Market Implied Funding Liquidity and Asset Prices

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Abstract

This study examines a market-wide liquidity measure based on systematic deviations from Put-Call parity in US equity option markets. We show that this implied funding liquidity measure significantly predicts future excess market returns and explains cross-sectional variations of stock returns. We provide evidence that investing in stocks with the largest exposure to the innovations in implied funding liquidity and shorting stocks with the smallest generate significant returns of about 7.3% per annum. We also observe that implied funding liquidity significantly predicts future changes in a number of macroeconomic variables over a horizon of six months. This result indicates that the funding liquidity measure obtained from the option markets provides forward-looking information about developments in the economy.

Furthermore, we also examine the relationship between implied funding liquidity and the cross section of excess returns arising from the carry trades, which are strategies for investing in high interest rate currencies while borrowing in low interest rate currencies. We show that this implied funding liquidity is significantly associated with high interest rate currencies. We also consider the asset-pricing implications of the funding liquidity for other asset classes such as hedge funds.

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Chapter 1. Introduction

Liquidity is important for price discovery and the efficiency of financial markets. Liquidity can be affected by trading costs, the fragmentation of market structure, financial regulatory constraints, or any barrier that prohibits the free movement of capital and investments. Recent developments in financial markets have highlighted a new source of *il*-liquidity, that is, a shortage of funding capital[1]. Theoretical studies (Brunnermeier and Pedersen, 2009; Vayanos and Wang, 2013; Foucault et al., 2013) suggest that tight funding conditions have an impact on market liquidity and asset prices as traders become unable to raise funds and subsequently face forced liquidation of their investments at depressed prices. Despite increasing theoretical guidance, empirical evidence documenting the effect of funding liquidity on asset prices remains very limited (Fontaine et al., 2015).

In this study, we seek to fill this gap and provide a comprehensive empirical analysis of the links between funding constraints and asset returns. We propose a funding liquidity measure by relating systematic violations of Put-Call parity in the option markets to a shortage of arbitrage capital. Option markets are important as they are liquid, facilitate high leverage (Black, 1972; Easley et al., 1998; Chakravarty et al., 2004) and option prices have return predictive power to the underlying equity market (Manaster and Rendleman, 1982; Cremers and Weinbaum, 2010; An et al., 2014). In addition, Cao and Wei (2010) find that information asymmetry is higher for options than for the underlying stock, which suggests that it is more efficient for trading in the option market if agents have information. In these markets, we focus on the Put-Call parity, a no-arbitrage relationship between stock and option prices in which there is no explicit assumption regarding the underlying return distribution or the behaviour of investors. During normal periods, traders, which include hedge funds and proprietary trading desks at investment banks, take advantage of the abundant supply of capital to exploit price deviations across markets. In such conditions, option prices move closer to their parity condition because of the presence of arbitrageurs. However, according to

[1] See, for example, ”Quick cash dries up: repo financing drying up quickly”, The Wall Street Journal, 16 March 2008; ”Collateral damage”, The Economist, 17 October 2015; ”Ten years on: Anatomy of the global financial meltdown”, Financial Times, 9 August, 2017; ”China Liquidity Stress Signs Build as Fund Cost Jumps at Auction”, Bloomberg News, 24 August, 2017; ”Scarce Liquidity Is a Growing Risk”, Bloomberg News, 13 June, 2018; ”Dollar Scarcity Sends Global Funding Costs Soaring”, The Wall Street Journal, 15 December, 2017; ”Investors Raise Alarm Over Liquidity Shortage”, The Wall Street Journal, 18 March, 2015.

Brunnermeier and Pedersen (2009), funding constraints limit the amount of capital available for arbitrage and cause dislocations as prices move away from their fundamental relationships. Based on the aggregate deviations from the Put-Call parity in the US equity option markets, we show that our implied funding liquidity measure provides incremental information to capture funding liquidity conditions for established proxies, including those developed by Brunnermeier et al. (2008), Fontaine and Garcia (2012) and Hu et al. (2013).

Implied funding liquidity is potentially critical for asset pricing. Fleckenstein et al. (2014) observe that sizeable recurring violations of arbitrage parity suggests the presence of forces that drive asset returns, and that these forces are not considered in the traditional frictionless asset pricing model. A number of studies (Amihud and Mendelson, 1986; Brennan and Subrahmanyam, 1996; Amihud, 2002; Acharya and Pedersen, 2005; Baker and Wurgler, 2006; Brunnermeier and Pedersen, 2009; Hu et al., 2013; Pasquariello, 2014) relate liquidity, investor sentiment, noise, or financial market dislocation to asset returns. Pasquariello (2014) argues that it is difficult to measure these frictions directly, but that it is helpful to study the aggregate violation of arbitrage parity across assets. Therefore, the implied funding liquidity measure could be a priced variable. The role of implied funding liquidity in asset returns is supported by the analysis proposed by Campbell (1996). When considering a pricing factor that represents changes in the investment opportunity set, he suggests that the variable must pass both time-series and cross-section tests. First, the variable must have the ability to forecast future market returns. Second, its innovations must affect a large cross-section of asset returns where risk is measured by the covariance of the innovations with asset returns. Both of these tests are equally important. Thus, even if a certain variable explains many asset returns, but fails to predict future returns, it will have zero risk price and can be excluded. Our empirical findings show that implied funding liquidity satisfies both these conditions in the asset pricing tests. In particular, implied funding liquidity significantly predicts future excess market returns, and explains the cross-sectional variations of US stock returns.

This study examines the US equity option data provided by OptionMetrics covering the period from 04 January 1996 to 31 August 2015[2]. This dataset reports end-of-day bid, ask and strike prices of American-style call and put options for a large cross-section of individual stocks, as well as the open interest, maturity date,

[2]This dataset has been extensively used in the literature, for instance, in Cremers and Weinbaum (2010), An et al. (2014), and Doran et al. (2013).

and volume. The dataset also provides details of implied volatility obtained by matching the option prices assumed in the Black and Scholes (1973) and Merton's (1973a) model with market prices. These volatility outputs are calculated on the basis of a binomial tree that includes dividend payments and the probability of the early exercise of the American-style options. We compute the absolute differences in the values of implied volatility between call and put options of the identical underlying stock with the same strike price and expiration date. The implied funding measure is then obtained from these absolute volatility differences across all strike prices, maturity dates, and across all stocks. We supplement the option data with daily data of US stocks obtained from the Center for Research in Security Prices (CRSP) for the same sample period. Following Fama and French (1992, 1993), we use their 25 portfolios based on size and book-to-market value and the 30 industry portfolios in the asset pricing tests.

Our findings show that implied funding liquidity significantly predicts market returns, and that its innovations[3] explain a large cross-section of US stock returns, consistent with previous illiquidity predictions (Næs et al., 2011; Chen et al., 2017). We employ standard forecast regressions by regressing excess market returns on the lagged implied funding liquidity measure. In particular, the measure can predict future changes in the S&P500 index and CRSP's value-weighted index up to a horizon of six months. That is, tighter funding constraints associated with greater deviations from Put-Call parity in option markets are negatively related to future market returns. We also show that funding liquidity is priced. The exposures (betas) to implied funding liquidity innovations significantly explain the cross-sectional variations in portfolio returns. The results remain robust after controlling for common factors in equity markets, including Fama and French's (1992) three factors and Carhart's (1997) momentum factor.

We then compare the implied funding liquidity measure with several widely used market and funding liquidity measures, including the Pástor and Stambaugh's (2003) measure (PS), Brunnermeier et al.'s (2008) Treasury-LIBOR (TED) spread, Hu et al.'s (2013) Noise measure (Noise), Fontaine and Garcia's (2012) measure (FG), Amihud's (2002) il-liquidity measure (Amihud), Corwin and Schultz's (2012) measure (CS), the relative spread (RS), and Sadka's (2006) measure (Sadka). We find that the implied funding liquidity measure remains consistently positive and significant after we control for alternative liquidity measures. Our findings

[3]These innovations are minus the natural logarithm difference of the implied funding liquidity measure. Thus, a positive (negative) innovation indicates an increase (decrease) in funding liquidity.

suggest that the implied funding liquidity measure tend to incorporate the forward-looking nature of the option markets, and potentially provides incremental information about equity returns beyond what is captured in the other existing liquidity measures. This characteristic is robust in both the foreign exchange and hedge fund markets. We show that the measure is significantly different from existing market and funding liquidity measures, and that it contains unique and additive information.

We also estimate the relationship between the implied liquidity measure and the investor sentiment indexes. Following the previous literature, we consider seven existing investor sentiment measures, including Baker and Wurgler's (2006) investor sentiment measure (BW), Huang et al.'s (2015) aligned investor sentiment index (HJTZ), the consumer sentiment index of University of Michigan (UMC), the Conference Board consumer confidence index (CB), Da et al.'s (2015) Financial and Economics Attitudes Revealed by Search (FEARS) index (DEG), Jiang et al.'s (2018) manager sentiment index (JLMZ), as well as CBOE Put-Call ratios, (PCR). Although our implied funding liquidity measure is constructed using option market data, its connection with the Put-Call ratios is not very strong, which is a good purity indicator for our measure, which is consistent to the findings of Hu et al. (2013). We find that our measure correlates positively with UMC and CB, and negatively with HJTZ and PCR. The coefficients for implied funding liquidity remain positive and significant after controlling for all established investor sentiment measures, suggesting that our measure contains additional information beyond existing investor sentiment indexes.

Prior studies also argue that investors may require compensation for holding assets with higher sensitivity to the funding liquidity measure (Pasquariello, 2014). Brunnermeier and Pedersen (2009) show that a negative beta to shocks in market-wide funding liquidity require high expected returns. In this study, we also construct a portfolio strategy to examine the economic value of the information content of implied funding liquidity. Based on the literature explaining the cross-section of equity returns (Fama and French, 1992), we develop ten portfolios of stocks based on their sensitivity, or beta, to the innovations in implied funding liquidity. Using US stock data, we find that investing in stocks with the largest exposure to the implied funding measure and shorting those with the lowest provides a US investors with significant excess returns of about 7.3% per annum. The return differences remain significant even after incorporating transaction costs into the portfolio strategy.

Our study is related to the growing literature on the measurement of funding liquidity. In particular, Brunnermeier et al. (2008) show that funding constraints affect the returns from currency investments and use the Treasury-LIBOR interest rate spread (the TED spread) to capture funding liquidity. In the US Treasury markets, Fontaine and Garcia (2012) developed a funding liquidity variable obtained from the new and old bond spread, while Hu et al. (2013) obtain the Noise measure from the deviations between observed bond yields and predicted yields calibrated on Nelson and Siegel's term structure model (1987)[4]. We argue that implied funding liquidity has incremental power to explain stock returns compared to the other existing liquidity measures in the literature. Unlike those based on past trading behaviour, implied funding liquidity incorporates forward-looking information from the option markets due to the presence of informed traders (Back, 1993; Biais and Hillion, 1994; Easley et al., 1998; Cao, 1999) or future hedging demand (Gârleanu et al., 2009). Therefore, our liquidity measure may carry information about asset returns in addition to those characterised in the existing literature. Our study shows that our liquidity proxy can predict future changes in these funding liquidity measures, and that the asset pricing effects associated with implied funding liquidity remain significant even after including a wide range of liquidity measures suggested in previous studies.

Our study also provides evidence supporting the links between financial market liquidity and the real economy. Developments from the 2007-2008 financial crisis have clearly shown that funding liquidity difficulties not only remain in the financial services sector but may also spread to the real economy. As Brunnermeier and Pedersen (2009) indicate, funding constraints faced by traders could significantly affect financial intermediation, making it more difficult for investors to purchase or sell securities. These problems could directly affect firm investments and have causal effects on the economy as companies rely on liquid financial markets for their securities in order to finance long-term investment projects (Levine, 1991; Bencivenga et al., 1995). In particular, Næs et al. (2011) provide evidence indicating that stock market liquidity affects investor participation in the stock markets and leads the business cycle in the US and in Norway. In this paper, we argue that the implied funding liquidity incorporates the forward-looking information of the option markets and therefore has predictive power for the development of the economy. Our empirical results show that implied funding liquidity significantly predicts the future changes of a number of macroeconomic variables,

[4]In the equity market, Chen and Lu (2017) construct a funding liquidity shock using the return spread between two beta-neutral portfolios formed using stocks with high and low margins.

including the unemployment rate, the Purchasing Managers' Index (PMI), the Consumer Price Index (CPI) and the nonfarm payroll for a horizon of up to one year.

We next examine whether there is relationship between Put-Call parity deviations and the presence of informed trading as argued by Lu and Lin (2015) and Rösch et al. (2017). Following Brown and Hillegeist (2007), we obtain the probability of informed trade (PIN) measure to control for the level of information asymmetry in the stock markets. Our results show that implied funding liquidity remains significant in explaining the variations of stock returns after controlling for the differences in the level of information asymmetry across stocks.

We construct several alternative implied funding liquidity measures with the purpose of robustness tests. Implied volatilities for deep in-the-money or out-of-the-money options deviate significantly from those obtained for at-the-money options. Following Pan (2002), we obtain only at-the-money option pairs, which are call and put options with strike prices between 0.95 and 1.05 times the underlying spot prices, to develop an adjusted implied funding liquidity measure. Second, Battalio and Schultz (2006) show that the deviations of Put-Call parity may be influenced by non-synchronicity in the reporting of the closing stock prices in the option and in the underlying stock markets. Therefore, we use the delta-gamma approximation to calculate the implied volatility for each option, and then compute implied funding liquidity based on this underlying price. Third, during the last global financial crises, most regulators of stock exchanges around the world imposed constraints or bans on short selling. We construct an alternative implied funding liquidity measure with samples extracting the underlying stocks with short-selling constrictions. Finally, we also develop a dollar volume weighted implied funding liquidity measure, and an equally weighted implied funding liquidity measure. Our findings show that our results are robust for these varieties of alternative measures of implied funding liquidity.

Prior studies have concentrated on the relationship between liquidity, especially equity market liquidity, and relative market anomalies (Amihud, 2002; Pástor and Stambaugh, 2003; Liu, 2006; Hu et al., 2013; Pasquariello, 2014); however, a growing body of literature (Christiansen et al., 2011; Menkhoff et al., 2012; Mancini et al., 2013; Orlov, 2016) has found that carry trade strategies[5] could yield significant excess returns due to the disparities. Many studies have found

[5]The carry trade strategy involves investing in high interest rate currencies with borrowing in low interest rate currencies.

that exchange rate changes do not compensate for the interest rate differences, and the so-called forward premium puzzle shows that currencies with high interest rates tend to appreciate, while currencies with low interest rates appear to depreciate (Fama, 1984). The carry trade strategy has risen based on this puzzle, and it has been studied for a long time. Engel (1984) and Fama (1984) give a simple but persuasive explanation for this puzzle on the basis of the existence of time-varying risk premiums. Investors' high-risk exposure will only reveive compensation from the carry trade if the high interest rate currencies cannot deliver a higher return during recessions. With regards to currency market liquidity, Mancini et al. (2013) find a significant variation in liquidity across exchange rates for equity and bond markets. Moreover, they find that the liquidity risk factor has a strong relationships with carry trade returns. However, Orlov (2016) shows that equity market illiquidity cannot explain the carry trade strategies. Prior studies (Cremers and Weinbaum, 2010; An et al., 2014) show that option prices may predict equity returns when informed investors trade options ahead of the underlying assets. This is because liquidity in the option markets is higher than the underlying asset market. Implied funding liquidity may also influence foreign exchange markets, and it is intuitive to consider whether exposure to the implied funding liquidity risk is able to explain the cross-sectional returns of the currency speculation. Despite the importance of implied funding liquidity, a question arises as to whether option prices carry any information about currency market anomalies.

This study examines carry trade portfolios by collecting monthly spot exchange rates and one month forward exchange rates versus the US dollars from Datastream. The data sample spans from January 1996 to August 2015. The full sample includes 49 currencies; the size of the sample has decreased since the launch of the euro in January 1999. We also study a smaller sub-sample of advanced countries, called 'developed countries'. The developed countries sample comprises 15 developed countries before 1999, and 10 developed countries following the launch of euro. Following Fama (1984), Menkhoff et al. (2012), and Hu et al. (2013), we rank currencies into portfolios based on their forward discount, which is the relative interest rate differential versus the US dollar market interest rate at the end of each month. At the end of each month t, we rank all the currencies into six portfolios. The first portfolio contains currencies with the lowest interest rates, and last portfolio contains those with the highest interest rates. We compute the log of the currency excess return for each portfolio by taking the equal weighted mean of the log currency excess returns. The difference of the first and last portfolio returns, $HMLFX$, is generally referred to as the return of carry trades, which are long high interest rate currencies and short low interest rate currencies. Our findings show that high returns from currency speculation is indeed a compensation for implied liquidity risk.

Our analysis is supported by the findings by Lustig et al. (2011), who constructed a slope factor for exchange rates; that is, high interest rate currencies have a higher slope than the low interest rates currencies. Furthermore, this factor can explain major cross-sectional variation in average excess returns among high and low interest rates currencies. They find that this slope factor identifies country-specific and global shocks, and that this factor has a relationship with changes in global stock market volatility. Menkhoff et al. (2012) investigate the relationship between global foreign-exchange volatility risk and the cross-sectional excess returns arising from the carry trade strategy. They find that currencies with high interest rates are negatively correlated with innovations in global foreign exchange volatility, and thus deliver low returns in times of unexpected high volatility, while low interest rate currencies provide a hedge by yielding positive returns.

A few recent studies (for example, Sadka, 2010; Franzoni et al., 2012; Hu et al., 2013; Chen and Lu, 2017) show that liquidity risk also plays an important role in determining cross-sectional hedge fund prices. We show that implied funding liquidity is a price-risk factor in the US equity market, and this study also examines whether implied funding liquidity is priced in hedge funds. Due to the fact of limited access to the Lipper Hedge Fund Database (TASS), for this study, we obtained monthly hedge fund indices from the Hedge Fund Research, Inc. (HFRI) to investigate whether implied funding liquidity influences aggregate hedge fund performance. There are 64 indices in our sample, spanning the period of January 1996 to August 2015. Our results show that implied funding liquidity contains information which has not been fully explained by other risk factors, and that funding liquidity matters in explaining cross-sectional variations in hedge fund portfolio returns. This result is consistent with Sadka (2010), Kessler and Scherer (2011), and Chen and Lu (2017).

Our study contributes to the literature on funding liquidity and its role in asset pricing. Mitchell et al. (2007) show that liquidity spirals cause prices to drop and rebound, as new capital arrives slowly. In addition, Moinas et al. (2016) find that shocks to funding liquidity influences market liquidity in the bond market, and that there is also weaker simultaneous feedback influence of market liquidity on funding liquidity. Hu et al. (2013) propose a measure of the illiquidity of the aggregate market using the average pricing errors in the US Treasuries. Chen and

Lu (2017) construct a funding liquidity shock using the return spread between two beta-neutral portfolios formed using stocks with high and low margins. In contrast, our study proposes a new funding liquidity measure based on the deviations of Put-Call parity, and it contains unique and incremental information beyond the well-known existing liquidity proxies, such as Hu et al.'s (2013) Noise measure, Brunnermeier et al.'s (2008) Treasury-LIBOR (TED) spread, and Fontaine and Gracia's (2012) measure.

The remainder of the thesis is organised as described in what follows. Chapter 2 provides an overview of liquidity, liquidity commonality, liquidity risk, Put-Call parity, and implied volatility. Chapter 3 summarises the literature related to implied funding liquidity. We present definitions of market liquidity and funding liquidity, and briefly discuss the 'liquidity spiral'. We also discuss the literature on the link between option and stock markets. In Chapter 4, we provide details of the empirical framework and the methodology used in this study. In the first section, we describe in details the construction of the implied funding liquidity measure, the portfolio strategy method, and the portfolio strategy in the currency market. Then, we present the asset-pricing test methodology used in this study: the time series predictability of asset returns and cross-sectional regression analysis. In this thesis, we employ historical stock and option data for the US equity option markets, spot and one month forward exchanges rates versus the US dollars, hedge fund indices, and certain macro variables. In Chapter 5, we discuss these data and their descriptive statistics. We then report empirical results in Chapter 6. In section 6.1, we examine whether the implied funding liquidity measure provides forward-looking information in addition to that contained in the current funding liquidity proxies, and whether implied funding liquidity predicts stock market returns. Section 6.2 presents the results for the asset-pricing tests of implied funding liquidity innovations in stock, currency, and hedge fund markets. Section 6.3 reports the results for the test of whether our implied funding liquidity measure provides incremental information about asset returns beyond what is captured in the existing well-known liquidity measures. In section 6.4, we estimate whether our liquidity measure still matters after controlling for the investor sentiment indexes. Section 6.5 shows the profitability of the portfolio strategy of investing in stocks with the largest exposures to implied funding liquidity innovations and shorting stocks with the lowest exposures to these liquidity innovations. Then, we check whether implied funding liquidity has any predictive power over developments in the real economy in section 6.6. We present results for some robustness tests in Chapter 7. In section 7.1, we estimate the influence of the presence of informed trading on our implied funding liquidity. After that, we generate several alternative implied funding liquidity measures for the purpose of robustness tests. We consider the influence of moneyness, non-synchronicity, short selling, dollar volume weight and equal weight. The final chapter concludes.

Chapter 2. Background Information

In this chapter, we present background information on the essential components of this study. Specifically, we provide an overview of liquidity, liquidity commonality, liquidity risk, Put-Call parity, and implied volatility. We begin with definitions and popular measures of liquidity. It is easy to understand the meaning of liquidity, though the term is difficult to define exactly. We present the typical features of liquidity and discuss some well-known liquidity measures, such as the bid-ask spread, and their characteristics. Then we turn to commonality in liquidity and outline the sources of liquidity commonality. Chordia et al. (2005) provide evidence that there is a common variation between daily aggregate spreads and depths among US stock and Treasury bond markets. We briefly show the detriments of commonality in liquidity, such as supply-side factors, institutional stock ownership, investor incentives, and investor sentiment. Third, we discuss liquidity risk, which is the risk that the liquidity of an asset will worsen when its owner wants to sell it in future (Amihud et al., 2013). Stock-price studies, such as Amihud and Mendelson (1986) and Brennan and Subrahmanyam (1996), show that compensation is required to hold illiquid assets. A number of recent studies (Chordia et al, 2000; Amihud, 2002; Acharya and Pedersen, 2005.) discuss liquidity risk, the systematic component of liquidity; they find that firm-specific liquidity is not constant and provide evidence for the pricing of exposure to liquidity shocks. Fourth, we discuss the Put-Call parity, an important principle in options. This was first discussed by Stoll (1969) in his study of the relationship between the prices of puts and calls. Finally, we show implied volatility which is the volatility used when Black and Scholes'(1973) and Merton's (1973a) model generates the market price of an option.

2.1 Liquidity

The concepts of liquidity and illiquidity are ambiguous as they covers different dimensions. As Kyle (1985) argues, the concept of liquidity is ambiguous partly due to the fact that it includes some transactional properties of the market, such as tightness, depth, and resilience. Simply put, liquidity is the ease and speed with which large amounts of a security can be trading with a low impact on prices and at a low cost (Amihud et al., 2005). It may be time-consuming or costly to trade an illiquid security, and investors may face the liquidity risk when they want to sell the security in future.

We begin by discussing the direct influence of trading costs on asset prices. When buying or selling assets, compensation for trading costs is required by investors. For example, if we have two assets with the same future cash flows but a higher trading cost is require to trade one of the asset (that is, it is less liquid), investors will pay less for the illiquid asset. This results in a lower price and a higher expected return for the asset. According to Amihud et al. (2005), generally, there are five sources of illiquidity or trading costs. First, exogenous transaction costs, including taxes on financial transactions, commission fees, and other trade processing fees. Second, demand pressure and risk to the inventory, caused by a mismatch of supply and demand in the market. Third, asymmetric information, for example, traders on one side might have more private information than those on the other. Fourth, it may be difficult to locate a counterpart who wants to trade a quantity of a particular security, especially in over-the-counter markets. Larger transactions influence market prices significantly. In other words, there is a market impact cost for larger transactions. Finally, bid ask spreads are another element of trading costs. In an asset market with quoted bid (buying) and ask (selling) prices, generally the bid price is higher than the ask price, which leads to bid-ask spreads.

Most financial markets have market makers[1] who are willing to buy or sell assets for their own accounts to narrow the trading gaps between individual purchases and sales. Market makers expect compensation because they accept inventory risk. In addition, adverse selection exacerbates the bid-ask spreads (Amihud et al., 2013). Asymmetrical information exists among traders about whether the asset is overpriced; adverse selection arises when a buyer has private information and knows that the asset is overpriced. Uninformed market makers will attempt to protect themselves by offering a lower price. On the other hand, an informed market maker will tend to ask for a higher selling price because it has positive information for a purchase. These discounts and premiums result in trading costs, or illiquidity, for uninformed trades.

Historically, financial economists ignored liquidity problems, and the concept of frictionless markets, that is, that securities could be traded without translation costs, was widely accepted. However, numerous studies (for example, Amihud and Mendelson, 1986, 1991; Amihud et al., 1997; Datar et al., 1998) have demon-

[1]Some markets trade by auction. The influence of the two trading approaches, auction and market making, on the stock prices is discussed by Amihud and Mendelson (1987).

strated that liquidity is an important feature of securities and financial markets. Liquidity risk is the risk that the liquidity of an asset will worsen when the owner wants to sell it in future. A liquidity crisis occurs when the illiquidity of many assets increases at the same time (Amihud et al., 2015).

Amihud and Mendelson (1986) use the bid-ask spread as an illiquidity proxy to evaluate the effect of illiquidity on asset pricing. They found a positive relationship between expected stock returns and illiquidity. In particular, at time t, the quoted bid-ask spread QBA_t for a stock can be computed as:

$$QBA_t = (ASK_t - BID_t)/PRI_t \tag{2.1}$$

where ASK_t and BID_t are the quoted ask and bid prices, respectively, at time t, whilst PRI_t is the mid-point between ASK_t and BID_t prices at time t.

The theoretical foundations for the relationship between expected asset returns and illiquidity are laid out by Amihud and Mendelson (1986), who empirically demonstrate that it is economically and statistically significant across stocks traded on the New York Stock Exchange (NYSE) and American Stock Exchange (AMEX) from 1961 to 1980. Moreover, they demonstrate that if rational investors have a long holding period, they would require a higher return for illiquidity, and that the bid-ask spread would reflect this compensation. This is known as the clientèle effect[2]. In other words, this relationship increases at a decreasing rate, or, graphically, it increases concavely. Furthermore, Amihud and Mendelson (1991) examine the influence of liquidity on the pricing of US government securities by comparing the yields of short-term U.S treasury notes and the bills with identical expirations of no more than six months. They find that the average bid-ask spreads for the notes and bills are 0.03% and 0.0078%, respectively, which shows that a security with high trading costs has a significantly higher yield. In addition, Chen et al. (2007) find that after controlling for variables that account for common bond, firm, and macroeconomic affect, illiquidity has a significantly

[2]A number of studies have paid attention to the clientèle effect, for example, Atkins and Dyl (1997), Dias and Ferreira (2004), Næs and Ødegaard (2009), and Anginer (2010). In particular, Atkins and Dyl (1997) find that stocks with lower bid-ask spreads are more actively traded after controlling for other risks in NYSE. Dias and Ferreira (2004) and Næs and Ødegaard (2009) show that there is a positive relation between the investor's holding period and the bid-ask spreads of the stocks that they hold in the Portuguese market and the OSLO Stock Exchange. What is more, after a study of 6600 households from a larger American discount broker, Anginer (2010) find that investors with longer investment horizons prefer to more illiquid securities, and those households earn significantly higher returns after amortized transaction costs.

positive influence on the yield spread. This positive influence exists for both investment grade bonds and speculative grade bonds, and the illiquidity premiums for speculative-grade bonds are larger.

However, the application of the quoted bid and ask prices is limited to small trading quantities, because a larger trading quantity influences the transaction price. In particular, a large trading quantity increases the bid price and decreases the ask price simultaneously, which leads to a market cost, and this cost becomes greater as the transaction size increases (Amihud et al., 2015). The reason Amihud and Mendelson (1986) measure stock illiquidity using the quoted bid-ask spread is because the availability of data for measuring trading costs was limited at that time. When intraday data became available, Brennan and Subrahmanyam (1996) obtained both the fixed component and the variable component of trading costs in order to estimate stock illiquidity. In particular, the fixed component is independent of the trade size, whilst the variable component increases with the trading size. They found that both the fixed and variable components of trading costs have positive and significant coefficients, and this indicates that trading costs are associated with a significant risk-adjusted return premium. In addition, they investigated the relationship between the illiquidity measure constructed from intraday data and the stock returns, and they found a significant relationship even after controlling for the Fama and French's (1993) three factors and having considered the influence of this on the stock price level.

Furthermore, Silber (1991) investigated the influence of illiquidity on stock returns of restricted securities, and he found that this trading restriction directly decreases the prices of stocks. In addition, Amihud et al. (2015) estimate the liquidity premium using stock market data from forty-five countries for the period 1990 to 2010. Nineteen markets were considered to be emerging markets. They used the average alpha coefficient to measure the excess return attributed to illiquidity. They found that the average alpha coefficient is a positive and significant. This coefficient is higher in emerging markets, which are relatively illiquid, while developed countries have a lower coefficient. More specifically, the average monthly premium was approximately 0.77% for the returns of the equally weighted portfolio, and, after controlling for six risk factors, the monthly alpha was still approximately 0.79%.

Eleswarapu and Reinganum (1993) obtained the bid-ask spread to estimate the liquidity premium in asset pricing, and they found that, for the 1961-1990 period, the positive relationship between the stock returns and the bid-ask spread was confined to January. According to Amihud and Mendelson (1986), in equilibrium, if investors want to trade more frequently, they will hold liquid stocks. Therefore, the trading frequency could be used to infer the liquidity of a stock. Datar et al. (1998) obtained the stock turnover rate as a measure of stock liquidity in order to investigate whether liquidity is negative relative to stock returns. In particular, the turnover rate, $STR_{i,d}$, is defined as the traded number of shares divided by the number of shares outstanding:

$$STR_{i,d} = VOL_{i,d}/SHARE_{i,d} \tag{2.2}$$

where, $VOL_{i,d}$ is the average monthly trading volume[3] at month d for firm i, and $SHARE_{i,d}$ is the shares outstanding of that firm.

The turnover rate, $STR_{i,d}$, may indicate the trading frequency. Amihud and Mendelson (1986) demonstrate that in equilibrium, active trading investors hold more liquid stocks, and therefore liquidity could be inferred from the trading frequency. Datar et al. (1998) found there is a strong relationship between cross-sectional variation in stock returns and liquidity. The expected returns are lower for the stocks with higher turnover rates, because they have higher liquidity. More specifically, after controlling for firm size, the book-to-market ratio, and market risk factors, they found that a decrease of 10% in the turnover rate is associated with a monthly 0.4% higher return. Unlike Eleswarapu and Reinganum (1993), they show that liquidity effect exists not only in January.

Liu (2006) proposes another illiquidity measure, named the turnover-adjusted number of zero daily volume, which aims to capture liquidity's multiple dimensions. This measure is a function of the number of trading days with zero trading volumes, and monthly trading turnover and can be computed as follows:

$$LLM = [NZ + \frac{1/Xmt}{Deflator}] \times \frac{21X}{NT} \tag{2.3}$$

where NZ is the number of zero trading volumes in the previous X months; Xmt denotes the total value of trading turnover[4] in the previous X months; $Deflator$

[3]Trading volume is the number of shares traded, and a higher trading volume means a higher interests in this share. The turnover rate is a better liquidity measure, as it also consider the shares outstanding which is the shareholder base (Datar et al., 1998).

[4]Daily turnover is defined as the ratio of the traded number of shares divided by the shares outstanding at the end of the day.

is selected subject to $0 < \dfrac{1/Xmt}{Deflator} < 1$, and NT denotes the total number of trading days in the previous X months.

Liu (2006) obtained data including all ordinary common stocks listed at the New York Stock Exchange(NYSE), the American Stock Exchange (AMEX), and the National Association of Securities Dealers Automated Quotations (NASDAQ) for the period of January 1960 to December 2003, and sorted them into ten portfolios based on this measure. He found that the difference between the returns of portfolios with the lowest liquidity and portfolios with the highest liquidity is significantly positive. After controlling for the Fama and French's (1993) three factors, this difference between the returns is 0.7% monthly. In addition, Liu (2010) conducted a detailed analysis of liquidity from 1926 to 2009 and he found that, compared to the size and value premium, the liquidity premium is more significant and robust. What is more, he shows that the liquidity-augmented capital asset pricing model (CAPM) provides a good explanation of expected returns.

Prior studies have evaluated the relationship between liquidity and historical returns; however, Loderer and Roth (2005) examined the influence of trading costs, measured by the relative bid-ask spread, on the stock P/E ratio directly and commentary stock prices using data from the Swiss exchange and the NASDAQ from 1995 to 2001. They found that the P/E ratio is significantly lower for stocks with a higher bid-ask spread. In addition, this relationship is similar when using trading volume instead of bid-ask spread as the liquidity measure. Fang et al. (2009) examined the relation between the bid-ask spread and the a firm's market-to-book ratio, and they found that the spread has a negative influence on stock value. In particular, a lower bid-ask spread results in a higher market-to-book ratio.

Gârleanu and Pedersen (2004) demonstrated the manner in which illiquidity arises as a result of the influence of private information on asset allocation and prices. Easley and O'Hara (2004) argue that uninformed investors are unable to infer information from prices because of asymmetrical information. Hence, they are at a disadvantage because it is impossible for them to shift their portfolio to incorporate new information. As a consequence, expected returns of an asset are influenced by this information risk. Using the probability of informed trading[5], PIN, Easley et al. (2002) showed that there is a positive and significant relation-

[5] The probability of informed trading is an estimate of the fraction of information-based orders, and it is based on the imbalance between buying and selling trades.

ship between the PIN and returns after taking other risk factors into consideration. Nevertheless, Duarte and Young (2009) showed that when a direct stock illiquidity proxy is used in the estimation, the influence of the PIN becomes statistically insignificant. Therefore, they argue that illiquidity effects unrelated to information asymmetry are able to explain the relationship between the PIN and the expected returns.

Amihud et al. (1997) estimated the effect of stock liquidity changes on a given financial asset over time, and they found that the stock market became more liquid because an upgraded trading system leads to a significant increase of stock prices. When the Tel Aviv Stock Exchange (TASE) changed from daily call caution trading to high frequency trading, the stocks and their underlying cash flows did not change; however, transferring to a new venue and trading mode improved their liquidity. It is exogenous for the change in trading venue, and this change does not convey information about the stocks, because the stock exchange managers make the decisions to change. Amihud et al. (1997) found that stocks enjoyed a large and permanent price increase of approximately 5.5% on average after the liquid trading venue was introduced. Moreover, they found that there are positive liquidity externalities[6] across related stocks and the the process of value discovery is also improved due to the improvement in the trading approaches. Similarly, Muscarella and Piwowar (2001) examined the transfer from call trading to continuous trading in the Paris Bourse, and found that the prices of stocks appreciated after the transfer, especially for those with improved subsequent liquidity. The results of studies by Amihud et al. (1997) and Muscarella and Piwowar (2001) show that market liquidity improved after the trading system transferring, and the stock prices increase as well.

2.2 Commonality in Liquidity

Prior studies on providing liquidity pay more attention to the attributes of individual assets (see section 2.1). For example, the bid-ask spread of a security is a measure of the cost of providing immediacy, and this cost is caused by inventory (Amihud and Mendelson, 1980), asymmetrical information (Glosten and Milgrom, 1985), or order process costs (Kyle, 1985). Chordia et al. (2000) introduced the concept of liquidity commonality which examines the common determinants of and correlated movements in liquidity measures. They found that an individual stock's bid-ask spreads are associated with the market- and industry-wide liquid-

[6] A liquidity externality means that the liquidity improvement of an asset will raise both its own value and related assets' values.

ity. This co-movement remains significant and material after controlling for individual sources of liquidity, such as volatility, trading volume, and price. Chordia et al. (2005) provide evidence for that there is a common variation in daily aggregate spreads and depths among US stock and Treasury bond markets. Avanidhar (2007) identified the commonality in liquidity between stock market and real estate investment trusts.

Commonality in liquidity is also identified in a global context. Brockman et al. (2009) found considerable commonality in both quoted spreads and depths on the majority of large exchanges, in both developed and developing countries, even after controlling for other well-known determinants. Using intraday data from 47 exchanges from 38 countries, they provide evidence for simultaneous contributions to commonality by four equally weighted liquidity indexes at the local exchange, industry, region, and global levels. Karolyi et al. (2012) examined liquidity commonality around the world, and argue that correlated trading activity leads to commonality varying across time. Moreover, Mancini et al. (2013) studied liquidity commonality across several major currencies, and US equity and bond market, and they show that systematic variation in liquidity is common across different assets and markets. They also found that liquidity risk factor innovation, constructed by buying the most illiquid and shorting the most liquid currencies, is able to explain the carry trade strategy.

We outline the existing literature on the sources of commonality in liquidity in the remainder of this section.

2.2.1 Supply-Side Factors

Recent studies show that liquidity commonality could arise from the supply of liquidity. Gromb and Vayanos (2002) examined the relationship between liquidity and capital intermediaries. They argue that intermediaries have a strong ability to absorb investors'demand shocks if there is a higher intermediary wealth level. Furthermore, Brunnermeier and Pedersen (2009) provide evidence that financial intermediaries are the source of liquidity of markets, but that they face funding constrictions. Financial intermediaries can obtain funding through posting margins or putting up securities they hold as collateral. In a period of financial distress, the intermediaries face problems of collateral depreciation or increasing margins, which decreases their ability to provide liquidity and makes them liquidate their positions on securities they hold. This worsened market liquidity makes further losses or margin increase, resulting in 'liquidity spirals'. Further literature on funding liquidity and options are discussed in Chapter 3.

Similar patterns are also identified by other studies. Bernardo and Welch (2004) and Morris and Shin (2004) show that due to mutually reinforcing liquidation, ’liquidity black holes’ are generated by traders with private trading limitations. Moreover, Gârleanu and Pedersen (2007) argue that tighter risk management by institutions due to higher fundamental volatility may result in market illiquidity, and this worsened liquidity further tightens risk management. Cespa and Foucault (2014) examine links between price informativeness and liquidity, and argue that providers of liquidity are able to estimate one asset’s value based on that of another asset. For instance, a decrease in the liquidity of one asset will influence the price informativeness of that asset, which leads to a decrease in liquidity in a related asset. Hence, a liquidity co-movement is caused by this phenomenon. Using the Chicago Board Options Exchange Market Volatility Index (VIX) as a proxy of marketwide uncertainty, Chung and Chuwonganant (2014) find that marketwide uncertainty has a considerable influence on liquidity, which is another source of the common determinant of stock liquidity. Finally, Hertich (2015) provides evidence in favour of variations in fundamentals. Using Granger causality tests, Hertich (2015) found that an adverse shock to credit risk leads to a decrease in liquidity. Possible reasons for this are that increasing perceptions result in it being riskier to hold an asset in an inventory. If the credit risk has a common influence, this phenomenon could be another source of liquidity commonality.

In summary, liquidity commonality arises and tightens when a market declines or market volatility increases significantly. Theses predictions of commonality in liquidity have been identified in US markets(Coughenour and Saad, 2004; Hameed et al., 2010). Furthermore, Karolyi et al. (2012) examine the relationship between liquidity commonality and supply-side factors from an international perspective. They found that greater liquidity commonality is associated with countries experiencing periods of high market volatility.

2.2.2 Institutional Stock Ownership

Using common stocks listed on NYSE/AMEX with a sample spanning from 1962 to 2005, Kamara et al. (2008) found that commonality in liquidity increases among the large-cap stocks in the US market, and that increase in institutional investing and index trading play an important role in this change[7]. Moreover, Koch et al.

[7]The growing institutional ownership is associated with correlated trading among stocks, and this results in buying or selling activities simultaneously, which leads to higher commonality in

(2016) provide evidence that stocks with high mutual fund ownership show larger liquidity commonality.

Furthermore, Ferreira and Matos (2008) show that institutional investors hold approximately three-quarters of the 2.6 trillions of holdings of non-US stocks among the US investors. Karolyi et al. (2012) found that liquidity commonality is higher in countries with more institutional investors and during periods of greater correlated trading activities.

2.2.3 Incentives of Investors

Investors' incentives to trade individual stocks determine the correlation of liquidity demand across stocks, resulting in the commonality in liquidity. The level of investor protection and the transparency of the information environment in a country influences these incentives (Morck et al., 2000; Jin and Myers, 2006). If protection for investors is weak, it is less attractive to informed arbitrage. Therefore, Morck et al. (2000) argue that if there are weak legal protections for the property rights of investors in a country, there would be fewer incentives to search for information on a specific firm. They found that there is a greater commonality among local stocks in countries where investors have weaker protections. In addition, Jin and Myers (2006) found that if the information environment is less transparent in a country, there would be greater commonality in returns.

2.2.4 Investor Sentiment

The literature on investor sentiment focuses on the aggregate expectation of participants in financial markets. Prior studies show that the investor sentiment has a relationship with stock market returns, and that investor sentiment may be a critical source of liquidity commonality (Brown and Cliff, 2004; Huberman and Halka, 2001; Froot and Dabora, 1999)[8].

Baker and Wurgler (2006) constructed an investor sentiment measure based on the first principal component of six standardised equity market-based sentiment measures, including NYSE turnover, the closed-end fund discount, the dividend premium, the stock share in new issues, and the first-day returns and number of initial public offerings (IPOs). They demonstrate that waves of investor sentiment

liquidity.

[8] For instance, Huberman and Halka (2001) argue that the liquidity commonality arises due to the noise trading effects, and Froot and Dabora (1999) indicate that shocks of sentiment in a specific country could lead to excess co-movement of equity returns in that country.

have large influence on many stocks simultaneously, although not to the same extent. Barberis et al. (2005) provide new evidence for sentiment-based theories of return co-movement. Hameed et al. (2010) found that commonality in liquidity could result from panic selling by investors, which is a potentially sentiment-based factor.

Pan and Poteshman (2006) found that CBOE Put-Call ratios, the volume of put option contracts / volume of call option contracts, in transactions involving new positions can forecast future stock returns. This suggests that informed traders obtain enhanced leverage in the option market in order to generate greater profit. They argue that if it is high in implicit leverage in the options market, options are relatively liquid. Jiang et al. (2018) propose a manager sentiment index based on the total textual tone of corporate financial disclosures, and they found that the manager sentiment strongly negatively predict future aggregate equity market returns.

However, with regard to the sign of the relationship between investor sentiment and liquidity commonality, the investor sentiment hypothesis does not offer a straightforward prediction.

2.3 Liquidity Risk

There were severe liquidity shocks in the international equity and bond markets during the 2007-2009 global financial crisis. The last crisis taught us that it is possible for market liquidity to deteriorate dramatically, which suggests that it is not constant. Both the liquidity of individual assets and of the whole market change over time. According to Amihud et al. (2013), there are a number of reasons why this occurs. First, information transparency partially influences liquidity; however, transparency varies over time. Second, Brunnermeier and Pedersen (2009) show that liquidity depends on liquidity providers and their access to funding. If liquidity providers face funding constraints, less liquidity will be provided. As a consequence, market liquidity declines at the same time for the majority of securities. Third, the liquidity provision becomes riskier if uncertainty increases.

The studies discussed in section 2.1 examined cross-sectional analysis of stocks with various trading costs, and it is evident that a stock's level of trading cost has a statistical relationship with its expected returns. That is, a higher trading cost will rewards a higher expected return across stocks. Nevertheless, Silber (1991) estimates the effect of illiquidity on stock returns in the context of stocks with restricted trading, and found that stock prices are decreased by trading restrictions.

The positive relationship between returns and liquidity across stocks has been examined since Amihud and Mendelson (1986), and Amihud (2002) estimates the influence of illiquidity shocks on stock returns over time. Amihud (2002) obtains the average across stocks of the daily ratio of absolute stock return to dollar volume as the illiquidity proxy, and shows that less liquid stocks are more sensitive to market-wide illiquidity shocks, which means that they have a greater liquidity risk than larger and more liquid stocks. The illiquidity measure, $ILLIQ_{i,j}$, used in the cross-sectional study for stock i is defined as:

$$ILLIQ_{i,j} = (1/ND_{i,j}) \sum_{t}^{ND_{i,j}} (|R_{i,t,j}|/VOLUME_{i,t,j}) \tag{2.4}$$

where $|R_{i,t,j}|$ denotes the absolute return of stock i on day t in period j, $VOLUME_{i,t,j}$ denotes the stock i's trading volume on day t in dollars, and is calculated by multiplying the closing price by the number of shares traded. $ND_{i,j}$ is the nonzero volume of trading days for stock i in period j. If a given trading volume has a larger influence on prices, it is less liquid for this stock. $ILLIQ_{i,j}$ can be considered a market impact measure.

Amihud (2002) obtained daily and monthly data from CRSP for the period 1963 to 1997 in order to examine the influence of illiquidity on stock returns. Consistent with Amihud and Mendelson (1986), the individual stock illiquidity $ILLTQ_{i,j}$ has a significant positive influence on the expected returns. In particular, a stock with a higher annual $ILLTQ_{i,j}$ has a higher return the next year, even after controlling for other factors, such as the systematic risk betas, size, dividend yield, and past returns. This positive relationship is significant over the year, but the stock returns are higher in January. Amihud (2002) calculated the monthly average of all individual stock illiquidity to generate a time series of market illiquidity, $ILLIQ$. He shows that there is a negative relationship between stock returns and contemporaneous unexpected illiquidity, and that illiquidity has a stronger effect on small firm stocks, which explains why their premiums' time series vary. In other words, less liquid stocks are more sensitive to market-wide illiquidity shocks than more liquid stocks[9].

[9]Liquidity shocks measure the changes in overall market liquidity compared with expectations (Amihud et al., 2013). If the changes are lasting, the aggregate asset returns will be influenced by the new liquidity level.

