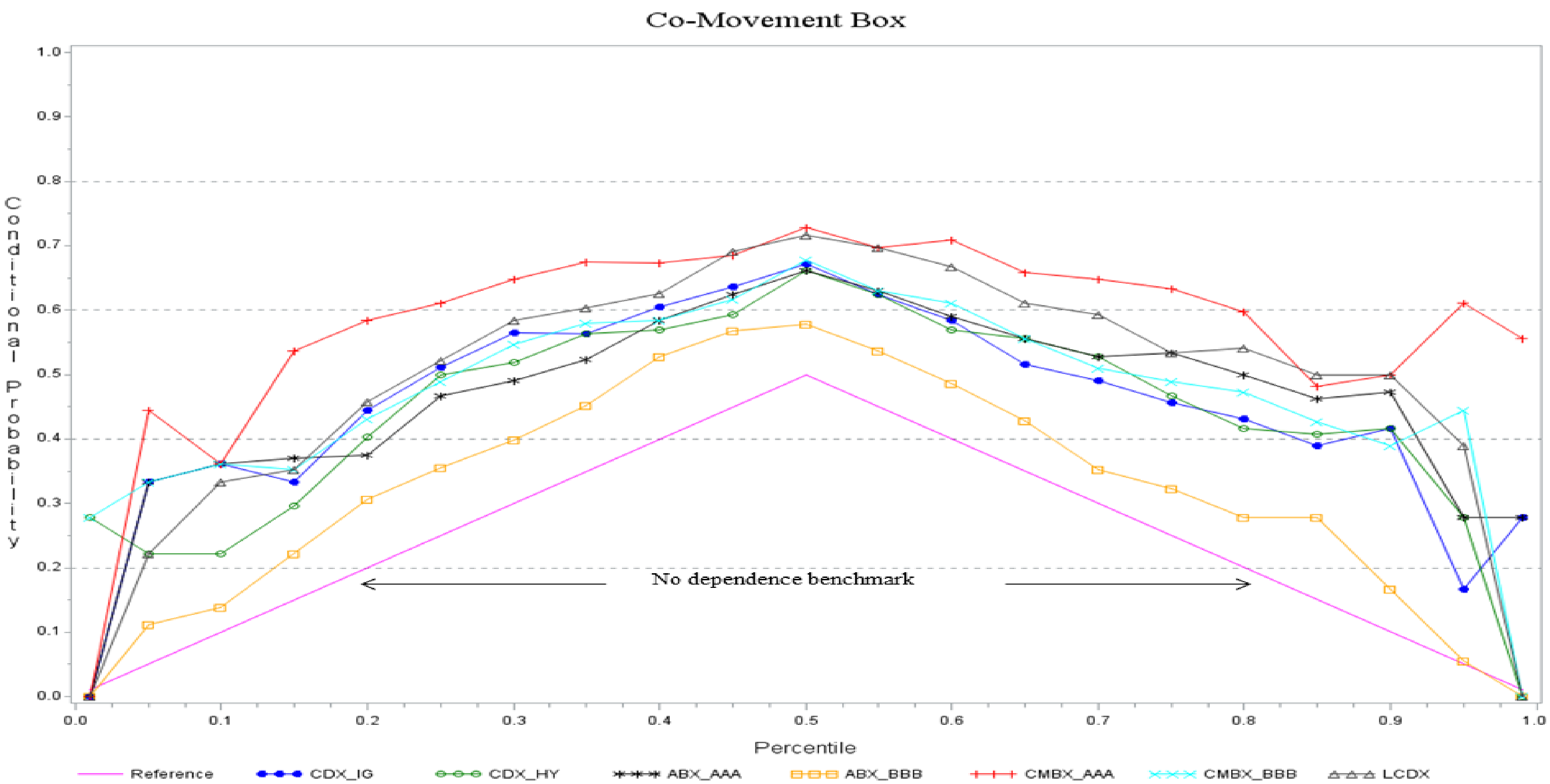
Table 2.7: Credit Market Contagion in Business Expansions, Contemporaneous Contagion Channel Variables

The table reports the results from multinomial logistic regressions which model the co-occurrence of extreme values in CDS indices. The dependent variable, OCCUR, takes the value zero if zero or one CDS indices have an extreme value during a given week (base case, no contagion), one if two or three CDS indices have an extreme value during a given week (low contagion case), and two if four or more CDS indices have an extreme value in a given week (high contagion case). A weekly data observation is classified as an extreme value during periods with tightening credit spreads, if it falls in the 10% of the spread distribution in the left tail. The regressions include the continuous contagion channel variables (winsorized at the 25th percentile of a high liquidity indication) and indicator variables corresponding to contemporaneous positive quartile realizations of the contagion channel variables. Reported below, the contagion channel variables include the TED spread, REPO rate minus 3 month Treasury (REPO), a prime broker index (PBI), a bank index (BANK), Amihud (2002) market liquidity measure, and Hu et al. (2013) market liquidity measure (Noise). The t-statistics are given in parentheses. Coefficients with ***, **, and * are statistically significant at the 1%, 5%, and 10% levels, respectively. The pseudo R^2 is the scaled coefficient of determination suggested by Nagelkerne (1991).

	Dependent Variable: OCCUR					
	Channel Variable= TEDSPRD	Channel Variable= REPO	Channel Variable= PBI	Channel Variable= BANK	Channel Variable= Amihud	Channel Variable= NOISE
Constant	-1.76***	-1.87***	-1.91***	-1.75***	-1.62***	-1.56***
(LOW)	(-9.83)	(-5.26)	(-9.70)	(-9.22)	(-9.05)	(-8.01)
Constant	-3.59***	-2.93***	-11.35***	-4.05***	-3.26***	-3.21***
(HIGH)	(-8.78)	(-5.28)	(-1.43)	(-7.40)	(-8.77)	(-7.71)
	Winsorized Continuous Channel Variables					
Cont. Chan. Winsorized variable_t (LOW)	0.01	-0.89	-0.13*	-0.02	-0.02	0.29
	(1.42)	(-0.97)	(-1.73)	(-1.35)	(-0.53)	(1.01)
Cont. Chan. Winsorized variable_t (HIGH)	0.02*	-1.29	-0.96	-0.04	0.00	0.03
	(1.57)	(-1.13)	(-1.33)	(-1.20)	(0.02)	(0.04)
	Indicator Variables					
Indicator_t	0.44	0.28	0.97***	0.45	0.30	0.58
(LOW)	(1.35)	(0.75)	(2.65)	(1.16)	(0.93)	(1.59)
Indicator_t	0.49	-0.89	10.72	1.74**	-0.23	0.36
(HIGH)	(0.67)	(-1.27)	(1.21)	(2.02)	(-0.28)	(0.45)
Pseudo R^2	0.02	0.02	0.14	0.02	0.01	0.01

Figure 2.1: Co-movement Box: Co-movements between Individual Filtered CDS Index Spread and Average of All Other CDS Index Spreads

The co-movement box plots the conditional probabilities, estimated by quantile regressions, that a CDS index has a filtered spread above or below a certain quantile conditional on the average of all other indices has a filtered spread in the same quantile. The two-piece 45° line represents the unconditional probability of no dependence. Conditional probabilities that lie above (below) the 45° line indicate positive (negative) co-movement between the two variables.