Bekaert et al. (2007) examined the influence of illiquidity shocks on returns for 19 emerging markets and the world index (the US), and found that the relationship is still significantly negative. Furthermore, they find that the relationship between return and illiquidity is stronger in less open markets that have more restrictions for foreign investors. However, Watanabe and Watanabe (2008) examined the relationship between aggregate liquidity fluctuations and the stock returns, and found that, in periods of heavy trading and high volatility, illiquidity shocks have a strong negative influence on returns. That is, the relationship between returns and illiquidity varies over time, and is higher during financial crises. Furthermore, De Jong and Driessen (2012) estimated the influence of liquidity shocks on the returns of corporate bonds. They obtain $ILLTQ$ to measure stock illiquidity and government bonds' bid-ask spreads are used to measure the illiquidity of bonds. After the market return is controlled, they found that there is a negative relation between bond returns and illiquidity shocks, and that the relation between return and illiquidity shocks is more negative for bonds with longer maturity and for lower-rated bonds. For instance, the total estimated liquidity risk premium is approximately 0.45% for US long-maturity investment-grade bonds, whilst the premium is around 1% for speculative-grade bonds due to the fact that they have higher exposures to liquidity factors.

In addition, Acharya et al. (2013) studied the influence of stock and Treasury bond liquidity shocks on US corporate bond returns for a sample period from 1973 to 2007. They found that junk bonds' prices plummet significantly with an unexpected rise in the illiquidity of bonds and stocks, while during a financial crisis, the more liquid investment-grade bonds' prices increase. Furthermore, Kessler and Scherer (2011) examined the relationship between liquidity shocks and the returns of nine hedge fund indices with different strategies and categories over the period 2003 to 2009, and found that there is a significant negative relationship between an increase in illiquidity and hedge fund returns even after controlling for 11 risk factors. In particular, they obtained a liquidity factor that accounts for six liquidity proxies of stocks, government bonds, corporate bonds, commodities, and foreign exchange. What is more, Mancini et al. (2013) systematically studied the relationship between liquidity in the foreign exchange market using data from Electronic Broking Services (EBS) for the period January 2007 to December 2009. As with the bond and stock markets, Mancini et al. (2013) found there are significant cross-sectional and temporal liquidity variations across different exchange rates, and that foreign exchange liquidity is primarily driven by foreign exchange market aggregate liquidity. They argue that liquidity is priced because the liquidity risk factor has a strong influence on carry trade returns during the sample period.

Prior studies have shown that market-wide liquidity shocks have a strong influence on asset returns, which means market-wide liquidity shocks may be a source of market risk. Pástor and Stambaugh (2003) examined whether assets should earn a premium for their exposure to market-wide liquidity shocks. They constructed a market liquidity measure based on temporary price changes because of order flow. In a given month, the market liquidity measure is defined as the equally weighted average of the individual stock's liquidity on the NYSE and the AMEX using daily data in that month. In particular, for stock k in month m, liquidity is the ordinary least squares estimate of Γ from the following regression:

$$r^e_{k,d+1,m} = \theta_{k,m} + \phi_{k,m} r_{k,d,m} + \Gamma_{k,m} sign(r^e_{k,d,m})(Volume_{k,d,m}) + \varepsilon_{k,d+1,m} \quad (2.5)$$

where $r_{k,d,m}$ is the stock k's return on day d in month m; $r^e_{k,d+1,m}$ is stock k's excess return above the CRSP value-weighted market return on day $d+1$ in month m; $Volume_{k,d,m}$ is the dollar volume for stock k on day d in month m; $\theta_{k,m}$ is the intercept; $\phi_{k,m}$ and $\Gamma_{k,m}$ are regression coefficients, and $\varepsilon_{k,d+1,m}$ is the error term. They only calculate the liquidity of a stock if there are more than 15 observations to estimate the regression, which means $d > 15$. A stock is considered to be illiquid if a decline in price is followed by a small upward price bounce during the next trading day at a given trading volume. The smaller the price reversal for a given volume, the more liquid the equity.

For a given month, Pástor and Stambaugh (2003) calculate the market-wide liquidity measure by averaging price reversal coefficients across equities in that month; unexpected changes in this aggregate liquidity measure are the shocks of liquidity. They sort stocks into ten portfolios using their liquidity beta, which is the estimated sensitivity of every stock's return on the market-wide liquidity measure. The found that the average return on stocks with high sensitivity to market-wide liquidity is 7.5% higher than those stocks with low sensitivity, even after controlling for Carhart's (1997) four factors.

Acharya and Pedersen (2005) also examined whether there is a premium for the exposure of an asset's return to market-wide liquidity shocks, and provide a theoretical framework to explain the return sensitivity to market liquidity as found by Pástor and Stambaugh (2003). According to Acharya and Pedersen's (2005) model, liquidity risk decreases prices and raises the required returns, and this contributes to much of the price decrease during periods of financial distress, such as the 2007-2009 financial crisis. Acharya and Pedersen (2005) obtain an adjusted Amihud's (2002) illiquidity measure with stock data from the NYSE and AMEX for the period 1963 to 1999 in order to explore the cross-sectional predictions of the model. They found that the relation between systematic liquidity and average stock returns is statistically significantly positive, and that an illiquidity shock will lead to a low contemporaneous return and a high predicted future return. Acharya and Pedersen (2005) show that the liquidity-adjusted CAPM model has a stronger explanatory ability than the standard CAPM.

Lin et al. (2011) estimated the sensitivity to liquidity shocks of monthly corporate bond returns using the unexpected changes in both the Amihud's (2002) liquidity measure and Pástor and Stambaugh's (2003) liquidity measure. Lin et al. (2011) estimated the liquidity beta controlling for the factors that influence bond returns, and then they examined whether the liquidity beta is priced by estimating the influence across bonds while controlling for other factors. They found that there is a statistically significantly positive relationship between average excess bond returns and liquidity risk, and that this relationship holds after controlling for rating, coupon, issue size, and the age of the bonds. In addition, they found that the annual bond return will increase by about 1% if the beta increases one standard deviation above its mean across bonds. A similar pattern between liquidity risk and returns is found by Sadka (2012) in the hedge fund market. Sadka (2012) found that hedge funds with a higher liquidity beta, which means they have larger exposure to liquidity shocks, earn significantly higher average returns. He sorted the funds into ten portfolios based on the liquidity beta, and found that the portfolio with the highest liquidity exposure has a 6% higher return annually than the portfolio with the lowest liquidity beta, even after controlling for the factors that influence hedge fund performance.

A growing body of literature (for example, Menkhoff et al., 2012; Mancini et al., 2013; Orlov, 2016) have found that carry trade strategies[10] can yield significant excess returns. Many studies have found that exchange rate changes do not compensate for interest rate differences, and the so-called forward premium puzzle shows that high interest rate currencies seem to appreciate, and low interest rate currencies appear to depreciate (Fama, 1984). The carry trade strategy has arisen

[10]The carry trade strategy involves investing in high interest rate currencies with borrowing in low interest rate currencies.

on the basis of this puzzle, and has been studied for a long time. Engel (1984) and Fama (1984) give a simple but persuasive explanation for this puzzle on the basis of the existence of time-varying risk premiums. Investors' high-risk exposure will receive compensation from the carry trade only if the high interest rate currencies cannot deliver a higher return during recessions.

The 2007-2009 financial distress shows that there is a link between a decline in liquidity of financial assets and the economic crisis. A few recent studies have paid attention to the relationship between aggregate liquidity and future economic growths. Næs et al. (2011) found that stock market liquidity has strong predictive power for real economy variables, such as gross domestic product (GDP) growth and changes in investments. They found that changes in the liquidity of the equity market have been related to the real economy since the Second World War. In particular, they obtained quarterly US market data in order to examine both the in-sample and out-of-sample predictability of stock market aggregate liquidity on real economic variables. They argue that variation in systematic liquidity is associated with a 'flight to quality' during economic crisis.

Moreover, using order flow measures, Beber et al. (2011) and Kaul and Kayacetin (2009) found that illiquidity could forecast macro economic changes, such as GDP and industrial production growth. In addition, Næs et al. (2011) and Chen et al. (2017) demonstrate a positive predictability of several illiquidity measures on macroeconomic outcomes. Chen et al. (2017) developed several proxies of trading costs in US stock market for the sample period 1926 to 2015. They show that these measures contain predictive information on equity market returns and economic growths. However, the current literature mainly examines illiquidity predictability on US markets (Kaul and Kayacetin, 2009; Beber et al., 2011; Bouwman et al., 2011; Næs et al., 2011; Chen et al., 2016, 2017; Ellington et al., 2017) and in other developed countries, such as Norway (Skjeltorp and Ødegaard, 2009), Switzerland (Meichle et al., 2011), UK (Smimou and Khallouli, 2015; Apergis et al., 2015; Galariotis and Giouvris, 2015), Germany (Apergis et al., 2015; Galariotis and Giouvris, 2015), and Australia (Rai, 2015; Lim and Giouvris, 2017).

2.4 Put-Call Parity

The Put-Call parity is an important principle in options, and is first discussed by Stoll (1969) in his paper on the relationship between the prices of puts and calls[11].

[11] Merton (1973b) extends and modifies the Put-Call parity model.

He argues that, because of arbitrage forces, there is an exact relationship[12] between a European call (C) and a European put (P) for the same underlying security, strike price and expiration date, which is

$$C + Ke^{-rT} = P + S \tag{2.6}$$

where r is the risk-free rate, C and P represent the call and put prices, respectively, with strike price K, S shows spot price of the underlying security in current market, and $PV(K)$ indicates the present value of the underlying security.

This relationship exists because puts, calls, and underlying securities are interrelated, and any two of them could be organised in such a way as to yield the profit and loss chances of the third instrument (Klemkosky and Resnick, 1979). If the prices of puts and calls deviate substantially from the Put-Call parity, investors have an opportunity to earn a risk-free return by building a riskless arbitrage position. The violation of Put-Call parity contains information about future stock returns (Cremers and Weinbaum, 2010).

For the American-style options, Merton (1973b) proposes the bounding inequalities:

$$S - K \leq C - P \leq S - PV(K) \tag{2.7}$$

where the left-hand side inequality indicates the possibility of direct exercise of the put options against the arbitrageur, while the right-hand side one shows the long-hedge boundary. The holder of the put is the arbitrageur in the long hedge, and could exercise the put option at any time if he can make profits by doing so.

If there is a violation of Put-Call parity, it is generally caused by the breaking of assumptions. For example, Ofek et al. (2004) demonstrate that short-sale constraints on the underlying stocks may lead to deviations from the Put-Call parity. However, Battalio and Schultz (2006) argue that short-sale constraints do not have large influence and that violations of the parity conditions become less significant when considering intra-day option data. Furthermore, Battalio and Schultz (2006) indicate that Put-Call parity deviations might not be material and are affected by the non-synchronicity of option and stock markets. In addition, Grundy

[12] American style options are allowed to exercise prior to maturity, and therefore Put-Call parity does not hold for American options unless holding them to the maturity.

et al. (2012) argue that apparent violations of the Put-Call parity boundary become significantly more frequent for banned stocks during a short sales ban period.

2.5 Implied Volatility

In 1973, Fischer Black and Myron Scholes introduced the first practical theoretical pricing model for options (Black and Scholes, 1973), the Black-Scholes model[13]. This model provides a simple tool for traders to estimate the option prices with a limited number of observable inputs. In the original form, the model tends to evaluate European-style options (that is, early exercise is not permitted) without dividend stocks.

In order to calculate the theoretical price of an option using the Black-Scholes model, minimum five parameters for the option and its underlying asset are required:

- The strike price of the option,
- The underlying asset's price,
- The interest rate over the life span of the option,
- The time to expiration, and
- The underlying asset's volatility.

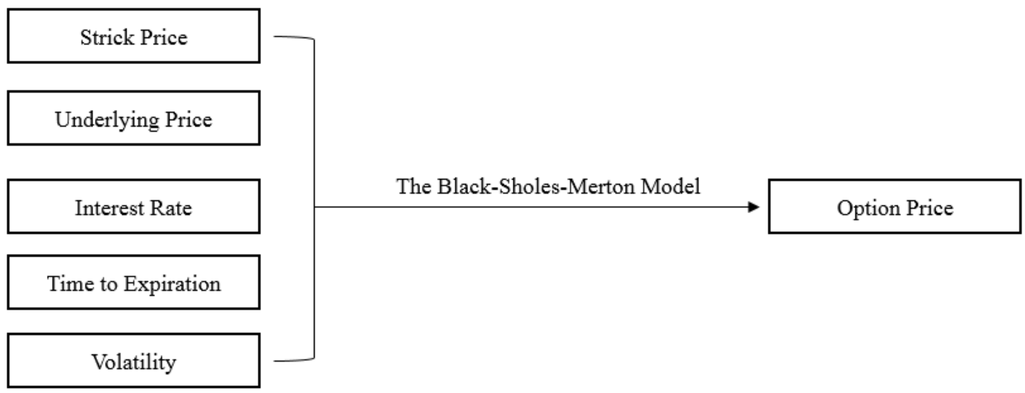


Figure 2.1: Calculation of Option Prices

The last is a realised volatility, and is computed from the underlying asset's price changes, which reflect past market changes. Nevertheless, the implied volatility is derived from the price of the option in the marketplace, which is different

[13]Robert Merton also contributed to the development of the original Black-Scholes model.

from its realised volatility. This characteristic means that implied volatility represents the marketplace's consensus on the future realised volatility of the underlying asset.

Implied volatility is the volatility when used with Black and Scholes's (1973) and Merton's (1973a) models to generate the market price of the option. In order to calculate implied volatility, a minimum of five parameters for the option and its underlying asset are required:

- The strike price of the option,
- The underlying asset's price,
- The interest rate over the life span of the option,
- The time to maturity, and
- The option price.

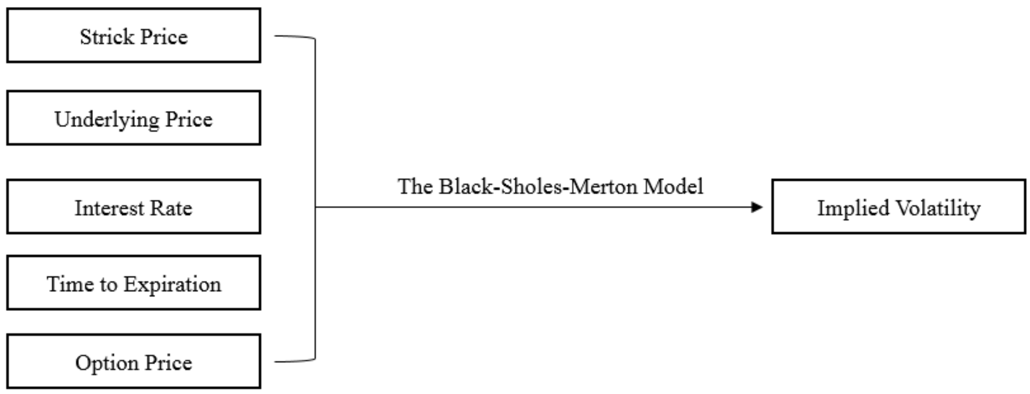


Figure 2.2: Calculation of Implied Volatility

Traditionally, both the Black-Scholes formula and the Cox-Ross-Rubinstein binomial model can be used to compute implied volatility [14]. In terms of the assumptions of the Black-Scholes formula, implied volatility is the market's estimation of the constant volatility parameter (Mayhew, 1995). If the underlying security's volatility varies over time, the implied volatility is the market's estimation of the average volatility over the remainder of the option life. In the Black-Scholes model, implied volatility represents the underlying asset's volatility, and hence it

[14]Even though, the implied volatility is generally associated with the stock (index) options, it also applies to other options. For instance, prior studies have demonstrated that the implied volatility can also be computed using exotic, commodity, bond or currency options (for instance, Ball et al., 1985; Amin and Morton, 1994; Nikkinen et al., 2006).

should be the same for options of different exercise prices for same underlying assets and time to maturity. In practice, the volatility is associated with expiration and strike prices. In other words, the relationship between implied volatility and strike prices are not constant[15].

In this study, we obtained option market data from IvyDB's OptionMetrics database[16]. The data also contain the implied volatility for each option contract, which is computed with using binomial model that captures dividend payment and the probability of early exercise of American options.

2.6 Summary

In this chapter, we have briefly discussed some essential background information to this study, including liquidity, commonality in liquidity, liquidity risk, Put-Call parity, and implied volatility.

First, we briefly presented definitions and popular measures of liquidity. As argued by Kyle (1985), the concept of liquidity is ambiguous partly due to the fact that it includes some transactional properties of the market, such as tightness, depth, and resiliency. Amihud et al. (2005) provide a simple definition for liquidity, the ease and speed of trading large amounts of a security with a low impact on prices at low cost. Moreover, we discussed the direct influence of trading costs on asset prices. Amihud and Mendelson (1986) use the bid-ask spread as an illiquidity proxy to evaluate the effect of illiquidity on asset pricing, and they found a positive relationship between expected stock returns and illiquidity. A few more studies (for example, Amihud and Mendelson, 1991; Amihud et al., 1997; Datar et al., 1998) have also demonstrated that liquidity is an important feature of the securities and financial markets.

Then, we presented literature on commonality in liquidity. After Chordia et al. (2005) first provided for that there is common variation between daily aggregate spreads and depths in US stock and Treasury bond markets, there have been a number of studies on this topic, for example, Brockman et al. (2009), Karolyi et al. (2012), and Mancini et al. (2013). In addition, we briefly showed the detriments of commonality in liquidity.

[15]The plot of strike price and the implied volatility for options with the same time to maturity looks like smiling, so it is named 'volatility smile'.

[16]OptionMetrics provides historical option price data and implied volatility, and we use all options for securities listed as common stocks in the OptionMetrics database. This dataset includes call and put option mid prices, their strike prices, open interest, volume, remaining time to expiration of the option (expressed in years).

Third, we summarised the literature related to liquidity risk, which is the risk that the liquidity of an asset will worsen when its owner wants to sell it in future (Amihud et al., 2013). The 2007-2009 financial crisis shows that it is possible for market liquidity to deteriorate dramatically, which suggests that the market liquidity is not constant. Pástor and Stambaugh (2003) and Acharya and Pedersen (2005) provide empirical evidence that the exposure to liquidity is priced. Prior studies have shown that there is a significant relationship between the average level of liquidity and liquidity risk.

Fourth, we presented theories on Put-Call parity, which was first discussed by Stoll (1969) in his paper on the relationship between the prices of puts and calls. Finally, we discussed the components for computing implied volatility, and the popular methods used.

Chapter 3. Funding Liquidity: Literature Review

Severe liquidity shocks were observed in global financial markets during the financial distress of 2007-2009. Starting in the US in 2007, this global financial distress has shown the importance of liquidity and liquidity risk and their influence on asset prices and on the workings of financial markets. In this chapter, we summarise the literature related to implied funding liquidity. First, we discuss market liquidity and funding liquidity. Brunnermeier and Pedersen (2009) present definitions for two kinds of liquidities: market liquidity and funding liquidity. They also provide a theory to explain the origins and underlying dynamics of a liquidity crisis, and discovered the relationship between market illiquidity and the shadow cost of funding. Then, we present the literature associated with the option market and funding liquidity. Third, we discuss the relationship between option and stock markets. Literature suggests that the option market is more informationally efficient than the equity market as a consequence of active informed trading.

3.1 Market Liquidity and Funding Liquidity

Liquidity externalities may result in a sudden drying up of liquidity (Amihud et al., 2013). In particular, the increasing willingness oto trade on one side of the market makes it more convenient for investors on the other side to trade; similarly, investors unwilling to trade reduce market liquidity for others. Therefore, investors avoiding trading could produce a downward spiral, resulting in a liquidity deterioration. Brunnermeier and Pedersen (2009) provide a theory to explain the origins and underlying dynamics of a liquidity crisis, and they discovered the relationship between market illiquidity and the shadow cost of funding. They present definitions for two different kinds of liquidities, market liquidity and funding liquidity. In particular, the ease of trading a referred to as market liquidity; funding liquidity is a shadow cost of capital, and is a property of both securities and traders. If it is easy to use a security as collateral to borrow, this security may be considered to have good funding liquidity. What is more, they show that liquidity spirals could be generated by the interaction of these two kinds of liquidity. In particular, traders with good funding liquidity may trade frequently, which improves market liquidity. In a similar manner, market liquidity may influence funding liquidity: it is easier to finance a trader's positions when the market has higher market liquidity with lower volatility, and the margin requirement will also be decreased. Hence, funding liquidity improves market liquidity and vice versa. That is, funding problems lead to market illiquidity, and market illiquidity exacerbates funding problems. This adverse feedback loop causes the markets spiral into a crisis. In addition, they show that there is a relationship between market liquidity and volatility, because a higher margin payment is required for trading a more volatile asset.

Brunnermeier and Pedersen (2009) shows that funding liquidity has a significant effect on market liquidity. In particular, when funding liquidity is insufficient, traders will not take many positions. As a result, market liquidity decreases and the volatility rises. Moreover, low future market liquidity is a risk for the funding of a trade, and consequently the margin requirement will increase. They demonstrate that such liquidity spirals explain the fragility of the financial system, because a shock to one market could have a disproportionate effect when the spiral spreads through the whole financial system, influencing other markets. Mitchell et al. (2007) show that liquidity spirals make price drop and rebound, because new capital arrives slowly. Furthermore, Moinas et al. (2016) examine the relationship between funding constraints and market liquidity shocks using an identification method based on the characteristic of the liquidity shocks' intrinsic endogeneity using data from the European Treasury bond market. They show that the shocks of funding liquidity influences market liquidity in the bond market, and that there is also a weaker influence of simultaneous feedback of market liquidity on funding liquidity. Aragon and Strahan (2012) estimated the influence of the funding liquidity of hedge funds on the market liquidity of the equity market. Using the failure of Lehman Brothers as an exogenous variable, they provide evidence that funding the liquidity of trades influences market liquidity.

Hu et al. (2013) propose a new proxy for the illiquidity of aggregate market using the average pricing errors in US Treasury bonds. In particular, they constructed a market-wide liquidity measure by examining the relationship between the amount of arbitrage capital in the market and the observed noises in US Treasury bonds. If there is a shortage of arbitrage capital, yields could vary more freely from the cure, resulting in more noise presented in prices. This market-wide measure captures episodes of liquidity crises of different origins across the entire financial system, and therefore it may provide more information than other liquidity proxies. They demonstrate that this market-wide proxy increases significantly during periods of financial distresses, for example, the 1987 equity market crash and the 2008-2009 global financial crisis. In addition, they found that this market-wide liquidity measure may explain cross-sectional variation in both hedge fund returns and currency carry trade strategies.

A growing body of literature is dedicated researching the influence of funding liquidity and required returns. In particular, prior studies (Gârleanu and Pedersen, 2011; Ashcraft et al., 2011; Frazzini and Pedersen, 2014; Chen and Lu, 2017) show the influence of funding conditions and margin requirements on asset prices. Due to the limitations of funding and leverage constraints, investors prefer assets with lower margin requirements. In other words, investors prefer to hold assets using less capital. Gârleanu and Pedersen (2011) provide evidence that the reason that the law of one price breaks down is that prices of assets with high margin requirements decrease compared to lower-margin assets with the same future cash flows. Furthermore, Ashcraft et al. (2011) found that there is a strong relationship between these lowered required returns and raised security prices.

Frazzini and Pedersen (2014) propose a betting-against-beta strategy, which is market neutral. In particular, this strategy involves buying assets with low betas whilst selling assets with high betas, and they found that the positive risk-adjusted returns produced by this strategy are significant. Moreover, they found that when funding constraints become tighter, risk-adjusted returns become lower. Chen and Lu (2017) built a traded funding liquidity measure with both cross-sectional and time series stock returns. Specifically, they extracted the shocks of funding liquidity from the difference between the returns of Frazzini and Pedersen's (2014) betting against beta portfolios with high and low margin stocks. They found that there is a positive relationship between the funding liquidity measure and the market liquidity measure. In addition, in hedge fund market, they showed that low-sensitivity funds may generate higher returns.

3.2 Option Markets and Funding Liquidity

Theoretical studies (Brunnermeier and Pedersen, 2009; Vayanos and Wang, 2013; Foucault et al., 2013) suggest that tight funding conditions impact on market liquidity and asset prices as traders become unable to raise funds, and subsequently face forced liquidation of their investments at depressed prices. Option markets are important as they are liquid, facilitate high leverage (Black, 1972; Easley et al., 1998), and because option prices have predictive power for returns (Cremers and Weinbaum, 2010; An et al., 2014). In such markets, we focus on Put-Call parity. This is a no-arbitrage relation, relating the European call and put option prices of the same underlying security with the same strike price and maturity date.

Sharpe et al. (1998) show that arbitrage is the process of earning a positive profit without risk by taking advantage of an asset's pricing spreads. Wealth could be obtained by arbitrage as no money is required in the beginning. Occasionally, arbitrage opportunities may exist, but they do not last in the long run, because trading will quickly remove any arbitrage opportunity. Moreover, not all arbitrage opportunities have practical value, because trading influences the market. Furthermore, trading costs, bid-ask spreads, and illiquidity also tend to quickly remove these chances.

Easley et al. (1998) show that buying a call or selling a put option includes a positive signal about future stock prices in normal time, because investors earn a profit from an increase in the stock price. In contrast, a negative signal about future prices is sent out with selling a call or buying a put option, because there is an expectation of decrease in the price of the underlying stock. Due to the private information problems, prices are not fully efficient as regards information. Hence, options may contain information about future prices of the underlying asset. Easley et al. (1998) found that, if investors with private information trade in the option market, the option prices may include information about the underlying assets, which is useful for forecasting future price changes of the underlying asset. That is, in the short run, if informed investors are present in the markets, the movement of option prices could deviate from the put-call parity and if so, option prices are no longer fully efficient. However, Baltussen et al. (2012) show that the diffusion of information from the option market into the underlying stock market is gradual, because exploitable signals are included in public option market information.

Furthermore, Cao and Wei (2010) argue that there is a strong relationship between market-wide option liquidity and the underlying stock market's movements, and information asymmetry is a critical basic driving force of liquidity. Theoretically, in the long run, the prices of call and put options will be in line with Put-Call parity because of arbitrage in the stock and option markets, which means that the price of the underlying stock will soon incorporate private information. However, regarding to the limitation of transactions costs, such as the difference in lending and borrowing rates, taxes, and margin requirements, option prices may deviate form put-call parity without an arbitrage opportunity (Cao and Wei, 2010). In particular, Cao and Wei (2010) used Ivy DB's OptionMetrics data to examine option market liquidity, and they found that there is a relationship between market-wide option liquidity and the underlying stock market's movements. They provide evidence of commonality for several liquidity measures, and that the commonality still exists after controlling for the underlying stock market's liquidity and volatility. They show that the influence is stronger on liquidity than inventory risk due to information asymmetry, and that market-wide option liquidity correlates with the underlying stock market's movements. In particular, the responds of option liquidity to upward and downward market movements is asymmetrical: calls react more in upward markets, while puts respond more in downward markets.

Bali and Hovakimian (2009) show a significantly positive relationship between the volatility spreads of call-put options and future returns by means of portfolio-level analyses and firm-level cross-sectional regressions. Moreover, they show that significant information flow from individual equity options to the underlying stock is observed, indicating informed trading in the market by traders with inside information; for options or stocks with higher volatility spreads, this information spillover is even more significantly stronger. Ofek et al. (2004) examine the put-call parity relation to the restriction of short sales, and show that Put-Call parity violations are asymmetrical in the direction of short sales constraints, and that the influence is associated with the cost and ease of short sales. After considering shorting costs and extreme assumptions of transaction costs, violations do not disappear. Moreover, violations may also be influenced by the option maturity and the stock market's valuations; this is consistent with the behaviour of over-optimistic stock investors and market segmentation theory in behavioural finance. In addition, Grundy et al. (2012) examined the relationship between bearish option strategies and short sales during the short-sale ban in the USA in the September 2008, and found that there is an option bid-ask spread increase and a decrease of option volumes for banned stocks compared to unbanned ones. Furthermore, a significant violation of the Put-Call parity boundary is seen during the ban period. Nonetheless, Battalio and Schultz (2006) found almost no evidence of violations of Put-Call parity using intraday options data in the presence of the short restrictions at the peak of the Internet bubble.

Bali and Hovakimian (2009) found that there is a relationship between the trading volume of options, the future volume, and the underlying stock's volatility; this suggests that the option's liquidity is associated with the stock market's liquidity and risk. Using the difference in implied volatility of paired call and put options for same underlying assets as a measure of the violations of the put-call parity, Cremers and Weinbaum (2010) show that stocks with relatively expensive calls are more profitable than stocks with relatively expensive puts. Specifically, high call-put volatility of stocks suggests more trading activities in the future, resulting in an increase of the liquidity of the stock. Hence, the spreads of the call and put implied volatilities could be used to forecast the drying up of market liquidity. Cremers and Weinbaum (2010) provide evidence that there is a strong relationship between deviations in the option price relative to Put-Call parity and the expected underlying stock returns. In addition, they obtained a smaller sample with rebate rates, a measure of the ease of short-selling in the equity lending market, and found that short-sales restrictions do not drive the deviations. Furthermore, this predictability reflects informed trading that first occurs in the options market, as suggested with by findings of Bali and Hovakimian (2009). The degree of predictability decreases in the long run.

However, Doran et al. (2013) found no significant relationship between the spreads of the implied volatility and the expected returns for at-the-money call options or put options. Using unique data on option volumes, they found that complicated company investors' option demand contributes to positive equity return predictability, while individual investors' demand drives negative call option return predictability. That is, the spreads of the implied volatilities carry information about both company fundamentals and option mispricing. What is more, using intraday data on 39 liquid American stocks and their corresponding options and concentrating on events when the two markets do not move together, Muravyev et al. (2013) found that the option prices do not carry extra economically significant information about expected stock returns beyond the information already reflected in the current prices of the underlying stocks.

An et al. (2014) argue that if there had been a large increase of call implied volatilities in the previous month, the underlying stock will earn high expected returns; in contrast, if a large increase of put implied volatility was observed in the prior month, the underlying asset will have low expected returns. However, Cremers and Weinbaum (2010) show that if the distribution of the underlying asset is skewed, which means that the call and put implied volatilities' deviations are noisy proxies of pressure, the deviations might not be zero. However, with regards to the relation between skewness and expected returns, different studies have different conclusions. For example, Xing et al. (2010) and Cremers and Weinbaum (2010) show that skewness is positively correlated with future returns, while Bali et al. (2011) and Conrad et al. (2013) found that there is a negative relationship between skewness and expected returns. Bali and Murray (2013) constructed skewness assets with a long option, a short option, and a long position of the underlying stock, and they found a strong negative relationship between risk-neutral skewness and the skewness of asset returns. The relationship holds after controlling for the market, size, book-to-market ratios, momentum, short-term reversal, spreads of the put-call implied volatility, and other option market factors.

3.3 Options and the Stock Market

Traditionally, options are treated as securities that can be replicated in continuous time with stocks and bonds (Black and Scholes, 1973). Nevertheless, some studies (for instance, Naik and Lee, 1990; Liu and Pan, 2003) argue that it is difficult to dynamically replicate options with stocks and bonds when some features are involved in the process of the underlying asset, such as stochastic discontinuities. Furthermore, Cao (1999) argues that agents will trade more effectively with options if they have information about future contingencies, which will result in an improvement of information efficiency. In other words, options may change the incentives to trade on private information about the underlying security. In addition, Back (1993) and Biais and Hillion (1994) show that, due to increased chances for leverage, informed traders are more likely to trade options than stocks.

Cao and Wei (2010) demonstrate that the phenomenon of information asymmetry is higher for options than for the underlying stock, which means that it is more efficient to trade in the option market if agents have information. In addition, the order flows of options also have information about future returns of the underlying stocks (Easley et al., 1998; Chakravarty et al., 2004; Pan and Poteshman, 2006). Using microstructure data, Ni et al. (2008) found that if traders are informed about future volatility, they would prefer the option market, and that option order flows can predict the stock volatility.

A number of studies argue that informed traders prefer the option market because of the absence of short-selling constraints, built-in downside protection, and chances to apply leverage (see, for instance, Easley et al., 1998; Chakravarty et al., 2004). Manaster and Rendleman (1982) estimate the predictability of option prices for the underlying stock market. They found that option-implied stock prices are the option market's expectation of the value of the underlying asset, and that additional information is included in the option-implied stock prices which is not fully reflected in the stock prices. Kumar et al. (1992) examined the behaviour of stock and option prices around block trades, and found that the behaviour of option prices differs significantly from stock price behaviour.

Jennings and Starks (1986) found that after earnings announcements, prices adjust quickly in the option market, while Mendenhall and Fehrs (1999) argue that, by means of insider trading, the speed of the adjustment of prices to earnings is raised by option trading before the earnings announcement. Amin and Lee (2010) present evidence that open interest in options increases before earnings announcements. In addition, Cao et al. (2005) show that option volume may forecast returns around the acquisition announcements, which means that informed traders are present in the option market before corporate events. Roll et al. (2010) find that the options/stock trading volume ratio (O/S) is higher around the earnings announcements, which indicates that more trading is present in the option market. Furthermore, they found that there is a positive relationship between post-announcement absolute returns and the pre-announcement O/S, and that this means that some of the pre-announcement options trading is informed.

Easley et al. (1998) obtained signed option trading volume data to demonstrate that information about equity price changes are included in the option market. Moreover, Chakravarty et al. (2004) found that approximately 17% of price discovery happens in the option market. Ofek et al. (2004) show that option-implied stock prices strongly predict future stock returns, and Taylor et al. (2010) argue that it is more informative of option forecasts for companies with more actively traded options. Yu et al. (2010) provide evidence for the superiority of option-implied volatility over either historical volatility or generalized auto regressive conditional heteroskedasticity (GARCH) type volatility predictability, and Xing et al. (2010) show volatility smirk forecasts future equity returns[1]. Chen et al. (2011) find that the option market is more efficient than the equity market when stock and option markets diverge. Cremers and Weinbaum (2010) demonstrate that information about future movements of stocks are included in the deviations from Put-Call parity, and it is more likely for option prices to deviate from Put-Call parity when there is more information risk for the underlying stocks.

3.4 Summary

In this chapter, we summarised the literature associated with implied funding liquidity. First, we presented a detailed review of the literature on market liquidity and funding liquidity. Brunnermeier and Pedersen (2009) provide a theory to explain the origins and underlying dynamics of a liquidity crisis; they discovered the

[1]The plot of implied volatilities against strike prices is a u-shped curve, which looks like a smile (Hull, 2015). This skewed pattern of implied volatilities is widely known as volatility smirk or volatility smile.

relationship between market illiquidity and the shadow cost of funding. They provide definitions for two different kinds of liquidities: market liquidity and funding liquidity. Market liquidity is the ease of trading securities; funding liquidity is a shadow cost of capital, and it is a property of both securities and traders. Then, we presented the literature related to the option market and funding liquidity. Third, we discussed the relationship between the option and stock markets. Previous studies (for example, Jennings and Starks, 1986; Easley et al., 1998; Chakravarty et al., 2004; Ofek et al., 2004; Cao and Wei, 2010; Chen et al., 2011) suggest that the option market is more informationally efficient than the equity market as a result of active informed trading.

Chapter 4. Empirical Procedures

In this chapter, we present the details of the empirical framework and the methodology used in this study. We start by discussing the empirical framework for the implied funding liquidity measure.

We construct a market-wide liquidity measure based on the absolute difference between the implied volatilities of the call and put options of the same underlying security with the same strike price and maturity date. In the first section of this chapter, we describe in details the construction of the implied funding liquidity measure based on Put-Call parity. Also, we show an equity portfolio strategy with implied funding liquidity, and a portfolio strategy in the currency market.

In order to investigate whether our implied funding liquidity risk is a price state variable, we concentrate on equity, foreign exchange and hedge fund markets. In section 4.2, we review the asset-pricing test methodology obtained in this study: the time-series predictability of asset returns and the cross-sectional regression analysis.

4.1 Implied Funding Liquidity

In this section, we present the empirical framework adopted in this study. More specifically, we explain Put-Call parity in the option markets and the procedure used to construct implied funding liquidity. We then describe the portfolio strategy used to evaluate the economic value of implied funding liquidity in a cross-section of US stocks. Finally, we describe the construction of the carry trade portfolio using currency and interest rates data.

4.1.1 Put-Call Parity and Implied Funding Liquidity

Put-Call parity is a no-arbitrage condition that relates the European call and put option prices of the same underlying security with the same strike price and maturity date. Let C and P denote the prices of a European call and a European put option with T time maturity and strike price of K. Both these options are written on the same non-dividend paying stock with the spot price of S. Using these securities, we considered two alternative investment portfolios as follows:

- Portfolio A: one European call option plus a zero-coupon bond that generates a payoff of K at time T.

- Portfolio B: one European put option plus one share of the stock.

Hull (2015) shows that these portfolios provide identical values at the expiry date T, so they must have the same value today. Therefore, the following condition must hold:

$$C + Ke^{-rT} = P + S \tag{4.1}$$

where r is the risk-free rate. Note that this relationship does not require any particular assumption on the return distribution of the underlying asset. However, this parity condition assumes the absence of short-sale constraints, margin requirements, and requires full synchronicity between option prices and the price of the underlying security[1].

Put-Call parity holds for European-style options of the same strike price and maturity date. Regarding American-style options which can be exercised early, Hull (2015) shows that the following inequalities apply:

$$S - K \leq C - P \leq S - Ke^{-rT} \tag{4.2}$$

Implied volatility is obtained using the model developed by Black and Scholes (1973) and Merton (1973a) to generate the market price of the option. According to Hull (2015), if Put-Call parity holds, the same values should apply for implied volatilities obtained from the call and put options. In the literature, a number of studies (for example, Amin et al., 2004; Cremers and Weinbaum, 2010) use these implied volatilities to assess Put-Call parity conditions. In particular, Cremers and Weinbaum (2010) show that the differences in implied volatilities of call and put options capture the price pressures in the option markets and significantly predict future changes in the underlying stock prices.

According to Hu et al. (2013) and Pasquariello (2014), in normal market con-

[1] For example, Ofek et al. (2004) demonstrate that short-sale constraints on the underlying stocks may lead to deviations from the Put-Call parity. Battalio and Schultz (2006) argue that short-sale constraints do not have large influence and violations of the parity conditions become less significant when considering intra-day option data. Furthermore, Battalio and Schultz (2006) indicate that Put-Call parity deviations might be affected by the non-synchronicity between option and stock markets. Grundy et al. (2012) argue that apparent violations of the Put-Call parity bound becomes significantly more frequent for banned stocks during the short sales ban period.

ditions traders take advantage of the availability of capital to exploit price deviations from the fundamental relationships. Thus, the presence of arbitrage forces limits further mispricing and helps reinforce the law of one price. However, shocks to capital matter when arbitrageurs face investor redemptions (Shleifer and Vishny, 1997), or, particularly, when margin requirements are tightened and lead to a liquidity spiral (Brunnermeier and Pedersen, 2009). As Mitchell et al. (2007) indicate, the shortage of arbitrage funding leads to the forced liquidation of investments and causes prices to deviate from the fundamental values.

This study examines the degree of funding constraints based on systematic deviations from Put-Call parity in the option markets. Cremers and Weinbaum (2010) provide evidence that differences in implied volatilities of call and put options contain information about future equity returns. We propose a market-wide liquidity measure based on the absolute difference between implied volatilities of the call and put options of the same underlying security with the same strike price and maturity date. Specifically, the implied funding liquidity measure, IFL_t, is obtained as follows:

$$IFL_t = \frac{\sum_{i=1}^{N} VW_{i,t} \times |IV_{i,t}^{C} - IV_{i,t}^{P}|}{\sum_{i=1}^{N} VW_{i,t}} \tag{4.3}$$

where $IV_{i,t}^{C}$ and $IV_{i,t}^{P}$ are the implied volatilities obtained from the call and put options of the same stock i with the same strike price and maturity date, respectively; $VW_{i,t}$ is the market capitalisation of stock i at time t; N is the quantity of stock at that time.

By construction, the implied funding liquidity (IFL) measure is strictly positive, and the IFL is strictly positive, which consistent with the majority of the aggregate illiquidity measures, such as Hu et al.'s (2013) Noise measure and Pasquariello's (2014) financial market dislocation index. According to Chen et al. (2017), there is both a statistical and economical motivation to apply a logarithmic transformation for these aggregate measures. More specifically, the aggregate illiquidity measures generally have positive skewness and kurtosis, and the natural logarithm transformation could dampen the non-stationary issue. In addition, Chen et al. (2017) show that the logarithm illiquidity measure can be decomposed into two components: aggregate volatility and a residual. Therefore, following Pasquariello (2014) and Chen et al. (2017), we use the natural logarithm transformation to capture the non-linear effects of funding constraints on stock returns. The IFL innovation excludes natural logarithic difference of the IFL:

$$\Delta IFL_t = -(\ln(IFL_t) - \ln(IFL_{t-1})) \times 100 \tag{4.4}$$

where ΔIFL_t denotes the innovation of the value-weighted absolute implied volatility spreads, IFL_t. A positive innovation associated with a decline in IFL reflects an increase in liquidity, while a negative innovation reflects a positive shock in IFL due to higher funding constraints.

Nonetheless, we construct five alternative implied funding liquidity measures for the purpose of a robustness test. The empirical results obtained from these alternative measures remain qualitatively unchanged. The results of these robustness checks are shown in the robustness Chapter 7

For instance, implied volatilities for deep in-the-money or out-of-the-money options deviate significantly from those obtained for at-the-money options. Following Pan (2002), we use only at-the-money option pairs, which are call and put options with the strike prices between 0.95 and 1.05 times the underlying spot prices, in order to construct adjusted implied funding liquidity.

Second, Battalio and Schultz (2006) show that the deviations of Put-Call parity may be influenced by non-synchronicity in the reporting of the closing stock prices in the option and in the underlying stock markets. Hence, we use the delta-gamma approximation (details about this method is discussed at section 7.3) to calculate the implied volatility for each option, and then the implied funding liquidity based on this underlying price.

Third, during the last global financial crisis, most regulators of stock exchanges around the world imposed restrictions or bands on short selling. We construct an alternative implied funding liquidity measure with samples extracting the underlying stocks with short-selling restrictions.

Fourth, we develop a dollar volume-weighted implied funding liquidity measure. Amihud (2002) illiquidity is widely used; this is the daily ratio of absolute stock return over its dollar volume. If there is a higher average daily volume, it is easier to execute a large amount of trading without significant influencing the market.

Fifth, we also develop an equally weighted average scheme to compute the implied funding liquidity measure.

4.1.2 Portfolio Strategy with Implied Funding Liquidity

In this study, we examine whether the innovations in implied funding liquidity can affect a large cross-section of stock returns. Following the empirical asset-pricing literature (Fama and French, 1992), we implement a portfolio strategy as follows: we sort stocks into ten portfolios based on exposure to the innovations in implied funding liquidity computed by using daily data over the past three years. We allocate one-tenth of the stocks with the lowest exposure to the first portfolio, $P1$; the next one-tenth of the stocks to the second portfolio, and so on, up to the top one-tenth to the portfolio, $P10$, with the largest exposure to innovations in implied funding liquidity. We keep the composition of the portfolios constant until the next year, when we form new portfolios based on exposure to implied funding liquidity innovations, as above. We then compute the returns for each portfolio. The difference between portfolios $P10$ and $P1$ indicate the returns obtained by investing in portfolio $P10$ and shorting portfolio $P1$. If the innovations in implied funding liquidity affect many stocks, we expect the difference between $P10$ and $P1$ to be positive and significant.

We recognise that transaction costs might significantly impact returns from the investment strategy (see Frazzini et al., 2015, for the importance of trading costs as a factor for investing in equity markets). We control for trading costs by directly incorporating the bid and ask prices of the constituent stocks when computing the returns for the long and short positions at the time of portfolio balancing. Assessing the economic value of the implied funding liquidity innovations, we expect the investments obtained from long $P10$ and short $P1$ portfolios to generate positive returns after adjusting for transaction costs.

We adjust for the costs of trading by incorporating the bid and ask prices when computing the returns for the long and short positions. In line with the previous literature (for instance, Krishnamurthy, 2002), we compute the profits (per unit of notional value) from each stock in the long position of the portfolio strategy as follows:

$$P_{b,t+k} - P_{a,t} \tag{4.5}$$

where $P_{b,t+k}$ denotes the stock bid price at time $t + k$, $P_{a,t}$ denotes the stock ask price at time t, and k is the investment holding period, which is one year. Similarly, the profit from each stock in the short position of the portfolio strategy is computed as follows:

$$P_{a,t+k} - P_{b,t} \tag{4.6}$$

If there is economic value to the pricing signals due to implied funding liquidity innovations, we expect that the returns from the long $P10$ and short $P1$ portfolios would generate positive and significant returns after adjusting for transaction costs.

4.1.3 Portfolio Strategy in the Currency Markets

In this study, we also examine whether implied funding liquidity matters for understanding the cross section of the exchange risk premiums by constructing the carry trade portfolios.

Following Fama (1984), Lustig et al. (2011), Menkhoff et al. (2012), and Hu et al. (2013), we use the following procedure to prepare the forward rates and spot rate data for the analysis: we use f to denote the log of the one month forward rate, and obtain s to denote the log of the spot rate.

The log excess return, re^m_{t+1}, for currency m at time t is equal to the payoff of longing in the currency in the forward market and shorting it in the spot market one month later, that is

$$re^m_{t+1} = f^m_t - s^m_{t+1} \tag{4.7}$$

Alternatively, we could identify the currency change in the spot market (Δs^m_{t+1}), and then calculate the log excess return of the difference between forward discounts ($f^m_t - s^m_t$) and the currency changes,

$$re^m_{t+1} = f^m_t - s^m_t - \Delta s^m_{t+1} \tag{4.8}$$

Based on the covered interest rate parity condition, in general, the forward discount, $f^m_t - s^m_t$, should be the same as the difference between the foreign and domestic risk-free rates (Akram et al., 2008):

$$f_t^m - s_t^m \approx i_t^{m\star} - i_t^m \tag{4.9}$$

where $i_t^{m\star}$ and i_t^m denote the foreign and domestic risk-free rates over the maturity period, respectively.