CHAPTER 3: AMBIGUITY AVERSION AND CORPORATE CASH HOLDINGS

3.1 Introduction

Firms hold cash instead of returning it to shareholders for a variety of reasons. One reason that has received extensive attention in the economics and finance literature is the precautionary motive for holding cash. The precautionary motive suggests that firms hold cash to protect against adverse shocks when the costs to access capital are more costly. Under the precautionary motive, firms should hold more cash when they have better investment opportunities as adverse shocks are more costly when the likelihood of missing out on profitable investment opportunities is greater. Prior research has found evidence consistent with the precautionary motive for holding cash and that the precautionary motive is strongest for financially constrained firms (Opler, Pinkowitz, Stulz, and Williamson 1999; Almeida, Campello, and Weisbach 2004; Bates, Kahle, and Stulz 2009; Duchin 2010). The objective of this study is to examine how ambiguity aversion within the investor base affects the precautionary motive for holding cash.

Ambiguity aversion, also known as uncertainty aversion, refers to a form of bounded rationality under which an individual prefers known risks over unknown risks (Gilboa and Schmeidler 1989; Epstein 1999). Ambiguity aversion is distinct from risk aversion in that ambiguity relates to uncertainty about the distribution of an asset's payoff while risk relates to uncertainty about the asset's payoff (Knight 1921). An asset would be considered risky if the standard deviation of its potential payoffs is large. Such a determination would require that the distribution of the asset's payoffs is known. On the other hand, an asset would be considered ambiguous if the distribution of its payoffs is unknown.

The payoffs to future investment opportunities are inherently both risky and ambiguous. It is unlikely investors know the complete distribution of payoffs to future investment opportunities. Given the unknown risks associated with future investment opportunities, investors who are ambiguity averse are likely to value future investment opportunities differently than investors without ambiguity aversion. By extension, investors who are ambiguity averse are also likely to value cash holdings differently because the precautionary motive for holding cash is related to the desire to avoid forgoing future investment opportunities.

Breuer, Rieger, and Soypak (2014b) develop a theoretical model that predicts a negative relationship between the value of cash and ambiguity aversion. In their model, ambiguity averse investors undervalue future investments with unknown risks. An undervaluation of future investments also reduces investors' valuation of cash held for precautionary reasons. Thus, investors with high levels of ambiguity aversion would prefer to receive dividends as opposed to firms holding cash for precautionary reasons. Our first objective is to empirically test the predictions of the theoretical model of Breuer et al. (2014b) in a United States setting. Specifically, we test whether the valuation of cash holdings depends on the extent of ambiguity aversion within a firm's shareholder base in the United States setting.

To measure the extent of ambiguity aversion within a firm's shareholder base, we assume individual investors are most likely to exhibit ambiguity aversion. Experimental economics research has documented that individuals sometimes act as if they prefer known risks over unknown risks (Ellsburg 1961). Given that ambiguity aversion is a form of bounded rationality, we expect retail investors are more likely to exhibit such bounded rationality than sophisticated investors. Furthermore, individuals are likely to have greater uncertainty regarding the distribution of payoffs from investment opportunities than sophisticated investors. On the other hand, in a related study, Heath and Tversky (1991) show that people prefer betting on their judgment when they feel knowledgeable and competent and they prefer betting on their skill. This is also consistent with March and Shapira (1987) that people, who consistently bet on highly ambiguous business propositions, resist the analogy between business decisions and games of chance. Thus, institutional investors would exhibit less ambiguity toward the professional decisions they face, given their level of competence, knowledge, and sophistication. Therefore, our proxy for the ambiguity aversion of a firm's shareholder base is the proportion of investors that are *not* institutional investors or mutual funds.

We examine whether the value of cash is related to this proxy for the extent of ambiguity aversion within a firm's shareholder base. The valuation of cash holdings is measured using the empirical model in Faulkender and Wang (2006). The value of cash holdings is determined by regressing long-window returns on changes in cash balances. Similar to Faulkender and Wang (2006), we run this model separately for firms that are financially constrained and those that are unconstrained. Consistent with the predictions of the theoretical model in Breuer et al. (2014b), we find the value of cash holdings is negatively associated with the extent of ambiguity aversion in a firm's shareholder base for firms that are financially constrained. We do not find an association between the value of cash holdings and ambiguity aversion for firms that are unconstrained.

The lower valuation of cash holdings by ambiguity averse investors begs the question as to whether firms adjust cash holdings in response to the extent of ambiguity aversion within their shareholder base and/or investors who are ambiguity averse flock to those firms with lower levels of cash holdings. Our findings support both scenarios. Prior research has found that managers cater dividend policy to investor preferences (Baker and Wurgler 2004; Breuer et al. 2014a). If managers cater cash holdings to investor preferences, firms with a large proportion of ambiguity averse investors would hold lower levels of cash than firms with a low proportion of ambiguity averse investors. To examine whether managers cater cash holdings to investor preferences and/or investors who are ambiguity averse flock to those firms with lower levels of cash holdings, we regress cash holdings on our proxy for the extent of ambiguity aversion within a firm's shareholder base. We find that firms with a higher proportion of ambiguity averse investors hold less cash. Similar to results on the valuation of cash holdings, we find this relationship only exists in financially constrained firms.

This study contributes to both the literature on cash holdings and the literature on catering. Prior research on cash holdings has not examined how bounded rationality can affect the valuation of cash holdings. We confirm the theoretical predictions of Breuer et al. (2014b) by showing that the extent of ambiguity aversion within a firm's shareholder base can affect the valuation of cash holdings. In turn, managers of financially constrained firms with a large proportion of ambiguity averse investors hold less cash. This suggests that managers cater a firm's cash holdings in response to the lower valuation of cash by ambiguity averse investors. Our finding also has implications for the temporal trend in cash holdings. In recent decades, corporate cash holdings have increased substantially. We find that the proportion of institutional investors has increased steadily over the same period and is highly correlated with the average cash ratio. The paper proceeds as follows: Section 3.2 summarizes the prior literature on corporate cash holdings and ambiguity aversion before stating our hypotheses. Section 3.3 details our sample selection process while Section 3.4 describes our ambiguity aversion measure. Section 3.5 presents our results before Section 3.6 concludes.

3.2 Prior Literature and Hypothesis Development

3.2.1 Motives for Cash Holdings

The economics and finance literature has espoused four main motives for why firms hold cash: the transaction motive, the precautionary motive, the agency motive, and the tax motive (Bates, Kahle, and Stulz 2009). The transaction motive suggests firms hold cash in order to avoid costly transaction costs associated with converting noncash assets into cash assets. The precautionary motive posits that firms hold cash as a precaution to adverse shocks in the economy, especially when it is costly to access to capital markets. This motive is more important for firms with better investment opportunities as adverse shocks are more costly for such firms because of the possibility of missing out on positive NPV projects. The agency motive for holding cash suggests that differences in the incentives of managers and shareholders cause managers to hold more cash than is optimal instead of paying it out to shareholders (Jensen 1986). The tax motive proposes multinational firms hold cash to avoid the tax consequences associated with repatriating foreign earnings (Foley at al. 2007).

While ambiguity aversion could have an impact on the other motives for holding cash, we focus on the precautionary motive as it is more likely to be impacted by ambiguity aversion. The payoffs to future investments are inherently uncertain, and it is unlikely that investors know the distribution of payoffs to future investments. Before discussing ambiguity aversion, we briefly review the prior literature on the prior findings regarding the precautionary motive for holding cash. Consistent with the precautionary motive for holding cash, Opler, Pinkowitz, Stulz, and Williamson (1999) find that firms hold more cash when they face riskier cash flows and they have poor access to capital markets. The precautionary motive is especially important for financially constrained firms with better investment opportunities as the expected costs of missing positive NPV projects are greater for these firms. Almeida, Campello, and Weisbach (2004) model the precautionary demand for cash and show that financially constrained firms hold more cash compared to unconstrained firms. Duchin (2010) examines cash holdings from a diversification perspective and finds the average cash holdings of stand-alone firms are almost double the cash holdings of diversified firms. This finding suggests diversified firms are well positioned to smooth investment opportunities and cash flows and, as a result, hold less precautionary cash.