Therefore, the log currency excess return can also be calculated as follows:

$$re_{t+1}^m \approx i_t^{m\star} - i_t^m - \Delta s_{t+1}^m \tag{4.10}$$

Some studies (for example, Frazzini et al., 2015) have shown that the investment strategy may be significantly influenced by transaction costs. Therefore, we adjust for trading costs by considering the bid and ask prices during the calculations of long and short positions.

In a manner similar to Lustig et al. (2011) and Menkhoff et al. (2012), we compute the net log currency return for a currency with a long position:

$$re_{t+1}^{m,l} = f_t^{m,b} - s_{t+1}^{m,a} \tag{4.11}$$

where $f_t^{m,b}$ denotes the bid forward rate for currency m at time t, and $s_{t+1}^{m,a}$ denotes the ask spot rate. In other words, this is equal to a strategy: the investor longs the foreign currency with the bid forward rate, $f^{m,b}$, at time t, and then shorts the currency at the ask spot rate, $s^{m,a}$, at time $t+1$.

Similarly, if an investor sells the currency and buys it back later, the net log currency excess return could be computed as follows:

$$re_{t+1}^{m,s} = s_{t+1}^{m,b} - f_t^{m,a} \tag{4.12}$$

Following Lustig et al. (2011) and Menkhoff et al. (2012), at the end of each month t, we rank all the currencies into six portfolios from low to high based on the forward discounts. Portfolio 1 contains currencies with the lowest interest rates, and portfolio 6 contains currencies with the highest interest rates. At the end of every month, we rebalance the portfolios. With regards to the developed countries sample, at the end of each month t, we rank all the developed currencies into five portfolios from low to high interest rates. Portfolio 1 contains the lowest interest rate currencies, and portfolio 5 contains the highest interest rate currencies with.

We compute the log currency excess return for each portfolio by taking the equally weighted mean of the log currency excess returns in that portfolio. Furthermore, we assume new positions will be estimated for every currency in the first month of our sample, and, in the last month, all the positions must be sold out.

In order to adjust the bid and ask prices, we assume that all of the first portfolio will be sold, whilst all the other portfolios will be bought. More specifically, for the sample of all countries, we adjust for transaction costs in short position for portfolio 1, and we use the long position to adjust the transaction costs for portfolios 2 to 6. For the sample of developed countries, we adjust for the transaction costs in short position to portfolio 1, and use the long position to adjust the transaction costs for portfolio 2 to 5.

The difference between the first and last portfolio returns, $HMLFX$, is generally called the return of carry trades, which is longing a high interest rate currency portfolio and shorting a low interest rate currency portfolio.

4.2 Asset Pricing Tests

Liquidity plays a fundamental role in the financial market. However, it involves different dimensions that might not be easily captured in a single measure. When considering a pricing factor that represents changes in the investment opportunity set, Campbell (1996) suggests that the variable must pass both time-series and cross-section tests. First, the factor must have the ability to forecast future market returns. Second, their innovations must affect a large cross-section of asset returns where risk is measured by their covariance with asset returns. Both of these tests are equally important. Thus, even if a certain variable may explain many asset returns, but fails to predict future returns, it will have zero risk price and can be excluded. This chapter summarises the methodology we use in this study.

In the remainder of this section, we present the details for the return predictability method of the implied funding liquidity measure. Then, we present the Fama and MacBeth (1973) regression techniques.

4.2.1 Time Series Predictability of Asset Returns

According to Campbell (1996), a variable important for asset prices needs to pass both time-series market return predictability and cross-section asset return tests.

A growing body of literature (Kaul and Kayacetin, 2009; Beber et al., 2011; Bouwman et al., 2011; Næs et al., 2011; Chen et al., 2016, 2017; Ellington et al., 2017) shows that liquidity measures contain predictive information on equity market returns and economic growths. In this study, we follow previous studies, such as Næs et al. (2011) and Chen et al. (2017), using linear method to estimate the time series predictability of asset returns.[2]

To assess the return predictability power of the implied funding liquidity measure, we use the monthly returns of the S&P500 index and the value-weighted average returns provided by CRSP as proxies for market returns. Campbell and Shiller (1988) and Siegel (1992) argue that other factors may predict future market returns, for example, the dividend yield of the S&P500 index, the real gross national product (GNP) growth rate, and the long-term government bond return. Therefore, we also control for these variables that are found to predict market returns.

In particular, the predictive regression model can be written as follows:

$$\begin{aligned}\sum_{t}^{t+h} r_t = \quad & \alpha + \beta_{IFL} \times IFL_{t-1} + \beta_r \times r_{t-1} + \beta_{DIV} \times DIV_{t-1} \\ & + \beta_{GNP} \times GNP_{t-1} + \beta_{LTG} \times LTG_{t-1} + \varepsilon_t\end{aligned} \tag{4.13}$$

where $\sum_{t}^{t+h} r_t$ is the sum of the market returns with an horizon h at month t; IFL_{t-1} is the funding liquidity measure for month t-1; DIV_{t-1} is the dividend yield of the S&P500 index for month t-1; GNP_{t-1} is the real GNP growth rate for month t-1; LTG_{t-1} is the long-term government bond return for month t-1, and r_{t-1} is the market excess return observed at t-1.

[2]Since it was first introduced by Sims (1980), vector autoregression (VAR) has been widely used in macroeconomic research. This analysis attempts to show that there is a relationship between implied funding liquidity and macroeconomic variables, for instance, Apergis et al. (2015) and Chen et al. (2017) just used in-sample forecasting in the context of my topics. It is not however designed to engage in a real-time forecasting exercise where richer tests such as Mariano-Diebold, Clark-MacCraken (2001) can be applied. Therefore, we do the empirical modelling based on linear regressions, but it can be extended for future research.

4.2.2 Cross-Sectional Regression Analysis

In section 4.1.2, we described the portfolio analysis for examining the relationship between the implied funding liquidity measure and stock returns. The portfolio method is a non-parametric analysis, which means no assumption is made regarding the variables; however,the disadvantage for the portfolio methodology is also straightforward that it is difficult to control for more variables in the course of the investigation into the relationship. Fama MacBeth's (1973) regression method is another statistical methodology which is widely used to estimate the relationship between variables in empirical asset pricing[3].

In a manner similar to the literature on empirical asset pricing (Fama and French, 1992, 1993), we employ Fama and MacBeth's (1973) two-stage approach as follows: we first obtain the exposure (beta) of each portfolio to the innovations in implied funding liquidity or other factors by regressing the portfolio returns on the innovations in implied funding liquidity or market factors[4] and save the estimated results (the estimates and p-values). Then, at the end of each month, we regress portfolio returns on their estimated betas in the first step for each risk factor. The time series of the regression estimates are used for the tests of statistical significance. We use the Newey and West (1987) approach to correct for heteroscedasticity and auto-correlation in these estimates.

In the first pass, we run each portfolio's returns against the time series of one or more risk factors, such as IFL innovation, the CAPM factor, Fama and French's (1992) three factors, and Carhart's (1997) momentum four factors, in order to ascertain the exposure to each factor. Thereafter, we run the cross-sectional portfolio returns to the factor exposures so that we can obtain a risk premium coefficients time series for each factor. Then, we find the mean of these coefficients, which is the premium expected for a unit's exposure to each risk factor over time.

More specifically, in the first pass, for m portfolio returns with f risk factors,

[3]The drawback for the Fama MacBeth (1973) regression analysis is that we need to make assumptions about the relationship between the relationship, and generally the assumption is that this relationship between the each dependent variable and the independent variable is linear (Bali et al., 2016).

[4]Following to Fama and French (1993) and Pasquariello (2014), in terms of the currency portfolios, instead of conducting a single time-series regression for each portfolio, and then a cross-sectional one, the estimation is run on the basis of a rolling window of size 36 (36 monthly observations are used for regressions). We use three years of observations to estimate the implied funding liquidity betas which are used as the explanatory variable in cross-sectional regressions each month for the following three years. This estimation is rolled forward and the procedure continues until approaching the end of the sample.

we run the m regressions with f factors for each one, obtaining the factor exposure βs:

$$\begin{aligned}
r_{1,t} &= \alpha_1 + \beta_{1,FT_1} FT_{1,t} + \beta_{1,FT_2} FT_{2,t} + \cdots + \beta_{1,FT_f} FT_{f,t} + \xi_{1,t} \\
r_{2,t} &= \alpha_2 + \beta_{2,FT_1} FT_{1,t} + \beta_{2,FT_2} FT_{2,t} + \cdots + \beta_{2,FT_f} FT_{f,t} + \xi_{2,t} \\
&\vdots \\
r_{m,t} &= \alpha_m + \beta_{m,FT_1} FT_{1,t} + \beta_{m,FT_2} FT_{2,t} + \cdots + \beta_{m,FT_f} FT_{f,t} + \xi_{m,t}
\end{aligned} \tag{4.14}$$

where $r_{i,t}$ is the portfolio return i at time t, $FT_{f,t}$ is the risk factor f at time t, and $\beta_{i,FT_f} FT_{f,t}$ is the factor exposure for portfolio i at time t. t spans from 1 to T, which is the sample period.

Thereafter, to test the exposure of the m portfolio returns to the f risk factors, we run cross-sectional regressions of the m portfolio returns on the f estimated $beta$s obtained from the last pass.

$$\begin{aligned}
r_{i,1} &= \lambda_{1,0} + \lambda_{1,1} \beta_{i,FT_1} + \lambda_{1,2} \beta_{i,FT_2} + \cdots + \lambda_{1,f} \beta_{i,FT_f} + \psi_{i,1} \\
r_{i,2} &= \lambda_{2,0} + \lambda_{2,1} \beta_{1,FT_1} + \lambda_{2,2} \beta_{i,FT_2} + \cdots + \lambda_{2,f} \beta_{i,FT_f} + \psi_{i,2} \\
&\vdots \\
r_{m,t} &= \lambda_{T,0} + \lambda_{f,1} \beta_{i,FT_1} + \lambda_{f,2} \beta_{i,FT_2} + \cdots + \lambda_{m,f} \beta_{i,FT_f} + \psi_{i,T}
\end{aligned} \tag{4.15}$$

where λs are the regression coefficients.

Now, we have obtained $f + 1$ series λ for each risk factor with a length of T. The means and standard deviations of estimates are obtained to estimate the parameters and sampling variation.

Since we have an estimate of the λ for each time series, we are able to compute a *t*-ratio as the average over T divided by its standard error. In other words, the empirical estimate for λ is the average value of each λ over T, which can be computed as follows:

$$\hat{\lambda} = \frac{1}{T} \sum_{t=1}^{T} \hat{\lambda}_t \tag{4.16}$$

where T is the number of cross-sectional regressions run in the second pass, and the standard errors of the estimate is:

$$\hat{\sigma}_{\lambda} = \sqrt{\frac{1}{T} \sum_{t=1}^{T} \sigma_{\lambda,t}^{2}} \tag{4.17}$$

Then, *t*-statistics is:

$$t_{\hat{\lambda}} = \frac{\hat{\lambda}}{\hat{\sigma}_{\lambda}} \tag{4.18}$$

In order to correct the heterosedasticity problem, Newey and West (1987) standard errors are used.

4.3 Summary

In this chapter, we have presented the empirical framework and methodologies that obtain in this study. First, we discussed the empirical framework of implied funding liquidity. This study examines the degree of funding constraints based on systematic deviations from Put-Call parity in the option markets. We proposed a market-wide liquidity measure based on the absolute difference between implied volatilities from the call and the put options of the same underlying security with the same strike price and maturity date. We also briefly discussed the portfolio strategy, with implied funding liquidity used to examine whether the innovations therein can affect a large cross-section of stock returns. In addition, we showed the construction of the carry trade portolios in the currency market.

Then, we summarised the methodology that obtains in this study. When considering a pricing factor that represents changes in the investment opportunity set, Campbell (1996) suggests that the variable must pass both time-series and cross-section tests. We began by presenting the details for the time-series predictability of asset returns. Thereafter, we presented the Fama and MacBeth (1973) two-stage regression techniques.

Chapter 5. Data and Descriptive Statistics

For this study, we obtained the historical stock and options data for the US equity option markets, spot and one month forward exchange rates versus the US dollars, hedge fund indices, and certain macro variables. In this chapter, we discuss the data sources and the descriptive statistics of these data.

5.1 Stock and Option Markets

In this study, we employ the historical price and implied volatility data for the US equity option markets obtained from OptionMetrics. This dataset includes call and put option prices, the strike prices, open interest, volume, and the remaining time to expiration of the option (expressed in years). For each option contract, the data also contain implied volatility obtained from a binomial model that captures dividend payment and the probability of the early exercise of American-style options. In addition to the option strike and mid-prices, the computation for implied volatility included inputs such as the LIBOR/eurodollar interest rates as well as the closing prices of the underlying asset. We obtained daily data for the sample period 04 January 1996 to 31 August 2015.

Following Cremers and Weinbaum (2010), we use the procedure described in what follows to prepare the option data for analysis. We removed options with zero price or volume. Options were also removed if the call price was more than the value of the underlying equity or if the value of a put was more than the value of the strike price. We matched each pair of call and put options of the identical underlying stock with the exact strike price and maturity. For each stock, we compute the daily equal average of the absolute difference between the implied volatilities of each pair of call and put options. Implied funding liquidity was obtained from these absolute deviations across all the stocks after taking account of the market capitalisation of each stock. Daily innovation in implied funding liquidity is defined as the negative natural logarithm difference of the liquidity measure and is used to assess the economic value of the liquidity measure. For the time-series and cross-section exercises, we used the end-of-the-month values to compute the monthly implied funding liquidity and its innovations.

We supplemented the option market data with the daily equity data from the CRSP for the same sample period. This dataset includes value-weighted market returns, the closing prices of the underlying stock, and the number of shares outstanding[1]. The CRSP data also provides details about the stock identification number, CUSIP, which allows the equity data to be merged with the option data. The daily stock data were used to assess the profitability of a strategy to exploit information from the implied funding liquidity. In addition to the stock and option data, following Petkova (2006), Pasquariello (2014) and Adrian et al. (2014), we obtained 25 size and book-to-market portfolios, and 30 industry portfolios from Kenneth French over the same sample period[2]. These portfolio returns were used for cross-sectional asset-pricing tests.

Table 5.1: Descriptive Statistics of Equity Options

Panel A: The number of stocks					
	Mean	Median	Std Dev	Minimum	Maximum
Firm No.	2840	2685	608	1682	4065
Panel B: Matched pairs of call and put options					
	Mean	Median	Std Dev	Minimum	Maximum
IV Pairs	63819	46037	36632	15211	207252
Panel C: The absolute difference in implied volatility					
Call Δ Quantiles	Mean	Median	Std Dev	Minimum	Maximum
[0th, 30th]	0.058	0.029	0.089	0.000	18.338
(30th, 40th]	0.050	0.023	0.087	0.000	11.945
(40th, 50th]	0.045	0.021	0.080	0.000	12.792
(50th, 60th]	0.042	0.020	0.076	0.000	8.503
(60th, 70th]	0.042	0.019	0.075	0.000	14.676
(70th, 100th]	0.045	0.021	0.071	0.000	15.685

Panel A reports the number of stocks in the equity option data on a daily basis over the sample period 4 January 1996 to 31 August 2015. Panel B shows the daily number of pairs of call and put options of the same stocks with the same strike price and maturity date. Panel C reports the absolute difference in implied volatility for pairs of call and put options based on the call option Δ quantiles.

Table 5.1 (Panels A and B) reports the annual number of companies and pairs of call and put options with the same strike prices and maturity dates together with the computed absolute implied volatility spreads. In total, there were approximately 63,819 matched pairs of call and put options for 2,840 different stocks for the 4 January to 31 August 2015 sample period. We observed a gradual increase in the number of unique firms and pairs of call and put options during the sample

[1] Market capitalisation of a stock equals the number of shares outstanding multiplied by the mid-quote closing price.

[2] We thank Kenneth French for providing the data, which is available at: `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`

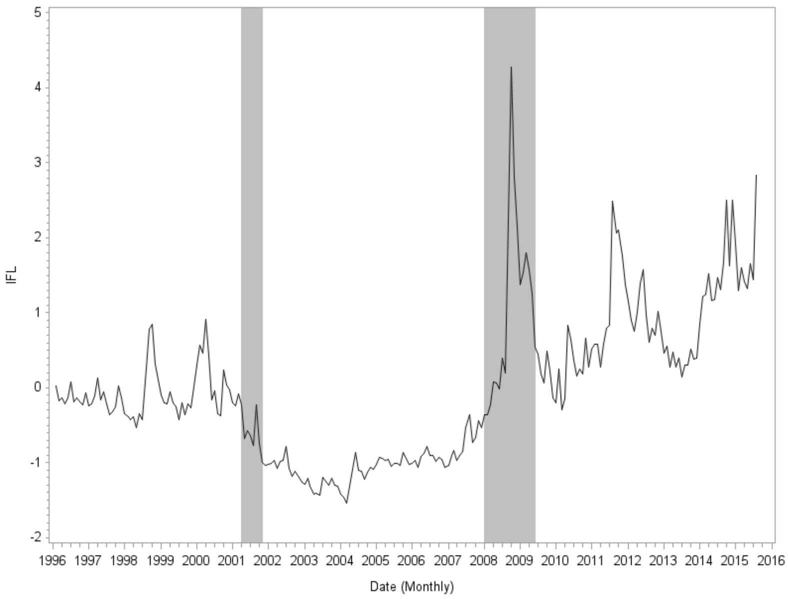
period. Panel C reports the absolute difference in implied volatilities based on the call option Δ. We observed smaller absolute differences for at-the-money options and greater deviations for deep in-the-money and out-of-the-money options.

Figure 5.1 shows the monthly level (Panel A) and innovations (Panel B) of the standardised implied funding liquidity measure from January 1996 to August 2015 with the National Bureau of Economic Research (NBER) recession periods in the light grey.[3] We observed sharp increases in the liquidity measure during episodes of financial stress, for example, the Asian crisis in 1997, the long-term capital management collapse in 1998, the dot-com bubble and collapse at the end of $1990s$, the sub-prime mortgage crisis in 2007, and the European debt crisis of 2009-2012. The largest jump in the liquidity measure occurred in October 2008. This coincided with the collapse of Lehman Brothers and the funding squeezes in inter-bank lending markets.

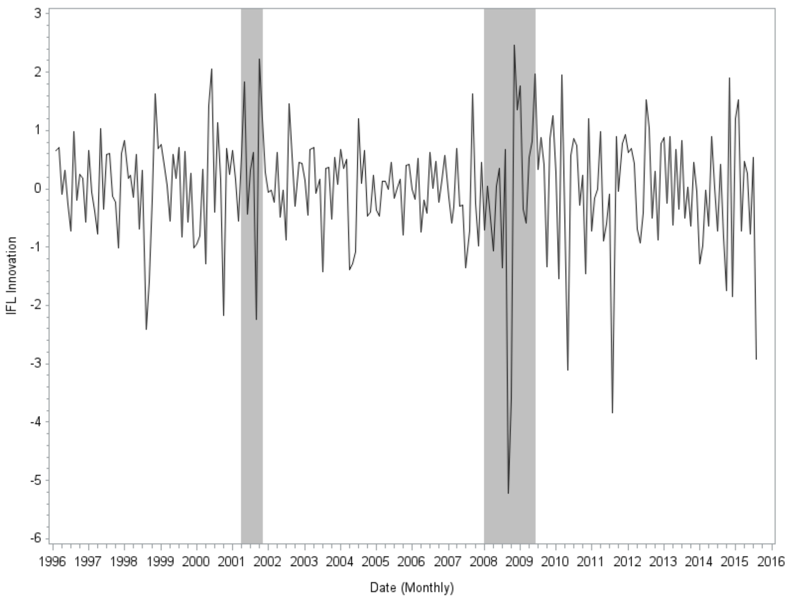
This figure suggests that large increases in the implied funding liquidity measure are associated with periods of macroeconomic and financial market distress. In such environments, funding constraints caused traders to close out positions early, leading to greater price deviations from fundamental relationships such as Put-Call parity in the option markets.

By construction, the implied funding liquidity (IFL) measure is strictly positive, and the IFL is strictly positive, which is consistent with the majority of aggregate illiquidity measures, such as Hu et al.'s (2013) Noise measure and Pasquariello's (2014) financial market dislocation index. Furthermore, we run the Augmented Dickey Fuller test for IFL with lag length of 1 on the basis of the SIC from a maximum lag length of 12, and the t-statistic implies that we could not reject the null hypothesis of a unit root. Then, we run the test for the first difference ΔIFL, and we reject the null hypothesis. This suggests that for the implied funding liquidity measure, we could not reject the null in level, but we could in differences. This is consistent to findings by Chen et al. (2017) who pointed out that aggregate illiquidity measures generally have positive skewness and kurtosis, and the natural logarithm transformation could dampen the non-stationary issue.

[3]The recession is a time series which is an interpretation of US Business Cycle Expansions and Contractions, and the data is available at the National Bureau of Economic Research (NBER) website: `http://www.nber.org/cycles/cyclesmain.html`



(a) Monthly Level



(b) Monthly Innovations

Figure 5.1: Implied Funding Liquidity

This figure presents the time series of the monthly level (Panel a) and innovations (Panel b) of the standardised implied funding liquidity measure over the 4 January 1996 to 31 August 2015 sample period. The light grey bars indicate the NBER recession periods. Implied funding liquidity is obtained from the absolute difference between the implied volatility of call and put option for the same stock with the same strike price and maturity date. The innovations are the negative natural logarithm difference of the implied funding liquidity measure.

Table 5.2: Descriptive Statistics of ΔIFL with Other Factors

	ΔIFL	MKT	SMB	HML	Mom	ΔPS	ΔTED	ΔFG	$\Delta Noise$
Mean	-0.244	0.564	0.257	0.185	0.456	0.002	-0.001	-0.003	-0.003
Median	0.562	1.29	0.14	0.04	0.63	0.004	-0.001	-0.013	-0.01
Minimum	-46.962	-17.23	-15.36	-13.11	-34.58	-0.271	-1.254	-1.019	-3.338
Maximum	21.837	11.35	19.18	13.91	18.38	0.287	1.351	1.178	5.01
Std Dev	8.943	4.571	3.338	3.334	5.417	0.067	0.204	0.312	0.741
Skewness	-1.169	-0.697	0.472	0.042	-1.498	-0.662	0.439	0.178	2.06
Kurtosis	4.27	1.01	5.453	2.996	9.556	3.215	17.199	1.487	20.579
AC(1)	-0.032	0.102	-0.065	0.116	0.077	-0.12	-0.008	0.087	0.467

The full sample period spans from 04 January 1996 to 31 August 2015. The table shows the descriptive statistics for equity market factors and the implied funding liquidity measures. ΔIFL is the innovation from the absolute deviation measure; MKT is the excess return on the market; SMB is the average return on the small stock portfolios minus the average return on the big stock portfolios; HML is the average return on the value portfolios minus the average return on the growth portfolios; Mom is the momentum factor; AC(1) is the first-order autocorrelation coefficients for each variable; the FG is measure constructed by Fontaine and Garcia (2012) and it measures the value of funding liquidity from the cross-section of Treasury securities, $Noise$ measure is the noise measure by Hu et al. (2013), PS liquidity measure is liquidity measure constructed by Pástor and Stambaugh (2003), and TED Spread is the spread between LIBOR and three-month Treasury bill rate. In order to compare to the funding liquidity, we find the first-difference of PS, TED, FG, and $Noise$, which are ΔPS, ΔTED, ΔFG, and $\Delta Noise$.

Table 5.2 presents the descriptive statistics of the equity market factors and the innovations in the implied funding liquidity measure, ΔIFL_t. The implied funding liquidity measure has high skewness and kurtosis, which is similar to the characteristics of other popular liquidity measures, such as PS. However, the serial correlation of implied funding liquidity is small, with an $AC(1)$ coefficient of -0.03. The TED spread and Noise also have high kurtosis; however, the Noise measure exhibits an $AC(1)$ coefficient of 0.467 while the serial auto-correlation coefficient for the TED spread is small.

Over the entire sample period, we observed a significant positive correlation between the innovations in implied funding liquidity and stock market returns. The correlation coefficient between the two variables is 0.226 and is significant at the 1% level. This finding indicates that funding squeezes are more likely to arise during market declines. The correlations between implied funding liquidity and other equity market factors including size, value, and momentum are insignificant.

The role of liquidity innovations in explaining the variations in asset returns has been widely discussed in a number of studies, such as Pástor and Stambaugh (2003), Brunnermeier et al. (2008), Hu et al. (2013), Fontaine et al. (2015), Amihud (2002), and Corwin and Schultz (2012). Moreover, in Table 6.1, we observe that the implied funding liquidity measure is contemporaneously associated with some existing liquidity measures, which suggests that our measure may contain additional information beyond existing liquidity measures.

In this study, we consider cross-sectional regressions including several existing liquidity measures, which are developed using data from stock market, or Treasury bonds[4]:

- Pástor and Stambaugh's (PS) measure (2003): Pástor and Stambaugh (2003) obtain the liquidity Γ from the regression:

  $$r_{t+1}^e = \theta + \phi r_t + \Gamma sign(r_t^e)(Volume_t) + \varepsilon_t$$

[4]The Pastor and Stambaugh's liquidity series are available from Lubos Pastor's website, which is `https://faculty.chicagobooth.edu/lubos.pastor/research/liq_data_1962_2016.txt`. We thank Jun Pan for providing the updated Noise measure, and it is available at `http://www.mit.edu/~junpan/`. The historical data for the FG measure is available from the Jean-Sebastien Fontaine's website, which is `http://jean-sebastienfontaine.com/wp-content/uploads/2009/11/FundingLiquiditFactor_19862017Q1.txt`. We are grateful to Professor Shane A. Corwin for providing SAS code for computing the CS measure, and it is available at `https://www3.nd.edu/~scorwin/HILOW_Estimator_Sample_002.sas`. The Sadka liquidity data are obtained from the Wharton Research Data Services (WRDS).

where r^e_{t+1} is the stock's excess return above the CRSP value-weighted market return on day $t+1$, θ is the intercept, ϕ and Γ are regression coefficients, and ε is the error term.

- Brunnermeier et al.'s (2008) Treasury-LIBOR (TED) spread: the TED spread is the difference between three-month eurodollar deposits yield, LIBOR, and the three-month US T-bills. The data of LIBOR and T-bills yields are available from the Economic Research Federal Reserve Bank of St. Louis.

- Hu et al.'s (2013) Noise measure (Noise): Hu et al. (2013) construct a market-wide liquidity proxy through the relationship between arbitrage capital availability and the observed noise in US Treasury bonds. A shortage of arbitrage capital will cause yields to violate the curve easily, leading to more noise in prices. This measure captures different liquidity crises across different markets, and is constructed by computing the root mean squared distance between the market yields and the model-implied yields:[5]

  $$Noise_t = \sqrt{\frac{1}{N_t}\sum_{i=1}^{N_t}[YID^i_t - YID^i(p_t)]^2}$$

  where p_t denotes the model parameter vector on day t, and N_t is the number of Treasury bonds with maturity spanning from one to ten years. For each of the N_t bonds, YID^i_t presents its yield observed in the market, and $YID^i(p_t)$ denotes the model's implied yield.

- Fontaine and Garcia's (2012) measure (FG): Fontaine and Garcia (2012) introduced the FG bond liquidity measure, Treasury security-based funding liquidity. The FG measure is based on cross-sectional US treasury securities (bills, notes, and bonds).

- Amihud's il-liquidity (2002) measure (Amihud): Amihud (2002) introduced the liquidity,

  $$Amihud = Average(\frac{|r_t|}{Volume_t})$$

  where r_t is the stock return on day t and $Volume_t$ is the currency value of volume on day t in units of the local currency.

- Corwin and Schultz's (2012) measure (CS): Corwin and Schultz (2012) used daily high and low prices to estimate bid-ask spreads. Intuitively, daily

[5] This measure is the dispersion in yields around the fitted curve.

high prices are correlated with buyer-initiated orders, while low prices are associated with seller-initiated orders. In particular, Corwin and Schultz (2012) compute the bid-ask spread estimator with daily high and low prices as follows:

$$CS = \frac{2(e^{\phi} - 1)}{1 + e^{\phi}}$$

where ϕ is calculated as $\phi = \frac{\sqrt{2\alpha} - \sqrt{\alpha}}{3 - 2\sqrt{2}} - \sqrt{\frac{\beta}{3 - 2\sqrt{2}}}$

where α and β are computed as $\alpha = \Sigma_{j=0}^{1}[ln(\frac{HIGH_{n+j}^{0}}{LOW_{n+j}^{0}})]^2$ and $\beta = [ln(\frac{HIGH_{n+1}^{0}}{LOW_{n+1}^{0}})]^2$,respectively, where $HIGH_{n+j}^{0}$ and LOW_{n+j}^{0} are the high and low prices from day n to day n+1. Overnight price changes are adjusted, and if the spread estimate is negative, zero is assigned.

- The relative spread (RS): this is the difference between ask and bid prices over the mid-price, $\frac{ASK_t - BID_t}{(ASK_t + BID_t)/2}$, where ASK_t is the offer price, and BID_t is the bid price on day t.

- Sadka's (2006) measure (Sadka): The Sadka liquidity proxy is the price impact induced by trades, and consists of two separate components, fixed and variable price effects. The measure is a non-traded, market-wide, and undiversifiable.

These existing liquidity measures, especially the Amihud's *il*-liquidty measure, have been widely used in previous studies, such as Pástor and Stambaugh (2003), Acharya and Pedersen (2005), Easley et al. (2002), Goyenko et al. (2009), Sadka (2006), Næs et al. (2011), Chen et al. (2017), and others.

Table 5.3 reports the correlation coefficients between implied funding liquidity and other liquidity measures. Over the entire sample, we observe the innovations in implied funding liquidity are negatively correlated with Noise, Amihud, RS, and CS. In addition, there are positive relationships between the innovations in implied funding liquidity and PS as well as Sadka.

In short, Table 5.3 indicates that the implied funding liquidity measure is associated with some existing liquidity measures, such as Noise, Amihud, RS, CS, PS, and Sadka, suggesting that our implied funding liquidity measure may contain additional information beyond existing liquidity measures.

Table 5.3: Correlations of Implied Funding Liquidity with Other Liquidity Measures

	ΔPS	ΔTED	ΔFG	ΔNOISE	ΔAmihud	ΔRS	ΔCS	ΔSadka
ΔIFL	0.1244**	-0.1925***	-0.0947	-0.1507**	-0.2183***	-0.5487***	-0.5110***	0.0860
ΔPS		-0.0091	-0.0303	0.0447	-0.1533**	-0.1410**	-0.1565**	0.0128
ΔTED			0.1608**	0.3995***	0.1892***	0.2937***	0.2230***	-0.0255
ΔFG				0.0417	0.0231	0.0895	0.0378	-0.1038
ΔNOISE					0.1553**	0.1509**	0.1438**	-0.0545
ΔAmihud						0.1523**	0.4261***	-0.2568***
ΔRS							0.7244***	-0.0831
ΔCS								-0.2266***

This table reports correlation coefficients between implied funding liquidity and eight existing liquidity measures: Pástor and Stambaugh's (2003) measure (PS), Brunnermeier et al.'s (2008) Treasury-LIBOR (TED) spread, Hu et al.'s (2013) Noise measure (Noise), Fontaine and Garcia's (2012) measure (FG), Amihud's (2002) il-liquidity measure (Amihud), Corwin and Schultz's (2012) measure (CS), the relative spread (RS), and Sadka's (2006) measure (Sadka). ΔIFL is the implied funding liquidity innovation. The full sample period spans January 1996 to August 2015. $*$, $**$, $***$ denote significant at the 10%, 5% and 1% levels, respectively.

5.2 Currency Markets

This section presents the currency and interest data used in the empirical analysis of the currency markets. We obtained the monthly spot exchange rates and one month forward exchange rates versus the US dollars from Datastream, and the data sample spans January 1996 to August 2015.[6]

For each currency, we use the last spot and forward exchange rates each month. For both the spot and forward rates, we obtain the mid bid-ask quotes in units of foreign currency per US dollar. The full sample includes 48 countries, denoted as 'Developed Countries'. Since the launch of the euro in January 1999, there are 49 currencies in total (we refer them as 'all countries' sample in this paper). Following Lustig et al. (2011) and Menkhoff et al. (2012), we also study a smaller sub-sample with 15 developed countries, denoted 'developed countries'[7] for comparison and robustness. Due to the introduction of the euro, the developed country sample has been reduced to 10 currencies. Table A.2 reports the entity and currency lists for both the all countries and developed countries samples.

Table 5.4 (Panel A) reports the descriptive statistics, including mean, *t* value, median, minimum, maximum, standard deviations, skewness and kurtosis, for the carry trade portfolios, and $P6 - P1$ of the all countries sample from January 1996 to August 2015. We observe that the carry trade portfolios generate a large cross-sectional spread in returns. In particular, carry trade portfolios' returns increase consistently from the portfolio $P1$ to the portfolio $P6$, which is consistent with Brunnermeier et al. (2008) and Menkhoff et al. (2012). The carry trade portfolio $P6$-$P1$ is obtained from investing those with the highest interest rates and shorting those with the lowest interest rates. This strategy generates an average excess return of approximately 0.64% per month or approximately 7.68% per annum. This long-short strategy return is significant at the 1% level.

The descriptive statistics for the carry trade portfolios, and $P5$-$P1$ of the developed countries, are reported in Table 5.4 (Panel B), and there is a less monotonic trend from portfolio $P1$ to the portfolio $P5$. The carry trade portfolio $P5$-$P1$ strategy generates an average excess return about 0.44% per month or about 5.28% per annum. This long-short strategy return is significant at the 10% level.

[6] This dataset has been extensively obtained in the prior literature, for example, in Lustig et al. (2011), Menkhoff et al. (2012), and the references therein.

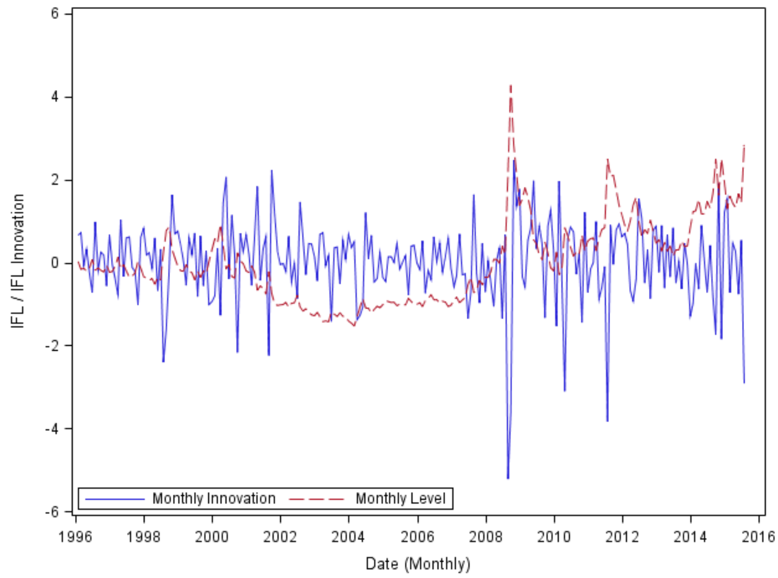
[7] According to the International Monetary Fund list of "advanced economies", which is available at: `http://www.imf.org/external/pubs/ft/weo/2016/01/pdf/text.pdf`

Table 5.4: Descriptive Statistics of Currency Portfolios

Panel A: All Countries							
Portfolio	P1	P2	P3	P4	P5	P6	P6-P1
Mean	-0.15	-0.03	0.11	0.24	0.30	0.49	0.64
t Value	-1.29	-0.32	0.97	2.12	2.40	3.38	4.89
Median	-0.19	0.04	0.07	0.14	0.37	0.57	0.84
Minimum	-7.48	-7.49	-6.09	-10.23	-9.63	-12.26	-10.38
Maximum	8.58	8.28	7.87	9.39	7.45	9.15	8.84
Std Dev	2.27	2.06	2.14	2.24	2.46	2.82	2.54
Skewness	0.28	0.08	0.08	-0.11	-0.43	-0.30	-0.58
Kurtosis	1.41	1.56	1.12	2.30	1.91	1.61	1.42

Panel B: Advanced Countries						
Portfolio	P1	P2	P3	P4	P5	P5-P1
Mean	-0.04	0.06	0.24	0.20	0.40	0.44
t Value	-0.28	0.38	1.66	1.37	2.51	3.05
Median	-0.15	0.08	0.30	0.31	0.43	0.70
Minimum	-8.61	-9.77	-10.54	-13.07	-12.10	-13.60
Maximum	10.17	8.28	7.89	8.58	10.89	10.14
Std Dev	2.86	2.82	2.79	2.85	3.10	2.81
Skewness	0.35	0.08	0.01	-0.37	-0.20	-0.80
Kurtosis	0.77	0.65	0.44	1.82	1.48	2.34

The full sample period spans January 1996 to August 2015. This table reports the descriptive statistics for currency portfolio returns sorted on the basis of monthly forward discounts. Portfolio $P1$ contains currencies with the lowest forward discount, and portfolio $P6$ (portfolio $P5$ for the developed countries sample) contains currencies with the highest forward discount. $P6$-$P1$ denotes the portfolio return of long in portfolio $P6$ (portfolio $P5$ for the advanced countries sample) and short in portfolio 1. All returns are excess returns in US dollars.



(a) Implied Funding Liquidity and Its Innovations

(b) Cumulative Carry Trade Returns

Figure 5.2: Carry Trade Portfolios' Returns

The upper panel of this figure presents the time series at the monthly level (the solid blue line) and innovations (the dotted red line) of the standardised implied funding liquidity measure. Implied funding liquidity is obtained from the absolute difference between the implied volatility of call and put options for the same stock with the same strike price and maturity date. The innovations are the negative natural logarithmic difference of the implied funding liquidity measure. The lower panel shows cumulative natural logarithm excess returns of the carry trade portfolio for all currencies (the solid blue line), and the developed countries (the dotted red line). The sample period is January 1996 to August 2015.

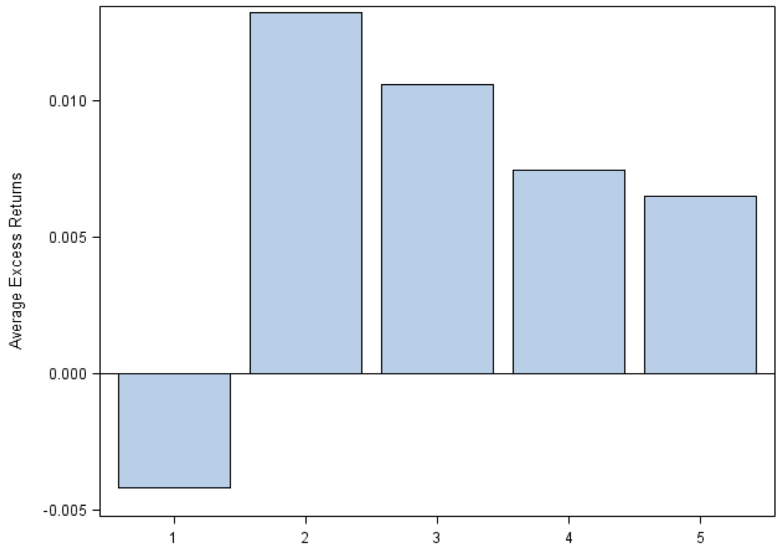
Figure 5.2 shows cumulative log returns for the carry trade portfolio HMLFX for all countries and the developed countries from January 1996 to August 2015[8]. We observe sharp decreases in the cumulative carry trade returns during episodes of financial stresses, for example, the Russian default and the 1998 long-term capital management collapses at the autumn of 1998, the great quant meltdown of 2007, the 2007-2009 recession, the European debt crisis of 2009, the 2012 Greek sovereign debt default, and the Chinese stock market crash in July 2015.

Moreover, we observe that the carry trades of the developed countries were more profitable before 1999, and thereafter the carry trades of all countries performed better, which means the currencies of the developing countries improved their carry trade returns significantly after 1999. However, the recessions in the early 1990s and 2000s, for instance, the Asian crisis in 1997, the dot-com bubble at the end of 1990s, and the September 11 attacks, did not influence the carry trades returns significantly. Furthermore, the major peak carry trade returns (such as 1997, 1999, 2005, 2008, and 2011) seem to be unrelated to the business cycle. As suggested by Burnside (2011), the carry trades cannot be explained by the standard business-cycle risk factors.

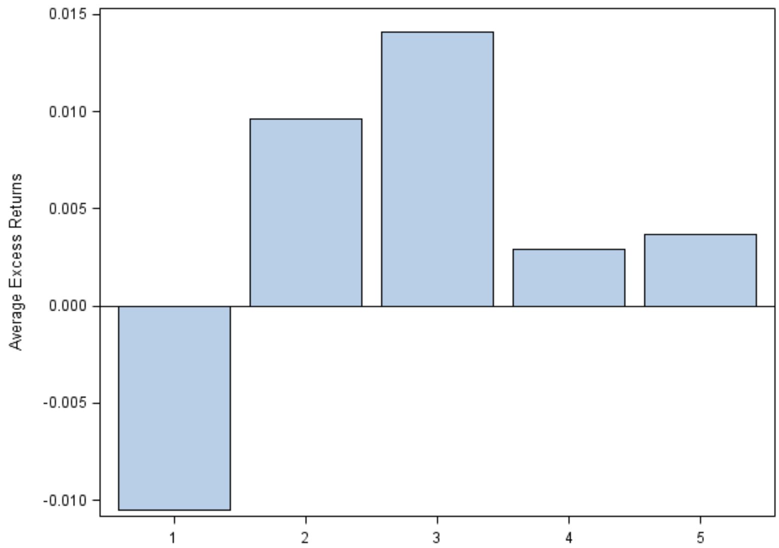
Before the asset-pricing analysis, we show a simple graphic analysis to visualize the relationship between implied funding liquidity and currency returns. Following Lustig et al. (2011), we rank the sample into five sub-samples based on the value of the implied funding liquidity innovation, ΔIFL . The first group consists of the first 20% of months with the lowest realisations of the implied funding liquidity innovation and the fifth group contains the 20% of months with the highest realizations. Thereafter, we compute the average excess returns for all these five groups for the carry trade portfolio, $HMLFX$.

Figure 5.3 presents the average excess returns for carry trade portfolios conditional on the implied funding liquidity innovations, ΔIFL. There are five categories from 1 to 5 shown on the x-axis of each panel. We see that the average returns for the carry trade portfolio, $HMLFX$, increase from portfolio 1, with the lowest realisations of the implied funding liquidity innovation, to the fifth group with the highest realisations. This analysis is straightforward, but it can show the relation between the implied funding liquidity innovation and the carry trade port-

[8] Lustig et al. (2011) notes the long short strategy portfolio as $HMLFX$, which is obtained from investing the ones with the highest interest rates and shorting those with the lowest interest rates. In this thesis, it denotes $P6$-$P1$ and $P5$-$P1$ for all countries and advanced countries, respectively.



(a) All Countries



(b) Advanced Countries

Figure 5.3: Excess Returns and Implied Funding Liquidity Innovations

This figure presents the average excess returns for carry trade portfolios conditional on the implied funding liquidity innovations, ΔIFL. The first group consists of the first 20% of months with the lowest realisations of the implied funding liquidity innovation and the fifth group contains the 20% of months with the highest realisations. Thereafter, we compute the average excess returns for all these five groups for the carry trade portfolio, $HMLFX$. The returns for all countries are shown in the upper panel, while the results for the developed countries are shown in the lower panel. The sample period is January 1996 to August 2015.

folios' returns. When the implied funding liquidity innovation is really poor, the carry trade portfolio performs poorly. Therefore, high interest rate currencies outperform low interest rate currencies when the market has a high implied funding liquidity innovation.

5.3 Descriptive Statistics of Hedge Fund Data

In this study, due to the fact of limited access to the Lipper Hedge Fund Database (TASS), for this study, we obtained monthly hedge fund indices from the Hedge Fund Research, Inc. (HFRI) to investigate whether implied funding liquidity influences aggregate hedge fund performance. The HFRI indices only include the hedge funds with a track record of more than 24 month or assets not less than US 50 million. Even though the characteristics of individual hedge funds are not available when we use the hedge fund indices, we could obtain the average performance information of an individual hedge fund in each index.

There are 64 indices in our sample, spanning from January 1996 to August 2015, and the details of the HFRI index characteristics are shown in Table A.5.[9] What is more, each hedge fund index in the sample characterises itself as one of the following primary strategy: equity hedge, event driven, macro, relative value, fund of funds, and emerging market.[10]

Prior literature show various factors are important in the analysis of hedge fund risk exposures (Fung and Hsieh, 1997, 2001, 2004, 2011), for example, the Carhart's (1997) four factors and the Fung and Hsieh's (2001, 2004) seven factors. Carhart's (1997) four factors are the market excess returns (MKT), high minus low book-to-market (HML), small minus big market capitalisation (SMB), and momentum (MOM). Fung and Hsieh's (2001, 2004) seven factors are, bond trend-following factor (PTFSBD), currency trend-following factor (PTFSFX), commodity trend-following factor (PTFSCOM), equity market factor (EMF), size spread factor (SSF), bond market factor (BMF), and credit spread factor (CSF). The details of the constriction methods for these factors are shown in Table A.3.

We obtained the Fung and Hsieh's (2001, 2004) seven factors from David Hsieh's data library[11], which also covers the sample period from January 1996

[9] A detailed definition of the indices and the description of the index constriction methodology is available at the webpage of the Hedge Fund Research, Inc. : `https://www.hedgefundresearch.com/hfri-index-characteristics`

[10] In addition, each index also belongs to a sub strategy, and a detailed list is presented in Table A.4.

[11] We thank David Hsieh for providing the data, which is available at: `https://faculty.`

to August 2015. The S&P500 and Russell 2000 index returns were obtained from Datastream. The 10-year treasury constant maturity yield and the Moody's Baa yield are available at the Board of Governors of the Federal Reserve System.

Table 5.5 reports the pairwise time-series Pearson correlation of the Carhart's (1997) four factors and the Fung and Hsieh's (2001, 2004) seven factors with the implied funding liquidity innovation, Δ IFL. The factors that are significantly correlated with Δ IFL are MKT, EMF, and CSF, whilst Δ IFL is not correlated with any of the other factors. The correlations are 0.2261, 0.2170, and -0.1783, respectively.