3.2.2 Ambiguity Aversion

Knight (1921) is often credited with distinguishing risk from ambiguity with the former characterized as uncertainty over an asset's payoff and the latter characterized as uncertainty over the distribution. While some sophisticated investors may know the distribution of an asset's payoffs, it seems implausible to assume unsophisticated investors know the distribution of payoffs of even the simplest assets. Experimental research has documented that individuals sometimes act as if they do not have a prior over the set of payoff distributions. The most well-known example of such behavior is the Ellsberg Paradox in which individuals make choices over two gambles (Ellsberg 1961). The individuals in the experiment often make choices that are inconsistent with a single prior over the probability distribution of the gambles. Other experiments have repeated the results of the Ellsberg Paradox in different settings. This experimental evidence led Gilboa and Schmeidler (1989) to propose “max-min” expected utility preferences in order to loosen the axioms of expected utility maximization. With max-min expected utility preferences, individuals make decisions to maximize utility under the model that leads to the lowest expected utility. In other words, investors evaluate an investment using worst case scenario beliefs. More recent research has generalized the max-min utility model to allow for the possibility that the individual is not so pessimistic to only evaluate the decision using worst case scenario beliefs. Either way, our hypotheses regarding cash holdings do not necessarily depend on max-min utility preferences, but the max-min utility model does provide a convenient framing to develop our hypotheses.

From the perspective of a firm’s manager, there is uncertainty regarding investment opportunities, cash flows, and access to external financing. If a manager exhibits ambiguity aversion, uncertainty over the probability distribution of any of these factors could help explain the level of a firm’s cash holdings. Chen et al. (2015) find that corporate cash holdings positively associated with uncertainty avoidance, another term for ambiguity aversion. They attribute this finding to managers from high uncertainty avoiding cultures being less tolerant for uncertainty associated with future cash-flows and thus hold more cash to compensate for this uncertainty.

While a manager’s aversion to ambiguity might explain excess cash holdings, prior research often assumes firms and their managers by extension are risk neutral. Unlike Chen et al. (2015), we examine the impact of ambiguity aversion from the perspective of investors. Another difference between our study and Chen et al. (2015) is that their uncertainty avoidance measure is derived from cross-country surveys of cultural preferences. Our ambiguity aversion is measured at the firm-level and focuses on the shareholder base of each firm. We also conduct separate analyses of constrained and unconstrained firms.

The most closely related paper to ours is Breuer, Rieger, and Soypak (2014b). They develop a theoretical model that predicts a negative relationship between the value of cash and ambiguity aversion among investors. A key assumption of their model is that the short-term returns of holding cash are certain whereas the long-term returns of the future investments to be funded with the cash are uncertain. As a result of this assumption, ambiguity averse investors undervalue future investments and in turn they reduce their valuation of cash held for precautionary reasons. Investors with high levels of ambiguity aversion would prefer to receive dividends as opposed to firms holding cash for precautionary reasons. They tests the predictions of their model and show that cash holdings are less valuable with increasing ambiguity aversion among investors. They also show that in countries where investors are more ambiguity averse, firms hold lower levels of cash holdings.

3.2.3 Hypotheses

We base our hypotheses on the predictions of the theoretical model in Breuer et al. (2014b). If investors are averse to ambiguity, we expect them to prefer firms hold less cash given that the payoffs to future investments that will be funded by the cash holdings are plagued by uncertainty. Thus, we state our first hypothesis in the alternative form:

H1: Ambiguity averse investors place a lower value on cash holdings.

If ambiguity averse investors place a lower value on cash holdings, it begs the question as to whether firms cater their cash holdings in response to the level of ambiguity aversion within their shareholder base. If firms cater cash holdings according to the preferences of the shareholder base, we would expect ambiguity aversion within a firm's shareholder base to be a significant explanatory variable for cash holdings. This leads to our second hypothesis:

H2: A firm's cash holdings is positively associated with the level of ambiguity aversion within a firm's shareholder base.

3.3 Data

This section describes the data employed in the empirical analysis. Our data convention follows Faulkender and Wang (2006). The data period covers from 1980 to 2014. We employ COMPUSTAT, CRSP, and Thomson Reuters databases. All financial and utility firms (SIC codes between 6,000 and 6,999 and between 4,900 and 4,999, respectively) are excluded. The annual stock returns from CRSP include distributions during the fiscal year.

We convert the data to real values in 2014 dollars using the consumer price index (CPI). Cash holdings are defined as cash and short term investments. Net assets are total assets minus cash holdings. The market value of equity is equal to number of shares multiplied by stocks closing price at the fiscal year-end. Earnings are before extraordinary items plus deferred tax credits, interest, and investment tax credits. Leverage is calculated as total debt divided by the sum of total debt and the market value of equity. Total dividends are equal to common dividends paid. Net financing is total equity issuance minus repurchases plus debt issuance minus debt redemption.

We winsorize the firm-specific variables and the dependent variable at the 1% tails using the full sample. We exclude firm-years for which net assets, the market value of equity, or dividends are negative. The final sample consists of 110,663 firm-years.

3.4 Ambiguity Aversion Measure

In this paper we employ a novel approach to measure ambiguity aversion. We use Kyle's (1985) distinction between informed traders and noise traders in order to identify the ambiguity averse investors. Informed traders have significant information regarding the marketplace and thus should be less ambiguity averse. On the other hand, noise traders do not have superior information and are more likely to exhibit ambiguity aversion. Our proxy for informed traders is the percentage of institutional ownership. Institutional investors should have significantly more information about the company compared to the individual investors. Therefore our ambiguity aversion measure is one minus the percentage of institutional ownership which is readily available on the Thomson Reuters databases for each firm. Figure 3.1 depicts the proportion of individual and institutional investors in the U.S. over years from 1980 to 2014. It is clear that the proportion of institutional investors has greatly increased in the recent decades. As a result the ambiguity aversion in the investor base has declined as the proportion of individual investors has decreased. In related literature, Breuer, Rieger, and Soypak (2014b) employ a country-level ambiguity measure. Their ambiguity aversion measure is derived from the preference parameters in the international test of risk attitudes (INTRA) survey based on the answers to well-known Ellsberg type urn game. The survey was conducted among 7,000 college students in 53 countries. In another study, Chen et al. (2015) explore the influence of uncertainty avoidance on precautionary cash holdings. They employ an uncertainty avoidance index (UAI) obtained from the Hofstede psychological survey of IBM employee values, conducted twice (1968 and 1972) in 72 countries. The UAI was derived from three questions in the survey that address rule orientation, employment stability, and stress. Note that the measures mentioned above are survey based, are not derived from financial data, and constructed at country level. However, our ambiguity aversion measure is derived from financial data and is at firm level.

3.5 Results

3.5.1 Value of Cash and Ambiguity Aversion

In this section, we study the impact of ambiguity aversion on the valuation of cash holdings. In a theoretical model, Breuer, Rieger, and Soypak (2014b) show that the market value contribution of cash holdings decreases for financially constrained firms as investors' ambiguity aversion increases. They also hypothesize that this relation is insignificant for financially unconstrained firms.

In order to test this conjecture, we adopt Faulkender and Wang's (2006) cash valuation model. The dependent variable in the model is stock returns in excess of the risk free rate. The main explanatory variable is the interaction term between ambiguity aversion and changes in cash holdings. We expect a negative and significant coefficient estimate for this interaction variable for the financially constrained firms and an insignificant coefficient estimate for the financially unconstrained firms.