The positive correlations suggest that market returns are correlated with a rise in liquidity, and the negative correlations suggest that credit deterioration is correlated with a liquidity squeeze. Interestingly, the trend-following factors do not correlate significantly with the implied funding liquidity innovation.

`fuqua.duke.edu/~dah7/HFRFData.htm`

Table 5.5: Correlations of Δ IFL with Carhart and Fung-Hsieh Factors

	MKT	SMB	HML	Mom	PTFSBD	PTFSFX	PTFSCOM	EMF	SSF	BMF	CSF
SMB	0.2460										
	(0.0001)										
HML	-0.2179	-0.0077									
	(0.0008)	(0.9072)									
Mom	-0.1863	0.0413	-0.1171								
	(0.0042)	(0.5291)	(0.0733)								
PTFSBD	-0.1803	-0.0432	-0.1170	0.0254							
	(0.0056)	(0.5098)	(0.0734)	(0.6981)							
PTFSFX	-0.1657	-0.0252	0.0247	0.1397	0.3243						
	(0.0109)	(0.7007)	(0.7068)	(0.0323)	(<.0001)						
PTFSCOM	-0.1207	-0.1001	-0.0552	0.1841	0.2185	0.3353					
	(0.0647)	(0.1260)	(0.3993)	(0.0046)	(0.0007)	(<.0001)					
EMF	0.9833	0.1312	-0.1808	-0.2091	-0.1890	-0.1698	-0.1123				
	(<.0001)	(0.0445)	(0.0054)	(0.0013)	(0.0036)	(0.0091)	(0.0859)				
SSF	0.2546	0.9546	-0.0076	0.0560	-0.0539	-0.0058	-0.0818	0.1353			
	(<.0001)	(<.0001)	(0.9083)	(0.3927)	(0.4112)	(0.9292)	(0.2114)	(0.0382)			
BMF	0.1618	0.1356	-0.0434	-0.0656	-0.2003	-0.2049	-0.1452	0.1510	0.0863		
	(0.0130)	(0.0378)	(0.5076)	(0.3168)	(0.0020)	(0.0016)	(0.0261)	(0.0206)	(0.1872)		
CSF	-0.2436	-0.2106	-0.0540	0.1212	0.2103	0.2635	0.1686	-0.2240	-0.1583	-0.6222	
	(0.0002)	(0.0012)	(0.4097)	(0.0635)	(0.0012)	(<.0001)	(0.0096)	(0.0005)	(0.0152)	(<.0001)	
$\triangle$ IFL	0.2261	0.0975	-0.0267	-0.0698	0.0431	-0.0363	-0.0860	0.2170	0.0944	0.0357	-0.1783
	(0.0005)	(0.1363)	(0.6842)	(0.2868)	(0.5113)	(0.5798)	(0.1888)	(0.0008)	(0.1491)	(0.5866)	(0.0061)

This table reports the pairwise time-series Pearson correlation of the Carhart (1997)'s four factors and the Fung and Hsieh (2001, 2004)'s seven factors with the implied funding liquidity innovation, Δ IFL. The Carhart (1997)'s four factors are the market excess returns (MKT), the high minus low book-to-market (HML), the small minus big market capitalisation (SMB), and the momentum (MOM). The Fung and Hsieh (2001, 2004)'s seven factors seven factors are, Bond Trend-Following Factor (PTFSBD), Currency Trend-Following Factor (PTFSFX), Commodity Trend-Following Factor (PTFS-COM), Equity Market Factor (EMF), Size Spread Factor (SSF), Bond Market Factor (BMF), and Credit Spread Factor (CSF). The sample period spans from January 1996 to August 2015.

5.4 Descriptive Statistics of Macroeconomic Variables

A few recent studies (Kaul and Kayacetin, 2009; Beber et al., 2011; Bouwman et al., 2011; Næs et al., 2011; Chen et al., 2016, 2017) have investigated the relationship between aggregate liquidity and future economic growth.

In a manner similar to Næs et al. (2011), we use four proxies to measure macroeconomic conditions: the growth of the unemployment rate (ΔUR), the growth of the CPI (ΔCPI), the growth of the PMI[12] (ΔPMI), and the growth of the payroll (ΔPayroll)[13]. Other macroeconomic variables, such as GDP and IP, were also discussed in prior studies (Chen et al., 2016, 2017), but for comparison purpose with prior studies, we keep our measure selections with the key paper (Næs et al., 2011). All the historical data are on a monthly frequency and they are available from the Economic Research Federal Reserve Bank of St. Louis.

Panel A of Table 5.6 reports the basic descriptive statistics, mean, median, minimum, maximum, standard deviations, skewness, kurtosis, and the first order autocorrelation coefficients for the macroeconomic variables with the full sample period from January 1996 to August 2015. The macroeconomic variables are clearly not normally distributed with high skewness and kurtosis, and the serial correlation of the ΔUR is small with an AC(1) of -0.0064.

Panel B of Table 5.6 presents the correlation coefficient between implied funding liquidity innovations and the changes in the macroeconomic variables. Note that an increase in implied funding liquidity indicates an increase in *il*-liquidity. We observe a significantly negative correlation between implied funding liquidity and ΔCPI and ΔPayroll. The correlation coefficients between implied funding liquidity and ΔCPI and ΔPayroll are -0.3151 and -0.1312, respectively, and are significant at the 1% and 5% levels. The ΔUR and ΔPMI are weakly related to the implied funding liquidity measure.

[12]The Purchasing Managers' Index is an economic indicator for manufacturing and service departments, and it provides information about the contemporary economic conditions to firm managers, analysts and especially purchasing managers.

[13]Before we difference those macroeconomic series, we run the Augmented Dickey Fuller test to check the stationarity. We run the ADF test for UR, CPI, PMI, and Payroll with lag length of 1 on the basis of the SIC from a maximum lag length of 12, and the t-statistics suggest that we could not reject the null hypothesis of a unit root. Hence, we run the test in first differences, and in this case, we reject the null hypothesis. Those test results suggest that the macroeconomic series are nonstationary in levels but are stationary in differences.

Table 5.6: Implied Funding Liquidity and Macroeconomic Variables

Panel A: Descriptive Statistics of Macroeconomic Variables				
	ΔUR	ΔPMI	ΔCPI	ΔPayroll
Mean	-0.0002	-0.0004	0.0018	0.0008
Median	0.0000	0.0000	0.0019	0.0011
Minimum	-0.0822	-0.0938	-0.0179	-0.0062
Maximum	0.0870	0.1412	0.0137	0.0041
Std Dev	0.0299	0.0363	0.0029	0.0017
Skewness	0.4259	0.3642	-1.4319	-1.5164
Kurtosis	0.2435	1.6236	10.9702	3.3119
AC(1)	-0.0064	0.1093	0.4137	0.7947

Panel B: Pearson Correlation Coefficients Prob > |r| under H0: Rho=0				
	ΔUR	ΔPMI	ΔCPI	ΔPayroll
IFL	0.0393	0.1059	-0.3151	-0.1312
	(0.5491)	(0.1054)	(<.0001)	(0.0446)
ΔUR		-0.1013	-0.0786	-0.4259
		(0.1216)	(0.2300)	(<.0001)
ΔPMI			-0.0886	0.0823
			(0.1759)	(0.2089)
ΔCPI				0.1936
				(0.0029)

Panel A in this table reports the basic descriptive statistics for the macroeconomic variables. ΔUR is the unemployment growth rate, ΔPMI is the PMI growth rate, ΔCPI is the CPI growth rate, and ΔPayroll is the payroll growth rate. AC(1) represents the first order autocorrelation coefficients for each variable. Panel B presents the correlation coefficients of implied funding liquidity and the macroeconomic variables. $IFL_{i,t}$ is implied funding liquidity. The p-value are presented in brackets. The sample period spans January 1996 to August 2015.

5.5 Investor Sentiment Measures

The role of investor sentiment in asset pricing has been widely discussed in the literature (Baker and Wurgler, 2006, 2007; Yu and Yuan, 2011; Huang et al., 2015; Da et al., 2015; Jiang et al., 2018), and it is possible that the explanatory power of implied funding liquidity for equity market returns are from existing investor sentiment indexes. Therefore, we estimate whether our implied funding liquidity measure contain unique and incremental information on asset returns beyond existing investor sentiment measures.

Following the previous literature (Baker and Wurgler, 2006, 2007; Huang et al., 2015; Da et al., 2015; Jiang et al., 2018), we consider seven investor sentiment measures including Baker and Wurgler's (2006) investor sentiment measure (BW), Huang et al.'s (2015) aligned investor sentiment index (HJTZ), the consumer sentiment index of University of Michigan (UMC), the Conference Board consumer confidence index (CB), Da et al.'s (2015) Financial and Economics Attitudes Revealed by Search (FEARS) index (DEG), Jiang et al.'s (2018) manager sentiment index (JLMZ), as well as CBOE Put-Call ratios, (PCR)[14].

- BW: this index is based on the first principal component of six standardised equity market-based sentiment measures including NYSE turnover, the closed-end fund discount, the dividend premium, stock share in new issues, first-day returns and the number of initial public offerings (IPOs).
- HJTZ: this index uses the partial least square approach to exploit more efficiently the information in the six equity sentiment proxies in Baker and Wurger's index.
- UMC: this index is based on telephone surveys about information on consumer expectations with regard to the economic outlook.
- CB: this index is based on a random sample to estimate current economic conditions and likely developments.

[14]The updated historical data for investor sentiment measures BW and HJTZ are available at Guofu Zhou's website, http://apps.olin.wustl.edu/faculty/zhou/. The consumer sentiment index of University of Michigan, UMC, are available at https://fred.stlouisfed.org/series/UMCSENT/. Financial and Economics Attitudes Revealed by Search (FEARS) index, DEG, is available at https://www3.nd.edu/~zda/fears_post_20140512.csv. We thank Jiang for providing the data for Jiang et al. (2018) manager sentiment index, JLMZ, which is available at http://jfe.rochester.edu/data.htm. CBOE Put-Call ratios, PCR, is available at the CBOE website, http://www.cboe.com/data/historical-options-data/volume-put-call-ratios

- DEG: this index is constructed based on the number of internet searches related to domestic concerns (for instance, ’recession’, ’unemployment, and ’bankruptcy’).

- JLMZ: this index is based on the total textual tone of corporate financial disclosures.

- PCR: this is the volume of put option contracts / volume of call option contracts.

Table 5.7: Implied Funding Liquidity and Investor Sentiment Indexes

Panel A: Statistics							
	ΔBW	$\Delta HJTZ$	ΔUMC	ΔCB	ΔDEG	$\Delta JLMZ$	ΔPCR
Mean	-0.0012	-0.0015	0.0111	0.0040	0.0016	0.0238	0.0022
Median	-0.0010	0.0010	-0.2000	0.0095	-0.0080	0.0390	-0.0083
Minimum	-0.5380	-0.7160	-12.7000	-1.0410	-6.4890	-2.3210	-0.2447
Maximum	0.5140	0.6730	11.2000	0.9030	7.4430	2.0360	0.2858
Std Dev	0.1264	0.1789	4.0544	0.2986	1.4926	0.4049	0.0893
Skewness	-0.5322	0.2205	-0.2355	-0.2071	0.5218	-0.6503	0.3673
Kurtosis	3.8338	3.7604	0.4647	1.0972	9.9306	12.4580	0.4925
AC(1)	0.1540	0.4590	-0.0800	-0.0030	-0.5410	0.1140	-0.3040
Panel B Correlation							
	ΔBW	$\Delta HJTZ$	ΔUMC	ΔCB	ΔDEG	$\Delta JLMZ$	ΔPCR
ΔIFL	-0.0016	-0.1519	0.1515	0.1587	0.0402	0.0576	-0.5016
	(-0.9806)	(0.0221)	(0.0201)	(0.0593)	(0.7081)	(0.4947)	(<.0001)
ΔBW		0.3495	-0.0093	-0.0294	-0.0795	-0.0137	0.1127
		(<.0001)	(0.8888)	(0.7281)	(0.4590)	(0.8710)	(0.2716)
$\Delta HJTZ$		1.0000	-0.0545	-0.1106	0.2197	0.0117	0.1335
			(0.4136)	(0.1899)	(0.0386)	(0.8900)	(0.1922)
ΔUMC			1.0000	0.5225	0.1615	0.1505	-0.0615
				(<.0001)	(0.1306)	(0.0727)	(0.5332)
ΔCB				1.0000	0.1239	0.1589	-0.0349
					(0.2474)	(0.0589)	(0.7357)
ΔDEG					1.0000	0.1748	0.1079
						(0.1013)	(0.4079)
$\Delta JLMZ$						1.0000	-0.0073
							1.0000

Panel A of this table reports the basic descriptive statistics for seven investor sentiment indices, including Baker and Wurgler’s (2006) investor sentiment measure (BW), Huang et al.’s (2015) aligned investor sentiment index (HJTZ), the consumer sentiment index of University of Michigan (UMC), the Conference Board consumer confidence index (CB), Da et al.’s (2015) Financial and Economics Attitudes Revealed by Search (FEARS) index (DEG), Jiang et al.’s (2018) manager sentiment index (JLMZ), as well as CBOE Put-Call ratios, (PCR). AC(1) represents the first order autocorrelation coefficients for each variable. Panel B presents the correlation coefficients between implied funding liquidity and the investor sentiment variables. ΔIFL is the implied funding liquidity innovation. The p-value are presented in brackets. The full sample period spans January 1996 to August 2015.

Panel A of Table 5.7 presents the summary statistics for the seven existing investor sentiment indices for the sample period of January 1996 to August 2015. We observe that asymmetry of the distribution of the sentiment indexes. For instance, BW has skewness of -0.5322 and a kurtosis of 3.8338. These patterns are similar to the characteristics of our implied funding liquidity measure, as shown in Table 5.2.

Panel B of Table 5.7 reports the correlation coefficients between implied funding liquidity and the investor sentiment variables. Over the entire sample, we observe a significant negative relationship (-0.1519) between the innovations in implied funding liquidity and those of HJTZ at 5% level. In addition, the innovation of implied funding liquidity is also significantly associated with the Put-Call ratios with a negative correlation coefficient of -0.5016 at the 1% level. Moreover, there is a positive correlation between innovations of implied funding liquidity and CB.

In short, Table 5.7 indicates that the implied funding liquidity measure is associated with some existing investor sentiment indexes, such as HJTZ, UMC, CB, and PCR, suggesting that our implied funding liquidity measure may contain additional information beyond existing investor sentiment indexes.

5.6 Summary

In summary, the main objective of this chapter has been to present the data sources and their descriptive statistics used in this study.

Using stock and option data from CRSP and OptionMetrics for the sample 4 January 1996 to 31 August 2015, we constructed the implied funding liquidity measure based on the systematic deviations from Put-Call parity in the US equity option markets. Figure 5.1 suggests that large increases in the implied funding liquidity measure are associated with periods of macroeconomic and financial market distress.

We obtained the monthly spot exchange rates and one month forward exchange rates versus the US dollars from Datastream. We observed that the carry trade portfolios generate a large cross-sectional spread in returns. When the implied funding liquidity innovation is really poor, the carry trade portfolio performs poorly. Therefore, high interest rate currencies outperform low interest rate currencies when the market has a high implied funding liquidity innovation.

In this study, we obtain the monthly hedge fund indices from the Hedge Fund Research, Inc. (HFRI) to investigate whether implied funding liquidity influences aggregate hedge fund performance. In a manner similar to Næs et al. (2011), we used four proxies to measure the macroeconomic conditions: ΔUR, ΔCPI, ΔPMI, and ΔPayroll. All the historical data are available from the Economic Research Federal Reserve Bank of St. Louis.

Following the previous literature (Baker and Wurgler, 2006, 2007; Huang et al., 2015; Da et al., 2015; Jiang et al., 2018), we considered seven investor sentiment measures detailed in section 5.5. We found that the implied funding liquidity measure is associated with some of the existing investor sentiment indexes: HJTZ, UMC, CB, and PCR.

Chapter 6. Empirical Results

In this chapter, we report the main empirical results. In section 6.1, we examine whether implied funding liquidity provides forward-looking information about funding liquidity in addition to that contained in the current funding liquidity proxies, and the stock market return predictability of implied funding liquidity. Section 6.2 presents the results for asset-pricing tests of the implied funding liquidity innovations in stock, currency, and hedge fund markets. Section 6.3 reports the results for the test of whether our implied funding liquidity measure potentially provides incremental information about asset returns beyond what is captured in the previous well-known liquidity measures. In section 6.4, we estimate whether our liquidity measure matters after controlling for even existing popular investor sentiment indexes. Section 6.5 shows the profitability of the portfolio strategy of investing in stocks with the largest exposures to implied funding liquidity innovations, and shorting stocks with the lowest exposures to these innovations. Finally, we check whether implied funding liquidity has any predictive power for developments in the real economy in section 6.6.

6.1 Implied Funding Liquidity, Funding Liquidity Measures, and the Market Return Predictability

In this section, we first examine whether implied funding liquidity can provide forward-looking information about funding liquidity in addition to that contained in the current funding liquidity proxies. Then, we examine the predictive power of the implied funding liquidity measure for market returns.

6.1.1 Implied Funding Liquidity and Funding Liquidity Measures

Funding liquidity is important for financial intermediation and investments. In the literature, a number of researchers, including Brunnermeier et al. (2008), Fontaine and Garcia (2012), Hu et al. (2013) have used various proxies to capture funding conditions. Following the arguments developed by Easley et al. (1998) and Gârleanu et al. (2009), we examine whether the implied funding liquidity can provide forward-looking information about funding liquidity in addition to that contained in the current proxies.

Panel A of Table 6.1 presents the contemporaneous correlation coefficients between implied funding liquidity innovations and the changes of other liquidity proxies. Note that a positive innovation in implied funding liquidity indicates an improvement in liquidity conditions, while that of the other three proxies shows an increase in *il*-liquidity. We observe a negative correlation between the current changes in implied funding liquidity and other liquidity variables. The correlation coefficients between implied funding liquidity and the Treasury-LIBOR spread and the Noise measure are -0.192 and -0.151, respectively, and significant at 1% level. The Fontaine and Garcia measure (2012) is weakly related to the $Noise$ measure and the implied funding liquidity measure.

Table 6.1: Implied Funding Liquidity and Other Funding Liquidity Measures

Panel A: Spearman Correlation Coefficients Prob > |r| under H0: Rho=0				
	ΔIFL	ΔTED	ΔFG	$\Delta Noise$
ΔIFL	1	-0.192***	-0.095	-0.151**
ΔTED	-0.192***	1	0.161**	0.400***
ΔFG	-0.095	0.161**	1	0.042
$\Delta Noise$	-0.151**	0.400***	0.042	1
Panel B: Predicting Other Liquidity Measures				
	ΔIFL_{t-1}	ΔTED_{t-1}	ΔFG_{t-1}	$\Delta Noise_{t-1}$
ΔTED	-0.0050***	-0.0912		
	(-2.95)	(-1.28)		
ΔFG	-0.0049**		0.0628	
	(-2.01)		(0.94)	
$\Delta Noise$	-0.0233***			0.4149***
	(-4.81)			(7.23)

Panel A of this table presents the contemporaneous correlation coefficients between implied funding liquidity and other funding liquidity measures. $\Delta IFL_{i,t}$ is the innovation from implied funding liquidity; the FG is Fontaine and Garcia's (2012) measure obtained from the Treasury markets, $Noise$ is Hu et al.'s (2013) measure, and TED is the Treasury-LIBOR spread. Panel B shows the results obtained by regressing the funding liquidity measures on their own lag values and the past innovations in implied funding liquidity:

$$LIQ_{i,t} = \alpha + \beta_1 \times LIQ_{i,t-1} + \beta_2 \times \Delta IFL_{i,t-1}$$

where $LIQ_{i,t}$ represents ΔTED, ΔFG, and $\Delta Noise$. The *t*-statistics are presented in brackets. *** indicates the significance at 1% level. The sample period spans 4 January 1996 to 31 August 2015.

Panel B of Table 6.1 provides evidence of the predictability of implied funding liquidity with respect to funding conditions. We regressed each of the funding liquidity measures on their own lag values and the past implied funding liquidity innovations. We found that the model with one lag was suitable for this analysis. The regression results show that implied funding liquidity is negatively and significantly related to the future changes of these funding liquidity measures. Except for the Noise measure, the past innovations of the Treasury-LIBOR spread and the Fontaine and Garcia (2012) measure remain insignificant when implied funding liquidity is included in the model. The results show that implied funding liquidity conveys forward-looking information about future funding liquidity conditions beyond what is currently captured by other funding liquidity measures.

6.1.2 Market Return Predictability

In a frictional market, the funding liquidity risk influences asset returns, and asset returns have an influence on both the capital structure of companies and investment decisions. Therefore, the funding liquidity may contain useful information about the future real economy. Levine and Zervos (1998) found that stock market liquidity may positively predict growth, even after controlling for political and economic influences. Furthermore, Næs et al. (2011) show that, after controlling for other price predictors, stock market liquidity still contains leading information about the real economy. In this section, we examine the predictive power of the implied funding liquidity measure for market returns.

According to Campbell (1996), a factor important for asset prices needs to pass both time-series market return predictability and the cross-section asset return tests. To assess the return predictability power of the implied funding liquidity measure, we use monthly returns of the S&P500 index and the value-weighted average returns provided by CRSP as proxies for market returns. Following the previously mentioned literature, we also control for variables that have been found to predict market returns, which include the dividend yield on the S&P500 index, the GNP growth rate, the long-term government bond return, and past market excess return. Our choice of the forecasting variables is motivated by previous studies such as Campbell and Shiller (1988) and Siegel (1992) indicating that the dividend yield on S&P500 index, the real GNP growth rate, and the long-term government bond return predict future market returns. The predictive regression model of equation 4.13 is obtained.

Table 6.2: Market Return Predictability

Panle A: CRSP Value-Weighted Market Returns						
	ΔIFL_{t-1}	r_{t-1}	DIV_{t-1}	GNP_{t-1}	LTG_{t-1}	Adj R^2
1	0.0006*	-0.0285	-0.0017	5.4432***	0.03804***	12.89%
(t-stat)	(1.70)	(-0.39)	(-0.19)	(3.51)	(2.71)	
3	0.0015***	0.9427***	0.0272**	12.3703***	0.04124**	57.02%
(t-stat)	(3.11)	(9.83)	(2.45)	(6.16)	(2.26)	
6	0.0019**	0.8967***	0.0883***	20.8510***	0.01250	35.13%
(t-stat)	(2.14)	(5.16)	(4.39)	(5.73)	(0.38)	
Panle B: S&P 500 Returns						
	ΔIFL_{t-1}	r_{t-1}	DIV_{t-1}	GNP_{t-1}	LTG_{t-1}	Adj R^2
1	0.0007**	-0.0767	-0.0005	6.1355***	0.0302**	13.25%
(t-stat)	(2.08)	(-1.05)	(-0.06)	(4.14)	(2.26)	
3	0.0015***	0.8733***	0.0261**	12.8945***	0.0282	52.82%
(t-stat)	(3.16)	(9.14)	(2.45)	(6.66)	(1.61)	
6	0.0018**	0.8651***	0.0820***	21.0921***	0.0031	33.33%
(t-stat)	(2.13)	(4.96)	(4.21)	(5.96)	(0.09)	

This table shows the predictability of the implied funding liquidity with horizons of one month, three months, and six months for CRSP Value Weighted Returns (Panel A) and S&P 500 Returns (Panel B). Dependent variables are the cumulative growth rates of each variable calculated over one, three and six months. IFL_t is the implied funding liquidity at t, and $MKTEX_t$ is the market excess returns, DIV_t is the dividend yield on $S\&P500$ index, GNP_t is the real GNP growth rate, LTG_t is the long-term government bond return. The full sample period spans from 04 January 1996 to 31 August 2015, the significance level is given as $*/**/***$ for 10%, 5% and 1% level, respectively.

Table 6.2 shows the results of the return-predictive regressions. Consistent with the previous literature, we observed that dividend yield and the GNP growth rate significantly predict future excess markets for a horizon of six months. However, the return-predictive power of long-term government is limited to three months for the CRSP market returns and to one month for the $S\&P500$ market returns. In particular, the result shows that implied funding liquidity is negatively and significantly related to future market returns. The predictive power of the implied funding liquidity measure is significant from one- to six-month horizons and remains consistent for both $S\&P500$ returns and the value-weighted market returns from CRSP. This result shows that greater funding squeezes observed by means of the parity deviations in option markets can significantly predict future changes in market prices.

6.2 Asset Pricing Tests

In the previous section, we examined the stock market return predictability of implied funding liquidity, and in this section we estimate whether implied funding liquidity innovations can explain the cross-sectional differences in stock, currency, and hedge fund markets.

In a manner similar to the method in the literature on empirical asset pricing (for example, Fama and French, 1992, 1993; Campbell et al., 1997; Lettau and Ludvigson, 2001; Acharya and Pedersen, 2005; Petkova, 2006), we employ Fama and MacBeth's (1973) two-stage approach as described as follows. We first obtained the exposure (beta) of each portfolio to innovations in implied funding liquidity or other factors by regressing the portfolio returns on the innovations in implied funding liquidity or the market factors over the whole sample period. Then, at the end of each month, we estimated the implied funding liquidity premium, $\lambda_{\Delta IFL}$, by running a cross-sectional regression of portfolio returns on their betas to each risk factor. The time-series of the regression estimates were used for the tests of statistical significance. We use the Newey and West (1987) approach to correct for heteroscedasticity and auto-correlation in these estimates.

According to Petersen (2009), Newey-West-adjusted standard errors perform better in asset-pricing tests than those obtained from the ordinary least squares approach suggested by Fama and MacBeth (1973). In this analysis, we consider the pricing effects of the implied funding liquidity innovations in addition to other factors in the US equity markets, including Fama and French's (1992) three factors and Carhart's (1997) momentum factor.

6.2.1 Cross-Sectional Analysis of Stock Returns

Having established the return-predictive power of implied funding liquidity, we examine whether innovations in this liquidity measure matter in explaining the cross-sectional differences in stock returns. Following Petkova (2006), Pasquariello (2014) and Adrian et al. (2014), we concentrate on 25 size and book-to-market equity portfolios and 30 industry portfolios for the asset-pricing tests for the period 1996-2015. The 25 size and book-to-market equity portfolios are formed on size and book-to-market, and every NYSE, AMEX, and NASDAQ stock is assigned to an industry portfolio based on its four-digit SIC code.

Table 6.3 reports the exposures (betas) to the implied funding liquidity innovations for the 25 size and book-to-market and 30 industry stock portfolio returns in Panel A and Panel B, respectively. Figures 6.1(a) and 6.1(b) display scatter plots of excess returns versus their ΔIFL betas for the 25 Portfolios and the 30 industry portfolios.

Note that the beta estimates in Table 6.3 are positive and significant for the majority of the portfolios. This suggests, consistent to Pasquariello (2014), that excess returns in the equity and industry portfolios tend to be higher corresponding with abnormally high implied funding liquidity. Among the 25 size and book-to-market portfolios, the small and low book-to-market portfolios registered the highest exposure to implied funding liquidity innovations. Of the industry portfolios, the steel industry experienced the highest beta. This means riskier portfolios are more difficult to value and harder to arbitrage, which is consistent with Baker and Wurgler (2006) and Pasquariello (2014). These results suggest that small firms, companies with low book-to-market or those in the steel industry are the most exposed to changes in funding liquidity conditions.

Figures 6.1(a) and 6.1(b) suggest that portfolios with higher IFL innovation betas have higher mean excess returns.

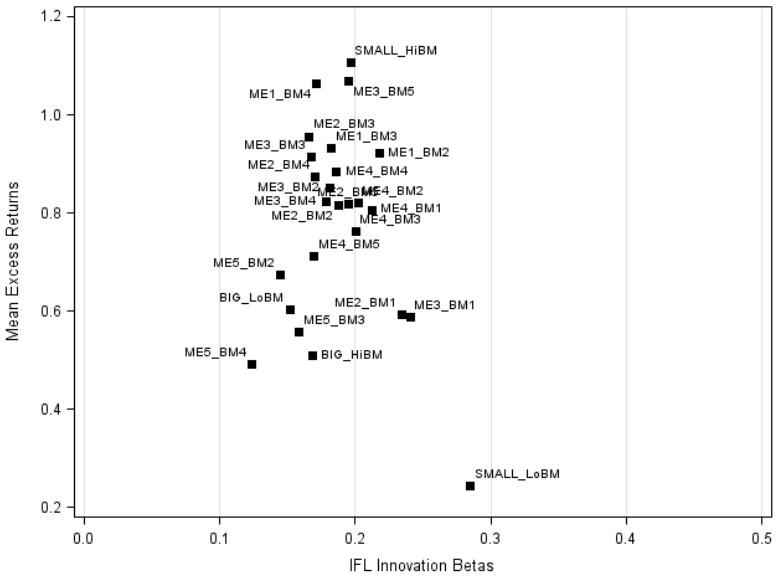
Table 6.4 reports the estimates and Newey-West adjusted t-statistics (in parentheses) obtained from the cross-sectional regressions. The estimates for Fama and French's (1992) three factors and Carhart's (1997) momentum factor are significant, showing that they are important in capturing equity market returns, as reported in the literature.

Table 6.3: Exposures to Implied Funding Liquidity Innovation

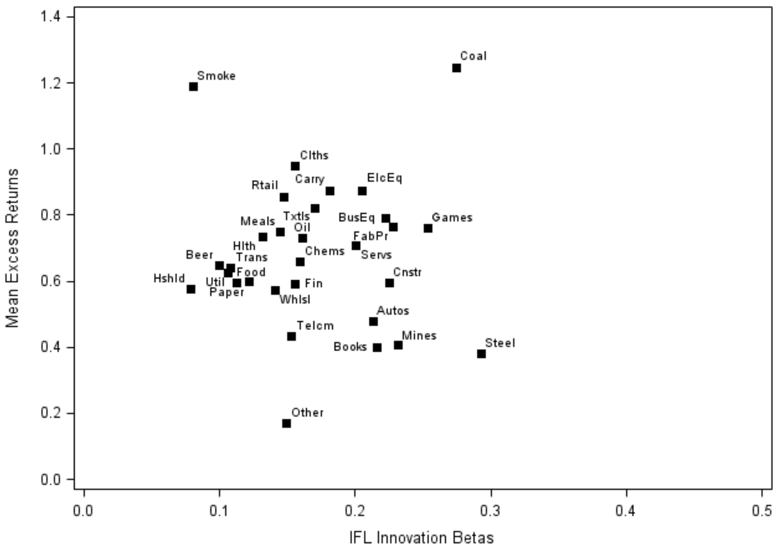
Panel A: 25 Size and Book-to-Market Portfolios					
Betas	Low B/M	2	3	4	High B/M
Small	0.29***	0.22***	0.18***	0.17***	0.20***
	(4.69)	(4.18)	(4.30)	(4.33)	(4.58)
2	0.23***	0.19***	0.17***	0.17***	0.19***
	(4.48)	(4.53)	(4.34)	(4.35)	(4.35)
3	0.24***	0.18***	0.17***	0.18***	0.19***
	(4.99)	(4.69)	(4.66)	(4.89)	(5.03)
4	0.21***	0.20***	0.20***	0.19***	0.17***
	(4.88)	(5.75)	(5.39)	(5.35)	(4.30)
Big	0.15***	0.14***	0.16***	0.12***	0.17***
	(4.67)	(4.78)	(4.92)	(3.77)	(4.34)

Panel B: 30 Industry Portfolios					
Industry	Betas	Industry	Betas	Industry	Betas
Autos	0.21***	Clths	0.16***	Food	0.11***
	(3.64)		(3.37)		(3.86)
Beer	0.10***	Cnstr	0.23***	Games	0.25***
	(2.81)		(5.00)		(4.97)
Books	0.22***	Coal	0.27***	Hlth	0.13***
	(5.24)		(2.88)		(4.43)
BusEq	0.22***	ElcEq	0.21***	Hshld	0.08**
	(3.73)		(4.37)		(2.51)
Carry	0.18***	FabPr	0.23***	Meals	0.14***
	(4.13)		(4.59)		(4.27)
Chems	0.16***	Fin	0.16***	Mines	0.23***
	(3.76)		(3.76)		(3.89)
Oil	0.16***	Steel	0.29***	Servs	0.20***
	(3.97)		(4.66)		(4.14)
Other	0.15***	Telcm	0.15***	Util	0.11***
	(3.53)		(3.91)		(3.73)
Paper	0.12***	Trans	0.11***	Smoke	0.08
	(3.25)		(2.88)		(1.55)
Rtail	0.15***	Txtls	0.17***	Whlsl	0.14***
	(4.13)		(2.72)		(4.10)

This table reports the exposures (beta) of portfolio returns to innovations in implied funding liquidity, ΔIFL, for the sample period 4 January 1996 to 31 August 2015. Panel A shows the estimates for the 25 size and book-to-market portfolios, while Panel B reports the coefficients for the 30 industry portfolios. Newey West t-statistics are shown in parentheses and $*$, $**$, $***$ denote significant at the 10%, 5% and 1% levels, respectively.



(a) 25 Portfolios



(b) 30 Industry Portfolios

Figure 6.1: ΔIFL Betas and Portfolio Excess Returns

This figure shows the scattered average portfolio excess returns versus their implied funding liquidity risk betas ($\beta_{\Delta IFL}$). Figure 6.1(a) is based on 25 size and book-to-market equity portfolios, and Figure 6.1(b) is based on 30 industry stock portfolios. IFL innovation betas and mean excess returns were estimated for each equity portfolio and the sample spans 4 January 1996 to 31 August 2015.

Table 6.4: Cross-Sectional Regressions of Stock Returns

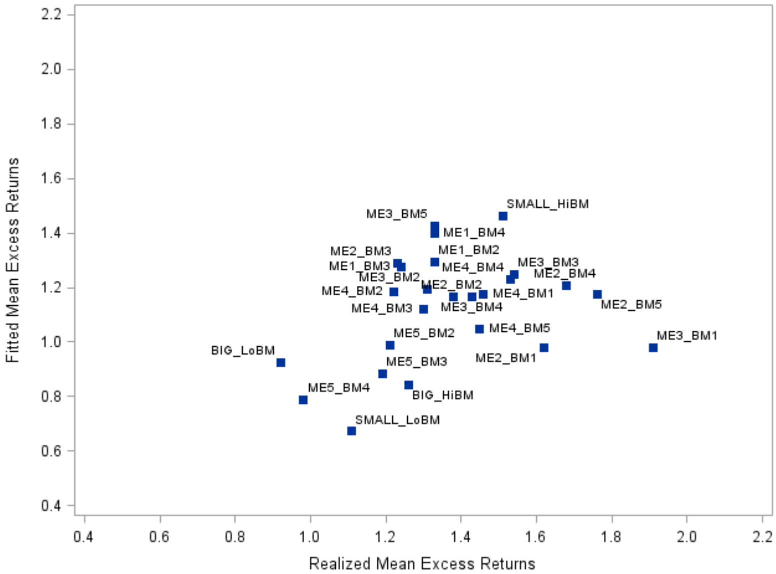
Panel A: 25 Portfolios							
Model	λ_0	$\lambda_{\Delta IFL}$	λ_{MKT}	λ_{SMB}	λ_{HML}	λ_{Mom}	R^2
Univariate	1.0189***	0.1876***					8.57%
	(25.87)	(29.60)					
CAPM	0.3976***	0.0194***	1.0287***				69.39%
	(10.46)	(5.83)	(34.58)				
FF	0.2299***	0.0111**	0.9965***	0.5188***	0.2734***		90.34%
	(6.35)	(2.57)	(77.11)	(3.89)	(3.54)		
FF, Mom	0.2469***	0.0113**	0.9868***	0.5220***	0.2645***	-0.0233***	90.48%
	(7.60)	(2.59)	(84.56)	(3.92)	(3.46)	(-3.13)	
Panel B: 30 Industry Portfolios							
Model	λ_0	$\lambda_{\Delta IFL}$	λ_{MKT}	λ_{SMB}	λ_{HML}	λ_{Mom}	R^2
Univariate	0.9197***	0.1708***					6%
	(21.55)	(18.32)					
CAPM	0.3420***	0.0145**	0.9564***				50.47%
	(8.92)	(2.76)	(17.17)				
FF3	0.2318***	0.0140**	1.0040***	0.0740**	0.3474***		58.10%
	(5.33)	(2.62)	(18.97)	(2.11)	(5.60)		
FF, Mom	0.2731***	0.0145**	0.9804***	0.0817**	0.3258***	-0.0566***	59.01%
	(6.97)	(2.76)	(18.86)	(2.32)	(5.15)	(-2.78)	

This table reports the estimates and Newey-West t-statistics (in bracket) from Fama and MacBeth (1973)'s two-stage regressions for the 25 size and book-to-market (Panel A) and 30 industry equity portfolios (Panel B) over the sample period from 04 January 1996 to 31 August 2015. ΔIFL is the funding liquidity innovations, MKT is the excess market return, SMB is the average return on the small stock portfolios minus the average return on the big stock portfolios; HML is the average return on the value portfolios minus the average return on the growth portfolios; MOM is a momentum factor. $*/{*}{*}/{*}{*}{*}$ denotes the significance level at 10%, 5% and 1% level, respectively.

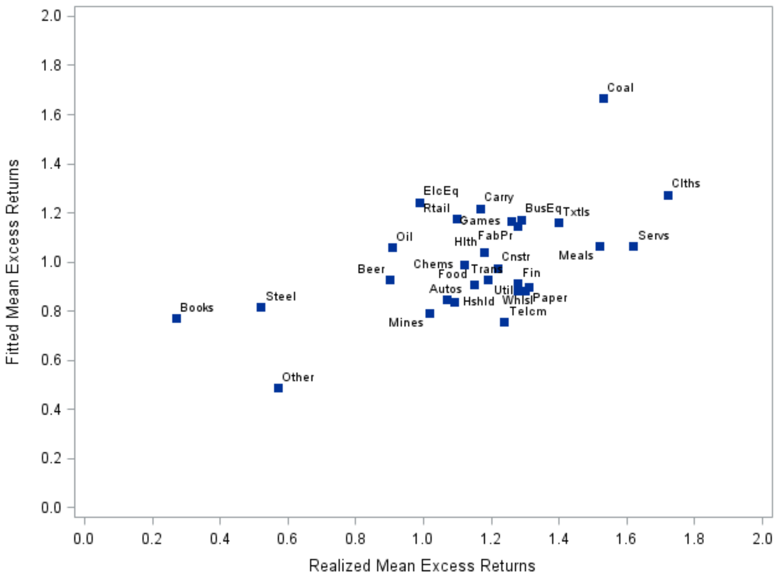
In particular, the estimates for implied funding liquidity are positive ($\lambda_{\Delta IFL} > 0$) and significant at the 1% level for both the 25 equity and 30 industry portfolios. The implied funding liquidity risk premiums are statistically and economically significant, and total 0.1876 and 0.1708 per unit of the ΔIFL beta for the equity and industry portfolios, respectively. The univariate model with implied funding liquidity explains approximately 8.6% and 6% of the cross-sectional variations in returns for the 25 size and book-to-market and 30 industry portfolios, respectively, suggesting that implied funding liquidity risk alone meaningfully explains of cross-sectional stock portfolio returns. In addition, the coefficients for implied funding liquidity remain robust when other equity market factors are included in the model. After controlling for the market variable, MKT, the estimates of $\lambda_{\Delta IFL}$ show that the implied funding liquidity risk premiums for both equity and industry portfolios are still statistically and economically significant, down to 0.0194 and 0.0145, respectively. Unsurprisingly, $\lambda_{\Delta IFL}$s are smaller than their univariate counterparts.

Accordingly, $\lambda_{\Delta IFL}$s are small and statistically significant relative to Fama and French's (1992) three traded factors (MKT, SMB, and HML), and Fama and French's (1992) three traded factors plus momentum (MKT, SMB, HML, and MOM). For instance, the estimated implied funding liquidity risk premium, $\lambda_{\Delta IFL}$, are 0.0113 and 0.0145, for the equity and industry portfolios, respectively. The five-factor model, controlling for MKT, SMB, HML, and MOM, with the implied funding liquidity measure register R-square values of 90.5% and 59% for the 25 size and book-to-market and 30 industry portfolios, respectively. Intuitively, this evidence is consistent with Pasquariello (2014). Stock portfolio with greater exposure to the implied funding liquidity risk performed more poorly. Investors do not desire higher implied funding liquidity risk exposure, and compensation is required for holding equity portfolios with higher risk exposure.

Figure 6.2 plots the actual versus predicted average returns from the one-factor model with implied funding liquidity for the 25 size and book-to-market portfolios (Figure 6.2(a)) and 30 industry portfolios (Figure 6.2(b)) from 4 January 1996 to 31 August 2015. There is a strong and positive relationship between the realised and the predicted average returns for these portfolios. Overall, this result indicates that the sensitivities of equity and industry portfolios to funding liquidity tend to proportionally explain their risk, which is not fully captured by other well-known priced factors.



(a) 25 Portfolios



(b) 30 Industry Portfolios

Figure 6.2: Realised vs Predicted Average Returns of Stock Returns

This figure presents the average realised versus predicted returns from the one-factor model with implied funding liquidity for the 25 size and book-to-market portfolios (Panel 6.2(a)) and 30 industry portfolio (Panel 6.2(b)). The sample spans from 4 January 1996 to 31 August 2015.

6.2.2 Cross-Sectional Analysis of Currency Returns

The empirical evidence in 6.2.1 shows that funding liquidity matters in explaining the cross-sectional variations in equity portfolio returns. In this sub-section, we use the similar method to understand the cross section of carry trade returns in the currency market. We examine the performance of carry trade portfolios of all countries and developed countries using individual currencies as discussed in Chapter 5.2.

We still use the Fama and MacBeth's (1973) two-stage approach described in Chapter 6.2.1 to estimate the implied funding liquidity innovation betas and risk premiums for the foreign exchange market.

Table 6.5 reports the estimates and Newey-West adjusted *t*-statistics (in parentheses) obtained from Fama and MacBeth's (1973) two-stage regressions for currencies of all countries (Panel A) and the currencies of developed countries (Panel B) over the sample period of January 1996 to August 2015. The estimates for Fama and French's (1992) three factors and Carhart's (1997) momentum factor are significant, showing that they are important to capture foreign exchange market returns.

In particular, the estimates for implied funding liquidity are positive and significant at the 1% level for currencies of all countries and the currencies of the developed countries. The one-factor model with implied funding liquidity explains 3.68% and 3.64% of the cross-sectional variations in returns for the currencies of all countries and the currencies of the developed countries, respectively. What is more, the coefficients for implied funding liquidity remain robust when other equity market factors are included in the model. The five-factor model with the implied funding liquidity measure registers R-square values of 15.48% and 15.39% for the currencies of all countries and developed countries, respectively.

Consistent with Lustig et al. (2011) and Pasquariello (2014), our findings show that implied funding liquidity risk helps explain the the carry trade. Currencies with low interest rate are associated with negative betas, resulting in funding currencies provide insurance against liquidity risk; the relationship between liquidity betas and currencies with high interest rate is positive, and therefore investment currencies offer exposure to the implied funding liquidity.

Table 6.5: Cross-Sectional Regressions of Currency Portfolio Returns

Model	λ_0	$\lambda_{\Delta IFL}$	λ_{Mkt_RF}	λ_{SMB}	λ_{HML}	λ_{Mom}	R^2
Panel A: All Countries							
Univariate	0.1059*	0.0570***					3.71%
	(2.09)	(6.90)					
CAPM	-0.0025	0.0288***	0.1771***				12.44%
	(-0.06)	(7.11)	(6.65)				
FF	-0.0550	0.0269***	0.1901***	0.0655***	0.1361***		15.47%
	(-1.44)	(7.10)	(6.78)	(7.21)	(8.22)		
FF, Mom	-0.0518	0.0270***	0.1879***	0.0663***	0.1347***	-0.0044*	15.48%
	(-1.40)	(7.06)	(6.69)	(7.38)	(8.02)	(-2.30)	
Panel B: Advanced Countries							
Model	λ_0	$\lambda_{\Delta IFL}$	λ_{Mkt_RF}	λ_{SMB}	λ_{HML}	λ_{Mom}	R^2
Univariate	0.1142	0.0579***					3.67%
	(1.72)	(5.69)					
CAPM	0.0050	0.0291***	0.1790***				12.36%
	(0.11)	(5.85)	(5.43)				
FF	-0.0475	0.0278***	0.1920***	0.0670***	0.1373***		15.41%
	(-1.00)	(5.83)	(5.50)	(5.82)	(6.70)		
FF, Mom	-0.0451	0.0276***	0.1900***	0.0673***	0.1359***	-0.0040	15.42%
	(-0.99)	(5.80)	(5.45)	(5.96)	(6.54)	(-1.76)	

This table reports the estimates and Newey-West *t*-statistics (in bracket) from Fama and MacBeth's (1973) two-stage regressions for the currencies of all countries (Panel A) and the currencies of the developed countries (Panel B) over the sample period from January 1996 to August 2015. ΔIFL is the funding liquidity innovations, MKT is the excess market return, SMB is the average return on the small stock portfolios minus the average return on the big stock portfolios; HML is the average return on the value portfolios minus the average return on the growth portfolios; MOM is a momentum factor. $*/{*}{*}/{*}{*}{*}$ denotes the significance level at 10%, 5% and 1% level, respectively.

6.2.3 Cross-Sectional Analysis of Hedge Fund Returns

The empirical evidence in 6.2.1 and 6.2.2 shows that implied funding liquidity matters in explaining the cross-sectional variations in both equity portfolio returns and foreign exchange market portfolio returns. In this sub-section, we examine the influence of implied funding liquidity on hedge fund performance. In a manner similar to Chen and Lu (2017), we examine the exposure of hedge fund portfolio returns to the innovations in implied funding liquidity ΔIFL, and then examine the time-series regressions in which ΔIFL is the dependent variable and various risk factors are the independent variables.