We include the three Fama and French (1993) factors, MKTRF, SMB, and HML in the model and control for various factors including change in earnings (ΔE_t), change in net assets (ΔNA_t), change in R&D expenditures (ΔRD_t), change in interest expense (ΔI_t), change in common dividends paid (ΔD_t), net financing (NF_t), cash holdings (C_t), change in cash holdings (ΔC_t), leverage (L_t), interaction term between lagged cash holdings and change in cash holdings (C_{t-1} x ΔC_t), interaction term between change in cash holdings and leverage (ΔC_t x L_t), and the ambiguity aversion measure. All firm specific control variables and the dependent variable are winsorized at the 1% tails. We deflate all firm specific control variables, except leverage, by the lagged market value of equity to avoid largest firms dominate the results. We also include year dummies. Table 3.1 displays summary statistics for the variables included in the model. Note that the mean excess stock return is -4.30% with a standard deviation of 3.25%. Recall that the excess returns are winsorized at the 1% tails. Also note that mean cash holdings level is at 19.62%, slightly higher than what's reported in Faulkender and Wang (2006), 17.26%, which covers the period up to 2001. In unreported results, the mean and median of the change in cash holdings are close to zero; 0.06% and -0.04%, respectively. This suggests that the distribution of the change in cash holdings is relatively symmetric. However, the distribution of cash holdings itself is not symmetric. In unreported results, the mean leverage ratio is at 23.04%, consistent with Faulkender and Wang (2006) and Opler et al. (1999).

In order to identify the level of financial constraints faced by firms, we employ three alternative schemes used in the previous literature to partition our sample: payout ratio, firm size, and firm age.

Payout ratio: The payout ratio is measured as total dividends, i.e. common dividends plus repurchases, over earnings. Following Almedia et al. (2004), we rank all firms based on their annual payout rations each year and classify the firms in the top (bottom) three deciles as financially unconstrained (constrained) firms. Firms with higher payout ratios are likely to meet their financial obligations, finance their investments, and do not benefit from precautionary cash holdings compared to the firms with lower payout ratios. Fazzari et al. (1988) also argue that financially constrained firms lower their payout ratios.

Firm size: Almedia et al. (2004) and Fazzari et al. (1988) argue that larger firms have better access to external capital markets and face fewer constraints to raise capital. Therefore, in order to identify financially constrained/unconstrained firms, we again rank all firms based on total assets each year and classify the firms in the top (bottom) three deciles as financially unconstrained (constrained) firms.

Firm age: Hadlock and Pierce (2012) rely on firm age to identify financially constrained firms. Following their work, we use firm age as a proxy to distinguish between financially constrained and unconstrained firms. We rank firms based on firm age each year and classify firm-years above (below) the median age as financially unconstrained (constrained) firms.

Table 3.2 displays the results for the cash valuation model. Note that, as expected, the coefficient estimate for the interaction term between changes in cash holdings and ambiguity aversion is negative and significant for the financially constrained firms. On the other hand, for financially unconstrained firms the results are insignificant. Remember that in this study, we examine the relation between precautionary corporate cash holdings and investors' ambiguity aversion and conjecture that ambiguity averse investors do not favor the corporate cash holdings held for long term investment projects for precautionary reasons, given that the returns on long term projects are uncertain. However, this argument is irrelevant for financially unconstrained firms which do not have difficulty to access external capital markets and do not hold cash for precautionary reasons. On the contrary, financially constrained firms have limited access to capital markets and therefore hold cash for precautionary reasons. However, ambiguity averse investors do not favor the cash holdings held for long term projects given that the returns are on such long term projects are ambiguous.

Given the lower valuation of cash holdings by ambiguity averse investors, we next analyze if firms adjust cash holdings in response to the extent of ambiguity aversion within their shareholder base in the next section.

3.5.2 Cash Holdings and Ambiguity Aversion

This section examines the relation between the level of corporate cash holdings and investors' ambiguity aversion. The previous section documents that the market value contribution of cash holdings decreases for financially constrained firms as investors' ambiguity aversion increases. If managers cater cash holdings to investor preferences and/or investors who are ambiguity averse flock to those firms with lower levels of cash holdings, firms with a larger base of ambiguity averse investors would hold lower levels of cash compared to the firms with a low proportion of ambiguity averse investors. We test this conjecture by regressing cash holdings on our proxy for the extent of ambiguity aversion within a firm's shareholder base.

The dependent variable in the model is the level of corporate cash holdings (cash plus marketable securities) normalized by net assets (total assets minus cash holdings). The explanatory variable of interest is our measure of ambiguity aversion which is measure by one minus the proportion of institutional investors in a firm's investor base.

Following Breuer, Rieger, and Soypak (2014b), the control variables included in the model are R&D expenditures, firm size, market-to-book ratio, market debt ratio calculated as total debt divided by the sum of total debt and the market value of equity, net working capital calculated as working capital minus cash holdings divided by total assets, capital expenditures, sale growth, cash flows, and common dividends paid. Table 3.3 exhibits the summary statistics for the variables included in the model. Note that the mean ambiguity aversion is around 65% which is the average over the period from 1980 to 2014. As Figure 3.1 depicted, the average ambiguity aversion in 2014 is around 55% which is consistent with the fact that the proportion of institutional investors has grown over the last decades.

Table 3.4 shows the results for the cash holdings model. The coefficient estimate for the ambiguity aversion variable is statistically significant and negative for financially constrained firms and it is insignificant for financially unconstrained firms. This result shows that firms with high proportion of ambiguity averse investors hold less cash which indicates that either managers cater to investors' preferences and lower the cash holdings and/or investors who are ambiguity averse flock to those firms with lower levels of cash holdings. Also note that, as the proportion of ambiguity averse investors declines the amount of cash held by the firm goes up. This result is also consistent with the fact that the proportion of institutional investors in the U.S. has increased in the last decades. We also know that the amount of corporate cash holdings has also elevated during the same period as exhibited in Figure 3.2. The correlation between the proportion of institutional investors and the average cash ratio is 92.9%.

3.5.3 Corporate Governance and Institutional Investors

The presence of institutional investors has been used in the literature as a measure of the quality of corporate governance. (see Dittmar and Mahrt-Smith, 1996) Investor oversight by institutional investors is an important control for entrenched managers. Dittmar and Mahrt-Smith (1996) discuss the ability of investors to pressure management to efficiently use excess cash resources and report that the value of cash holdings decreases with poor corporate governance as measured by the proportion of institutional blockholders.

Our ambiguity measure is a function of the proportion of institutional investors in a firm's investor base. Therefore, our measure might also be measuring the quality of corporate governance along with ambiguity aversion. This might lead to a bias in our estimates of the impact of ambiguity aversion on corporate cash holdings due to the potential correlated omitted variable problem.

In order to deal with this potential bias, we control for corporate governance in our models by employing the Gompers, Ishii, and Metrick (2003) index. (G-Index)[1] A firm's score in the G-Index is based on the number of shareholder rights-decreasing provisions a firm has, such as poison pills and golden parachutes. High values of the G-Index indicate poor corporate governance.

[1] Data on the G-Index is available on Andrew Metrick's website for the period 1990-2006.

We include the G-Index as an independent variable in the cash valuation model described in section 3.5.1. The results are presented in Table 3.5. Note that the results exhibited in Table 3.5 are weaker compared to the original results exhibited in Table 3.2.[2] The coefficient on the interaction term between ambiguity aversion and changes in cash holdings is negative and significant at the 10% level when financially constrained firms are determined by dividend payout ratio and firm age. However, the coefficient estimate is not significant when financially constrained firms are determined by firm size.

We also control for corporate governance in the cash holdings model presented in section 3.5.2. The results are exhibited in Table 3.6. After controlling for corporate governance, our ambiguity aversion measure is still significant for the financially constrained firms sorted by dividend payout ratio and firm age. These results show that our ambiguity aversion measure is an important factor affecting corporate cash balances for financially constrained firms even after we control for corporate governance.