Table 6.6: Exposure to Implied Funding Liquidity Innovation of Hedge Fund

	Betas		Betas		Betas		Betas
HFRIACT	0.16***	HFRIEDSS	0.10***	HFRIFOFC	0.06***	HFRIMDT	0.06***
	(4.65)		(5.77)		(7.39)		(4.73)
HFRIAWC	0.09***	HFRIEHFG	0.16***	HFRIFOFD	0.08***	HFRIMENA	0.12***
	(7.47)		(5.34)		(6.69)		(4.93)
HFRIAWED	0.12***	HFRIEHFV	0.12***	HFRIFOFM	0.05***	HFRIMI	0.04***
	(7.06)		(5.16)		(4.55)		(3.66)
HFRIAWEH	0.11***	HFRIEHI	0.11***	HFRIFOFS	0.11***	HFRIMMS	0.07***
	(5.54)		(6.28)		(6.57)		(6.79)
HFRIAWJ	0.08***	HFRIEHMS	0.09***	HFRIFWI	0.09***	HFRIMTI	0.05***
	(4.94)		(4.74)		(7.05)		(2.78)
HFRIAWM	0.06***	HFRIEM	0.16***	HFRIFWIC	0.09***	HFRINA	0.09***
	(4.58)		(6.01)		(7.12)		(5.42)
HFRIAWRV	0.08***	HFRIEMA	0.13***	HFRIFWIE	0.08***	HFRIRVA	0.07***
	(5.88)		(4.94)		(6.23)		(9.17)
HFRICAI	0.12***	HFRIEMG	0.14***	HFRIFWIG	0.10***	HFRISEN	0.18***
	(9.05)		(5.78)		(7.10)		(5.06)
HFRICHN	0.14***	HFRIEMLA	0.18***	HFRIFWIJ	0.09***	HFRISHSE	-0.15***
	(3.89)		(5.75)		(7.02)		(-4.20)
HFRICIS	0.25***	HFRIEMNI	0.02***	HFRIHLTH	0.09***	HFRISRE	0.08***
	(5.10)		(3.96)		(4.47)		(5.46)
HFRICRDT	0.08***	HFRIENHI	0.14***	HFRIIND	0.22***	HFRISTI	0.11***
	(6.05)		(5.75)		(3.66)		(3.40)
HFRICRED	0.08***	HFRIFI	0.07***	HFRIJPN	0.09***	HFRITECH	0.09***
	(5.21)		(9.10)		(4.20)		(4.60)
HFRIDSI	0.09***	HFRIFIHY	0.09***	HFRIMACT	0.02	HFRIVOL	0.08***
	(7.08)		(8.21)		(1.18)		(7.20)
HFRIDVRS	0.09***	HFRIFIMB	0.03***	HFRIMAI	0.05***	HFRIWEU	0.08***
	(6.26)		(3.03)		(7.20)		(6.87)
HFRIEDI	0.10***	HFRIFISV	0.04***	HFRIMCOM	0.03*	HFRIWOMN	0.09***
	(7.85)		(3.62)		(1.93)		(5.61)
HFRIEDMS	0.14***	HFRIFOF	0.08***	HFRIMCUR	0.01	HFRIWRLD	0.07***
	(7.17)		(7.19)		(1.56)		(6.08)

This table reports the exposures (betas) of hedge fund portfolio returns to the innovations in implied funding liquidity ΔIFL for the full sample period of January 1996 to August 2015. The hedge fund index tickers and characteristics are presented in Table A.5. Newey West *t*-statistics are shown in bracket and $*$, $**$, $***$ denote significant levels at 10%, 5% and 1%, respectively.

Table 6.6 reports OLS estimates of the funding liquidity ΔIFL betas, $\beta_{i,\Delta IFL}$, of different hedge fund indices which are the slope coefficients for the time-series regressions on ΔIFL. Notice that the beta estimates are positive and significant for the majority of the portfolios. Among the hedge fund portfolios, the HFRIEMLA registers the highest exposure to implied funding liquidity innovations. Moreover, HFRISHSE is the only portfolio with a negative beta.

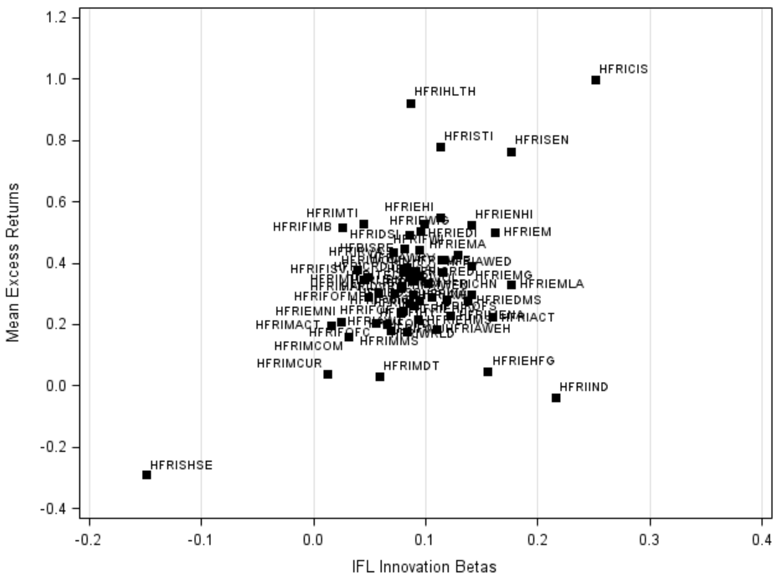


Figure 6.3: ΔIFL Betas and Portfolio Excess Returns of Hedge Fund Indices

This figure shows the scattered average portfolio excess returns versus their ΔIFL factor of the hedge fund indices. The sample spans 1 January 1996 to 31 August 2015.

Prior literature shows that various factors are important in the analysis of hedge fund risk exposure (Fung and Hsieh, 1997, 2001, 2004, 2011). Therefore, in the multivariate time-series regressions analysis, we use the Carhart's (1997) four factors and Fung and Hsieh's (2001, 2004) seven factors. Table 6.7 reports the estimates of monthly percentage risk premiums, $\lambda_{\Delta IFL}$, for the univariate and multivariate betas of the hedge fund portfolios. Table 6.7 shows that a significantly positive relationship between implied funding liquidity innovation and the hedge fund returns even after controlling for other risk factors. This result is consistent with Sadka (2010), Kessler and Scherer (2011), and Chen and Lu (2017). Once all the risk factors are included, the alpha is 0.21 with an adjust R^2 31.67%. These results show that implied funding liquidity contains information that has not been fully explained by other risk factors, and that funding liquidity matters in explaining the cross-sectional variations in hedge fund portfolio returns.

Figure 6.4 plots the actual versus predicted average returns from the one factor model with implied funding liquidity for the hedge fund portfolio. The sample spans January 1996 to August 2015. There is a strong, positive relationship between the realised and the predicted average returns for these hedge fund port-

Table 6.7: Regression Results of Hedge Fund Returns

Model	λ_0	$\lambda_{\Delta IFL}$	λ_{Mkt_RF}	λ_{SMB}	λ_{HML}	λ_{Mom}	λ_{PTFSBD}	λ_{PTFSFX}	$\lambda_{PTFSCOM}$	λ_{EMF}	λ_{SSF}	λ_{BMF}	λ_{CSF}	R^2
Univariate	0.4991***	0.0909***												18.48%
	(16.59)	(12.18)												
CAPM	0.3047***	0.0443***	0.2785***											49.81%
	(9.46)	(14.54)	(8.54)											
FF	0.2817***	0.0403***	0.2817***	0.0466**	-0.0430**									54.07%
	(8.80)	(13.56)	(9.04)	(2.40)	(-2.32)									
FF, Mom	0.2712***	0.0400***	0.2829***	0.0449**	-0.0513**	-0.0044								55.69%
	(8.67)	(13.48)	(9.36)	(2.35)	(-2.65)	(-0.54)								
Fung	0.3359***	0.0332***					-0.9370***	0.8847***	-0.3042	24.9420***	6.2122***	0.1090	-1.8765***	59.39%
	(13.23)	(16.69)					(-4.64)	(7.52)	(-1.47)	(8.84)	(2.87)	(0.85)	(-7.40)	
FF, Mom, Fung	0.1990***	0.0264***	0.6257***	-0.0705	-0.0520***	-0.0013	-0.9331***	0.7850***	-0.1613	-36.322**	4.8180	0.0334	-1.8705***	64.85%
	(4.46)	(13.05)	(3.82)	(-1.07)	(-3.58)	(-0.17)	(-4.68)	(6.86)	(-0.99)	(-2.43)	(0.79)	(0.28)	(-8.09)	

This table reports the estimates of monthly percentage risk premiums ΔIFL for univariate and multivariate betas of the hedge fund portfolios. OLS estimates of the funding liquidity ΔIFL betas which is the slope coefficients from the time-series regressions of the monthly hedge fund excess returns on ΔIFL. The multivariate time-series regressions include the Carhart's (1997) four factors and Fung and Hsieh's (2001, 2004) seven factors with the implied funding liquidity innovation, ΔIFL. The full sample period spans January 1996 to August 2015. The Newey West t statistics are shown in bracket and the significance level is labelled in $*/{*}{*}/{*}{*}{*}$ for 10%, 5% and 1% level, respectively.

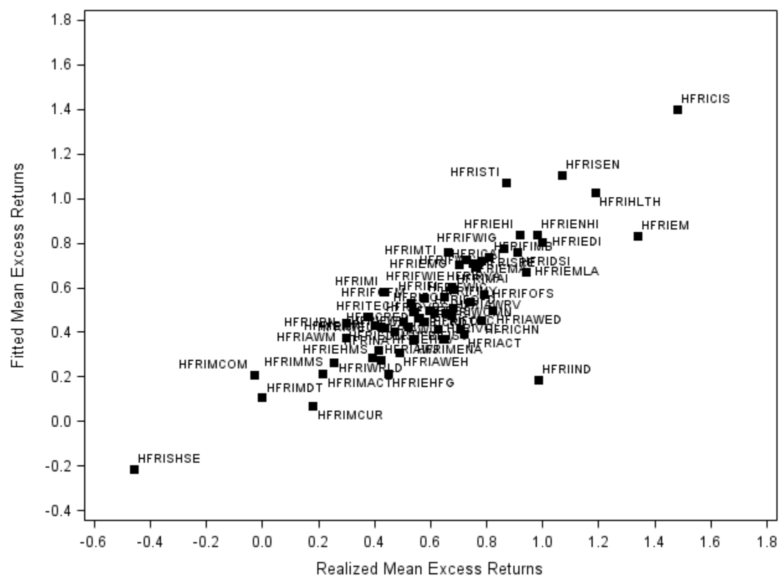


Figure 6.4: Realised vs Predicted Average Returns of Hedge Fund Returns

This figure presents the actual versus predicted average returns from the one factor model with implied funding liquidity for the hedge fund portfolio. The sample spans January 1996 to August 2015

folios. This result indicates that funding liquidity matters in explaining the cross-sectional variations in hedge fund market portfolio returns.

6.3 Comparison with Other Liquidity Measures

Prior studies suggest that liquidity varies over time and that liquidity risk matters in asset pricing. In particular, a growing body of empirical works (Pástor and Stambaugh, 2003; Brunnermeier et al., 2008; Hu et al., 2013; Fontaine et al., 2015; Amihud, 2002; Corwin and Schultz, 2012) show that liquidity innovations explain the variations in asset returns. We argue that our liquidity measure incorporates the forward-looking nature of the option markets. Therefore, the implied funding liquidity measure potentially provides incremental information about asset returns beyond what is captured in well-known existing liquidity measures. In other words, we next estimate the marginal contribution of ΔIFL to the cross-sectional stock portfolio returns, while accounting for their sensitivities to other current liquidity measures.

In Table 6.1, we show that the implied funding liquidity measure is contemporaneously associated with some existing liquidity measures, which suggests that our measure may contain additional information beyond that of exiting liquidity measures. In this section, we further empirically investigate the connection between our implied funding liquidity measure and other liquidity measures documented in the literature.

We considered the cross-sectional regressions that include the Pástor and Stambaugh's (2003) measure (PS), Brunnermeier et al.'s (2008) Treasury-LIBOR (TED) spread, Hu et al.'s (2013) Noise measure (Noise), Fontaine and Garcia's (2012) measure (FG), Amihud's (2002) il-liquidity measure (Amihud), Corwin and Schultz's (2012) measure (CS), the relative spread (RS), and Sadka's (2006) measure (Sadka) in addition to the implied funding liquidity measure. Detailed descriptions of these alternative liquidity proxies are provided in section 5.1. In this analysis, we used the CAPM with the implied funding liquidity factor as the benchmark for performance comparison.

6.3.1 Equity Returns

Table 6.8 shows the estimates of the liquidity measures for the 25 size-to-book portfolios, and the liquidity measures for the 30 industry portfolios in Panel A and Panel B, respectively.

Panel A of Table 6.8 shows the estimates of the liquidity measures for the 25 size-to-book portfolios. Among the liquidity measures, we find that the Brunnermeier et al.'s (2008) TED measure and Fontaine and Garcia's (2012) FG measure register significant coefficients, while Pastor and Stambaugh's PS (2003), Hu et al.'s Noise (2013) measures and the relative spreads are insignificant. In particular, implied funding liquidity remains positive and significant. The model with all the liquidity variables registers an R-square of 71.22%. Interestingly, when we include both Noise and implied funding liquidity measures in the regression, our measure remains significant at the 1% level but Noise becomes insignificant, and the R-square (69.63%)is similar to that using our measure only in Table 6.4. These findings are consistent with the highly correlated relationship between Noise and our measure in Table 6.1 (Panel A), suggesting that our measure empirically dominates the Noise measure in the equity market.

More importantly, our implied funding liquidity measure remains consistently positive and significant when we control for alternative liquidity measures. We find that our measure remains statistically significant and economically large, but that the coefficients on other liquidity proxies become volatile. Moreover, when we control for all the liquidity measures, aside from the Noise measure, all the other measures are significant with an R-square of 71.19%.

Table 6.8: Cross-sectional Regressions with Liquidity Measures

Model	λ_0	$\lambda_{\Delta IFL}$	λ_{MKT}	λ_{PS}	λ_{TED}	λ_{FG}	λ_{Noise}	λ_{Amihud}	λ_{RS}	λ_{CS}	λ_{Sadka}	R^2
Panel A: 25 Portfolios												
+PS	0.4648***	0.0271***	1.0242***	0.2719								69.63%
	(11.23)	(6.27)	(31.67)	(0.26)								
+TED	0.7865***	0.0243***	1.0174***		-0.5873***							70.00%
	(8.32)	(6.27)	(32.87)		(-3.85)							
+FG	0.4633***	0.0252***	1.0280***			-0.2817***						69.92%
	(11.32)	(6.65)	(34.29)			(-5.82)						
+NOISE	0.6088***	0.0288***	1.0199***				-0.0433					69.94%
	(5.65)	(7.92)	(30.87)				(-1.30)					
+Amihud	0.6527***	0.0288***	1.0191***					-0.0554***				69.68%
	(13.07)	(7.39)	(33.50)					(-4.93)				
+RS	0.6434***	0.0278***	1.0203***						-4.7359*			69.64%
	(7.52)	(7.19)	(33.52)						(-1.87)			
+CS	0.4671***	0.0275***	1.0250***							-0.1967		69.55%
	(6.13)	(7.01)	(34.53)							(-0.04)		
+Sadka	0.4204***	0.0251***	1.0317***								3.2470***	70.34%
	(9.69)	(6.47)	(34.73)								(7.54)	
+ALL	-0.1512	0.0208***	1.0358***	-0.9189	-0.5438***	-0.4201***	0.0575	-0.1924***	10.6026*	60.4095***	2.7647***	72.19%
	(-1.38)	(6.47)	(31.42)	(-1.04)	(-3.31)	(-6.24)	(1.01)	(-9.73)	(1.75)	(6.63)	(6.75)	
Panel B: 30 Industry Portfolios												
+PS	0.4330***	0.0102*	0.9478***	2.7008*								50.89%
	(6.97)	(1.87)	(17.21)	(1.98)								
+TED	0.8528***	0.0095*	0.9459***		-0.7774***							50.91%
	(7.52)	(1.77)	(16.41)		(-4.88)							
+FG	0.4253***	0.0116**	0.9588***			-0.2579***						50.77%
	(6.97)	(2.12)	(16.69)			(-4.78)						
+NOISE	0.6936***	0.0161***	0.9466***				-0.0801***					50.78%
	(7.67)	(2.82)	(16.27)				(-3.86)					
+Amihud	0.6293***	0.0151**	0.9497***					-0.0597***				50.70%
	(7.04)	(2.60)	(16.45)					(-3.69)				
+RS	0.6293***	0.0141**	0.9508***						-5.3694*			50.48%
	(4.93)	(2.49)	(16.36)						(-1.87)			
+CS	0.4716***	0.0138**	0.9557***							-2.9517		50.53%
	(2.97)	(2.44)	(16.45)							(-0.28)		
+Sadka	0.3874***	0.0116**	0.9620***								2.8735***	50.98%
	(6.55)	(2.11)	(16.65)								(4.78)	
+ALL	-0.1783	0.0050	0.9568***	1.4176	-0.7622***	-0.3071***	-0.0078	-0.1674***	17.7736***	59.2579***	2.3766***	53.67%
	(-1.07)	(0.93)	(17.09)	(1.06)	(-4.25)	(-5.20)	(-0.20)	(-5.45)	(3.13)	(3.55)	(4.53)	

This table reports the estimates and the Newey West t-statistics (in the bracket) from the cross-sectional regressions. Let IFL denote the implied funding liquidity measure, MKT the excess market return, PS Pástor and Stambaugh's (2003) measure, TED Brunnermeier et al.'s (2008) Treasury-LIBOR spread, $Noise$ Hu et al.'s (2013) Noise measure, FG Fontaine and Garcia's (2012) measure, $Amihud$ Amihud's (2002) il-liquidity measure, CS Corwin and Schultz's (2012) measure, RS the relative spread, and $Sadka$ Sadka's (2006) measure. The significance level is written in $*/**/***$ for 10%, 5% and 1% level, respectively.

The same patterns can also be seen in Panel B for the industry portfolios. The TED measure and FG measure register the same sign and significant estimates at the 1% level while the coefficients, PS, Noise and the relative spreads remain insignificant. The R-square with all liquidity variables and the market return is approximately 52.92%. The same patterns can be observed in the regression results for the 30 industry portfolios in Panel B. We observe that the coefficients for implied funding liquidity remain positive and significant after controlling for established liquidity measures in the US equity markets.

Our findings suggest that the implied funding liquidity measure tends to incorporate the forward-looking nature of the option markets, and potentially provides incremental information about equity returns beyond what is captured in the previous liquidity measures.

6.3.2 Currency Portfolios

Panel A of the table 6.9 shows the estimates of the liquidity measures for the currencies of all countries, whilst Panel B shows the estimates of the liquidity measures for the currencies of the developed countries.

Panel A shows that among the liquidity measures, we observe that the PS, TED, and FG measures are significant while the Noise measure is not always significant. Importantly, implied funding liquidity remains positive and significant. The model including the market return factor and all the liquidity variables reports an R-square of 14.74%. We see the same patterns in Panel B, which reports the regression results for developed countries. The TED and FG measures register the same signs as above and are significant at the 1% level, the PS measure registers the same signs as above and is significant at 10% level, while the impacts of the Noise measures is insignificant. The R-square with all liquidity variables and the market return is approximately 17.12%. We observe that implied funding liquidity remains significant in explaining currency return variations even when controlling for established liquidity measures in the foreign exchange markets.

Our findings show that implied funding liquidity provides incremental information about the currency market beyond what has been captured in the previous well-known liquidity measures.

Table 6.9: Cross-sectional Regressions with Liquidity Measures: Currency Portfolios

Model	λ_0	$\lambda_{\Delta IFL}$	λ_{MKT}	λ_{PS}	λ_{TED}	λ_{FG}	λ_{Noise}	λ_{Amihud}	λ_{RS}	λ_{CS}	λ_{Sadka}	R^2
Panel A: All Countries												
+PS	0.1574	0.0190***	0.1673***	-1.5071								15.31%
	(1.56)	(10.10)	(5.44)	(-1.73)								
+TED	0.4849**	0.0139***	0.1550***		-0.5893***							15.62%
	(3.49)	(6.72)	(5.10)		(-6.37)							
+FG	0.1603	0.0139***	0.1668***			-0.3880***						17.12%
	(1.62)	(6.53)	(5.20)			(-6.67)						
+NOISE	0.2308*	0.0177***	0.1603***				-0.0208***					14.46%
	(2.33)	(7.50)	(5.06)				(-4.61)					
+Amihud	0.1248	0.0168***	0.1638***					0.0107				14.58%
	(1.69)	(7.70)	(5.02)					(0.95)				
+RS	0.3831**	0.0175***	0.1569***						-5.8555***			14.51%
	(3.49)	(7.33)	(5.03)						(-10.70)			
+CS	0.6293***	0.0179***	0.1585***							-30.2670***		15.56%
	(7.30)	(7.87)	(4.99)							(-4.43)		
+Sadka	0.1720	0.0177***	0.1611***								-0.7941**	14.99%
	(1.79)	(7.93)	(5.06)								(-2.92)	
+ALL	0.6241***	0.0145***	0.1699***	-2.0353*	-0.3165**	-0.3911***	0.0730***	-0.0096	0.0538	-31.965**	-1.0805***	21.47%
	(5.54)	(13.83)	(5.36)	(-2.19)	(-3.18)	(-9.70)	(4.31)	(-0.68)	(0.03)	(-2.53)	(-4.37)	
Panel B: Advanced Countries												
+PS	0.1142	0.0362***	0.1815***	-2.0706								14.36%
	(1.83)	(6.75)	(5.81)	(-1.61)								
+TED	0.6389***	0.0285***	0.1628***		-0.9458***							15.77%
	(4.14)	(6.31)	(5.55)		(-5.23)							
+FG	0.1182	0.0294***	0.1806***			-0.5176***						16.29%
	(1.96)	(5.80)	(5.66)			(-9.20)						
+NOISE	0.3038**	0.0352***	0.1687***				-0.0551**					13.93%
	(2.86)	(6.28)	(5.43)				(-2.94)					
+Amihud	0.0850	0.0333***	0.1763***					0.0102				13.28%
	(1.45)	(6.27)	(5.53)					(1.36)				
+RS	0.5332**	0.0343***	0.1644***						-10.9190***			13.80%
	(3.95)	(6.24)	(5.43)						(-4.82)			
+CS	0.8104***	0.0348***	0.1690***							-44.6800***		14.19%
	(8.29)	(6.34)	(5.45)							(-10.30)		
+Sadka	0.1341*	0.0344***	0.1730***								-1.0781*	13.93%
	(2.31)	(6.32)	(5.52)								(-2.42)	
+ALL	0.8743***	0.0305***	0.1812***	-2.8957*	-0.5787*	-0.4617***	0.0717**	0.0011	0.5620	-44.631***	-1.4989**	21.19%
	(6.01)	(7.81)	(5.90)	(-2.25)	(-2.40)	(-5.82)	(2.62)	(0.08)	(0.37)	(-6.26)	(-3.50)	

This table reports the estimates and Newey-West t-statistics (in bracket) from Fama and MacBeth's (1973) two-stage regressions for currencies of all countries (Panel A) and developed countries (Panel B) over the sample period of January 1996 to August 2015. ΔIFL is the funding liquidity innovations, MKT is the excess market return, PS Pástor and Stambaugh's (2003) measure, TED Brunnermeier et al.'s (2008) Treasury-LIBOR spread, $Noise$ Hu et al.'s (2013) Noise measure, FG Fontaine and Garcia's (2012) measure, $Amihud$ Amihud's (2002) il-liquidity measure, CS Corwin and Schultz's (2012) measure, RS the relative spread, and $Sadka$ Sadka's (2006). $*/**/***$ denotes the significance level at 10%, 5% and 1% level, respectively.

6.3.3 Hedge Fund Returns

In the cross-sectional regressions of the hedge fund portfolios, we consider the PS measure, the TED spread, the Noise, and FG measures in addition to the implied funding liquidity innovations. The multivariate time-series regressions still control for the Carhart's (1997) four factors and Fung and Hsieh's (2001, 2004) seven factors with the implied funding liquidity innovation, ΔIFL.

Table 6.10 shows the regression estimates of the liquidity measures for the hedge fund portfolios. Among the liquidity measures, we find that the PS, TED, and FG measures are significant at the 1% level while the Noise measure is insignificant. Importantly, implied funding liquidity remains positive and significant. The model including the market return factor and all of the liquidity variables reports an R-square of 32.17%. We observe that the implied funding liquidity remains significant in explaining hedge fund return variations even controlling for established liquidity measures.

6.4 Comparison with Investor Sentiment Measures

In section 6.3, we found that our implied funding liquidity measure empirically dominates the Noise measure in the equity market, which might suggest the individual investors may trade on 'noise' and emotions rather than facts. Investor sentiment results in investors believing in future cash flows and investment risks that have not been justified. A number of studies show that investor sentiment may lead to prices diverging from their fundamental values (De Long et al., 1990; Baker and Wurgler, 2006, 2007, 2012; Yu and Yuan, 2011; Huang et al., 2015; Da et al., 2015; Jiang et al., 2018), and that investor sentiment matters in explaining stock returns.

Furthermore, Table 5.7 reports that the implied funding liquidity measure is associated with some existing investor sentiment indexes, such as HJTZ, UMC, CB, and PCR, which suggests that our implied funding liquidity measure may contain additional information beyond what is captured by the existing investor sentiment indices. In this section, we estimate whether our liquidity measure matters after controlling for these indices.

Following the previous literature, we consider seven existing investor sentiment measures documented in section 5.5. We include these indices in the cross-sectional regressions with the implied funding liquidity measure. In order to com-

Table 6.10: Cross-sectional Regressions with Liquidity Measures: Hedge Funds

Model	λ_0	$\lambda_{\Delta IFL}$	λ_{MKT}	λ_{PS}	λ_{TED}	λ_{FG}	λ_{Noise}	λ_{Amihud}	λ_{RS}	λ_{CS}	λ_{Sadka}	R^2
+PS	0.3463***	0.0444***	0.2733***	3.0442***								52.75%
	(7.92)	(13.92)	(8.36)	(7.32)								
+TED	0.5856***	0.0462***	0.2691***		-0.4205***							54.88%
	(6.24)	(14.66)	(8.33)		(-3.26)							
+FG	0.3687***	0.0487***	0.2800***			-0.1350***						52.86%
	(8.18)	(13.96)	(8.46)			(-3.29)						
+NOISE	0.3980***	0.0492***	0.2794***				-0.0181					53.14%
	(5.00)	(12.99)	(8.32)				(-1.39)					
+Amihud	0.4593***	0.0494***	0.2762***					-0.0377***				52.95%
	(7.04)	(13.73)	(8.40)					(-3.36)				
+RS	0.6610***	0.0503***	0.2696***						-8.1482***			53.93%
	(5.94)	(13.49)	(8.21)						(-3.79)			
+CS	0.3949***	0.0488***	0.2795***							-4.2751		52.85%
	(3.81)	(13.54)	(8.49)							(-0.61)		
+Sadka	0.3094***	0.0474***	0.2796***								431.326***	54.71%
	(7.09)	(13.82)	(8.51)								(6.45)	
+ALL	0.3161**	0.0336***	0.2662***	3.5113***	-0.6046***	-0.0401	0.1571***	-0.0631***	-11.288***	20.2351	375.024***	61.77%
	(2.56)	(14.90)	(8.16)	(6.58)	(-3.76)	(-0.94)	(7.38)	(-3.33)	(-2.80)	(1.22)	(6.10)	

This table reports the estimates of monthly percentage risk premiums ΔIFL for univariate and multivariate betas of the hedge fund portfolios. OLS estimates of the funding liquidity ΔIFL beta which is the slope coefficients from the time-series regressions of the monthly hedge fund excess returns on ΔIFL. The multivariate time-series regressions include Carhart's (1997) four factors, Fung and Hsieh's (2001, 2004) seven factors with the implied funding liquidity innovation, ΔIFL. PS Pástor and Stambaugh's (2003) measure, TED Brunnermeier et al.'s (2008) Treasury-LIBOR spread, $Noise$ Hu et al.'s (2013) Noise measure, FG Fontaine and Garcia's (2012) measure, $Amihud$ Amihud's (2002) il-liquidity measure, CS Corwin and Schultz's (2012) measure, RS the relative spread, and $Sadka$ Sadka's (2006). The full sample period spans January 1996 to August 2015. The Newey West t statistics are shown in bracket and the significance level is labelled in $*/**/***$ for 10%, 5% and 1% level, respectively.

pare performance, we use the univariate model with the implied funding liquidity factor as a benchmark.

6.4.1 Equity Returns

Panel A of Table 6.11 presents the estimates of the investor sentiment measures for the 25 size-to-book portfolios, while Panel B reports the estimates for the 30 industry portfolios.

Overall, in Panel A of Table 6.11, we find that implied funding liquidity remains positive and significant at the 1% level after controlling for the investor sentiment indexes. Aside from the DEG, all other investor sentiment proxies are significant at the 1% level. For example, after controlling for the BW, the model has an R-square of 12.64%. After considering all of the seven investor sentiment measures in relation to our implied funding liquidity measure, the model registers an R-square of 36.65%.

Similar patterns are observed in Panel B of Table 6.11 for the industry portfolios, except for UMC, which is not significant when we control for all the indexes. Table 5.7 indicates that UMC has a high correlation of 0.1515 with our measure, and this is consistent with the insignificance of UMC. Most importantly, our implied funding liquidity measure is still statistically significant when controlling for alternative investor sentiment proxies in the bivariate regressions. The R-square with all investor sentiment variables is approximately 32.85%.

Although our implied funding liquidity measure is constructed using option market data, its connection with PCR is not very strong, which is a good indicator of the purity of our measure, which is consistent with the findings in Hu et al. (2013). The coefficients for implied funding liquidity remain positive and significant after controlling for established investor sentiment measures, suggesting that our measure contains additional information beyond that in existing investor sentiment indices in the US stock market.

6.4.2 Currency Portfolios

Panel A of Table 6.12 presents the estimates of the liquidity measures for the currency portfolios of all countries, while Panel B reports the estimates of the liquidity measures for the currency portfolios of the developed countries.

Table 6.12 (Panel A) shows that, in the currency market, implied funding liq-

Table 6.11: Cross-sectional Regressions with Investor Sentiment Measures

Panel A: 25 Portfolios										
	λ_0	$\lambda_{\Delta IFL}$	$\lambda_{\Delta BW}$	$\lambda_{\Delta HJTZ}$	$\lambda_{\Delta UMC}$	$\lambda_{\Delta CB}$	$\lambda_{\Delta DEG}$	$\lambda_{\Delta JLMZ}$	$\lambda_{\Delta PCR}$	R^2
+BW	0.5534***	0.1909***	4.5357***							12.64%
	(6.00)	(28.92)	(7.01)							
+HJTZ	0.4461***	0.1606***		-4.8766***						14.49%
	(4.76)	(27.68)		(-14.94)						
+UMC	0.5859***	0.1718***			0.2892***					15.63%
	(6.31)	(24.48)			(12.60)					
+CB	0.6156***	0.1435***				5.5077***				18.30%
	(6.78)	(19.18)				(18.03)				
+DEG	0.5067***	0.1905***					0.1325**			12.34%
	(5.38)	(28.61)					(2.54)			
+JLMZ	0.5318***	0.2083***						6.1172***		22.15%
	(5.69)	(32.84)						(23.43)		
+PCR	0.4650***	0.1364***							-13.763***	15.02%
	(5.00)	(19.06)							(-31.04)	
+ALL	0.6560***	0.0709***	12.8344***	-8.7190***	0.0681**	4.2241***	0.3063***	6.0341***	-10.224***	35.65%
	(7.36)	(10.90)	(16.12)	(-33.46)	(2.63)	(11.69)	(6.68)	(26.84)	(-20.23)	
Panel B: 30 Industry Portfolios										
+BW	0.7376***	0.1939***	3.9014***							12.01%
	(11.26)	(13.93)	(3.29)							
+HJT	0.6081***	0.1481***		-7.3634***						14.82%
	(10.03)	(12.47)		(-15.23)						
+UMC	0.7530***	0.1803***			0.2049***					14.10%
	(13.29)	(12.02)			(6.50)					
+CB	0.7930***	0.1522***				4.8301***				16.14%
	(13.71)	(10.35)				(10.94)				
+DEG	0.6918***	0.1943***					-0.1059			11.71%
	(11.16)	(14.04)					(-1.66)			
+JLMZ	0.7201***	0.2095***						5.5068***		18.84%
	(11.64)	(14.65)						(16.98)		
+PCR	0.6607***	0.1457***							-12.166***	13.38%
	(10.72)	(12.50)							(-11.33)	
+ALL	0.7973***	0.0719***	12.8511***	-11.026***	-0.0228	4.3295***	0.1739**	5.8220***	-8.3525***	32.85%
	(13.86)	(5.93)	(9.06)	(-14.78)	(-0.66)	(9.64)	(2.25)	(17.02)	(-8.02)	

This table reports the estimates and Newey West t-statistics (in the bracket) from the cross-sectional regressions. IFL denotes the implied funding liquidity measure. We consider seven investor sentiment indexes, including Baker and Wurgler's (2006) investor sentiment measure (BW), Huang et al.'s (2015) aligned investor sentiment index (HJTZ), the consumer sentiment index of University of Michigan (UMC), the Conference Board consumer confidence index (CB), Da et al.'s (2015) Financial and Economics Attitudes Revealed by Search (FEARS) index (DEG), Jiang et al.'s (2018) manager sentiment index (JLMZ), as well as CBOE Put-Call ratios, (PCR). +All indicates regressions with all of the relevant variables in the model. The significance level is written in $*/{*}{*}/{*}{*}{*}$ for 10%, 5% and 1% level, respectively.

Table 6.12: Cross-sectional Regressions with Investor Sentiment Measures of Currency Portfolios

	λ_0	$\lambda_{\Delta IFL}$	$\lambda_{\Delta BW}$	$\lambda_{\Delta HJTZ}$	$\lambda_{\Delta UMC}$	$\lambda_{\Delta CB}$	$\lambda_{\Delta DEG}$	$\lambda_{\Delta JLMZ}$	$\lambda_{\Delta PCR}$	R^2
Panel A: All Countries										
+BW	0.3058***	0.0646***	2.3506***							10.81%
	(4.90)	(5.90)	(5.61)							
+HJTZ	0.2571***	0.0526***		-1.9313***						12.26%
	(4.41)	(4.86)		(-4.89)						
+UMC	0.2745***	0.0658***			-0.0185					9.99%
	(4.69)	(5.89)			(-1.92)					
+CB	0.2711***	0.0683***				-0.4275*				10.21%
	(4.52)	(6.34)				(-2.21)				
+DEG	0.2771***	0.0650***					-0.1044*			10.94%
	(4.59)	(5.98)					(-2.45)			
+JLMZ	0.2888***	0.0701***						1.9300***		16.29%
	(4.71)	(5.98)						(5.91)		
+PCR	0.2711***	0.0522***							-3.1259***	10.67%
	(4.69)	(6.55)							(-3.92)	
+ALL	0.2756***	0.0498***	3.9217***	-3.2945***	-0.0069	-0.6294**	-0.0053	2.2986***	-1.6739**	26.46%
	(4.64)	(6.77)	(5.72)	(-5.57)	(-0.59)	(-2.66)	(-0.13)	(6.16)	(-2.58)	
Panel B: Developed Countries										
+BW	0.4110***	0.0812***	3.3741***							9.42%
	(5.33)	(5.92)	(7.26)							
+HJTZ	0.3371***	0.0618***		-3.1139***						10.99%
	(4.76)	(6.15)		(-4.58)						
+UMC	0.3687***	0.0824***			-0.0176					8.05%
	(4.84)	(6.13)			(-1.73)					
+CB	0.3646***	0.0850***				-0.4424				8.97%
	(4.80)	(5.97)				(-1.35)				
+DEG	0.3691***	0.0819***					-0.1758**			9.20%
	(4.94)	(5.98)					(-3.42)			
+JLMZ	0.3848***	0.0880***						2.4020***		13.30%
	(5.10)	(6.06)						(7.34)		
+PCR	0.3581***	0.0591***							-5.5841**	10.59%
	(5.14)	(5.71)							(-2.97)	
+ALL	0.3687***	0.0503***	5.9631***	-4.8526***	-0.0090	-0.6626	-0.0227	2.8646***	-3.8131*	25.72%
	(4.86)	(5.17)	(6.95)	(-5.20)	(-0.67)	(-1.49)	(-0.38)	(7.67)	(-2.09)	

This table reports the estimates and Newey West t-statistics (in the bracket) from the cross-sectional regressions for the currency portfolios. IFL denotes the implied funding liquidity measure. We considered seven investor sentiment indexes, including Baker and Wurgler's (2006) investor sentiment measure (BW), Huang et al.'s (2015) aligned investor sentiment index (HJTZ), the consumer sentiment index of University of Michigan (UMC), the Conference Board consumer confidence index (CB), Da et al.'s (2015) Financial and Economics Attitudes Revealed by Search (FEARS) index (DEG), Jiang et al.'s (2018) manager sentiment index (JLMZ), as well as CBOE Put-Call ratios, (PCR). +All indicates regressions with all of the relevant variables in the model. The significance level is written in $*/**/***$ for 10%, 5% and 1% level, respectively.

uidity remains positive and significant at the 1% level after controlling for the investor sentiment indexes. Aside from UMC, all other investor sentiment proxies are significant. When we include all of the seven investor sentiment measures with our implied funding liquidity measure in one model, the model registers an R-square of 26.46%, and the estimate for our measure ($\lambda_{\Delta IFL}$) is 0.0498 which is significant at the 1% level.

For comparisons, the results for the developed countries are reported in Panel B of Table 6.12, in which we observe similar patterns. Our implied funding liquidity measure is still statistically significant when controlling for alternative investor sentiment proxies in the bivariate regressions, even though some investor indexes, such as UMC and CB, become insignificant. The R-square with all investor sentiment variables is approximately 25.72%.

In short, the coefficients for implied funding liquidity remain positive and significant after controlling for well-known investor sentiment indexes, which suggests that our measure contains additional information beyond that in existing investor sentiment indexes in the foreign exchange market.

6.4.3 Hedge Fund Returns

Table 6.13 presents the estimates of the liquidity measures for the hedge fund portfolios.

As with the patterns in equity market and the currency market, Table 6.13 shows that, in the hedge fund market, the implied funding liquidity remains positive and significant at the 1% level after controlling for the investor sentiment indexes. Except for UMC, all other investor sentiment indices are significant at the 1% level in both the bivariate model and the model including all variables. After including all of the seven investor sentiment measures with our implied funding liquidity measure in one model, the model registers an R-square of 38.78%, and the estimate for our measure ($\lambda_{\Delta IFL}$) is 0.0569, which is significant at the 1% level.

The coefficients for implied funding liquidity remain positive and significant after controlling for well-known investor sentiment indexes, which suggests that our measure contains additional information beyond that in existing investor sentiment indexes in the hedge fund market.

Table 6.13: Cross-sectional Regressions with Investor Sentiment Measures of Hedge Fund

	λ_0	$\lambda_{\Delta IFL}$	$\lambda_{\Delta BW}$	$\lambda_{\Delta HJTZ}$	$\lambda_{\Delta UMC}$	$\lambda_{\Delta CB}$	$\lambda_{\Delta DEG}$	$\lambda_{\Delta JLMZ}$	$\lambda_{\Delta PCR}$	R^2
+BW	0.2865***	0.0968***	2.1116***							25.08%
	(9.10)	(12.30)	(7.97)							
+HJTZ	0.2238***	0.0826***		-2.2010***						27.39%
	(6.59)	(12.86)		(-8.44)						
+UMC	0.2614***	0.0958***			0.0146					25.41%
	(7.91)	(12.73)			(1.58)					
+CB	0.2764***	0.0878***				0.9928***				26.51%
	(8.50)	(13.08)				(5.60)				
+DEG	0.2578***	0.0971***					-0.0486***			24.49%
	(7.94)	(12.32)					(-5.85)			
+JLMZ	0.2729***	0.0993***						0.9175***		26.28%
	(8.75)	(12.17)						(6.86)		
+PCR	0.2474***	0.0813***							-4.2250***	26.56%
	(7.41)	(11.20)							(-7.10)	
+ALL	0.2914***	0.0569***	4.7855***	-3.2389***	-0.0565***	1.4546***	0.0640***	0.9625***	-3.1325***	38.79%
	(9.38)	(11.91)	(9.28)	(-8.71)	(-8.38)	(7.82)	(4.46)	(7.06)	(-5.49)	

This table reports the estimates and Newey West t-statistics (in the bracket) from the cross-sectional regressions. IFL denotes the implied funding liquidity measure. We considered seven investor sentiment indexes, including Baker and Wurgler's (2006) investor sentiment measure (BW), Huang et al.'s (2015) aligned investor sentiment index (HJTZ), the consumer sentiment index of University of Michigan (UMC), the Conference Board consumer confidence index (CB), Da et al.'s (2015) Financial and Economics Attitudes Revealed by Search (FEARS) index (DEG), Jiang et al.'s (2018) manager sentiment index (JLMZ), as well as CBOE Put-Call ratios, (PCR). +All indicates regressions with all of the relevant variables in the model. The significance level is written in $*/**/***$ for 10%, 5% and 1% level, respectively.

6.5 The Economic Value of Implied Funding Liquidity

The findings reported in the previous sections suggest that implied funding liquidity predicts future market returns and explains the cross-sectional variations of stock returns. In this section, first we examine the profitability of the portfolio strategy of investing in the stocks with the largest exposures to implied funding liquidity innovations, and shorting the stocks with the lowest exposures to these liquidity innovations. Then, we estimate the profitability of the portfolio strategy using the currency forward discounts. Due to the fact of limited access to the Lipper Hedge Fund Database (TASS), we do not check the economic value of implied funding liquidity in the hedge fund market.

We sort stocks into ten portfolios based on these exposures, which are obtained by regressing the monthly stock returns to the monthly liquidity innovations over the past three years. We keep the composition of the portfolios constant over the horizon of one year and rebalance the portfolios once a year. For all stocks in our sample, the monthly returns are computed based on the mid-quote price. As in the existing literature (Menkhoff et al., 2012), we use an equal-weighting scheme to compute the average portfolio returns from the constituent stock returns. The analysis is based on monthly equity data obtained from the CRSP for the period 4 January 1996 to 31 August 2015.

Panel A of Table 6.14 shows the descriptive statistics of the monthly returns for portfolios constructed based on exposure to implied funding liquidity. We observe that sorting stocks based on this exposure generates a large cross-sectional spread in returns. In particular, stock returns increased consistently from the portfolios with the lowest exposure to the portfolios with the largest exposure to implied funding liquidity innovations. This evidence is further supported by the monotonicity MR test statistic developed by Patton and Timmermann (2010) which rejects the null hypothesis of non-monotonicity with a p-value approaching zero. The strategy of investing in those with the largest exposure and shorting those with the lowest exposure to implied funding liquidity innovations generated an average excess return of 0.61% per month or approximately 7.3% per annum. This long-short strategy return is significant at the 10% level. The Sharpe ratio for the investment is approximately 0.45.

We recognise that transaction costs matter in equity markets. Therefore, we integrated bid and ask prices for the long and short positions when the portfolios were rebalanced. Panel B of Table 6.14 displays the returns from the long and short positions with and without controlling for transaction costs. Note that the average return from the long-short portfolios is reduced to 0.50% per month or about 6.04% per year. The Sharpe ratio for the long-short investments is slightly reduced at 0.37. Returns obtained from buying stocks with the largest exposure and selling those with the lowest are statistically significant at the 10% level and remain economically significant. This evidence indicates that implied funding liquidity innovations generate a large cross-section spread in stock returns and that their effects are not affected by transaction costs.

Table 6.14: Equity Portfolio Characteristics Based on the Exposure to ΔIFL

Panel A: Portfolio Sorted Returns								
	Mean (%)	t Value	Std. (%)	Skew	Kurt	AC(1)	SR	IFL Betas
P1	8.53	1.59	6.30	0.67	3.91	0.12	0.39	-0.40
P2	11.58	3.10	4.40	-0.18	3.25	0.20	0.76	-0.07
P3	12.41	3.49	4.18	-0.49	4.28	0.23	0.86	0.02
P4	12.11	3.44	4.14	-0.52	2.76	0.21	0.84	0.09
P5	12.60	3.31	4.48	-0.48	2.57	0.23	0.81	0.15
P6	13.69	3.32	4.85	-0.20	1.74	0.20	0.82	0.21
P7	13.70	3.02	5.33	-0.39	1.57	0.23	0.74	0.28
P8	14.57	2.82	6.07	-0.28	1.84	0.24	0.69	0.37
P9	15.68	2.53	7.28	0.09	1.66	0.25	0.62	0.50
P10	15.79	1.99	9.34	0.49	1.70	0.23	0.49	0.98
MR p-value $<$ 0.001								
Panel B: High Minus Low Portfolio Returns								
	Mean (%)	t Value	Std.	Skew	Kurt	AC(1)	SR	
P10 - P1	7.27	1.83	4.68	1.01	3.44	0.29	0.45	
Adj. P10 - P1	6.04	1.82	4.67	1.01	3.46	0.29	0.37	
Panel C: Economic Uncertainty								
	Mean (%)	t Value	Std.	Skew	Kurt	AC(1)	SR	
High Sentiment	8.29	1.96	4.23	1.37	3.86	0.51	0.67	
Low Sentiment	5.97	1.87	4.44	1.21	3.15	0.22	0.47	
Panel D: VIX								
	Mean (%)	t Value	Std.	Skew	Kurt	AC(1)	SR	
High Sentiment	7.41	1.88	4.99	1.81	3.63	0.47	0.51	
Low Sentiment	5.47	1.79	4.21	1.00	3.07	0.18	0.45	

Panel A of this table reports the returns for portfolios sorted based on the exposures of stock returns to the innovations in implied funding liquidity. The portfolios are formed every year based on the exposures over the previous three years and the constituent stock returns are equally weighted. P10 denotes the portfolio with the largest exposures while P1 has the stocks with the lowest exposures. MR denotes the Patton and Timmermann's (2010) test statistics that examine the monotonic relation of the decile portfolios. Panel B reports the returns from investing in portfolios with the highest exposures to implied funding liquidity innovations and shorting the stocks with the lowest. Panel C and Panel D report returns varies across high and low sentiment states for the economic uncertainty index and VIX, respectively. The analysis is based on the monthly equity data obtained from the CRSP for the period 4 January 1996 to 31 August 2015. Newey West t-statistics are shown in bracket and $*/{*}{*}/{*}{*}{*}$ denotes the significance level at 10%, 5% and 1% level, respectively.

In order to examine whether the ability of the Put-Call parity to explain returns varies across high and low sentiment states, we follow Beber et al. (2009) and Bali et al. (2017) to consider two regimes: high (mean + 1 standard deviation from the mean) and low sentiments. We use two state variables, the economic uncertainty and CBOE VIX[1].

Panel C and Panel D of the table 6.14 report returns varies across high and low sentiment states for the economic uncertainty index and VIX, respectively. Note that the average return from the long-short portfolios of high sentiment for the economic uncertainty and VIX are approximately 8.29% and 7.41% per year, respectively. Also, the long-short portfolios for the low sentiment regime are lower compared with that of high sentiment regime, but they are still significant. These findings show that our implied funding liquidity represents a new risk factor.

Table 6.15: Currency Portfolio Characteristics Based on Exposure to ΔIFL

Panel A: Portfolio Sorted Returns							
	Mean (%)	t Value	Std. (%)	Skew	Kurt	AC(1)	SR
P1	-0.21	-1.81	1.79	0.26	1.12	0.02	-0.41
P2	-0.14	-1.25	1.73	0.05	1.64	0.10	0.56
P3	-0.15	-1.24	1.83	0.05	1.64	0.10	0.95
P4	0.03	0.20	2.05	-0.02	0.94	-0.04	-0.28
P5	0.07	0.47	2.20	-0.23	1.39	0.03	-0.28
P6	0.07	0.47	2.23	-0.23	1.39	0.03	0.05
P7	0.22	1.51	2.20	-0.57	3.03	0.10	0.11
P8	0.24	1.51	2.41	-0.57	3.03	0.10	0.11
P9	0.43	2.48	2.62	-0.47	2.47	0.10	0.34
P10	0.47	2.48	2.90	-0.47	2.48	0.10	0.35
MR p-value $<$ 0.001							
Panel B: High Minus Low Portfolio Returns							
	Mean (%)	t Value	Std.	Skew	Kurt	AC(1)	SR
P10 - P1	0.68	4.20	2.49	-0.25	1.07	0.13	0.56

Panel A of this table reports the returns for currency portfolios sorted based on the exposures of forward discounts to the innovations in implied funding liquidity. The portfolios are formed every year based on the exposure over the previous three years and the constituent forward discounts are equally weighted. P10 denotes the portfolio with the largest exposure while P1 has the forward discounts with the lowest exposures. MR denotes Patton and Timmermann's (2010) test statistics that examine the monotonic relation of the decile portfolios. Panel B reports the returns from investing in portfolios with the highest exposures to implied funding liquidity innovations and shorting the stocks with the lowest. The analysis is based on the forward discounts for the period January 1996 to August 2015. Newey West *t*-statistics are shown in bracket and $*$/$**$/$***$ denotes the significance level at 10%, 5% and 1% level, respectively.

Similarly, we build the same portfolio strategy for the currency markets. Table 6.15 (Panel A) reports the descriptive statistics of the monthly currency returns for portfolios constructed based on exposure to implied funding liquidity. We observe

[1] Jurado et al. (2015) provide a factor-based index of economic uncertainty. We obtain the one-month economic uncertainty index. We thank Dr Sydney C Ludvigson for providing data of the economic uncertainty index, and it is available at his website: `https://www.sydneyludvigson.com/data-and-appendixes/`. The historical data of VIX is available at `https://fred.stlouisfed.org/series/VIXCLS`.

similar patterns. For example, currency returns increased consistently from the portfolios with the lowest exposure to the portfolios with the largest exposure to implied funding liquidity innovations, and the monotonicity MR test statistic developed by Patton and Timmermann (2010) which rejects the null hypothesis. The strategy of investing in those with the largest exposure and shorting those with the lowest exposure to implied funding liquidity innovations generated an average excess return of 0.68% per month or approximately 8.16% per annum.

Consistent with Mancini et al. (2013), our implied funding liquidity measure can explain the popular carry trade strategy. This suggests that our implied funding liquidity measure probably drives part of the strategy return, indicating that the implied funding liquidity risk is priced in the foreign exchange markets.

6.6 Implied Funding Liquidity and Macroeconomic Variables

Intuitively, the forward-looking nature of our implied funding liquidity measure make it reasonable as a predictor for the real economy. If market funding illiquidity worsens, it should contain information about the future macro-economy. Having established the link between implied funding liquidity and stock returns, we examine whether implied funding liquidity has any predictive power over developments in the real economy. In a manner similar to Næs et al. (2011), we use four proxies to capture the changes in the macroeconomic conditions: the unemployment rate, the PMI, the CPI, and the Nonfarm payroll. Other macroeconomic variables, such as GDP and IP, were also discussed in prior studies (Chen et al., 2016, 2017), but for comparison purpose with prior studies, we keep our measure selections with the key paper (Næs et al., 2011). Following Levine and Zervos (1998) and Næs et al. (2011), we assess the predictability of the implied funding liquidity measure in a time-series model as follows:

$$\sum_{t}^{t+h} Z_{i,t} = \alpha + \beta_{IFL} \times IFL_t + \beta_t \times r_{t-1} + \varepsilon_t \tag{6.1}$$

where $\sum_{t}^{t+h} Z_{i,t}$ is the cumulative change of the macroeconomic variable i over an horizon of h at time t; IFL_{t-1} is the funding liquidity measure for month t-1; r_{t-1} denotes the excess return of the $S\&P500$ at time t-1. We used monthly data for this analysis from January 1996 to August 2015. In addition, Newey and West (1987) standard errors are reported.

Table 6.16: Macroeconomic Variables

Panel A: Unemployment Rate			
Horizon (in months)	IFL_{t-1}	$MKTEX_{t-1}$	Adj R-Sq
3	1.29***	-0.24***	8.88%
(t-stat)	(2.93)	(-2.90)	
6	2.5105***	-0.4664***	11.49%
(t-stat)	(3.34)	(-3.31)	
9	3.05***	-0.69***	10.56%
(t-stat)	(2.87)	(-3.48)	
12	2.95**	-0.95***	9.43%
(t-stat)	(2.17)	(-3.71)	
Panel B: Purchasing Manager Index			
Horizon (in months)	IFL_{t-1}	$MKTEX_{t-1}$	Adj R-Sq
3	0.81	-0.45***	10.48%
(t-stat)	(1.48)	(-4.40)	
6	-0.35	-0.2846*	0.43%
(t-stat)	(-0.39)	(-1.69)	
9	-1.85*	-0.15	0.51%
(t-stat)	(-1.69)	(-0.73)	
12	-3.01**	-0.08	2.12%
(t-stat)	(-2.51)	(-0.39)	
Panel C: CPI Rate			
Horizon (in months)	IFL_{t-1}	$MKTEX_{t-1}$	Adj R-Sq
3	-0.22***	0.021***	14.75%
(t-stat)	(-4.91)	(2.43)	
6	-0.34***	0.028**	15.88%
(t-stat)	(-5.23)	(2.36)	
9	-0.44***	0.014	15.17%
(t-stat)	(-5.71)	(1.02)	
12	-0.50***	0.03*	17.98%
(t-stat)	(-5.92)	(1.97)	
Panel D: Nonfarm Payroll			
Horizon (in months)	IFL_{t-1}	$MKTEX_{t-1}$	Adj R-Sq
3	-0.14***	0.019***	11.03%
(t-stat)	(-3.75)	(2.71)	
6	-0.28***	0.04***	13.46%
(t-stat)	(-3.96)	(3.26)	
9	-0.38***	0.06***	12.93%
(t-stat)	(-3.67)	(3.41)	
12	-0.42***	0.09***	11.61%
(t-stat)	(-3.13)	(3.55)	

This table shows the predictability of implied funding liquidity for unemployment (Panel A), PMI rate (Panel B), CPI rate (Panel C), and the nonfarm payroll (Panel D) over horizons of three months, six months, nine months, and one year. IFL_{t-1} is the implied funding liquidity at t-1, and $MKTEX_{t-1}$ is the market excess returns. Newey-West adjusted t-statistics are presented in parentheses. The full sample period spans January 1996 to August 2015, the significance level is labelled as $*/**/***$ for 10%, 5% and 1%, respectively.

Table 6.16 show the results from the time-series regressions with horizons of one month, three months, six months, nine months, and one year for the unemployment rate (Panel A), PMI rate (Panel B), CPI rate (Panel C) and nonfarm payroll (Panel D). We observe that excess market return can predict future changes in a number of macro variables including, for instance, the unemployment rate and nonfarm payroll.

Interestingly, implied funding liquidity is positively and significantly related to unemployment rate changes, while it is negatively and significantly related to PMI, CPI rate changes and nonfarm payroll growth. This is consistent with the result in Section 4.2. Tighter funding squeezes lead to stock market declines and worsen macroeconomic conditions.

6.7 Summary

In summary, we presented the main empirical results in this chapter. The results in section 6.1 show that implied funding liquidity conveys forward-looking information about future funding liquidity conditions beyond what is currently captured by other funding liquidity measures. Moreover, the predictive power of the implied funding liquidity measure is significant from one- to six-month horizons and remains consistent for both $S\&P500$ returns and the value-weighted market returns from CRSP.

Section 6.2 presented the results for asset-pricing tests of the implied funding liquidity innovations in stock, currency, and hedge fund markets. Overall, the results indicates that the sensitivities of equity and industry portfolios to funding liquidity tend to proportionally explain their risk, which is not fully captured by other well-known priced factors.

Section 6.3 reported the results for the test of whether our implied funding liquidity measure potentially provides incremental information about asset returns beyond what is captured in the previous well-known liquidity measures. In section 6.4, the coefficients for implied funding liquidity remained positive and significant after controlling for established investor sentiment measures, suggesting that our measure contains additional information beyond existing investor sentiment indexes in the U.S. stock market.

The evidence in section 6.5 indicates that implied funding liquidity innovations generate a large cross-section spread in stock returns and that their effects are not affected by transaction costs. In section 6.6, we observed implied funding liquidity is positively and significantly related to unemployment rate changes, while it was negatively and significantly related to PMI and CPI rate changes and nonfarm payroll growth.

Chapter 7. Robustness Tests

In this chapter, we begin by estimating the influence of the presence of informed trading for our implied funding liquidity. Then, we demonstrate that our results are robust to a range of alternative measures of implied funding liquidity.

First, in section 7.2, we consider the influence of moneyness in the construction of our implied funding liquidity measure. Following Pan (2002), we obtain only at-the-money option pairs, which are call and put options with the strike prices between 0.95 and 1.05 times the underlying spot prices, to compute an at-the-money adjusted implied funding liquidity measure.

Second, deviations of Put-Call parity may result from non-synchronicity in reporting of the closing stock prices in the option and underlying stock markets (Battalio and Schultz, 2006). Therefore, we use the delta-gamma approximation method to compute the implied volatility for each option, and then the adjusted implied funding liquidity measure based on this underlying price in section 7.3.

Third, as most regulators of stock exchanges around the world imposed restrictions or bans on short-selling in the financial crises, we construct an alternative implied funding liquidity measure with the samples extracting the underlying stocks with short-selling constrictions in section 7.4.

Finally, we form a dollar volume-weighted implied funding liquidity measure in section 7.5, and an equally weighted implied funding liquidity measure in section 7.6.

7.1 Information Asymmetry

Previous studies (Lu and Lin, 2015; Rösch et al., 2017) show that there is a relationship between Put-Call parity deviations and the presence of informed trading. This relation arises because informed traders might use the options to trade on their information advantage. Based on the literature, such as Brown and Hillegeist (2007), we used the probability of informed trade (PIN) measure to control for the level of information asymmetry in the stock markets. The PIN measure was computed as follows:

$$PIN = (\mu * \alpha)/(\mu * \alpha + 2 * \epsilon) \tag{7.1}$$

where μ indicates informed traders' trading intensities, α shows the probability of an information event, and ϵ represents uninformed traders' trading intensities (trades per day). Following Venter and De Jongh (2006), we use the PIN measure on a quarterly basis[1].

To control for the influence of information asymmetry in stock returns, we perform the following procedure. First, at the end of each quarter, we sort individual stocks into 25 equal number portfolios created at the intersection of five groups, based on the exposure to implied funding liquidity (β) and five groups based on the PIN measure. Second, we obtain the return differences from investing in stocks with the highest exposure and shorting stocks with the lowest exposure to implied funding liquidity for each group of the PIN measure. The return difference indicates the asset-pricing effects of implied funding liquidity after controlling for the differences in the level of informed trading across stocks.

Table 7.1: Portfolio Characteristics Based on PIN and the Exposure to ΔIFL

	β1	β2	β3	β4	β5	β5-β1
PIN1	0.4009	0.6742	1.0458	1.3501	2.3393	1.9384*
	(0.35)	(0.90)	(1.42)	(1.54)	(1.77)	(1.77)
PIN2	1.3721	1.3772	1.5665	1.5595	1.9972	0.6250
	(1.13)	(1.89)	(2.11)	(1.79)	(1.69)	(0.51)
PIN3	0.6723	1.4062	1.2240	1.3341	2.1016	1.4293
	(0.56)	(1.87)	(1.76)	(1.66)	(1.70)	(1.07)
PIN4	0.0367	0.6670	0.7932	0.5948	1.3056	1.2689*
	(0.03)	(0.91)	(1.33)	(0.88)	(1.13)	(0.91)
PIN5	-0.7985	-0.4789	-0.2767	-0.2911	-0.6410	0.1575
	(-0.69)	(-0.86)	(-0.57)	(-0.50)	(-0.63)	(0.12)
PIN5 - PIN1	-1.1994	-1.1531***	-1.3225**	-1.6412***	-2.9803***	
	(-1.23)	(-2.68)	(-2.61)	(-2.78)	(-3.15)	

This table reports the descriptive statistics for quarterly returns of portfolios sorted based on the exposures of stock returns to the innovations in implied funding liquidity and the PIN measure for the sample period January 1996 to August 2015. On a quarterly basis, we sort stocks into five equal groups based on the exposures to implied funding liquidity innovations (β) jointly with five equal groups based on the PIN measure. β5-β1 denotes the return difference from investing in stocks with the highest exposure and shorting stocks with the lowest exposure to implied funding liquidity. PIN5-PIN1 denotes the return from long and short positions in portfolios with the highest PIN measure versus ones with the lowest PIN measure. *t*-statistics of the returns are shown in parentheses and $*$, $**$, $***$ denote significance levels of 10%, 5% and 1% level, respectively.

[1] We thank Stephen Brown for providing the variable, and it is available at `http://scholar.rhsmith.umd.edu/sbrown/pin-data?destination=node/998`

Table 7.1 presents the results of the robustness checks for information asymmetry. As with the results of Brown and Hillegeist (2007), we observe a negative relationship between stock returns and the PIN measure. That is, average returns are lower for stocks with a higher level of informed trading. Importantly, the return difference between stocks with the highest and lowest exposures to implied funding liquidity innovations is positive for all groups sorted based on the PIN measure, and the effect remains most pronounced for the group with the lowest PIN. The results show that implied funding liquidity remains significant in explaining the variations of stock returns after controlling for the differences in the level of information asymmetry across stocks.

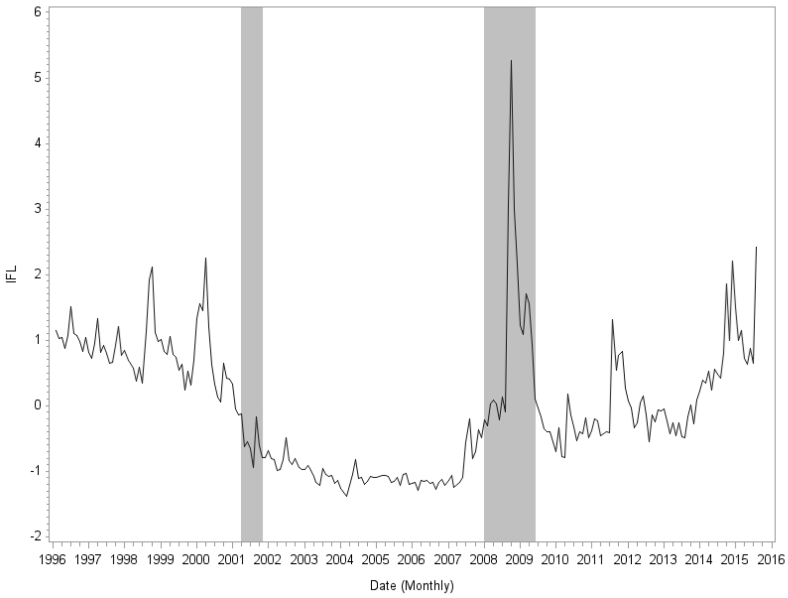
7.2 At-the-Money Options

In the previous chapters, implied funding liquidity was computed across all calls and puts with various strike prices and maturity dates. As reported in Table 5.1, the absolute deviations from Put-Call parity were greater for deep in-the-money or out-of-the-money options. This is consistent with the established fact in the literature that implied volatilities for deep in-the-money or out-of-the-money options deviate significantly from those obtained for at-the-money options. We therefore sought to perform further robustness checks for these patterns in implied volatilities. Following Pan (2002), on each date, we collected at-the-money option pairs, which are call and put options with the strike prices between 0.95 and 1.05 times the underlying spot prices[2]. Then we could calculate the adjusted IFL and ΔIFL with functions 4.3 and 4.4 with the at-the-money option samples.

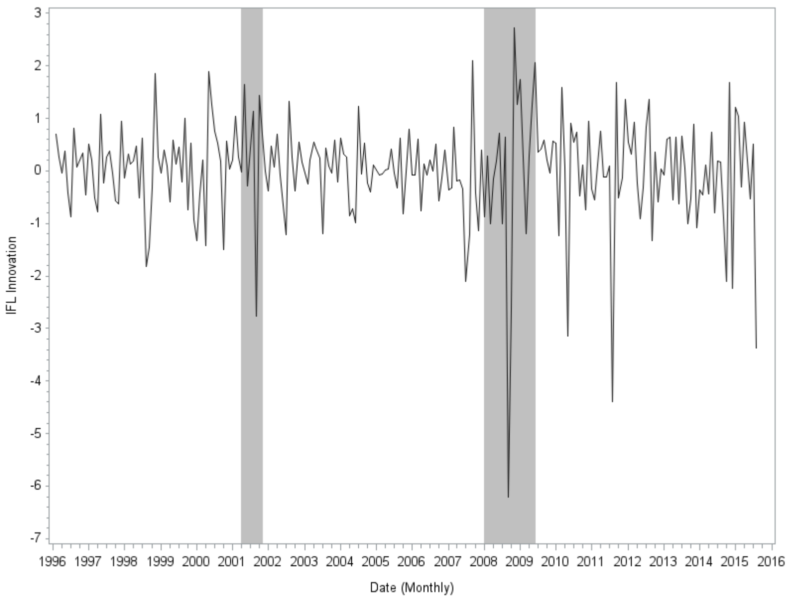
Figure 7.1 shows the standardised monthly time-series of the adjusted implied funding liquidity measure with at-the-money options from January 1996 to August 2015 with the NBER recession periods in the light grey. We still see significant increases in the liquidity measure during the previously mented episodes of financial stress. The largest jump in the liquidity measure occurred in October 2008 which coincided with the collapse of Lehman Brothers and the funding squeezes in interbank lending markets. Compared to Figure 5.1, we observe that even though we still had the sample pattern for the implied funding liquidity measure, the magnitude of peak values is larger.

In order to estimate the return-predictability power of the at-the-money option

[2]Hull (2015) indicates that if the stick price of an option is the same as the spot price of its underlying asset, it is at the money. Following prior studies, such as Fleming and Ostdiek (1996) and Dumas et al. (1998), we defined the moneyness of at the money as follows: an option is at the money if the ratio of maturity prices to spot prices is between 0.95 and 1.05.



(a) Monthly Level



(b) Monthly Innovations

Figure 7.1: At-The-Money Option Adjusted Implied Funding Liquidity

This figure presents the time series of the monthly level (Panel a) and innovations (Panel b) of the standardised adjusted implied funding liquidity measure with at-the-money option pairs for the sample from 4 January 1996 to 31 August 2015. The shaded areas contain the NBER's Business Cycle dates.

adjusted implied funding liquidity measure, we still obtained monthly returns of the S&P500 index and the value-weighted average returns provided by CRSP as market return measures. Similarly, we control for variables that are found to predict market returns, including the dividend yield on the $S\&P500$ index, the real GNP growth rate, the long-term government bond return, and the past market excess return. We still used the predictive regression model 4.13.

Table 7.2: Market Return Predictability with At-The-Money Option Adjusted Implied Funding Liquidity

Panel A: CRSP Value-Weighted Market Returns						
	$\triangle IFL_{t-1}$	r_{t-1}	DIV_{t-1}	GNP_{t-1}	LTG_{t-1}	Adj R^2
1	0.0003	-0.0094	-0.0016	5.4278***	0.0373***	12.27%
(t-stat)	(1.22)	(-0.13)	(-0.19)	(3.49)	(2.63)	
3	0.0011***	0.9710***	0.0272*	12.3824***	0.0381**	57.02%
(t-stat)	(3.12)	(10.38)	(2.45)	(6.16)	(2.08)	
6	0.0011*	0.9476***	0.0884***	20.8212***	0.0098	34.57%
(t-stat)	(1.70)	(5.57)	(4.37)	(5.69)	(0.29)	
Panel B: S&P 500 Returns						
	$\triangle IFL_{t-1}$	r_{t-1}	DIV_{t-1}	GNP_{t-1}	LTG_{t-1}	Adj R-Sq
1	0.0004	-0.0562	-0.0004	6.1234***	0.0293**	13.34%
(t-stat)	(1.56)	(-0.78)	(-0.05)	(4.11)	(2.17)	
3	0.0011***	0.9001***	0.0262**	12.9071***	0.0252	55.57%
(t-stat)	(3.17)	(9.63)	(2.46)	(6.66)	(1.44)	
6	0.0011*	0.9123***	0.0821***	21.0707***	0.0005	34.27%
(t-stat)	(1.70)	(5.32)	(4.20)	(5.93)	(0.02)	

This table shows the predictability of the adjusted implied funding liquidity with horizons of one month, three months, and six months for CRSP value-weighted returns (Panel A) and S&P500 Returns (Panel B). The at-the-money option adjusted implied funding liquidity measure is computed from options with strike prices between 0.95 and 1.05 times the underlying spot prices. Dependent variables are the cumulative growth rates of each variable calculated over one, three and six months. IFL_{t-1} is the at-the-money adjusted implied funding liquidity at $t-1$, and $MKTEX_{t-1}$ is the market excess returns. The full sample period spans January 1996 to August 2015, the significance levels are presented as $*/{*}{*}/***$ for 10%, 5% and 1%, respectively.

Table 7.2 shows the results of the return predictive regressions for the at-the-money option adjusted implied funding liquidity measure with horizons of one month, three months, and six months for CRSP value-weighted returns (Panel A) and S&P500 returns (Panel B). We observe that the most coefficients for the at-the-money option adjusted liquidity measure remain positive and significant for horizons of three and six months. Specifically, compared to the results in 6.2, we find that it was not statistically significant for a horizon of one month, and the magnitude of the coefficients is smaller. The result shows that predictability is still significant, though it is weaker than the initial implied funding liquidity mea-

Table 7.3: Exposures to At-The-Money Option Adjusted Implied Funding Liquidity

Panel A: 25 Portfolios Formed on Size and Book-to-Market					
Betas	Low B/M	2	3	4	High B/M
Small	0.15***	0.11***	0.09***	0.09***	0.10***
	(3.19)	(2.76)	(2.92)	(2.82)	(3.13)
2	0.12***	0.10***	0.08***	0.09***	0.10***
	(2.97)	(3.18)	(2.78)	(2.88)	(3.01)
3	0.13***	0.09***	0.09***	0.10***	0.11***
	(3.43)	(3.12)	(3.44)	(3.59)	(3.87)
4	0.11***	0.12***	0.12***	0.11***	0.10***
	(3.44)	(4.33)	(4.08)	(4.19)	(3.24)
Big	0.08***	0.08***	0.09***	0.06**	0.10***
	(3.09)	(3.58)	(3.67)	(2.59)	(3.37)

Panel B: 30 Industry Portfolios					
Industry	Betas	Industry	Betas	Industry	Betas
Autos	0.12***	FabPr	0.12***	Paper	0.06**
	(2.65)		(3.18)		(2.12)
Beer	0.06**	Fin	0.08**	Rtail	0.08***
	(2.44)		(2.47)		(3.00)
Books	0.11***	Food	0.07***	Servs	0.09**
	(3.39)		(3.29)		(2.58)
BusEq	0.12***	Games	0.13***	Smoke	0.06*
	(2.64)		(3.40)		(1.66)
Carry	0.12***	Hlth	0.07***	Steel	0.15***
	(3.49)		(2.88)		(3.22)
Chems	0.09***	Hshld	0.03	Telcm	0.08***
	(2.86)		(1.46)		(2.62)
Clths	0.07**	Meals	0.08***	Trans	0.05*
	(2.05)		(3.26)		(1.65)
Cnstr	0.11***	Mines	0.15***	Txtls	0.06
	(3.22)		(3.36)		(1.27)
Coal	0.20***	Oil	0.11***	Util	0.08***
	(2.76)		(3.53)		(3.43)
ElcEq	0.10***	Other	0.07**	Whlsl	0.08***
	(2.88)		(2.03)		(2.92)

This table reports OLS estimates of the at-the-money option adjusted funding liquidity ΔIFL betas, $\beta_{i,\Delta IFL}$, which is the slope coefficients from the time-series regressions on ΔIFL for the sample period from 4 January 1996 to 31 August 2015. The implied funding liquidity measure is computed from options with strike prices between 0.95 and 1.05 times the underlying spot prices. Panel A uses the 25 monthly stock excess returns whilst Panel B obtains the 30 monthly industry portfolios. The full sample period spans January 1996 to August 2015. Newey West t-statistics are shown in parentheses and $*$, $**$, $***$ denote significance levels of 10%, 5% and 1%, respectively.

sure. The predictive power of the at-the-money option adjusted implied funding liquidity remains robust after controlling for other forecasting variables including dividend yield, the GNP growth rate and long-term government bond returns.

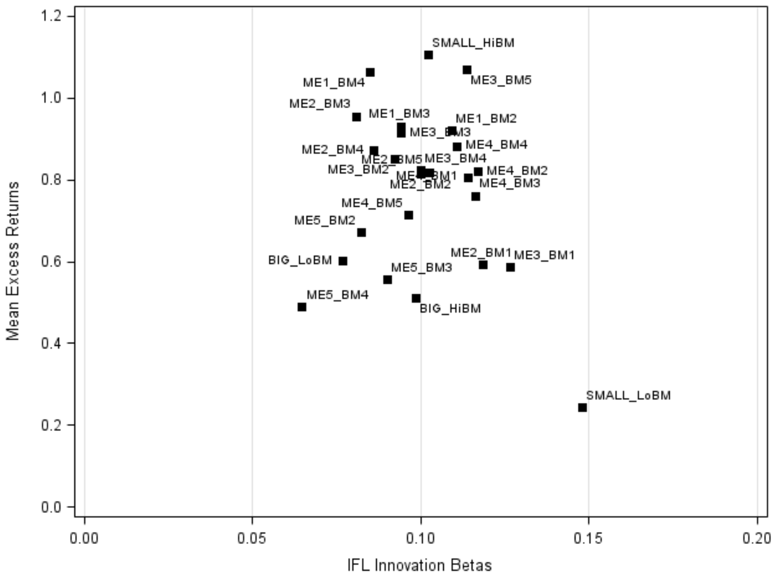
After establishing the return-predictive power of the at-the-money option adjusted implied funding liquidity, we examine whether the innovations in this adjusted liquidity measure matter in explaining the cross-sectional differences in stock returns. Following Petkova (2006), Pasquariello (2014) and Adrian et al. (2014), we still use 25 size and book-to-market portfolios and 30 industry portfolios for the asset-pricing tests with Fama and MacBeth's (1973) two-stage approach. Moreover, we consider the pricing effects of the implied funding liquidity innovations in addition to other factors in the US equity markets including Fama and French's (1992) three factors and Carhart's (1997) momentum factor.

Table 7.3 reports the exposures to at-the-money option adjusted implied funding liquidity innovations for 25 size and book-to-market and 30 industry stock portfolio returns. As with to table 6.3, we observe that the beta estimates are positive and significant for the majority of both the equity and industry portfolios; this means that the excess returns of the portfolios tend to be higher corresponding with abnormally larger adjusted implied funding liquidity.

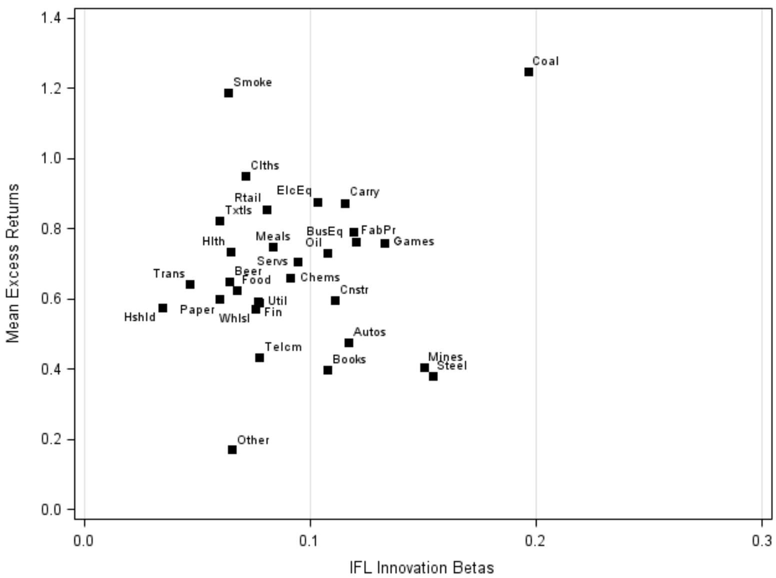
Within the 25 stock portfolios, the small size with low book-to-market portfolio registers the highest exposure (0.15) to the adjusted implied funding liquidity innovations, and is economically and statistically significant at the 1% level. Among the industry portfolios, the one with the highest beta estimate (0.20) lies in the coal portfolio. These results suggest that small firms, companies with low book-to-market and those in the coal industry are the most exposed to the variations in funding liquidity, which is consistent with the results in Table 6.3.

Figures 7.2(a) and 7.2(b) show scatter plots of excess returns versus their at-the-money option adjusted ΔIFL betas for the 25 portfolios and 30 industry portfolios, respectively. Aside from the small and low BM portfolio ($SMALL\_LoBM$) and smoke industry portfolio ($Smoke$), Figure 7.2 indicates that portfolios with higher IFL innovation betas had larger mean excess returns, which is consistent with 6.1.

Table 7.4 presents the coefficients and Newey-West adjusted *t*-statistics (in parentheses) obtained from the cross-sectional regressions with the at-the-money option adjusted implied funding liquidity measure. The estimates for the adjusted implied funding liquidity are still positive ($\lambda_{\Delta IFL} > 0$) and significant at the 1%



(a) Monthly Level



(b) Monthly Innovations

Figure 7.2: At-The-Money Option Adjusted ΔIFL Betas and Portfolio Excess Returns

This figure shows the scattered average portfolio excess returns versus their at-the-money option adjusted implied funding liquidity risk betas ($\beta_{\Delta IFL}$). Figure 7.2(a) is based on the 25 size and book-to-market equity portfolios, and Figure 7.2(b) on 30 industry stock portfolios. IFL Innovation betas and mean excess returns are estimated for each equity portfolio and the sample spans 4 January 1996 to 31 August 2015.

Table 7.4: Cross-Sectional Regressions with At-The-Money Option Adjusted Implied Funding Liquidity

Panel A: 25 Portfolios							
Model	λ_0	$\lambda_{\Delta IFL}$	λ_{MKT}	λ_{SMB}	λ_{HML}	λ_{Mom}	R^2
Univariate	0.9813***	0.1008***					4.55%
	(25.15)	(28.85)					
CAPM	0.3915***	0.0135***	1.0330***				69.41%
	(10.26)	(4.17)	(33.68)				
FF	0.2272***	0.0098**	0.9977***	0.5192***	0.2732***		90.37%
	(6.28)	(2.55)	(75.33)	(3.90)	(3.54)		
FF, Mom	0.2447***	0.0101**	0.9876***	0.5224***	0.2641***	-0.0239***	90.52%
	(7.53)	(2.61)	(83.21)	(3.93)	(3.46)	(-3.17)	
Panel B: 30 Industry Portfolios							
Model	λ_0	$\lambda_{\Delta IFL}$	λ_{MKT}	λ_{SMB}	λ_{HML}	λ_{Mom}	R^2
Univariate	0.8856***	0.0932***					3.23%
	(21.23)	(15.17)					
CAPM	0.3383***	0.0121**	0.9584***				50.54%
	(8.91)	(2.73)	(17.37)				
FF	0.2281***	0.0116**	1.0059***	0.0746**	0.3472***		58.16%
	(5.27)	(2.60)	(19.22)	(2.13)	(5.60)		
FF, Mom	0.2699***	0.0124***	0.9818***	0.0823**	0.3254***	-0.0573***	59.06%
	(6.88)	(2.91)	(19.08)	(2.35)	(5.15)	(-2.84)	

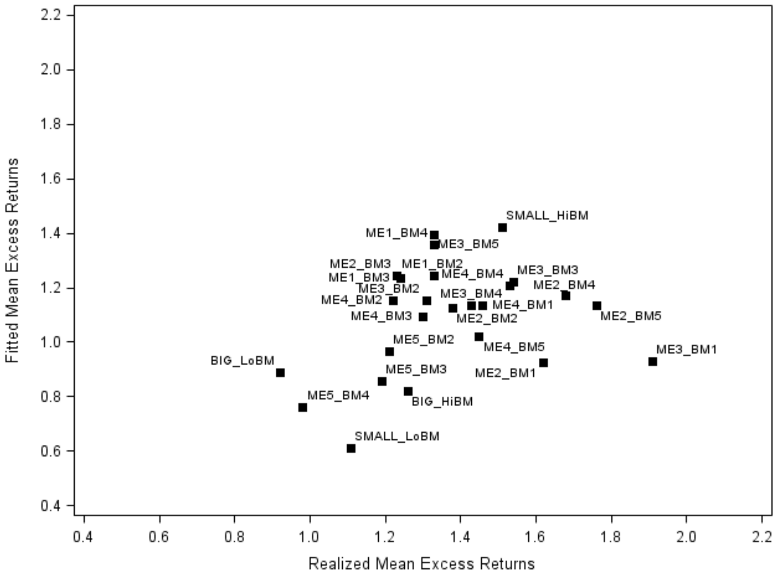
This table reports the estimates and Newey-West t-statistics (in bracket) from Fama and MacBeth (1973)□s two-stage regressions for the 25 size and book-to-market (Panel A) and 30 industry equity portfolios (Panel B) over the sample period from 4 January 1996 to 31 August 2015. ΔIFL is the innovations in the adjusted implied funding liquidity measure, which is computed from options with strike prices between 0.95 and 1.05 times the underlying spot prices, MKT is the excess market return, SMB is the average return on the small stock portfolios minus the average return on the big stock portfolios; HML is the average return on the value portfolios minus the average return on the growth portfolios; MOM is a momentum factor. $*/{*}{*}/{*}{*}{*}$ denotes the significance level at 10%, 5% and 1% level, respectively.

level for both of the 25 equity and 30 industry portfolios, even though implied funding liquidity risk premiums are unsurprisingly smaller than their counterparts shown in Table 6.4. Specifically, $\lambda_{\Delta IFL}$ amounts to 0.1008 and 0.0932 per unit of the ΔIFL beta for the equity and industry portfolios, respectively. In addition, the univariate model with the adjusted implied funding liquidity explains approximately 4.55% and 3.23% of the cross-sectional variations in returns for the 25 size and book-to-market and 30 industry portfolios. This evidence suggests that the adjusted implied funding liquidity risk alone still meaningfully explains cross-sectional stock portfolio returns, even though this explanation is relatively weaker compared to the results in Table 6.4.

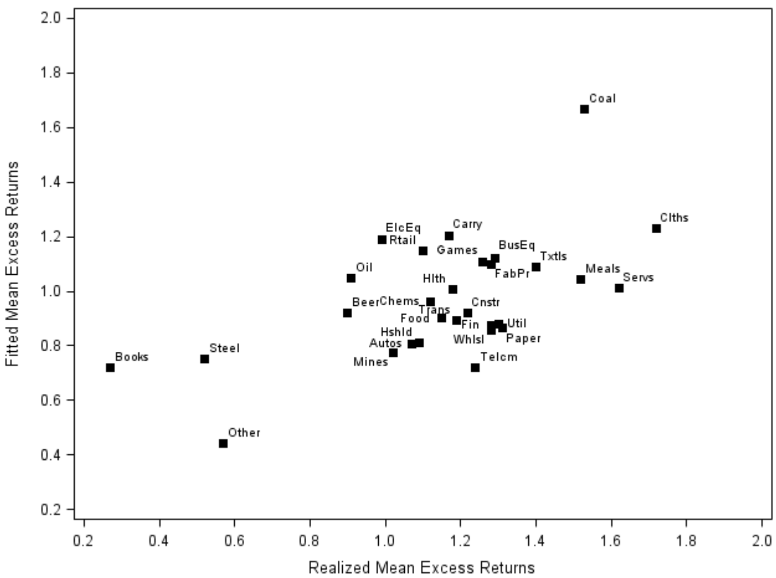
Furthermore, the estimates in Table 7.4 for Fama French's (1992) three factors and Carhart's (1997) momentum factor with adjusted implied funding liquidity are significant, suggesting that they are still important in capturing equity market returns after controlling for the moneyness.

The estimates for the adjusted implied funding liquidity measure remain positive and significant. The four-factor model with the implied funding liquidity measure registers R-square values of 90.52% and 59.06% for the 25 size and book-to-market, and 30 industry portfolios, respectively. Accordingly, $\lambda_{\Delta IFL}$s are smaller but still statistically significant relative to Fama and French's (1992) three traded factors (MKT, SMB, and HML), and Fama and French's (1992) three traded factors plus momentum (MKT, SMB, HML, and MOM). For example, the estimated adjusted implied funding liquidity risk premiums, $\lambda_{\Delta IFL}$, for the four and five factor models are 0.0101 and 0.0124, respectively. In addition, the five-factor model, controlling for MKT, SMB, HML, and MOM, with the adjusted implied funding liquidity measure does well with R-square values of 90.52% and 59.06% for the 25 size and book-to-market and 30 industry portfolios, respectively. This evidence is consistent with Pasquariello (2014); equity portfolios with greater exposure to the implied funding liquidity risk performed worse after taking the influence of moneyness into account.

Figure 7.3 plots the actual versus predicted average returns from the one-factor model with the at-the-money option adjusted implied funding liquidity for the 25 size and book-to-market portfolios (7.3(a)) and 30 industry portfolios (7.3(b)) from 4 January 1996 to 31 August 2015. Figures 7.3(a) and 7.3(b) shows that there is a strong, positive relationship between the realised and the predicted average returns for these portfolios.



(a) 25 Portfolios



(b) 30 Industry Portfolios

Figure 7.3: Realised vs Predicted Average Returns with At-The-Money Option Adjusted Implied Funding Liquidity

This figure presents the average realised versus predicted returns from the one-factor model with at-the-money option adjusted implied funding liquidity for the 25 size and book-to-market portfolios (Panel 7.3(a)) and 30 industry portfolios (Panel 7.3(b)). The sample spans 4 January 1996 to 31 August 2015.

Overall, this evidence indicates that the sensitivities of equity and industry portfolios to funding liquidity still tend to proportionally explain their risk which is not fully captured by other well-known priced factors after we have taken moneyness into consideration.

Prior studies (Pástor and Stambaugh, 2003; Brunnermeier et al., 2008; Hu et al., 2013; Fontaine et al., 2015; Amihud, 2002; Corwin and Schultz, 2012) show that liquidity innovations explain the variations in asset returns. For comparisons, we considered seven existing liquidity measures documented in the literature in the cross-sectional regressions: PS, TED, Noise, FG, Amihud, CS, RS, and Sadka in addition to the at-the-money option adjusted implied funding liquidity measure.

In this analysis, we used the CAPM with the at-the-money option adjusted implied funding liquidity factor as the benchmark for performance comparison. Panel A of Table 7.5 shows the estimates of the liquidity measures for the 25 size-to-book portfolios, whilst Panel B shows the estimates of the liquidity measures for the 30 industry portfolios.

Panel A of Table 7.5 shows that, among the liquidity measures, the TED, FG , Amihud, and Sadka measures are significant at the 1% level while the PS, Noise, and CS measures are insignificant. As with Table 6.8, the at-the-money option adjusted implied funding liquidity remains positive and significant at the 1% level. The model including the market return factor and all the liquidity variables reports an R-square of 72.23%.

In Panel B of Table 7.5, which presents the regression results for the industry portfolios, we observe similar patterns. The TED, FG, Amihud, and Sadka measures register the same signs as above and are significant at the 1% level while the impacts of the PS, Noise, and CS measures are not always significant. The R-square of all liquidity variables and the market return is about 72.23%. We observe that the adjusted implied funding liquidity remains significant in explaining stock return variations even when controlling for established liquidity measures in the US equity markets.

In short, our findings suggest that the implied funding liquidity measure incorporates the forward-looking nature of the option markets, and, after taking the moneyness into account, our measure potentially provides incremental information about asset returns beyond what is captured in the previous liquidity measures.

As documented in the literature, prior studies show that investor sentiments

Table 7.5: Cross-sectional Regressions with Liquidity Measures: At-the-Money Options

Model	λ_0	$\lambda_{\Delta IFL}$	λ_{MKT}	λ_{PS}	λ_{TED}	λ_{FG}	λ_{Noise}	λ_{Amihud}	λ_{RS}	λ_{CS}	λ_{Sadka}	R^2
Panel A: 25 Portfolios												
+PS	0.4555***	0.0222***	1.0287***	-0.0386								69.67%
	(10.99)	(7.72)	(30.78)	(-0.04)								
+TED	0.7779***	0.0200***	1.0203***		-0.5852***							70.05%
	(8.37)	(7.14)	(31.81)		(-3.91)							
+FG	0.4556***	0.0212***	1.0308***			-0.2875***						69.99%
	(11.11)	(7.17)	(33.17)			(-5.91)						
+NOISE	0.6060***	0.0232***	1.0235***				-0.0451					70.01%
	(5.51)	(7.61)	(30.03)				(-1.34)					
+Amihud	0.6332***	0.0225***	1.0236***					-0.0523***				69.73%
	(12.65)	(7.46)	(32.49)					(-4.65)				
+RS	0.6236***	0.0223***	1.0243***						-4.4392*			69.69%
	(7.29)	(7.48)	(32.48)						(-1.75)			
+CS	0.4424***	0.0222***	1.0287***							0.8552		69.61%
	(5.90)	(7.40)	(33.38)							(0.18)		
+Sadka	0.4131***	0.0200***	1.0351***								3.2100***	70.38%
	(9.52)	(6.56)	(33.55)								(7.41)	
+ALL	-0.1741	0.0180***	1.0392***	-1.1966	-0.5312***	-0.4250***	0.0487	-0.1910***	11.4827*	60.4574***	2.7300***	72.23%
	(-1.60)	(8.47)	(30.58)	(-1.44)	(-3.39)	(-6.31)	(0.83)	(-9.69)	(1.86)	(6.73)	(6.65)	
Panel B: 30 Industry Portfolios												
+PS	0.4555***	0.0222***	1.0287***	-0.0386								69.67%
	(10.99)	(7.72)	(30.78)	(-0.04)								
+TED	0.7779***	0.0200***	1.0203***		-0.5852***							70.05%
	(8.37)	(7.14)	(31.81)		(-3.91)							
+FG	0.4556***	0.0212***	1.0308***			-0.2875***						69.99%
	(11.11)	(7.17)	(33.17)			(-5.91)						
+NOISE	0.6060***	0.0232***	1.0235***				-0.0451					70.01%
	(5.51)	(7.61)	(30.03)				(-1.34)					
+Amihud	0.6332***	0.0225***	1.0236***					-0.0523***				69.73%
	(12.65)	(7.46)	(32.49)					(-4.65)				
+RS	0.6236***	0.0223***	1.0243***						-4.4392*			69.69%
	(7.29)	(7.48)	(32.48)						(-1.75)			
+CS	0.4424***	0.0222***	1.0287***							0.8552		69.61%
	(5.90)	(7.40)	(33.38)							(0.18)		
+Sadka	0.4131***	0.0200***	1.0351***								3.2181***	70.38%
	(9.52)	(6.56)	(33.55)								(7.41)	
+ALL	-0.1741	0.0180***	1.0392***	-1.1966	-0.5312***	-0.4250***	0.0487	-0.1910***	11.4827*	60.4574***	2.7386***	72.23%
	(-1.60)	(8.47)	(30.58)	(-1.44)	(-3.39)	(-6.31)	(0.83)	(-9.69)	(1.86)	(6.73)	(6.65)	

This table reports the estimates and the Newey West t-statistics (in the bracket) from the cross-sectional regressions with other liquidity measures. Let ΔIFL denotes the innovations in the at-the-money option adjusted implied funding liquidity measure, and MKT the excess market return. We considered the Pastor and Stambaugh's (PS) measure (2003), Brunnermeier et al.'s Treasury-LIBOR (TED) spread (2008), Hu et al.'s Noise (Noise) measure (2013), Fontaine and Garcia's (FG) measure (2012), Amihud's il-liquidity (Amihud) measure (2002), Corwin and Schultz's (CS) measure (2012), the relative spread (RS), and Sadka's (Sadka) measure (2006). The significance level is written in $*/**/***$ for 10%, 5% and 1% level, respectively.