3.6 Concluding Remarks

This study investigates the relation between precautionary corporate cash holdings and ambiguity aversion of investors. We conjecture that ambiguity averse investors do not favor the cash held by firm for precautionary reasons for the long term projects, given that the returns on long term projects are ambiguous, especially to individual investors.

We employ a novel ambiguity aversion measure following Kyle's (1985) distinction between noise and informed traders. We consider individual and institutional

[2] Note that new results are based on data from 1990 to 2006 due to data availability constraints, whereas the original results included the period from 1980 to 2014.

investors as proxies for noise and informed traders, respectively. Individual investors exhibit more ambiguity aversion compared to the institutional investors given that institutional investors have significant information regarding the marketplace. Therefore, our measure for ambiguity aversion is one minus the proportion of institutional investors.

Employing our ambiguity aversion measure, in a setting similar to Faulkender and Wang's (2006) cash valuation model we show that the value of cash holdings is negatively associated with the extent of ambiguity aversion in a firm's shareholder base for firms that are financially constrained. Given this result, next, we examine if managers adjust cash holdings in response to the extent of ambiguity aversion within their shareholder base. If managers cater cash holdings to investor preferences and/or investors who are ambiguity averse flock to those firms with lower levels of cash holdings, then firms with a large proportion of ambiguity averse investors would hold lower levels of cash than firms with a high proportion of institutional investors. Our results confirm that financially constrained firms with a higher proportion of ambiguity averse investors hold less cash.

This study contributes to the corporate cash holdings literature by establishing a link between investors' ambiguity aversion and cash holdings, by employing a novel measure for investors' ambiguity aversion.

Table 3.1: Summary Statistics: Value of Cash and Ambiguity Aversion

This table provides summary statistics for the variables included in the cash valuation model for the sample of firm-years from U.S. based publicly traded firms over the period 1980 to 2014. Excess return is stock return over the risk free rate. Ambiguity aversion is measured as one minus the percentage of the institutional investors. All variables except leverage, ambiguity aversion, and excess stock return are deflated by the lagged market value of equity. C_t is cash plus marketable securities, E_t is earnings before extraordinary items plus interest, deferred tax credits, and investment tax credits, and NA_t is total assets minus cash holdings. I_t is interest expense, D_t are common dividends paid. Lt, market leverage, is market debt ratio calculated as total debt divided by the sum of total debt and the market value of equity. NF_t, net financing, is total equity issuance minus repurchases plus debt issuance minus debt redemption, and RD_t are R&D expenditures. Δ denotes the 1-year change. All company specific variables are winsorized at the 1% tails.

Variable	Mean	Median	SD	Min	Max
Excess $Returns_t$	-0.0430	-0.0452	0.0325	-0.1461	0.0106
SMB_t	0.0225	0.0039	0.1164	-0.2329	0.2841
HML_t	0.0327	0.0371	0.1558	-0.3940	0.2724
Market $Return_t$	0.0853	0.1069	0.1774	-0.3839	0.3515
ΔE_t	-0.0183	-0.0071	0.3562	-3.7577	3.7577
ΔNA_t	0.0320	0.0015	1.8126	-19.1472	19.1973
ΔRD_t	0.0011	0.0000	0.0528	-0.5096	0.5096
ΔI_t	0.0036	0.0000	0.1186	-1.4138	1.4039
ΔD_t	-0.0001	0.0000	0.0130	-0.1184	0.1184
NF_t	0.0436	0.0006	0.2834	-1.1576	1.8293
C_{t-1}	0.1962	0.1011	0.2935	0.0000	2.1908
(Centered) ΔC_t	0.0000	-0.0010	0.2745	-2.1914	2.1902
(Centered) L_t	0.0000	-0.0735	0.2396	-0.2304	0.7139
(Centered) Ambiguity Aversion	0.0000	0.0671	0.2979	-0.6491	0.3509
ΔC_tXAmbiguity Aversion	0.0015	0.0000	0.0816	-1.2606	1.4092
C_{t-1} X ΔC_t	-0.0377	0.0000	0.3172	-4.8011	1.1993
ΔC_t X L_t	0.0028	0.0001	0.0886	-1.4958	1.5590

Table 3.2: Value of Cash and Ambiguity Aversion

This table presents the results of regressing the excess stock returns on firm specific variables across groups of financially constrained (C) and unconstrained (U) firms from 1980 to 2014. We determine financially constrained/unconstrained firms by payout ratio, firm size, and firm age. The dependent variable in all models is r_{it}-r_f, the excess stock return over the risk free rate, r_f. The main variable of interest is ΔC_t x Ambiguity Aversion. Ambiguity aversion is measured as one minus the percentage of the institutional investors. C_t is cash plus marketable securities, E_t is earnings before extraordinary items plus interest, deferred tax credits, and investment tax credits, and NA_t is total assets minus cash holdings. It is interest expense, D_t are common dividends paid. L_t, market leverage, is market debt ratio calculated as total debt divided by the sum of total debt and the market value of equity. NF_t is total equity issuance minus repurchases plus debt issuance minus debt redemption. RD_t are R&D expenditures. All variables, except market leverage, ambiguity aversion and excess stock return, are deflated by the lagged market value of equity. Δ denotes the 1-year change. All company specific variables are winsorized at the 1% tails. White (1980) heteroscedastic consistent standard errors, corrected for correlation across observations of a given firm are used. t-values are reported in parentheses. Significance levels at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Independent Variables	Payout Ratio		Size		Age	
	C	U	C	U	C	U
ΔC_tXAmbiguity Aversion	-0.0043**	-0.0012	-0.0027***	-0.0002	-0.0165**	0.0001
	(-2.07)	(-0.79)	(-3.15)	(-1.34)	(-2.08)	(1.34)
SMB_t	0.8035***	6.0092***	-0.5952	6.0197***	1.1650**	-0.0570
	(4.36)	(71.79)	(-1.42)	(35.24)	(1.97)	(-0.9)
HML_t	-0.1242	0.3622***	0.0646	-0.7645***	0.1090	0.0740*
	(-1.01)	(6.7)	(0.23)	(-6.03)	(0.73)	(1.75)
Market $Return_t$	0.0458	0.0802	0.4220	1.7316***	0.0701	0.1591***
	(0.41)	(1.59)	(1.55)	(16.56)	(0.48)	(5.05)
ΔE_t	-0.0001	0.0000*	0.0001	0.0000***	-0.0003	0.0000
	(-0.19)	(-1.70)	(1.42)	(2.78)	(-0.45)	(1.29)
ΔNA_t	0.0003*	0.0000	0.0001***	0.0000***	0.0003	0.0000
	(1.71)	(0.81)	(4.55)	(-3.57)	(0.47)	(-0.59)
ΔRD_t	-0.0085**	-0.0147***	0.0005	-0.0011***	-0.0061	0.0001
	(-2.35)	(-5.34)	(0.87)	(-3.88)	(-1.32)	(0.36)
ΔI_t	-0.0035*	-0.0011	-0.0006**	0.0002*	-0.0143	0.0000
	(-1.93)	(-1.23)	(-2.48)	(1.83)	(-1.55)	(1.12)
ΔD_t	-0.0001	-0.0045	0.0000	0.0001	0.0048**	0.0010
	(-0.02)	(-0.73)	(0.00)	(0.07)	(2.06)	(1.14)
NF_t	0.0006	-0.001***	0.0004***	0.0000	0.0033***	0.0000
	(0.61)	(-2.66)	(2.58)	(0.12)	(2.62)	(-0.29)
C_{t-1}	-0.0006	0.0001	-0.0024***	-0.0001	0.0027*	-0.0001
	(-0.44)	(1.57)	(-5.79)	(-1.11)	(1.80)	(-1.42)
ΔC_t	0.0021***	0.0002	0.0009**	0.0000	0.0120***	0.0000
	(3.86)	(0.28)	(2.17)	(0.31)	(7.66)	(0.05)

Table 3.2: Value of Cash and Ambiguity Aversion (Continued)

L_t	-0.1937***	-0.2923***	-0.6592***	-1.0424***	-0.2970***	-0.1266***
	(-5.86)	(-9.19)	(-11.46)	(-16.67)	(-5.54)	(-11.07)
C_{t-1} X ΔC_t	0.0000	0.0000***	0.0000***	0.0000	-0.0001***	0.0000
	(-1.63)	(2.86)	(-4.76)	(-0.65)	(-3.08)	(-1.40)
ΔC_t X L_t	-0.0012	-0.0007	-0.0007	0.0003**	-0.0082*	-0.0001
	(-0.7)	(-1.15)	(-0.99)	(2.36)	(-1.95)	(-0.79)
Ambiguity Aversion	-0.4595***	-0.0382	-7.839***	-0.1912***	-0.3502***	-0.0077
	(-6.24)	(-1.27)	(-59.11)	(-19.07)	(-4.42)	(-0.78)
Constant	0.4725***	-3.3607***	4.1856***	-4.1615***	-3.4923***	0.1325
	(6.71)	(-99.43)	(8.84)	(-74.92)	(-57.26)	(1.23)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,596	28,513	23,929	26,015	22,291	18,533
Adj-R^2	0.46	0.43	0.35	0.22	0.40	0.46

Table 3.3: Summary Statistics: Cash Holdings and Ambiguity Aversion

This table provides summary statistics for the variables included in the cash holdings model for the sample of firm-years from U.S. based publicly traded firms over the period 1980 to 2014.Cash over net assets is corporate cash holdings, cash plus marketable securities, divided by net assets, total assets minus cash holdings. Ambiguity Aversion is measured as one minus the percentage of the institutional investors. R&Dt are R&D expenditures denominated by net sales. Size is measured as the total assets in 2014 dollars. MBt, the market-to-book ratio, is measured as the market value of equity plus book value of debt divided by total assets. Lt, market leverage, is market debt ratio calculated as total debt divided by the sum of total debt and the market value of equity. NWCt, net working capital, is calculated as working capital minus cash holdings divided by total assets. Capext, capital expenditures, is denominated by total assets. SGt is the sale growth defined as net sales in year t divided by net sales in year t-1. CFt, cash flow, is demonited by total assets. Dt are common dividends paid denominated by total assets. All company specific variables are winsorized at the 1% tails.

Variable	Mean	Median	SD	Min	Max
Cash/Net Assets$_t$	0.4201	0.0998	1.0030	0.0000	7.0718
Ambiguity Aversion	0.6491	0.7162	0.2979	0.0000	1.0000
R&D$_t$	0.1770	0.0000	0.8695	0.0000	7.7740
Size$_t$	25.5256	2.6770	74.9710	0.0068	489.0752
MB$_t$	1.7173	1.1396	1.9345	0.2278	17.5037
L$_t$	0.2304	0.1570	0.2396	0.0000	0.9443
NWC$_t$	0.0768	0.0798	0.2765	-2.5766	0.5658
Capex$_t$	0.0677	0.0442	0.0742	0.0000	0.4528
SG$_t$	1.1607	1.0535	0.6161	0.2209	6.3230
CF$_t$	0.0299	0.0852	0.3009	-2.9748	0.3670
D$_t$	0.0093	0.0000	0.0199	0.0000	0.1211

Table 3.4: Cash Holdings and Ambiguity Aversion

This table presents the results of regressing the corporate cash holdings divided by net assets on firm specific variables across groups of financially constrained (C) and unconstrained (U) firms from 1980 to 2014. We determine financially constrained/unconstrained firms by payout ratio, firm size, and firm age. The dependent variable in all models is corporate cash holdings, cash plus marketable securities, divided by net assets, total assets minus cash holdings. The main variable of interest is Ambiguity Aversion, which is measured as one minus the percentage of the institutional investors. R&Dt are R&D expenditures denominated by net sales, size is measured as the total assets, MBt, the market-to-book ratio, is measured as the market value of equity plus book value of debt divided by total assets. Lt, market leverage, is market debt ratio calculated as total debt divided by the sum of total debt and the market value of equity. NWCt, net working capital, is calculated as working capital minus cash holdings divided by total assets. Capext, capital expenditures, is denominated by total assets. SGt is the sale growth defined as net sales in year t divided by net sales in year t-1. CFt, cash flow, is demonited by total assets. Dt are common dividends paid denominated by total assets. All company specific variables are winsorized at the 1% tails. White (1980) heteroscedastic consistent standard errors, corrected for correlation across observations of a given firm are used. t-values are reported in parentheses. Significance levels at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Independent	Payout Ratio		Size		Age	
Variables	C	U	C	U	C	U
Ambiguity Aversion	-0.3955*	0.0005	-1.4757***	-0.0009	-0.3313**	0.0052
	(-1.78)	(0.26)	(-3.55)	(-0.64)	(-2.01)	(1.03)
$R\&D_t$	0.0493***	0.0214***	0.0137***	0.0006	0.0108	0.0050
	(3.13)	(4.01)	(2.63)	(1.06)	(1.59)	(1.19)
$Size_t$	-0.0001	0.0004***	0.3483*	0.0002***	-0.0011	0.0004***
	(-0.06)	(4.18)	(1.71)	(2.87)	(-0.22)	(2.70)
MB_t	-0.0792	-0.2001***	-0.8998***	-0.1029**	0.5382**	-0.2881***
	(-0.59)	(-3.88)	(-4.37)	(-2.18)	(2.03)	(-2.91)
L_t	-2.0189***	-0.8864***	-1.4159***	-0.6107***	-1.0561***	-1.2607***
	(-6.88)	(-17.26)	(-9.89)	(-17.42)	(-8.38)	(-12.61)
NWC_t	-1.3850***	-1.1553***	-1.5668***	-0.7349***	-0.5056**	-1.5835***
	(-6.37)	(-13.59)	(-6.87)	(-7.83)	(-2.43)	(-10.50)
$Capex_t$	-0.0050	-0.0047***	-5.7897***	-0.0072***	-0.0206	-0.0044***
	(-0.73)	(-4.92)	(-5.81)	(-8.75)	(-0.54)	(-2.94)
SG_t	0.0015	0.0126*	0.0003	0.0001	0.0001	0.0002
	(1.03)	(1.71)	(1.20)	(1.02)	(0.03)	(1.11)

Table 3.4: Cash Holdings and Ambiguity Aversion (Continued)

CF_t	-0.0490***	-0.0075***	-5.1345***	-0.0025***	0.0290	-0.0141***
	(-3.55)	(-6.47)	(-7.57)	(-2.58)	(0.54)	(-8.40)
D_t	0.1336	-0.0101**	0.0499	-0.0001	-0.0305	0.0007
	(1.28)	(-2.17)	(1.01)	(-0.58)	(-1.29)	(0.76)
Constant	2.8758***	1.152***	3.1937***	0.8393***	1.2540***	1.5348***
	(6.24)	(20.29)	(7.18)	(16.89)	(9.05)	(14.29)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,518	24,156	26,614	27,624	26,614	18,792
Adj R^2	0.05	0.08	0.06	0.03	0.06	0.04

Table 3.5: Value of Cash and Ambiguity Aversion (Robustness Test with G-Index)