Table 7.6: Cross-sectional Regressions with Investor Sentiment Measures: At-the-Money Options

	λ_0	$\lambda_{\Delta IFL}$	$\lambda_{\Delta BW}$	$\lambda_{\Delta HJTZ}$	$\lambda_{\Delta UMC}$	$\lambda_{\Delta CB}$	$\lambda_{\Delta DEG}$	$\lambda_{\Delta JLMZ}$	$\lambda_{\Delta PCR}$	R^2
Panel A: 25 Portfolios										
+BW	0.4080***	0.0891***	4.0778***							6.02%
	(4.45)	(18.62)	(6.27)							
+HJTZ	0.3084***	0.0624***		-6.6174***						9.59%
	(3.31)	(15.60)		(-21.63)						
+UMC	0.4801***	0.0812***			0.3429***					10.59%
	(5.20)	(16.31)			(15.18)					
+CB	0.5375***	0.0628***				6.5301***				14.73%
	(5.99)	(12.13)				(22.25)				
+DEG	0.3689***	0.0899***					0.1737***			5.86%
	(3.93)	(18.85)					(3.35)			
+JLMZ	0.3851***	0.1042***						5.9992***		15.19%
	(4.14)	(23.40)						(23.50)		
+PCR	0.3497***	0.0372***							-19.124***	11.23%
	(3.76)	(6.98)							(-38.13)	
+ALL	0.6082***	-0.0006	14.2529***	-9.9133***	0.0547**	4.9498***	0.3648***	5.7628***	-14.047***	34.67%
	(6.85)	(-0.13)	(17.61)	(-37.17)	(2.15)	(13.90)	(7.89)	(26.13)	(-25.49)	
Panel B: 30 Industry Portfolios										
+BW	0.5914***	0.0920***	3.4279***							6.43%
	(9.17)	(9.73)	(2.85)							
+HJTZ	0.4786***	0.0552***		-9.0368***						11.14%
	(7.91)	(6.85)		(-17.33)						
+UMC	0.6427***	0.0861***			0.2609***					9.50%
	(11.64)	(8.79)			(8.75)					
+CB	0.7110***	0.0682***				5.8964***				12.86%
	(12.73)	(7.06)				(13.69)				
+DEG	0.5521***	0.0926***					-0.0639			6.15%
	(9.08)	(9.86)					(-0.99)			
+JLMZ	0.5734***	0.1055***						5.3925***		12.95%
	(9.43)	(10.97)						(16.86)		
+PCR	0.5413***	0.0445***							-17.474***	9.94%
	(8.86)	(5.56)							(-14.63)	
+ALL	0.7485***	-0.0015	14.3149***	-12.256***	-0.0366	5.0737***	0.2340***	5.5418***	-12.295***	31.90%
	(13.02)	(-0.18)	(9.75)	(-15.64)	(-1.07)	(11.53)	(2.95)	(16.71)	(-11.19)	

This table reports the estimates and Newey West t-statistics (in the bracket) from the cross-sectional regressions. IFL denotes the at-the-money option adjusted implied funding liquidity measure. We considered seven investor sentiment indexes, including Baker and Wurgler's (2006) investor sentiment measure, BW, the aligned investor sentiment index of Huang et al. (2015), HJTZ, the consumer sentiment index of University of Michigan, UMC, the Conference Board consumer confidence index, CB, the Financial and Economics Attitudes Revealed by Search (FEARS), the investor sentiment index of Da et al. (2015), DEG, the Jiang et al. manager sentiment index (2018), JLMZ, and CBOE Put-Call ratios, PCR. +All indicates regressions with all of the relevant variables in the model. The significance level is written in $*/**/***$ for 10%, 5% and 1% level, respectively.

may lead to prices diverging from their fundamental values (De Long et al., 1990; Baker and Wurgler, 2006, 2007, 2012; Yu and Yuan, 2011; Huang et al., 2015; Da et al., 2015; Jiang et al., 2018). Moreover, in section 6.4, we found that our implied funding liquidity measure contains additional information beyond what is captured by the existing investor sentiment indexes. Now, we estimate whether our at-the-money option adjusted liquidity measure matters after controlling for the investor sentiment indexes.

For the purpose of comparison, we still consider the seven existing investor sentiment indexes documented in section 5.5. We include these indices in the cross-sectional regressions with the implied funding liquidity measure. Note that we use the univariate model with the adjusted implied funding liquidity factor as a benchmark model.

Panel A of Table 7.6 presents the estimates of the investor sentiment measures for the 25 size-to-book portfolios. Accordingly, we find that the implied funding liquidity remains positive and significant at the 1% level after controlling for the investor sentiment indices in the bivariate regressions. Compared with the results in Table 6.11, we observe that the R-squares decreases, which suggests that the power of our implied funding liquidity measure in the asset-pricing test decreases. However, most importantly, our adjusted implied funding liquidity measure is still statistically significant when controlling for alternative investor sentiment proxies in the bivariate regressions.

Panel B reports the estimates for the 30 industry portfolios, and we observe similar patterns for the industry portfolios, except the UMC, which is not significant. Generally, the coefficients for the adjusted implied funding liquidity remain positive and significant after controlling for established investor sentiment measures in the bivariate models, which suggests that, after controlling for the moneyness our measure contains additional information beyond existing investor sentiment indexes in the US stock market.

7.3 Non-Synchronicity

Battalio and Schultz (2006) showed that deviations of Put-Call parity may be influenced by non-synchronicity in the reporting of the closing stock prices in the option and in the underlying stock markets. To address this problem, we focus on the same prices agreed in the two markets, for instance, the daily low price of the underlying stock. Due to the fact of limited access to the interday data, following

Windcliff et al. (2006), we use the delta-gamma approximation to calculate implied volatility for each option, and hence, implied funding liquidity based on this underlying price. In particular, the procedure is detailed as follows.

First, we obtain the difference between the closing price used the option market, and the daily low price: $\Delta P = PRC - LOW$, where ΔP is the change in stock price, PRC is the closing price, and LOW is the low price. Then, we use the delta-gamma approximation to calculate the changes in call and option prices, dC and dP, respectively:

$$\begin{aligned} dC &= delta * \Delta P + 0.5 * gamma * (\Delta P)^2 \\ dP &= -delta * \Delta P + 0.5 * gamma * (\Delta P)^2 \end{aligned} \tag{7.2}$$

Second, we use vega approximation to calculate the changes of implied volatilities of $dCVol$ and $dPVol$, respectively:

$$\begin{aligned} dCVol &= dC/vega \\ dPVol &= dP/vega \end{aligned} \tag{7.3}$$

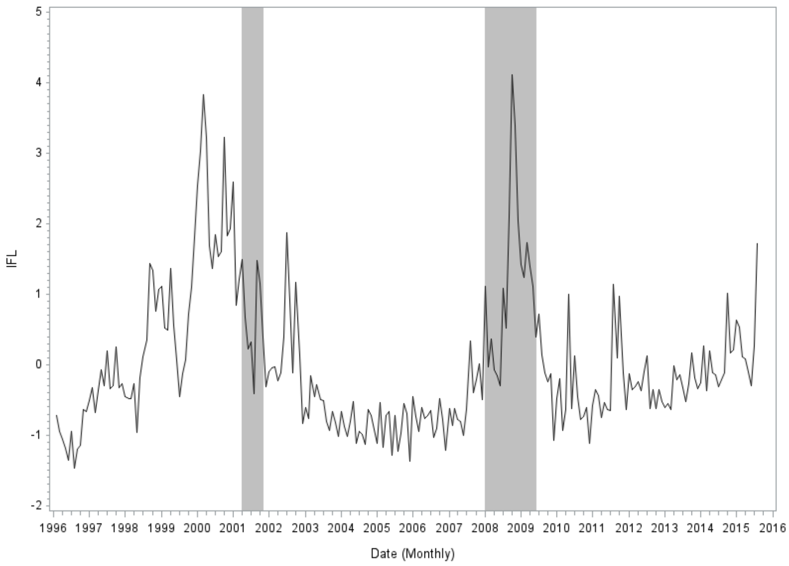
We now have non-synchronicity adjusted implied volatilities for call and put options as follows:

$$\begin{aligned} AdjCVol &= cVol + dCVol \\ AdjPVol &= pVol + dPVol \end{aligned} \tag{7.4}$$

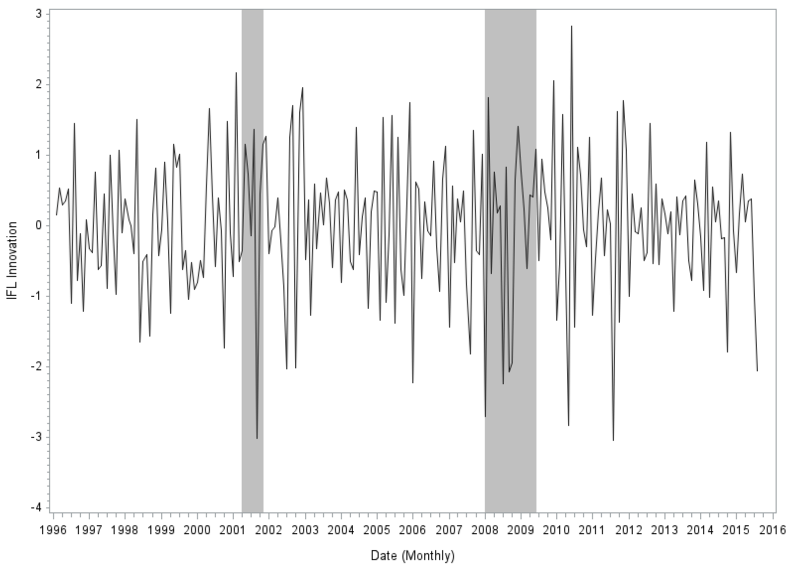
where $cVol$ and $pVol$ are the initial implied volatilities for call and put options, respectively.

Finally, we can calculate the adjusted IFL and ΔIFL with functions 4.3 and 4.4 using the non-synchronicity adjusted implied volatility spreads above.

Figure 7.4 shows the standardised monthly time-series of the non-synchronicity adjusted implied funding liquidity measure from January 1996 to August 2015, and the NBER recession periods are indicated with the light grey bars. We still



(a) Monthly Level



(b) Monthly Innovations

Figure 7.4: Non-Synchronicity Adjusted Implied Funding Liquidity

This figure presents the time series of the monthly level (Panel a) and innovations (Panel b) of the standardised non-synchronicity adjusted implied funding liquidity measure for the sample from 4 January 1996 to 31 August 2015. The shaded areas contain the NBER's Business Cycle dates.

see significant increases in the liquidity measure during the previously mentioned episodes of financial crises. The largest jump in the liquidity measure occurred in October 2008 which coincided with the collapse of Lehman Brothers and the funding squeezed in inter-bank lending markets. Compared with Figure 5.1, we observed that even though we still had the sample pattern for the implied funding liquidity measure, the magnitude of peak values is smaller. For instance, the adjusted implied funding liquidity innovation at the European debt crisis of 2009-2012 was larger than that in October 2008.

In order to estimate the return-predictability power of the non-synchronicity adjusted implied funding liquidity measure, we still obtained monthly returns of the S&P500 index and the value-weighted average returns provided by CRSP as market return measures. Similarly, we controlled for variables that are found to predict market returns, including the dividend yield on the $S\&P500$ index, the real GNP growth rate, the long-term government bond return, and the past market excess return. We still used the predictive regression model 4.13.

Table 7.7: Market Return Predictability with Non-Synchronicity Adjusted Implied Funding Liquidity

Panel A: CRSP Value-Weighted Market Returns						
	$\triangle IFL_{t-1}$	r_{t-1}	DIV_{t-1}	GNP_{t-1}	LTG_{t-1}	Adj R^2
1	0.0005***	0.0144	-0.0021	5.3114***	0.0327**	14.75%
(t-stat)	(2.68)	(0.21)	(-0.25)	(3.47)	(2.32)	
3	0.0008***	1.0408***	0.0265**	12.1069***	0.0333*	57.15%
(t-stat)	(3.21)	(11.41)	(2.39)	(6.03)	(1.81)	
6	0.0011**	1.0190***	0.0874***	20.5208***	0.0024	35.28%
(t-stat)	(2.24)	(6.16)	(4.35)	(5.64)	(0.07)	
Panel B: S&P 500 Returns						
	$\triangle IFL_{t-1}$	r_{t-1}	DIV_{t-1}	GNP_{t-1}	LTG_{t-1}	Adj R^2
1	0.0006***	-0.0234	-0.0010	5.9576***	0.0243*	16.43%
(t-stat)	(3.11)	(-0.34)	(-0.12)	(4.07)	(1.82)	
3	0.0009***	0.9739***	0.0254**	12.5936***	0.0198	56.13%
(t-stat)	(3.56)	(10.67)	(2.40)	(6.54)	(1.12)	
6	0.0011***	0.9887***	0.0811***	20.7246***	-0.0072	35.15%
(t-stat)	(2.36)	(5.91)	(4.18)	(5.87)	(-0.22)	

This table shows the predictability of the non-synchronicity adjusted implied funding liquidity with horizons of one month, three months, and six months for CRSP value-weighted returns (Panel A) and S&P 500 Returns (Panel B). Dependent variables are the cumulative growth rates of each variable calculated over one, three and six months. IFL_{t-1} is non-synchronicity adjusted implied funding liquidity at t-1, and $MKTEX_{t-1}$ is the market excess returns. The full sample period spans January 1996 to August 2015, the significance levels are represented as $*$/$**$/$***$ for 10%, 5% and 1%, respectively.

Table 7.7 shows the results of the return predictive regressions for the non-synchronicity adjusted implied funding liquidity measure with horizons of one month, three months, and six months for CRSP value-weighted returns (Panel A) and S&P 500 Returns (Panel B). We observe that the most coefficients for the adjusted liquidity measure remain positive and significant for horizons of three and six months. In particular, compared with the results in 6.2, we find that it is not statistically significant for an horizon of one month, and the magnitude of the coefficients is smaller. The results show that predictability is still significant, though it is weaker than the initial implied funding liquidity measure. The predictive power of adjusted implied funding liquidity remains robust after controlling for other forecasting variables including dividend yield, the GNP growth rate, and long-term government bond returns.

Having estimated the predictive power of non-sychronicity adjusted implied funding liquidity, we now examine whether the innovations in this adjusted liquidity measure could explain the cross-sectional differences in stock returns. Consistent with the main empirical test, we follow Petkova (2006), Pasquariello (2014) and Adrian et al. (2014) using Fama and and MacBeth's (1973) two-stage approach for the asset-pricing tests with 25 size and book-to-market portfolios and 30 industry portfolios. In addition, we control the pricing influence of other factors in the US equity markets including Fama and French's (1992) three factors and Carhart's (1997) momentum factor.

Panel A and Panel B of Table 7.8 report the exposures to non-sychronicity adjusted implied funding liquidity innovations for 25 size and book-to-market and 30 industry stock portfolio returns, respectively. Compared to Table 6.3, we observe that beta estimates are mainly positive, significant for the majority of 25 equity portfolios, while the beta estimates for the industry portfolios are not as statistically significant as their counterparts in Table 6.3.

Among the 25 stock portfolios, the big and 3nd book-to-market registers the highest exposure (0.05) to adjusted implied funding liquidity innovations, and is economically and statistically significant at the 1% level. With regard to the industry portfolios, the one with the highest beta estimate (0.05) lies in the aircraft, ships, and railroad equipment portfolio ($Carry$). These results suggest that the influence of implied funding liquidity becomes weaker after we controlling for the non-sychronicity.

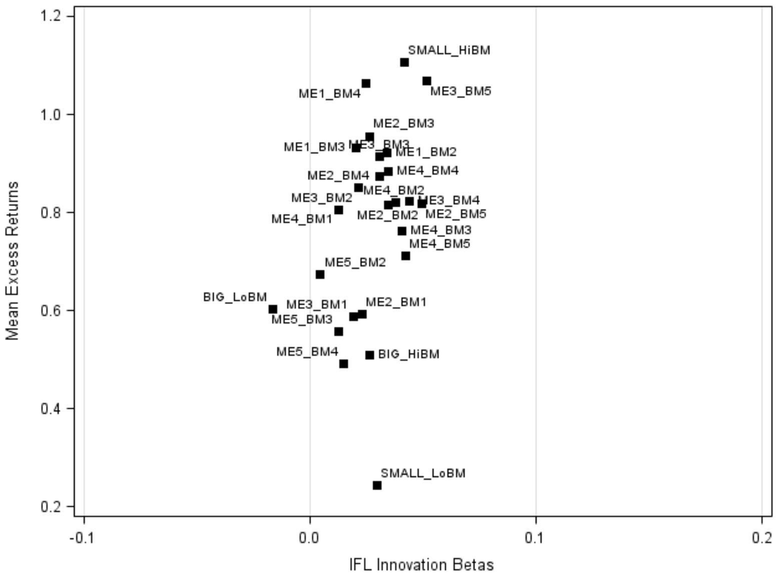
Figures 7.5(a) and 7.5(b) show scatter plots of excess returns versus their non-

Table 7.8: Exposures to Non-Sychronicity Adjusted Implied Funding Liquidity

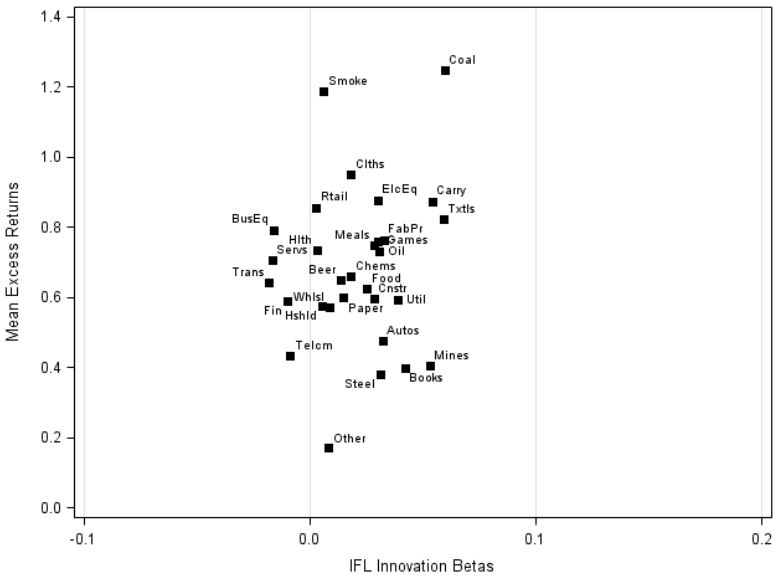
Panel A: 25 Portfolios Formed on Size and Book-to-Market					
Betas	Low B/M	2	3	4	High B/M
Small	0.03	0.02	0.02	0.01	0.04***
	(1.22)	(1.31)	(1.23)	(1.03)	(2.63)
2	0.03	0.03***	0.02**	0.04***	0.00
	(1.64)	(2.61)	(2.01)	(4.18)	(0.55)
3	0.02	0.03**	0.03***	0.04***	0.01
	(1.26)	(2.13)	(2.82)	(3.63)	(1.32)
4	0.02	0.03**	0.04***	0.03***	0.01
	(1.64)	(2.26)	(3.56)	(3.13)	(1.20)
Big	-0.02***	0.05***	0.05***	0.04***	0.03*
	(-2.82)	(3.06)	(3.74)	(3.04)	(1.80)

Panel B: 30 Industry Portfolios					
Industry	Betas	Industry	Betas	Industry	Betas
Autos	0.03	FabPr	0.03**	Paper	0.01
	(1.37)		(2.09)		(1.01)
Beer	0.01	Fin	-0.01	Rtail	0.00
	(0.73)		(-0.75)		(0.20)
Books	0.04***	Food	0.03*	Servs	-0.02
	(2.69)		(1.89)		(-1.19)
BusEq	-0.02	Games	0.03	Smoke	0.01
	(-0.83)		(1.62)		(0.21)
Carry	0.05***	Hlth	0.00	Steel	0.03
	(3.00)		(0.26)		(1.43)
Chems	0.02	Hshld	0.01	Telcm	-0.01
	(1.13)		(0.36)		(-0.66)
Clths	0.02	Meals	0.03*	Trans	-0.02
	(0.92)		(1.93)		(-1.29)
Cnstr	0.03*	Mines	0.05*	Txtls	0.06**
	(1.68)		(1.78)		(2.11)
Coal	0.06	Oil	0.03	Util	0.04**
	(1.19)		(1.56)		(2.44)
ElcEq	0.03**	Other	0.01	Whlsl	0.01
	(2.03)		(0.48)		(0.69)

This table reports OLS estimates of the non-sychronicity adjusted funding liquidity ΔIFL betas $\beta_{i,\Delta IFL}$ which is the slope coefficients from the time-series regressions on ΔIFL. Panel A uses the 25 monthly stock excess returns whilst Panel B obtains the 30 monthly industry stock excess returns. The full sample period spans January 1996 to August 2015. The Newey West t statistics are shown in parentheses and $*$, $**$, $***$ denote significence levels at 10%, 5% and 1%, respectively.



(a) Monthly Level



(b) Monthly Innovations

Figure 7.5: Non-Sychronicity Adjusted ΔIFL Betas and Portfolio Excess Returns

This figure shows the scattered average portfolio excess returns versus their non-sychronicity Adjusted implied funding liquidity risk betas ($\beta_{\Delta IFL}$). Figure 7.5(a) is based on the 25 size and book-to-market equity portfolios, and Figure 7.5(b) on 30 industry stock portfolios. IFL Innovation betas and mean excess returns are estimated for each equity portfolio and the sample spans 4 January 1996 to 31 August 2015.

sychronicity adjusted ΔIFL betas for the 25 Portfolios and 30 industry portfolios, respectively. Aside from the small and low BM portfolio ($SMALL\_LoBM$), Figure 7.2 indicates that portfolios with higher ΔIFL betas have bigger mean excess returns, which is consistent with 6.1, though this relationship becomes relatively weaker.

Table 7.9 reports the coefficients and Newey-West adjusted t-statistics (in parentheses) obtained from the cross-sectional regressions with the non-synchronicity adjusted implied funding liquidity measure.

Although adjusted implied funding liquidity risk premiums are smaller than their counterparts in Table 6.4, estimates for adjusted implied funding liquidity are still positive ($\lambda_{\Delta IFL} > 0$) and significant at the 1% level for both of the 25 equity and 30 industry portfolios in the univariate model. In particular, $\lambda_{\Delta IFL}$ amounts to 0.0277 and 0.0204 per unit of the ΔIFL beta for the equity and industry portfolios, respectively. Moreover, the univariate model with the adjusted implied funding liquidity explains approximately 0.74% and 0.49% of the cross-sectional variations in returns for the 25 size and book-to-market and 30 industry portfolios. This suggests that, after controlling for the non-sychronicity, the implied funding liquidity risk alone still has a meaningful explanation of cross-sectional stock portfolio returns, even though it is relatively weaker compared to the results in Table 6.4.

In addition, we see that the coefficients for Fama and French's (1992) three factors and the momentum factor are significant with adjusted implied funding liquidity, suggesting that they are still important in capturing equity market returns after controlling for the non-sychronicity. More specifically, the four-factor model with adjusted implied funding liquidity measure registers R-square values of 90.50% and 59.02% for the 25 size and book-to-market and 30 industry portfolios, respectively.

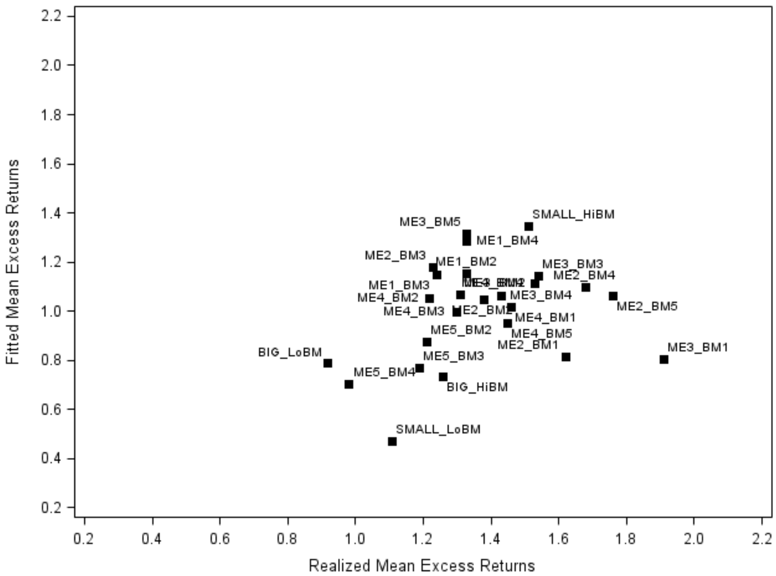
Accordingly, $\lambda_{\Delta IFL}$s are smaller but still statistically significant relative to Fama French three factors, and Fama French three traded factors plus momentum. For Instance, the estimated adjusted implied funding liquidity risk premiums, $\lambda_{\Delta IFL}$, for the equity and industry portfolios are 0.0274 and 0.0201, respectively. This evidence is consistent with Battalio and Schultz (2006). Stock portfolio with greater exposure to the implied funding liquidity risk performe worse after taking the influence of non-sychronicity into consideration.

Figure 7.6 plots the actual versus predicted average returns from the one-factor

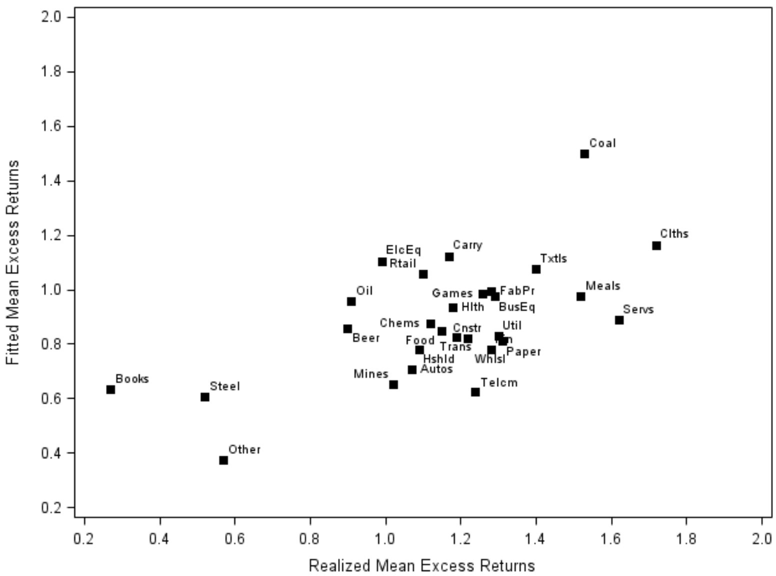
Table 7.9: Cross-Sectional Regression Results with Non-Sychronicity Adjusted Implied Funding Liquidity

Panel A: 25 Portfolios							
Model	λ_0	$\lambda_{\Delta IFL}$	λ_{MKT}	λ_{SMB}	λ_{HML}	λ_{Mom}	R^2
Univariate	0.9801***	0.0277***					0.74%
	(24.93)	(9.63)					
CAPM	0.3930***	0.0274***	1.0408***				70.00%
	(10.27)	(9.55)	(34.50)				
FF	0.2268***	0.0066**	1.0032***	0.5153***	0.2688***		90.36%
	(6.25)	(2.23)	(68.34)	(3.84)	(3.54)		
FF, Mom	0.2435***	0.0066**	0.9937***	0.5184***	0.2600***	-0.0231***	90.50%
	(7.48)	(2.24)	(74.32)	(3.87)	(3.45)	(-3.11)	
Panel B: 30 Industry Portfolios							
Model	λ_0	$\lambda_{\Delta IFL}$	λ_{MKT}	λ_{SMB}	λ_{HML}	λ_{Mom}	R^2
Univariate	0.8832***	0.0204***					0.49%
	(21.23)	(5.58)					
CAPM	0.3385***	0.0201***	0.9654***				50.73%
	(9.01)	(5.51)	(17.56)				
FF	0.2287***	0.0097***	1.0125***	0.0685*	0.3407***		58.10%
	(5.32)	(3.64)	(19.40)	(1.96)	(5.52)		
FF, Mom	0.2695***	0.0098***	0.9893***	0.0762**	0.3191***	-0.0564***	59.02%
	(6.88)	(3.67)	(19.18)	(2.17)	(5.08)	(-2.76)	

This table reports the estimates and Newey-West t-statistics (in bracket) from Fama and MacBeth's (1973) two-stage regressions for the 25 size and book-to-market (Panel A) and 30 industry equity portfolios (Panel B) of the sample period from 4 January 1996 to 31 August 2015. ΔIFL is the innovations in the non-sychronicity adjusted implied funding liquidity measure; MKT is the excess market return; SMB is the average return on the small stock portfolios minus the average return on the big stock portfolios; HML is the average return on the value portfolios minus the average return on the growth portfolios; MOM is a momentum factor. $*/**/***$ denotes the significance levels at 10%, 5% and 1%, respectively.



(a) 25 Portfolios



(b) 30 Industry Portfolios

Figure 7.6: Realised vs Predicted Average Returns with Non-Sychronicity Adjusted Implied Funding Liquidity

This figure presents the average realised versus predicted returns from the one-factor model with non-sychronicity adjusted implied funding liquidity for the 25 size and book-to-market portfolios (Panel 7.6(a)) and 30 industry portfolio (Panel 7.6(b)). The sample spans 4 January 1996 to 31 August 2015.

model with non-sychronicity adjusted implied funding liquidity for the 25 size and book-to-market portfolios (7.6(a)) and 30 industry portfolios (7.3(b)) from 4 January 1996 to 31 August 2015. As shown in Figures 7.3(a) and 7.6(b), there is still a strong and positive relationship between the realised and the predicted average returns for these portfolios.

This evidence suggests that the sensitivities of equity and industry portfolios to funding liquidity still tend to proportionally explain their risk, which is not fully captured by other well-known priced factors after we control for non-sychronicity.

For comparison purpose, we consider eight existing liquidity measures documented in the literature (for instance, Pástor and Stambaugh, 2003; Brunnermeier et al., 2008; Hu et al., 2013; Fontaine et al., 2015; Amihud, 2002; Corwin and Schultz, 2012) in the cross-sectional regressions: PS, TED, Noise, FG, Amihud, CS, RS, and Sadka in addition to the non-synchronicity adjusted implied funding liquidity measure. In particular, we use the CAPM with non-synchronicity adjusted implied funding liquidity measure as the benchmark for performance comparison. The estimates of liquidity measures are presented in Table 7.10.

Panel A of Table 7.10 shows that the TED, FG, Amihud, and Sadka measures are significant at the 1% level, but PS, Noise, and CS measures are insignificant. Similar to Table 6.8, the non-synchronicity adjusted implied funding liquidity remains positive and significant at the 1% level. When we include all the liquidity measures jointly in the regression, aside from the Noise measure, all other measures are significant, and the model reports an R-square of 72.68%. Consistent with the findings in Table 6.8, this shows that our measure empirically dominates the Noise measure in the equity market.

In Table 7.10 (Panel B), which presents the regression results for the industry portfolios, we observe similar patterns. The TED, FG , Amihud, and Sadka measures register the same signs as above and are significant at 1% level, while impacts of the PS, Noise, and CS measures are not always significant. When including all liquidity measures together, only the Noise measure is not significant. The R-square with all liquidity variables and the market return is about 53.85%. After controlling for established liquidity measures in the US equity markets, we find that the adjusted implied funding liquidity remains significant in explaining stock return variations.

In short, our findings suggest that the adjusted implied funding liquidity measure is still forward-looking, and it potentially provides incremental information

Table 7.10: Cross-sectional Regressions with Liquidity Measures: Non-Synchronicity

Model	λ_0	$\lambda_{\Delta IFL}$	λ_{MKT}	λ_{PS}	λ_{TED}	λ_{FG}	λ_{Noise}	λ_{Amihud}	λ_{RS}	λ_{CS}	λ_{Sadka}	R^2
Panel A: 25 Portfolios												
+PS	0.4531***	0.0295***	1.0442***	-0.6945								70.20%
	(10.97)	(9.57)	(30.52)	(-0.70)								
+TED	0.7417***	0.0273***	1.0331***		-0.5202***							70.52%
	(8.22)	(9.05)	(31.86)		(-3.55)							
+FG	0.4552***	0.0282***	1.0432***			-0.2788***						70.51%
	(11.10)	(9.03)	(33.35)			(-5.86)						
+NOISE	0.5803***	0.0290***	1.0378***				-0.0376					70.53%
	(5.33)	(9.10)	(30.60)				(-1.13)					
+Amihud	0.5967***	0.0283***	1.0376***					-0.0417***				70.22%
	(12.57)	(9.02)	(32.73)					(-3.86)				
+RS	0.4740***	0.0288***	1.0411***						-0.4976			70.20%
	(5.41)	(8.75)	(32.65)						(-0.19)			
+CS	0.3439***	0.0291***	1.0424***							7.2024		70.14%
	(5.10)	(9.28)	(33.57)							(1.60)		
+Sadka	0.4174***	0.0254***	1.0461***								2.8571***	70.78%
	(9.53)	(7.38)	(33.67)								(6.21)	
+ALL	-0.3369***	0.0266***	1.0549***	-1.8298**	-0.5112***	-0.4267***	0.0163	-0.1895***	17.5776**	62.1283***	2.4087***	72.68%
	(-3.01)	(8.70)	(30.92)	(-2.27)	(-3.26)	(-6.29)	(0.28)	(-9.73)	(2.73)	(6.88)	(5.51)	
Panel B: 30 Industry Portfolios												
+PS	0.4273***	0.0202***	0.9574***	1.8715								51.15%
	(6.98)	(6.14)	(17.67)	(1.42)								
+TED	0.8130***	0.0198***	0.9530***		-0.7106***							51.17%
	(7.42)	(5.84)	(16.61)		(-4.66)							
+FG	0.4216***	0.0213***	0.9660***			-0.2509***						51.08%
	(7.02)	(5.89)	(16.92)			(-4.68)						
+NOISE	0.6809***	0.0222***	0.9567***				-0.0778***					51.09%
	(7.80)	(5.97)	(16.57)				(-3.78)					
+Amihud	0.5931***	0.0213***	0.9598***					-0.0505***				50.96%
	(7.10)	(5.91)	(16.74)					(-3.34)				
+RS	0.5098***	0.0216***	0.9623***						-2.3305			50.77%
	(4.32)	(5.94)	(16.65)						(-0.85)			
+CS	0.3862**	0.0220***	0.9648***							2.2943		50.83%
	(2.50)	(5.96)	(16.72)							(0.22)		
+Sadka	0.3878***	0.0188***	0.9687***								2.5629***	51.20%
	(6.64)	(5.78)	(16.88)								(4.50)	
+ALL	-0.3002*	0.0186***	0.9654***	0.5866	-0.6922***	-0.3114***	-0.0465	-0.1653***	22.9808***	59.7543***	2.1036***	53.85%
	(-1.82)	(6.96)	(17.67)	(0.45)	(-3.99)	(-5.24)	(-1.26)	(-5.42)	(3.94)	(3.57)	(4.17)	

This table reports the estimates and the Newey West t-statistics (in the bracket) from the cross-sectional regressions with other liquidity measures. Let ΔIFL denotes the innovations in the non-synchronicity adjusted implied funding liquidity measure, and MKT the excess market return. We considered Pástor and Stambaugh's (2003) measure (PS), Brunnermeier et al.'s (2008) Treasury-LIBOR (TED) spread, Hu et al.'s (2013) Noise measure (Noise), Fontaine and Garcia's (2012) measure (FG), Amihud's (2002) il-liquidity measure (Amihud), Corwin and Schultz's (2012) measure (CS), the relative spread (RS), and Sadka's (2006) measure (Sadka). The significance levels are written in $*/**/***$ for 10%, 5% and 1%, respectively.

Table 7.11: Cross-sectional Regressions with Investor Sentiment Measures: Non-Synchronicity

	λ_0	$\lambda_{\Delta IFL}$	$\lambda_{\Delta BW}$	$\lambda_{\Delta HJTZ}$	$\lambda_{\Delta UMC}$	$\lambda_{\Delta CB}$	$\lambda_{\Delta DEG}$	$\lambda_{\Delta JLMZ}$	$\lambda_{\Delta PCR}$	R^2
Panel A: 25 Portfolios										
+BW	0.3271***	0.0546***	4.0618***							3.17%
	(3.56)	(17.72)	(6.28)							
+HJTZ	0.2474**	0.0343***		-7.5828***						8.21%
	(2.65)	(13.51)		(-21.81)						
+UMC	0.4066***	0.0433***			0.3442***					7.72%
	(4.40)	(12.88)			(15.09)					
+CB	0.4904***	0.0316***				6.8664***				12.90%
	(5.48)	(9.50)				(24.00)				
+DEG	0.2840***	0.0546***					0.0606			2.89%
	(3.02)	(15.79)					(1.09)			
+JLMZ	0.2897***	0.0586***						5.5032***		11.01%
	(3.10)	(19.53)						(20.71)		
+PCR	0.3207***	-0.0033							-22.676***	10.41%
	(3.42)	(-1.02)							(-49.39)	
+ALL	0.6441***	0.0539***	16.1804***	-11.098***	0.0528*	5.2781***	0.5209***	5.6141***	-19.130***	36.02%
	(7.16)	(14.30)	(19.59)	(-39.39)	(2.02)	(14.95)	(10.08)	(24.29)	(-30.36)	
Panel B: 30 Industry Portfolios										
+BW	0.5079***	0.0546***	3.4274***							3.71%
	(7.97)	(8.79)	(2.85)							
+HJTZ	0.4242***	0.0275***		-9.9599***						9.94%
	(7.14)	(5.42)		(-16.53)						
+UMC	0.5647***	0.0462***			0.2622***					6.84%
	(10.47)	(6.85)			(8.60)					
+CB	0.6601***	0.0336***				6.2710***				10.96%
	(12.25)	(5.28)				(14.52)				
+DEG	0.4646***	0.0582***					-0.1843***			3.53%
	(7.86)	(9.72)					(-2.94)			
+JLMZ	0.4766***	0.0582***						4.8880***		9.21%
	(8.02)	(9.45)						(15.90)		
+PCR	0.5061***	0.0002							-21.300***	8.92%
	(8.49)	(0.04)							(-14.15)	
+ALL	0.7818***	0.0494***	16.0531***	-13.321***	-0.0381	5.3654***	0.3762***	5.4111***	-16.881***	32.71%
	(13.35)	(7.28)	(10.69)	(-15.56)	(-1.07)	(12.11)	(4.46)	(16.48)	(-11.81)	

This table reports the estimates and Newey West t-statistics (in the bracket) from the cross-sectional regressions. IFL denotes the implied funding liquidity measure. We considered seven investor sentiment indexes, including Baker and Wurgler's (2006) investor sentiment measure (BW), Huang et al.'s (2015) aligned investor sentiment index (HJTZ), the consumer sentiment index of University of Michigan (UMC), the Conference Board consumer confidence index (CB), Da et al.'s (2015) Financial and Economics Attitudes Revealed by Search (FEARS) index (DEG), Jiang et al.'s (2018) manager sentiment index (JLMZ), as well as CBOE Put-Call ratios, (PCR). +All indicates regressions with all of the relevant variables in the model. The significance level is written in $*/**/***$ for 10%, 5% and 1% level, respectively.

about asset returns beyond what is captured in the existing liquidity measures after we take the non-synchronicity into consideration.

In section 6.4, we found that the implied funding liquidity measure contains additional information beyond what is captured by the exiting investor sentiment indexes. Now, we estimate whether the non-synchronicity adjusted liquidity measure still matters after controlling for the investor sentiment indices.

Following the previous literature (De Long et al., 1990; Baker and Wurgler, 2006, 2007, 2012; Yu and Yuan, 2011; Huang et al., 2015; Da et al., 2015; Jiang et al., 2018), we still considered seven existing investor sentiment measures documented in section 5.5. As comparisons, we use the univariate model with the implied funding liquidity measure as a benchmark. Similar to Table 6.11, Panel A of Table 7.11 presents the estimates of investor sentiment proxies for the 25 size-to-book portfolios, while Panel B reports the estimates for 30 industry portfolios.

Excluding the DEG and PCR, Table 6.11(Panel A) shows that the adjusted implied funding liquidity remains positive and significant at the 1% level after controlling for the existing investor sentiment indexes in the bivariate models. We also run a regression including all sentiment proxies with our liquidity measure, and find that our measure remains statistically significant and economically large with a R-squre of 36.02%.

Panel B of Table 6.11 reports the estimates for the industry portfolios. Adjusted implied funding liquidity remains significant and positive at the 1% level except for PCR in the bivariate models. However, our implied funding liquidity measure is still statistically significant when we include all investor sentiment indices in one regression. In the regression with all proxies, UMC is not significant, which is consistent with the characteristics in Table 6.11. The R-square with all investor sentiment variables is approximately 32.71%.

The coefficients for adjusted implied funding liquidity remain positive and significant after controlling for seven existing investor sentiment measures, which suggests that our measure contains additional information beyond existing investor sentiment indexes in the stock market after controlling for the non-synchronicity.

7.4 Short-Sale Restrictions

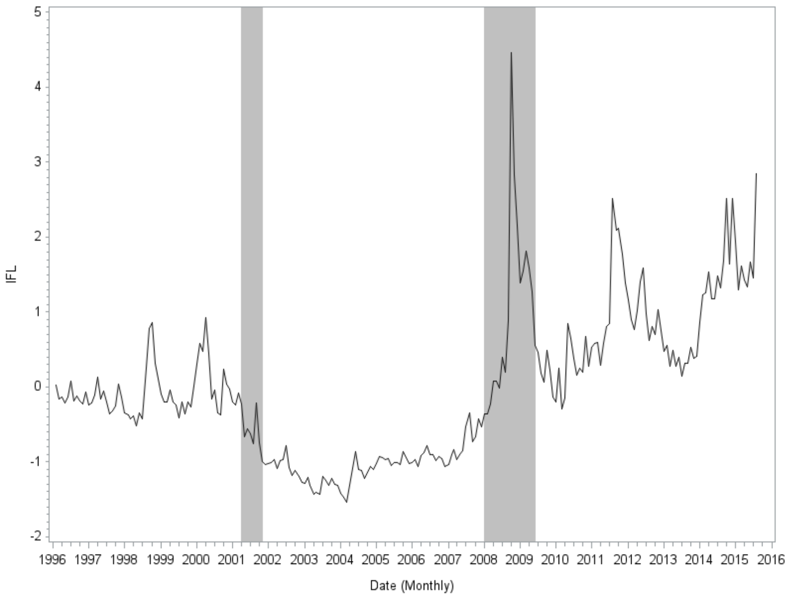
In the 2007 sub-prime mortgage crisis and the 2009-2012 European debt crisis, most regulators of the stock exchange around the world imposed restrictions or bans on short selling. For example, The Securities and Exchange Commission (SEC), together with with the UK Financial Services Authority, announced a temporary short selling ban on financial stocks[3]. Following Beber and Pagano (2013), during the financial distress period, we determine whether there was a short-sale ban, and if so, the applications to when and which stocks. Then, we could calculate the adjusted IFL and ΔIFL with functions 4.3 and 4.4 with the samples extracting the underlying stocks with short selling constrictions.

Figure 7.7 shows the monthly level (Panel A) and innovations (Panel B) of the standardised implied funding liquidity measure after adjusting short selling bans from January 1996 to August 2015. We see significant rises in the liquidity measure during financial stress periods, for instance, the Asian crisis in 1997, the Long-Term Capital Management collapse in 1998, the dot-com bubble and collapse at the end of $1990s$, the sub-prime mortgage crisis in 2007, the European debt crisis of 2009-2012. The largest increase in the liquidity measure occurred in October 2008 which coincided with the collapse of Lehman Brothers and the funding squeezes in inter-bank lending markets. Consistent with Beber and Pagano (2013),Figure 7.7 showed that the imposed short-sale ban during the financial distress periods are are associated with a significant liquidity disruption, that is, with an increase in the adjusted implied funding liquidity measure. For instance, the IFL increased from approximately 4.3 to 4.5, while the ΔIFL decreased from around -5.2 to -6.8.

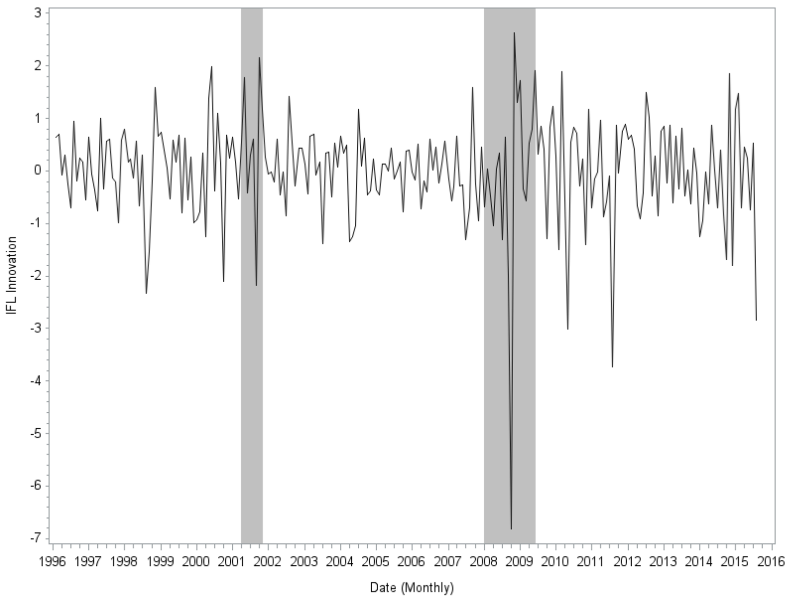
We still use monthly returns of the S&P500 index and the value-weighted average returns provided by CRSP as market return measures to estimate the return predictability power of the short selling ban adjusted implied funding liquidity measure. Similarly, we also controlled for variables that are found to predict market returns, including the dividend yield on the $S\&P500$ index, the real GNP growth rate, the long-term government bond return, and the past market excess return. We still used the predictive regression model 4.13.