This table presents the results of regressing the excess stock returns on firm specific variables across groups of financially constrained (C) and unconstrained (U) firms from 1990 to 2006. We determine financially constrained/unconstrained firms by payout ratio, firm size, and firm age. The dependent variable in all models is r_{it}-r_f, the excess stock return over the risk free rate, r_f. The main variable of interest is ΔC_t x Ambiguity Aversion. Ambiguity aversion is measured as one minus the percentage of the institutional investors. C_t is cash plus marketable securities, E_t is earnings before extraordinary items plus interest, deferred tax credits, and investment tax credits, and NA_t is total assets minus cash holdings. I_t is interest expense, D_t are common dividends paid. L_t, market leverage, is market debt ratio calculated as total debt divided by the sum of total debt and the market value of equity. NF_t is total equity issuance minus repurchases plus debt issuance minus debt redemption. RD_t are R&D expenditures. G-Index is the Gompers, Ishii, and Metrick (2003) governance measure. All variables, except market leverage, ambiguity aversion, G-Index and excess stock return, are deflated by the lagged market value of equity. Δ denotes the 1-year change. All company specific variables are winsorized at the 1% tails. White (1980) heteroscedastic consistent standard errors, corrected for correlation across observations of a given firm are used. t-values are reported in parentheses. Significance levels at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Independent	Payout Ratio		Size		Age	
Variables	C	U	C	U	C	U
ΔC_tXAmbiguity Aversion	-0.5477*	0.3519	-0.1038	-1.8794	-1.2534*	-1.4372
	(-1.79)	(0.35)	(-1.40)	(-0.71)	(-1.85)	(-0.30)
SMB_t	0.0035	0.0073	0.0109***	-0.0266	2.7248**	5.4891***
	(0.63)	(0.84)	(3.76)	(-1.68)	(2.33)	(10.24)
HML_t	-0.0083***	0.0148*	-0.0047	0.0089	3.7897***	3.4519***
	(-2.94)	(-1.9)	(-1.44)	(0.96)	(4.83)	(6.66)
Market $Return_t$	-0.0039	-0.0164***	-0.0092*	0.0105	2.9702***	1.3501**
	(-0.68)	(-3.70)	(-1.80)	(1.03)	(2.95)	(2.32)
ΔE_t	0.1930	0.8576**	0.2395	0.5520	4.2798**	1.7971**
	(1.23)	(2.21)	(0.65)	(1.26)	(-2.40)	(2.11)
ΔNA_t	-0.0030	0.1290*	0.0280	-0.2083	-0.4155	0.5072
	(-0.07)	(1.83)	(0.69)	(-1.12)	(-1.10)	(1.58)
ΔRD_t	-2.7936**	1.3664	0.5839	-7.6824***	-5.5885	-13.423**
	(-2.19)	(0.54)	(0.24)	(-7.91)	(-1.43)	(-2.23)
ΔI_t	0.2681	-6.2179**	3.1936*	-0.9194	-12.7378	-5.5709
	(0.25)	(-2.50)	(2.01)	(-0.19)	(-0.67)	(-1.50)
ΔD_t	-4.147**	2.1604	-2.6607**	21.1745***	-25.7263	-4.2056
	(-2.31)	(1.13)	(-2.49)	(3.05)	(-0.55)	(-0.33)
NF_t	-0.2899	-1.1276***	0.5633	1.6587**	1.0308	-0.8381
	(-1.15)	(-2.68)	(1.67)	(2.95)	(0.55)	(-0.97)

Table 3.5: Value of Cash and Ambiguity Aversion (Robustness Test with G-Index) (Continued)

C_{t-1}	0.4230**	1.0786***	0.6917***	1.4700**	0.2162	-0.5240
	(2.45)	(4.36)	(3.29)	(2.25)	(0.14)	(-0.41)
ΔC_t	0.7924	2.0295***	0.0824	-0.5427	4.2152***	2.3465
	(1.56)	(3.61)	(0.19)	(-0.22)	(3.75)	(1.33)
L_t	-0.445**	-0.2825	-0.5350*	-0.3307	1.1944	-1.1873**
	(-2.41)	(-1.64)	(-1.84)	(-1.54)	(1.08)	(-2.08)
C_{t-1} X ΔC_t	0.0290	-0.7626	0.5156*	-4.432**	-3.4530	2.0324
	(0.08)	(-1.23)	(1.71)	(-2.66)	(-1.55)	(0.77)
ΔC_t X L_t	-0.4422	-0.1000	0.2683	4.8806	13.2976***	-2.0921
	(-0.42)	(-0.04)	(0.19)	(1.64)	(3.12)	(-0.38)
Ambiguity Aversion	0.0838	-0.2515**	-0.0851	-0.8451***	-1.097**	-0.7405
	(0.45)	(-2.23)	(-0.58)	(-4.04)	(-1.90)	(-0.94)
G-Index	-0.008**	0.0031	-0.0012***	-0.0052*	-0.0136*	-0.0192
	(-2.05)	(0.74)	(-2.74)	(-1.76)	(-1.83)	(-0.67)
Constant	0.5525	0.7201***	-0.0732	0.1658	-3.5045***	-3.5687***
	(1.31)	(5.44)	(-0.22)	(0.75)	(-8.06)	(-9.49)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,982	5,717	5,483	6,294	5,812	6,591
Adj-R^2	0.29	0.44	0.28	0.26	0.46	0.37

Table 3.6: Cash Holdings and Ambiguity Aversion (Robustness Test with G-Index)

This table presents the results of regressing the corporate cash holdings divided by net assets on firm specific variables across groups of financially constrained (C) and unconstrained (U) firms from 1990 to 2006. We determine financially constrained/unconstrained firms by payout ratio, firm size, and firm age. The dependent variable in all models is corporate cash holdings, cash plus marketable securities, divided by net assets, total assets minus cash holdings. The main variable of interest is Ambiguity Aversion, which is measured as one minus the percentage of the institutional investors. RD_t are R&D expenditures denominated by net sales, size is measured as the total assets, MB_t, the market-to-book ratio, is measured as the market value of equity plus book value of debt divided by total assets. L_t, market leverage, is market debt ratio calculated as total debt divided by the sum of total debt and the market value of equity. NWC_t, net working capital, is calculated as working capital minus cash holdings divided by total assets. $Capex_t$, capital expenditures, is denominated by total assets. SG_t is the sale growth. CF_t is the cash flow. D_t are common dividends paid. G-Index is the Gompers, Ishii, and Metrick (2003) governance measure. All company specific variables are winsorized at the 1% level. White (1980) heteroscedastic consistent standard errors, corrected for correlation across observations of a given firm are used. t-values are reported in parentheses. Significance levels at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Independent Variables	Payout Ratio		Size		Age	
	C	U	C	U	C	U
Ambiguity Aversion	-0.1295*	0.0698	-0.0924	-0.2260	-0.3769**	0.0961
	(-1.73)	(0.74)	(-0.92)	(-1.25)	(-2.63)	(1.53)
$R\&D_t$	0.8803*	0.7094	0.8108	-0.5374	-4.3766*	-0.1815
	(1.77)	(1.28)	(1.29)	(-1.47)	(-2.15)	(-0.34)
$Size_t$	-0.0002	-0.0004**	0.0017	-0.0004*	-0.0001	-0.0001*
	(-0.90)	(-2.21)	(0.22)	(-2.06)	(-0.22)	(-1.76)
MB_t	0.0074	-0.0197	0.0293	0.0167*	0.1408***	-0.0119
	(0.36)	(-0.77)	(-1.50)	(1.88)	(5.18)	(-1.23)
L_t	-0.3464***	-0.3598**	-0.5500***	-0.0037	-0.6079	-0.2088***
	(-3.31)	(-2.45)	(-3.68)	(-0.04)	(-0.97)	(-2.98)
NWC_t	-0.4198***	-0.4019***	-0.4504**	-0.2197****	-1.9295***	-0.1638**
	(-2.84)	(-3.89)	(-2.67)	(-1.94)	(-4.96)	(-2.55)
$Capex_t$	-0.7050	-0.5939*	-1.3105***	-0.4108	-4.4783***	-0.3211*
	(-1.54)	(-1.71)	(-3.07)	(-1.22)	(-5.34)	(-1.77)
SG_t	0.0274	-0.0857	0.0326	-0.0035	-1.3575***	0.0047
	(0.38)	(-0.72)	(0.68)	(-0.11)	(-4.46)	(0.15)
CF_t	0.3486**	0.1409	0.4051**	-0.4249	0.0418	-0.1158
	(2.47)	(-0.60)	(2.52)	(-1.76)	(0.04)	(-1.25)

Table 3.6: Cash Holdings and Ambiguity Aversion (Robustness Test with G-Index) (Continued)

D_t	-1.6878	1.9142	3.3981	0.9827***	-98.0167**	-0.0681
	(-0.96)	(0.66)	(1.14)	(3.34)	(-3.50)	(-0.16)
G-Index	0.0046*	0.0089	0.0071**	0.0027	0.0070	-0.0002
	(1.85)	(0.88)	(2.11)	(1.02)	(0.95)	(-0.11)
Constant	0.3276***	0.2298	0.1034	0.1836*	3.2318***	0.1986***
	(4.84)	(0.91)	(0.94)	(1.89)	(4.81)	(3.09)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,564	6,533	6,898	6,129	6,613	4,972
Adj R^2	0.35	0.19	0.30	0.12	0.33	0.24

Figure 3.1: Investor Base: Individual vs. Institutional Investors

The figure exhibits the yearly average proportion of individual vs. institutional investors for the sample of firm-years from U.S. based publicly traded firms over the period 1980 to 2014.

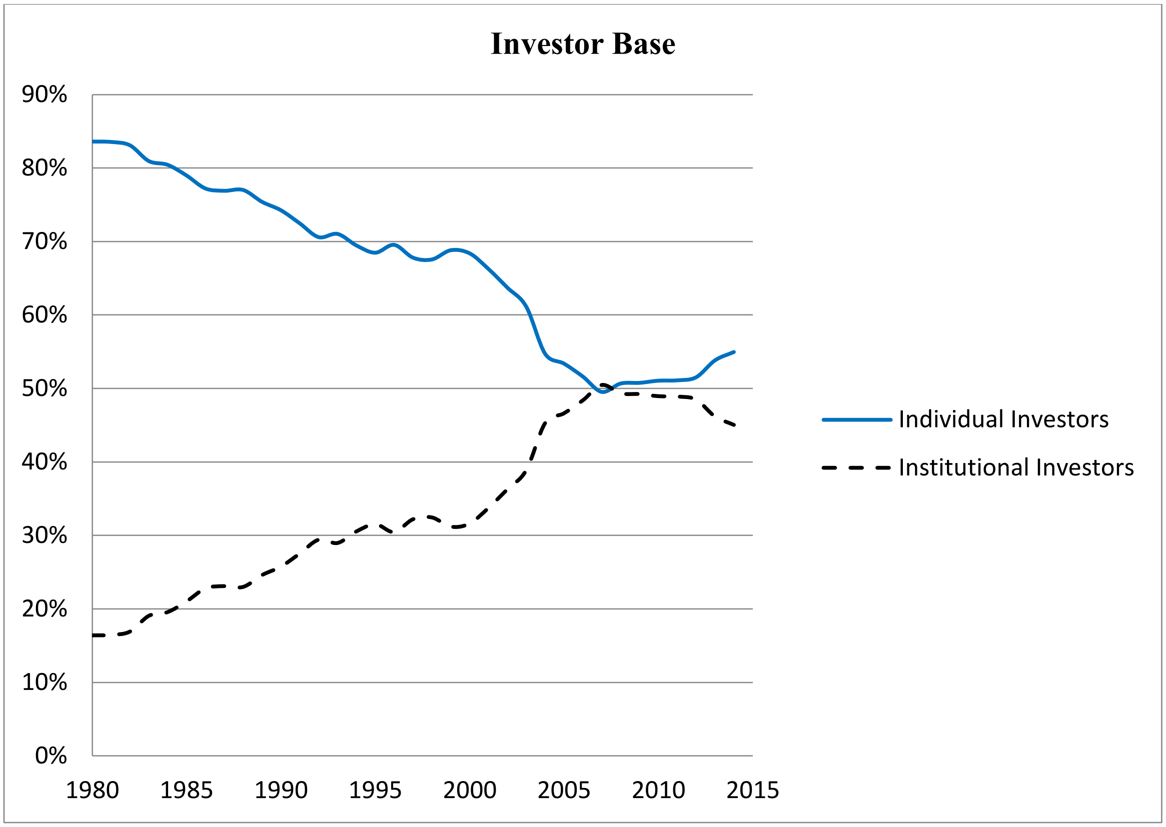
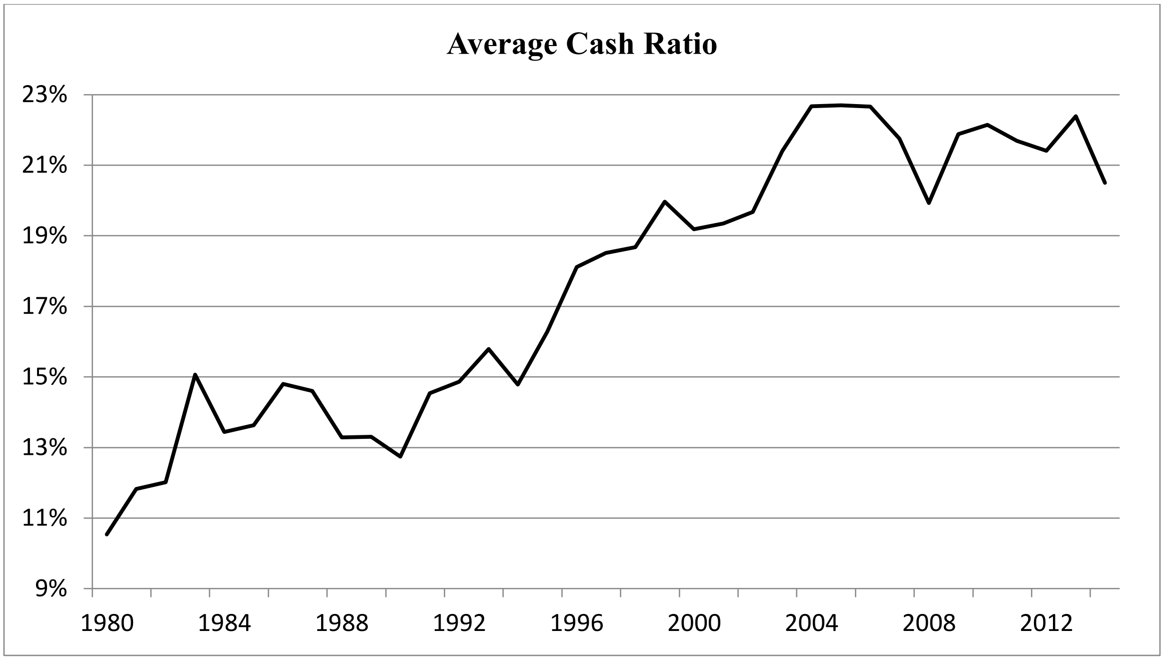


Figure 3.2: Corporate Cash Holdings

The figure exhibits the average cash ratio measured as the corporate cash holdings over total assets for U.S. based publicly traded firms over the period 1980 to 2014.



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