Table 7.12 shows the results of the return predictive regressions for the short-selling adjusted implied funding liquidity measure with horizons of one month, three months, and six months for CRSP value-weighted returns (Panel A) and S&P500 returns (Panel B). We observe that the most coefficients for the liquidity measure after adjusted for short selling ban remains positive and significant for horizons of one, three and six months. Compared to the results before controlling

[3]See, "SEC Halts Short Selling of Financial Stocks to Protect Investors and Markets", which is available at `https://www.sec.gov/news/press/2008/2008-211.htm`



(a) Monthly Level



(b) Monthly Innovations

Figure 7.7: Short-Sale Adjusted Implied Funding Liquidity

This figure presents the time series of the monthly level (Panel a) and innovations (Panel b) of the standardised short selling ban adjusted implied funding liquidity measure over the sample from 04 January 1996 to 31 August 2015. The shaded area contains the National Bureau of Economic Research's Business Cycle dates.

for the short selling ban in 6.2, we find that it was statistically significant for an horizon of one month, and the coefficients for the horizons of three and six months became stronger. The predictive power of the short selling ban adjusted implied funding liquidity remains robust after controlling for other forecasting variables including dividend yield, the GNP growth rate and long-term government bond returns. Consistent to previous studies (Beber and Pagano, 2013), our results indicate that short selling bans decrease liquidity.

Table 7.12: Market Return Predictability with Short-Selling Adjusted Implied Funding Liquidity

Panel A: CRSP Value-Weighted Market Returns						
	$\triangle IFL_{t-1}$	r_{t-1}	DIV_{t-1}	GNP_{t-1}	LTG_{t-1}	Adj R^2
1	0.0008**	-0.0416	-0.0014	5.4358***	0.0388***	13.64%
(t-stat)	(2.14)	(-0.56)	(-0.16)	(3.53)	(2.78)	
3	0.0014***	0.9397***	0.0277**	12.3183***	0.0430**	56.88%
(t-stat)	(3.01)	(9.72)	(2.49)	(6.12)	(2.36)	
6	0.0018**	0.8905***	0.0889***	20.7892***	0.0147	35.09%
(t-stat)	(2.11)	(5.09)	(4.42)	(5.71)	(0.45)	
Panel B: S&P 500 Returns						
	$\triangle IFL_{t-1}$	r_{t-1}	DIV_{t-1}	GNP_{t-1}	LTG_{t-1}	Adj R^2
1	0.0009**	-0.0887	-0.0002	6.1209***	0.0311**	15.01%
(t-stat)	(2.50)	(-1.21)	(-0.02)	(4.15)	(2.33)	
3	0.0014***	0.8707***	0.0266**	12.8443***	0.0300*	55.39%
(t-stat)	(3.04)	(9.05)	(2.49)	(6.62)	(1.71)	
6	0.0018**	0.8576***	0.0826***	21.0345***	0.0052	34.83%
(t-stat)	(2.14)	(4.89)	(4.25)	(5.95)	(0.16)	

This table shows the predictability of the short-selling adjusted implied funding liquidity with horizons of one month, three months, and six months for CRSP Value-Weighted Returns (Panel A) and S&P500 Returns (Panel B). Dependent variables are the cumulative growth rates of each variable calculated over one, three and six months. IFL_{t-1} is the at-the-money adjusted implied funding liquidity at $t-1$, and $MKTEX_{t-1}$ is the market excess returns. The full sample period spans from January 1996 to August 2015, the significance level is given in $*/**/***$ for 10%, 5% and 1% level, respectively.

We had examined the predictive power of the short selling ban adjusted implied funding liquidity, and we now estimate whether the innovations in this adjusted liquidity measure could explain the cross-sectional differences in stock returns. Following prior studies (For instance, Petkova, 2006; Pasquariello, 2014; Adrian et al., 2014), we still obtained Fama and MacBeth's (1973) two-stage method to do the asset pricing tests with 25 size and book-to-market portfolios and 30 industry portfolios. In addition, we also control for other factors including Fama and French's (1992) three factors and Carhart's (1997) momentum factor.

Table 7.13: Exposures to Short-Selling Adjusted Implied Funding Liquidity

Panel A: 25 Size and Book-to-Market Portfolios					
Betas	Low B/M	2	3	4	High B/M
Small	0.21***	0.22***	0.19***	0.18***	0.28***
	(5.15)	(4.42)	(4.55)	(4.60)	(4.84)
2	0.24***	0.20***	0.18***	0.19***	0.20***
	(4.79)	(4.89)	(4.79)	(4.92)	(4.69)
3	0.24***	0.18***	0.17***	0.19***	0.21***
	(5.14)	(4.88)	(5.01)	(5.25)	(5.58)
4	0.21***	0.20***	0.21***	0.19***	0.17***
	(5.03)	(5.99)	(5.80)	(5.70)	(4.59)
Big	0.17***	0.15***	0.16***	0.14***	0.15***
	(4.45)	(5.03)	(5.23)	(4.28)	(4.82)

Panel B: 30 Industry Portfolios					
Industry	Betas	Industry	Betas	Industry	Betas
Autos	0.24***	FabPr	0.23***	Paper	0.13***
	(4.28)		(4.79)		(3.71)
Beer	0.12***	Fin	0.17***	Rtail	0.15***
	(3.51)		(4.27)		(4.45)
Books	0.22***	Food	0.11***	Servs	0.20***
	(5.65)		(4.18)		(4.37)
BusEq	0.21***	Games	0.26***	Smoke	0.07
	(3.67)		(5.34)		(1.49)
Carry	0.17***	Hlth	0.13***	Steel	0.28***
	(4.03)		(4.57)		(4.61)
Chems	0.15***	Hshld	0.09***	Telcm	0.15***
	(3.75)		(3.12)		(3.96)
Clths	0.18***	Meals	0.15***	Trans	0.11***
	(4.00)		(4.52)		(2.92)
Cnstr	0.23***	Mines	0.24***	Txtls	0.19***
	(5.42)		(4.08)		(3.20)
Coal	0.25***	Oil	0.16***	Util	0.11***
	(2.65)		(4.10)		(3.61)
ElcEq	0.21***	Other	0.16***	Whlsl	0.15***
	(4.59)		(3.92)		(4.51)

This table reports OLS estimates of the short selling adjusted funding liquidity ΔIFL betas $\beta_{i,\Delta IFL}$ which is the slope coefficients from the time-series regressions on ΔIFL for the sample period from 04 January 1996 to 31 August 2015. Panel A uses the 25 monthly stock excess returns whilst Panel B obtains the 30 monthly industry Panel A shows the estimates for the 25 size and book-to-market portfolios while Panel B reports the coefficients for the 30 industry portfolios. returns. Newey West t-statistics are shown in bracket and $*, **, ***$ denote significant levels at 10%, 5% and 1% level, respectively.

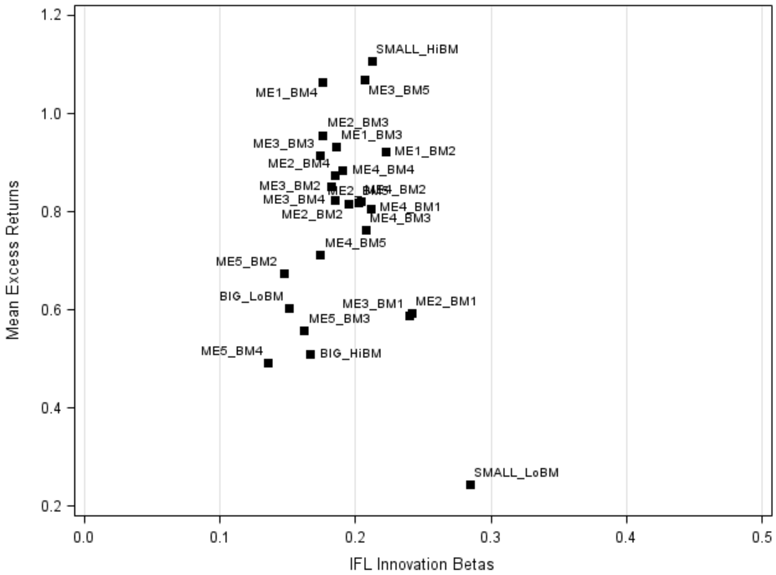
Table 7.13 shows the exposures to short-selling adjusted implied funding liquidity innovations for 25 size and book-to-market and 30 industry stock portfolio returns, respectively. Accordingly, the beta estimates are positive and significant for both the equity and industry portfolios, suggesting that excess returns of the portfolios tend to be higher corresponding with abnormally larger adjusted implied funding liquidity.

In particular, among the 25 Fama and French's stock portfolios, the small and high book-to-market has the highest exposure (0.28) to the adjusted implied funding liquidity innovations, and it is economically and statistically significant at the 1 percent level. In terms of the industry portfolios, the one with the highest beta estimate (0.28) lies in the steel portfolio. These results suggest that small firms, companies with high book to market or those in the stell industry are the most exposed to the variations in funding liquidity. These results are consistent to the results in Table 6.3, and this suggests that there is no strong influence of the short selling on our implied funding liquidity.

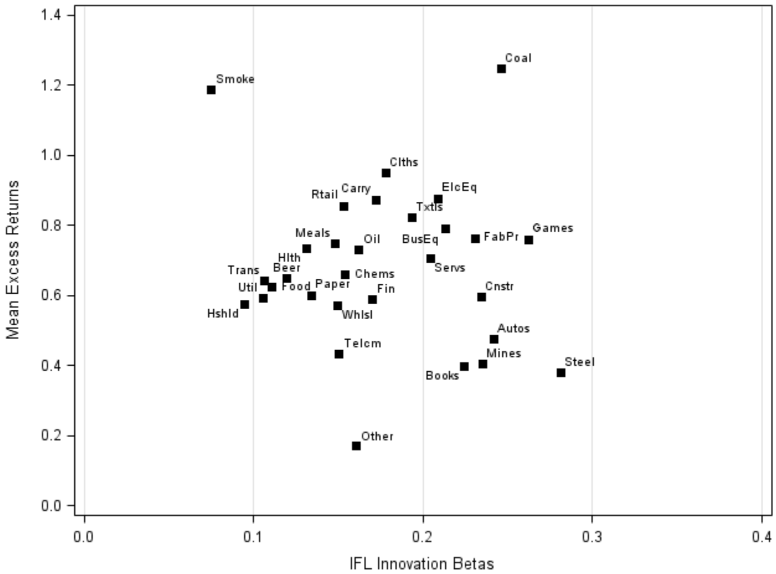
Figures 7.8 shows scatter plots of excess returns versus their short selling adjusted ΔIFL betas for the 25 Portfolios and 30 industry portfolios. Beside the Small and Low BM portfolio ($SMALL\_LoBM$) and smoke industry portfolio ($Smoke$), portfolios with higher IFL innovation betas had bigger mean excess returns, which is highly consistent with Figure 6.1.

Table 7.14 reports the coefficients and Newey-West adjusted *t*-statistics (in parentheses) obtained from the cross-sectional regressions with the short selling adjusted implied funding liquidity measure.

Table 7.14 shows that the estimates for adjusted implied funding liquidity are still positive ($\lambda_{\Delta IFL} > 0$) and significant at the 1% level for both of the 25 equity and 30 industry portfolios, and the adjusted implied funding liquidity risk premiums are similar to their counterparts in Table 6.4. In particular, in the univariate model, $\lambda_{\Delta IFL}$ amounts to 0.1929 and 0.1749 per unit of ΔIFL beta for equity and industry portfolios, respectively. Moreover, the univariate model with the adjusted implied funding liquidity explain 9.64 percent and 6.75 percent of the cross-sectional variations in returns for the 25 size and book-to-market and 30 industry portfolios. This suggests that the adjusted implied funding liquidity risk alone still has a strong explanation of cross-sectional stock portfolio returns, and compared to the results in Table 6.4, there is no significant change after taking short selling into account.



(a) Monthly Level



(b) Monthly Innovations

Figure 7.8: Short-Selling Adjusted ΔIFL Betas and Portfolio Excess Returns

This figure shows the scattered average portfolio excess returns versus their adjusted implied funding liquidity risk betas ($\beta_{\Delta IFL}$). Figure 7.8(a) is based on 25 size and book-to-market equity portfolios, and Figure 7.8(b) is based on 30 industry stock portfolios. IFL Innovation betas and mean excess returns were estimated for each equity portfolio and the sample spans from 04 January 1996 to 31 August 2015.

Table 7.14: Cross-Sectional Regressions Excluding Short-Selling Adjusted Implied Funding Liquidity

Panel A: 25 Portfolios							
Model	λ_0	$\lambda_{\Delta IFL}$	λ_{MKT}	λ_{SMB}	λ_{HML}	λ_{Mom}	R^2
Univariate	1.0202***	0.1929***					9.64%
	(25.89)	(30.22)					
CAPM	0.3999***	0.0223***	1.0258***				69.43%
	(10.50)	(6.71)	(34.51)				
FF	0.2290***	0.0087**	0.9974***	0.5187***	0.2724***		90.32%
	(6.36)	(2.26)	(76.52)	(3.89)	(3.54)		
FF, Mom	0.2458***	0.0088**	0.9878***	0.5219***	0.2636***	-0.0232***	90.46%
	(7.60)	(2.28)	(83.31)	(3.92)	(3.45)	(-3.11)	
Panel B: 30 Industry Portfolios							
Model	λ_0	$\lambda_{\Delta IFL}$	λ_{MKT}	λ_{SMB}	λ_{HML}	λ_{Mom}	R^2
Univariate	0.9208***	0.1749***					6.75%
	(21.70)	(20.00)					
CAPM	0.3435***	0.0162**	0.9546***				50.49%
	(8.99)	(2.70)	(16.87)				
FF	0.2304***	0.0107*	1.0054***	0.0740**	0.3463***		58.08%
	(5.28)	(1.77)	(18.68)	(2.10)	(5.59)		
FF, Mom	0.2715***	0.0109*	0.9820***	0.0816**	0.3247***	-0.0564***	59.00%
	(6.89)	(1.83)	(18.54)	(2.31)	(5.15)	(-2.77)	

This table reports the estimates and Newey-West t-statistics (in bracket) from Fama and MacBeth (1973)□s two-stage regressions for the 25 size and book-to-market (Panel A) and 30 industry equity portfolios (Panel B) over the sample period from 04 January 1996 to 31 August 2015. ΔIFL is the short selling adjusted funding liquidity innovations; MKT is the excess market return; SMB is the average return on the small stock portfolios minus the average return on the big stock portfolios; HML is the average return on the value portfolios minus the average return on the growth portfolios; MOM is a momentum factor. $*/**/***$ denotes the significance level at 10%, 5% and 1% level, respectively.

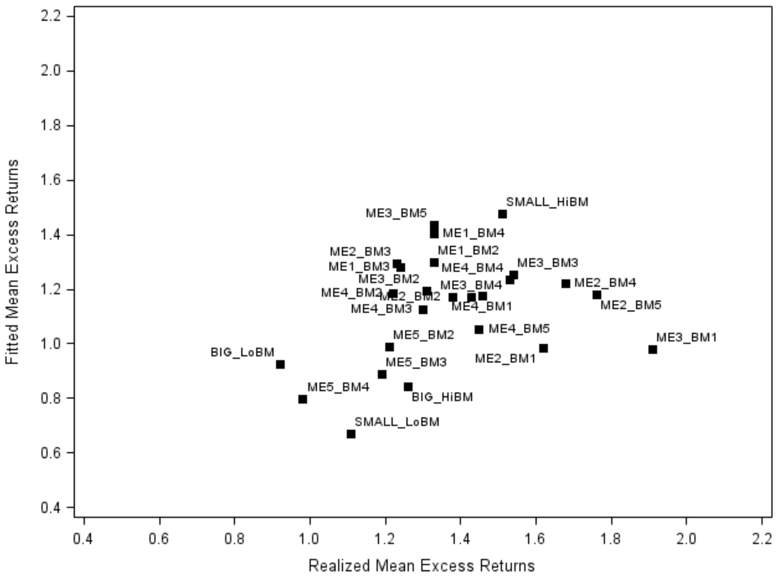
In addition, the estimates in Table 7.14 for the adjusted implied funding liquidity are significant after controlling for Fama French's (1992) three factors and Carhart's (1997) momentum factor, and this shows that the implied funding liquidity is still important in capturing equity market returns after controlling for the short selling constrictions.

In particular, the five-factor model (Fama French three traded factors plus momentum) with adjusted implied funding liquidity measure registers R-square values of 90.46 percent and 59.00 percent for the 25 size and book-to-market, and 30 industry portfolios, respectively. Table 7.14 shows that $\lambda_{\Delta IFL}$s are still statistically and economically significant. For instance, the estimated adjusted implied funding liquidity risk premiums, $\lambda_{\Delta IFL}$, are 0.0088 and 0.0109, respectively. This evidence is consistent with (Beber and Pagano, 2013), suggesting that short selling bans decrease liquidity, but our implied funding liquidity measure is still significant after controlling for the short selling constrictions.

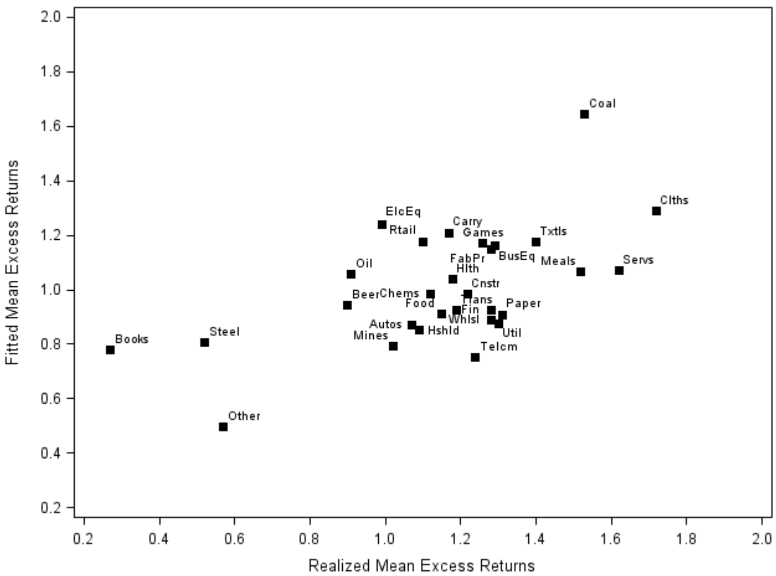
Figure 7.9(a) and 7.9(b) plots the actual versus predicted average returns from the one-factor model with the short selling ban adjusted implied funding liquidity for the 25 size and book-to-market portfolios (Panel a) and 30 industry portfolio (Panel b). Similar to Figure 6.2, there is a strong and positive relationship between the realised and the predicted average returns for these portfolios, which suggests that the implied funding liquidity matters in explaining the cross-sectional variations in equity portfolio returns, even after taking the short selling constrictions into account.

As comparisons, we controlled for eight existing liquidity measures documented in the literature. As a benchmark, we used the CAPM with short selling adjusted implied funding liquidity for performance comparison. Table 7.15 (Panel A) presents the estimates of the liquidity measures for the 25 size-to-book portfolios, while Panel B reports the estimates of the liquidity measures for the 30 industry portfolios.

Table 7.15 (Panel A) indicates that the TED, FG , Amihud, and Sadka measures are significant while PS, Noise, and CS measures are insignificant, which is similar to Table 6.8. The short selling adjusted implied funding liquidity remains positive and significant at the one percent level in all models. Specifically, our measure is still statistically and economically significant at the one percent level when the model includes the market return factor and all liquidity variables with an R-square of 72.19 percent. This suggests that our measure dominates the PS,



(a) 25 Portfolios



(b) 30 Industry Portfolios

Figure 7.9: Realised vs Predicted Average Returns of Stock Returns: Short-Selling Restrictions

This figure presents the average realised versus predicted returns from the one-factor model with adjusted implied funding liquidity for the 25 size and book-to-market portfolios (Panel a) and 30 industry portfolio (Panel b). The sample spans 4 January 1996 to 31 August 2015.

Table 7.15: Cross-sectional Regressions with Liquidity Measures: Short-Selling Restrictions

Model	λ_0	$\lambda_{\Delta IFL}$	λ_{MKT}	λ_{PS}	λ_{TED}	λ_{FG}	λ_{Noise}	λ_{Amihud}	λ_{RS}	λ_{CS}	λ_{Sadka}	R^2
Panel A: 25 Portfolios												
+PS	0.4667***	0.0299***	1.0206***	0.3776								69.69%
	(11.25)	(7.20)	(31.51)	(0.37)								
+TED	0.7703***	0.0261***	1.0155***		-0.5556***							70.03%
	(8.17)	(6.69)	(32.93)		(-3.65)							
+FG	0.4648***	0.0277***	1.0250***			-0.2768***						69.97%
	(11.34)	(7.33)	(34.25)			(-5.80)						
+NOISE	0.6041***	0.0311***	1.0171***				-0.0414					70.00%
	(5.58)	(8.09)	(30.89)				(-1.24)					
+Amihud	0.6395***	0.0303***	1.0170***					-0.0512***				69.73%
	(12.80)	(7.65)	(33.50)					(-4.58)				
+RS	0.6306***	0.0303***	1.0176***						-4.3540*			69.69%
	(7.33)	(7.64)	(33.43)						(-1.71)			
+CS	0.4581***	0.0302***	1.0219***							0.4954		69.61%
	(6.03)	(7.58)	(34.44)							(0.10)		
+Sadka	0.4222***	0.0277***	1.0287***								3.23***	70.39%
	(9.72)	(7.04)	(34.69)								(7.52)	
+ALL	-0.1500	0.0194***	1.0354***	-0.7389	-0.5210***	-0.4142***	0.0567	-0.1859***	10.4011	58.8075***	2.77***	72.19%
	(-1.37)	(6.30)	(31.43)	(-0.85)	(-3.15)	(-6.18)	(0.99)	(-9.44)	(1.71)	(6.39)	(6.78)	
Panel B: 30 Industry Portfolios												
+PS	0.4344***	0.0132**	0.9454***	2.7113*								50.90%
	(7.02)	(2.11)	(16.91)	(1.99)								
+TED	0.8468***	0.0099	0.9453***		-0.7659***							50.90%
	(7.51)	(1.65)	(16.16)		(-4.85)							
+FG	0.4262***	0.0134**	0.9571***			-0.2551***						50.78%
	(7.02)	(2.16)	(16.38)			(-4.75)						
+NOISE	0.6909***	0.0174**	0.9451***				-0.0790***					50.79%
	(7.76)	(2.71)	(15.98)				(-3.81)					
+Amihud	0.6224***	0.0158**	0.9486***					-0.0575***				50.69%
	(7.15)	(2.49)	(16.18)					(-3.65)				
+RS	0.6231***	0.0158**	0.9491***						-5.1789*			50.49%
	(4.94)	(2.49)	(16.08)						(-1.82)			
+CS	0.4675***	0.0157**	0.9538***							-2.6164		50.54%
	(2.96)	(2.48)	(16.17)							(-0.25)		
+Sadka	0.3884***	0.0134**	0.9602***								2.86***	50.99%
	(6.61)	(2.17)	(16.35)								(4.77)	
+ALL	-0.1791	0.0035	0.9574***	1.4747	-0.7642***	-0.3061***	-0.0067	-0.1662***	17.6957***	59.0632***	2.38***	53.64%
	(-1.08)	(0.58)	(16.84)	(1.11)	(-4.28)	(-5.19)	(-0.17)	(-5.47)	(3.11)	(3.54)	(4.54)	

This table reports the estimates and the Newey West t-statistics (in the bracket) from the cross-sectional regressions with other liquidity measures. Let ΔIFL denotes the innovations in the at-the-money option adjusted implied funding liquidity measure, and MKT the excess market return. We considered the Pastor and Stambaugh's (PS) measure (2003), Brunnermeier et al.'s Treasury-LIBOR (TED) spread (2008), Hu et al.'s Noise (Noise) measure (2013), Fontaine and Garcia's (FG) measure (2012), Amihud's il-liquidity (Amihud) measure (2002), Corwin and Schultz's (CS) measure (2012), the relative spread (RS), and Sadka's (Sadka) measure (2006). The significance level is written in $*/**/***$ for 10%, 5% and 1% level, respectively.

Noise, and CS measures after we taking the short selling constrictions into account.

In Panel B of Table 7.15, we could observe that aside from the CS measure, all other measures are significant when we combine any one of them with our measure, and our measure still significant at the one percent level. However, when we include all liquidity variables and the market return factor jointly in one model, our implied funding liqudity measure becomes insignificant and the model has an R-square about 53.64 percent.

We observe that the adjusted implied funding liquidity remains significant in explaining stock return variations even controlling for established liquidity measures. Our findings show that the implied funding liquidity measure does incorporate the forward-looking nature, and it provides incremental information about equity returns beyond what is captured in the previous liquidity measures after taking the short selling constrictions into account.

Prior studies (for instance, De Long et al., 1990; Baker and Wurgler, 2006, 2007, 2012; Yu and Yuan, 2011; Huang et al., 2015; Da et al., 2015; Jiang et al., 2018) show that investor sentiment indexes could result in prices diverging from their fundamental values, and Table 5.7 shows that the implied funding liquidity measure is associated with some existing investor sentiment indexes. Now, we will investigate the conncection between our implied funding liquidity measure and investor sentiment indexes after controlling for the short selling restrictions.

We still considered seven existing investor sentiment measures documented in section 5.5, including Baker and Wurgler's (2006) investor sentiment measure, BW, the aligned investor sentiment index of Huang et al. (2015), HJTZ, the consumer sentiment index of University of Michigan, UMC, the Conference Board consumer confidence index, CB, the Financial and Economics Attitudes Revealed by Search (FEARS) the investor sentiment index of Da et al. (2015), DEG, the Jiang et al. manager sentiment index (2008), JLMZ, and CBOE Put-Call ratios, PCR. Detailed descriptions of these investor sentiment proxies are provided in Section 5.5. We included these indexes in the cross-sectional regressions with the adjusted implied funding liquidity measure. For performance comparison purpose, we used the univariate model with the implied funding liquidity measure as a benchmark.

Results of the estimates of the investor sentiment measures for the 25 size-to-book portfolios are summarised in Table 7.16 (Panel A), while Panel B reports the

Table 7.16: Cross-sectional Regressions with Investor Sentiment Measures: Short-Selling Restrictions

	λ_0	$\lambda_{\Delta IFL}$	$\lambda_{\Delta BW}$	$\lambda_{\Delta HJTZ}$	$\lambda_{\Delta UMC}$	$\lambda_{\Delta CB}$	$\lambda_{\Delta DEG}$	$\lambda_{\Delta JLMZ}$	$\lambda_{\Delta PCR}$	R^2
Panel A: 25 Portfolios										
+BW	0.5937***	0.2049***	6.6869***							15.89%
	(6.40)	(33.00)	(9.95)							
+HJTZ	0.4645***	0.1767***		-5.0039***						17.53%
	(4.94)	(30.61)		(-13.86)						
+UMC	0.5609***	0.1774***			0.2025***					16.57%
	(6.02)	(26.14)			(8.41)					
+CB	0.5949***	0.1496***				4.5931***				18.84%
	(6.53)	(20.56)				(14.21)				
+DEG	0.5169***	0.2003***					0.0864			15.08%
	(5.48)	(32.95)					(1.66)			
+JLMZ	0.5366***	0.2126***						5.9705***		24.54%
	(5.72)	(35.60)						(22.42)		
+PCR	0.4900***	0.1584***							-13.241***	17.84%
	(5.24)	(25.86)							(-34.20)	
+ALL	0.6660***	0.1018***	13.4211***	-8.7908***	0.0333	3.6266***	0.2987***	6.1584***	-9.3267***	37.03%
	(7.41)	(16.36)	(17.30)	(-31.04)	(1.25)	(9.95)	(6.68)	(27.05)	(-20.49)	
Panel B: 30 Industry Portfolios										
+BW	0.7718***	0.2029***	6.0325***							14.21%
	(12.07)	(16.97)	(5.21)							
+HJTZ	0.6254***	0.1631***		-7.4761***						16.98%
	(10.66)	(16.03)		(-14.28)						
+UMC	0.7267***	0.1861***			0.1140***					14.98%
	(13.04)	(12.75)			(3.18)					
+CB	0.7690***	0.1555***				3.9164***				16.39%
	(13.62)	(11.59)				(8.46)				
+DEG	0.6975***	0.2004***					-0.1512**			13.63%
	(11.60)	(16.72)					(-2.39)			
+JLMZ	0.7202***	0.2098***						5.3484***		20.40%
	(12.00)	(17.04)						(16.89)		
+PCR	0.6779***	0.1604***							-12.110***	15.40%
	(11.34)	(16.34)							(-10.37)	
+ALL	0.8091***	0.1063***	13.4214***	-11.065***	-0.0587	3.6841***	0.1643**	5.9599***	-7.3025***	34.23%
	(14.01)	(9.13)	(9.70)	(-14.48)	(-1.57)	(8.44)	(2.08)	(17.49)	(-7.27)	

This table reports the estimates and Newey West t-statistics (in the bracket) from the cross-sectional regressions. IFL denotes the short selling adjusted implied funding liquidity measure. We considered seven investor sentiment indexes, including Baker and Wurgler's (2006) investor sentiment measure, BW, the aligned investor sentiment index of Huang et al. (2015), HJTZ, the consumer sentiment index of University of Michigan, UMC, the Conference Board consumer confidence index, CB, the Financial and Economics Attitudes Revealed by Search (FEARS), the investor sentiment index of Da et al. (2015), DEG, the Jiang et al. manager sentiment index (2018), JLMZ, and CBOE Put-Call ratios, PCR. +All indicates regressions with all of the relevant variables in the model. The significance level is written in $*/**/***$ for 10%, 5% and 1% level, respectively.

estimates for the 30 industry portfolios.

According to Panel A of Table 7.16, we observed that the adjusted implied funding liquidity are positive and significant at the one percent level after controlling for the investor sentiment indexes in both the bivariate models and the one regression with all the indexes. Similar to Table 6.11, except for the Financial and Economics Attitudes Revealed by Search (FEARS) the investor sentiment index of Da et al. (2015), DEG, all other investor sentiment proxies are significant at the one percent level in the bivariate models. In the regression with all the measures, the model registers an R-square of 36.65 percent.

Similar patterns were shown Table 7.16 (Panel B) for the industry portfolios, except the consumer sentiment index of University of Michigan, UMC, which is not significant in the regression with all the measures together. Importantly, our adjusted implied funding liquidity measure is still statistically significant when controlling for alternative investor sentiment proxies in the bivariate regressions. The R-square with all investor sentiment variables is about 34.23 percent.

After controlling for the investor sentiment indexes, the coefficients for our short selling adjusted implied funding liquidity remains positive and significant, and this is evident that our measure contains additional information beyond existing investor sentiment indexes in the stock market.

7.5 Dollar Volume Weight

Previous studies argued that there is a reversal relationship between market average of liquidity and trading activity (Chordia et al., 2001; Amihud, 2002; Pástor and Stambaugh, 2003; Chen et al., 2017). In practice, traders obtained average daily volume to estimate how ease to trade an equity: if there is a higher average daily volume, it is easier to execute large number of trading without significant influence the market. Amihud (2002) illiquidity, daily ratio of absolute stock return over its dollar volume, is a widely used illiquidity measure.

Following Chordia et al. (2001), Amihud (2002) and Pástor and Stambaugh (2003), we controlled total dollar volume, number of shares outstanding multiplied by the quoted price, when we constructed our implied funding liquidity measure. In this section, we controlled the dollar volume during the construction of our implied funding liquidity measure. More specifically, the implied funding liquidity measure, IFL_t, was obtained as follows:

$$IFL_t = \frac{\sum_{i=1}^{N} DV_{i,t} \times |IV_{i,t}^{C} - IV_{i,t}^{P}|}{\sum_{i=1}^{N} DV_{i,t}} \tag{7.5}$$

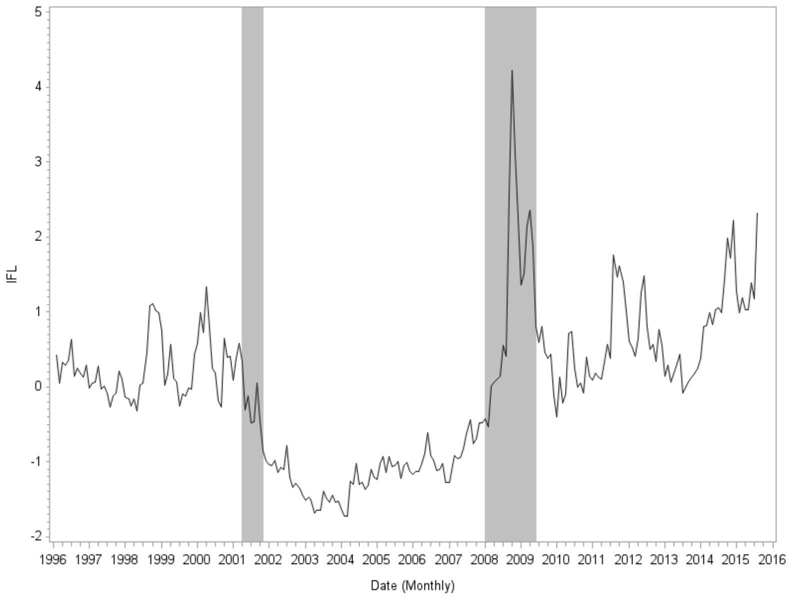
Where $IV_{i,t}^{C}$ and $IV_{i,t}^{P}$ are the implied volatilities obtained from the call and put options of the same stock i with the same strike price and maturity date; $DV_{i,t}$ is the total dollar volume of stock i at time t; N is the number of stock at that time.

Then, we could calculate the dollar volume weighted ΔIFL with using function 4.4.

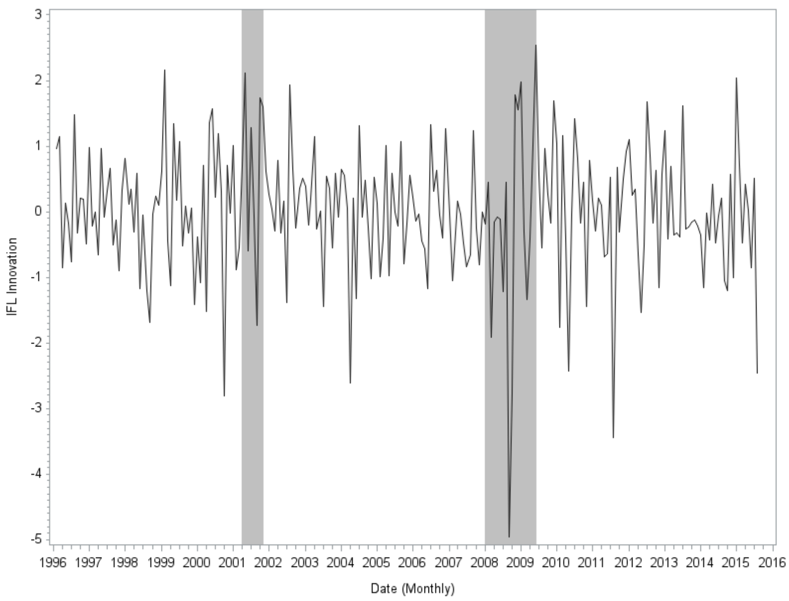
Figure 7.10 indicates the monthly level (Panel A) and innovations (Panel B) of the standardised dollar volume weighted implied funding liquidity measure from January 1996 to August 2015. Similar to Figure 5.1, we saw sharp plummets of ΔIFL during financial stress periods. We observed that the largest decrease still occurred in October 2008 which coincided with the collapse of Lehman Brothers and the funding squeezes in inter-bank lending markets. Panel (b) of Figure 7.10 demonstrates that the dollar volume weighted ΔIFL increased around 0.4 to -4.8 compared to the value weighted implied funding liquidity innovation.

In order to estimate the return predictability power of the dollar volume weighted implied funding liquidity measure, we still obtained monthly returns of the $S\&P500$ index and the value-weighted average returns provided by CRSP as market return measures. Similarly, we controlled for variables that are found to predict market returns, including the dividend yield on the $S\&P500$ index, the real GNP growth rate, the long-term government bond return, and the past market excess return. We still used the predictive regression model 4.13.

Table 7.17 shows the results of return predictive regressions for the dollar volume weighted implied funding liquidity measure with horizons of one month, three months, and six months for CRSP Value-Weighted Returns (Panel A) and S&P 500 Returns (Panel B). We observed that most coefficients for the dollar volume weighted liquidity measure remain positive and significant for horizons of one, three and six months. Interestingly, compared with the results in 6.2, we find that it was not statistically significant for a horizon of one month, and the magnitude of the coefficients is smaller. The predictive power of the dollar volume weighted implied funding liquidity remains robust after controlling for other forecasting variables including dividend yield, the GNP growth rate and long-term



(a) Monthly Level



(b) Monthly Innovations

Figure 7.10: Dollar Volume Weighted Implied Funding Liquidity

This figure presents the time series of the monthly level (Panel a) and innovations (Panel b) of the standardised dollar volume weighted implied funding liquidity measure over the sample from 04 January 1996 to 31 August 2015. The shaded area contains the NBER's business cycle dates.

government bond returns.

Table 7.17: Market Return Predictability with Dollar Volume Weighted Implied Funding Liquidity

Panel A: CRSP Value-Weighted Market Returns						
	$\triangle IFL_{t-1}$	r_{t-1}	DIV_{t-1}	GNP_{t-1}	LTG_{t-1}	Adj R^2
1	0.0008**	-0.0222	-0.0015	5.4522***	0.0371***	13.72%
(t-stat)	(2.18)	(-0.31)	(-0.17)	(3.54)	(2.64)	
3	0.0015***	0.9716***	0.0276**	12.3570***	0.0396**	57.21%
(t-stat)	(3.26)	(10.44)	(2.49)	(6.16)	(2.17)	
6	0.0022**	0.9237***	0.0888***	20.8566***	0.0100	35.68%
(t-stat)	(2.51)	(5.49)	(4.44)	(5.75)	(0.30)	
Panel B: S&P 500 Returns						
	$\triangle IFL_{t-1}$	r_{t-1}	DIV_{t-1}	GNP_{t-1}	LTG_{t-1}	Adj R^2
1	0.0008**	-0.0660	-0.0002	6.1390***	0.0293**	14.72%
(t-stat)	(2.37)	(-0.93)	(-0.03)	(4.16)	(2.19)	
3	0.0014***	0.9035***	0.0265**	12.8812***	0.0269	55.44%
(t-stat)	(3.08)	(9.66)	(2.48)	(6.64)	(1.53)	
6	0.0020**	0.8929***	0.0825***	21.0972***	0.0009	35.19%
(t-stat)	(2.38)	(5.25)	(4.26)	(5.98)	(0.03)	

This table shows the predictability of dollar volume weighted implied funding liquidity with horizons of one month, three months, and six months for CRSP value-weighted Returns (Panel A) and S&P 500 returns (Panel B). Dependent variables are the cumulative growth rates of each variable calculated over one, three and six months. IFL_{t-1} is the dollar volume weighted implied funding liquidity at $t-1$, and $MKTEX_{t-1}$ is the market excess returns. The full sample period spans January 1996 to August 2015, the significance levels are presented as $*/{*}{*}/{*}{*}{*}$ for 10%, 5% and 1%, respectively.

The predictive power of the dollar volume weighted implied funding liquidity had been estimated, and we now examine whether the innovations in this adjusted liquidity measure could explain the cross-sectional differences in stock returns. Using Fama and MacBeth's (1973) two-stage approach for the asset pricing tests, we used 25 size and book-to-market portfolios and 30 industry portfolios. Furthermore, we consider the pricing effects of the implied funding liquidity innovations in addition to other factors in the US equity markets including Fama and French's (1992) three factors and Carhart's (1997) momentum factor.

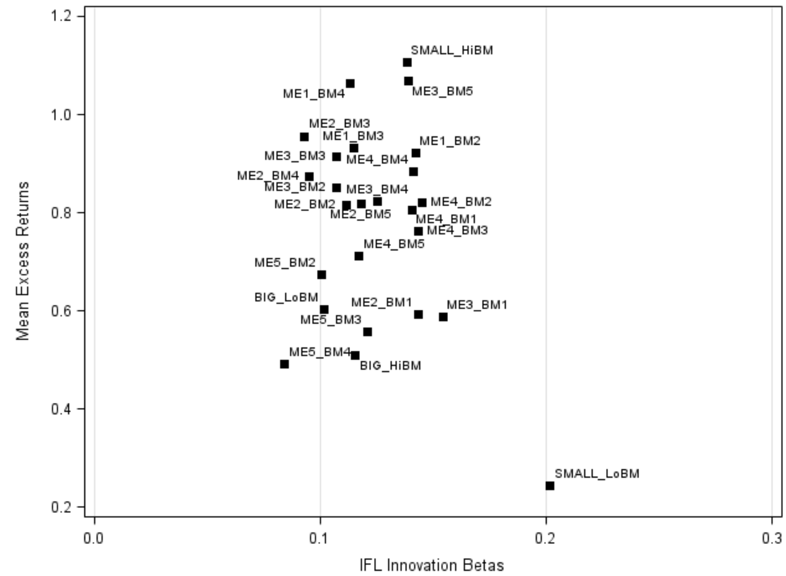
Table 7.18 reports the exposures to dollar volume weighted implied funding liquidity innovations for 25 size and book-to-market and 30 industry stock portfolio returns. Accordingly, we observe that the beta estimates are positive and significant for the majority of both the equity and industry portfolios, suggesting that excess returns of the portfolios have a tendency to be larger corresponding with abnormally greater dollar volume weighted implied funding liquidity.

Table 7.18: Exposures to Dollar Volume Weighted Implied Funding Liquidity Innovation

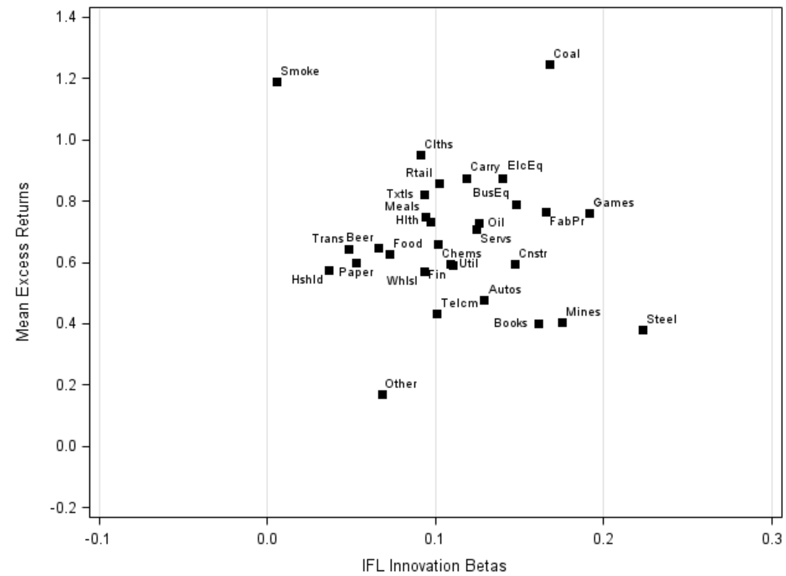
Panel A: 25 Size and Book-to-Market Portfolios					
Betas	Low B/M	2	3	4	High B/M
Small	0.20***	0.14***	0.15***	0.14***	0.14***
	(3.19)	(2.62)	(3.05)	(3.08)	(3.09)
2	0.14***	0.11**	0.11***	0.15***	0.10***
	(2.63)	(2.57)	(2.64)	(3.90)	(3.18)
3	0.11**	0.09**	0.11***	0.14***	0.12***
	(2.60)	(2.33)	(2.84)	(3.67)	(3.60)
4	0.11***	0.09**	0.13***	0.14***	0.08**
	(2.74)	(2.32)	(3.27)	(3.89)	(2.47)
Big	0.10***	0.12**	0.14***	0.12***	0.12***
	(3.00)	(2.52)	(3.44)	(2.86)	(2.87)

Panel B: 30 Industry Portfolios					
Industry	Betas	Industry	Betas	Industry	Betas
Autos	0.13**	FabPr	0.17***	Paper	0.05
	(2.12)		(3.20)		(1.36)
Beer	0.07*	Fin	0.11**	Rtail	0.10***
	(1.82)		(2.58)		(2.77)
Books	0.16***	Food	0.07**	Servs	0.12**
	(3.74)		(2.56)		(2.48)
BusEq	0.15**	Games	0.19***	Smoke	0.01
	(2.39)		(3.60)		(0.10)
Carry	0.12**	Hlth	0.10***	Steel	0.22***
	(2.59)		(3.14)		(3.41)
Chems	0.10**	Hshld	0.04	Telcm	0.10**
	(2.32)		(1.12)		(2.49)
Clths	0.09*	Meals	0.09***	Trans	0.05
	(1.90)		(2.68)		(1.25)
Cnstr	0.15***	Mines	0.18***	Txtls	0.09
	(3.11)		(2.85)		(1.44)
Coal	0.17*	Oil	0.13***	Util	0.11***
	(1.71)		(2.99)		(3.55)
ElcEq	0.14***	Other	0.07	Whlsl	0.09***
	(2.86)		(1.54)		(2.61)

This table reports OLS estimates of the dollar volume weighted implied funding liquidity ΔIFL betas $\beta_{i,\Delta IFL}$ which is the slope coefficients from the time-series regressions on ΔIFL for the sample period from 04 January 1996 to 31 August 2015. Panel A shows the estimates for 25 size and book-to-market portfolios while Panel B reports the coefficients for the 30 industry portfolios. The full sample period spans January 1996 to August 2015. Newey West *t*-statistics are shown in bracket and $*$, $**$, $***$ denote significant levels at 10%, 5% and 1% level, respectively.



(a) Monthly Level



(b) Monthly Innovations

Figure 7.11: Dollar Volume Weighted ΔIFL Betas and Portfolio Excess Returns

This figure shows the scattered average portfolio excess returns versus the dollar volume weighted implied funding liquidity risk betas ($\beta_{\Delta IFL}$). Figure 7.11(a) is based on the 25 size and book-to-market equity portfolios, and Figure 7.11(b) on 30 industry stock portfolios. IFL Innovation betas and mean excess returns are estimated for each equity portfolio and the sample spans from January 1996 to August 2015.

The small and low book-to-market portfolio has the highest exposure (0.20) to the dollar volume weighted implied funding liquidity innovations among the 25 Fama and French's equity portfolios, and it is economically and statistically significant at the 1 percent level. In addition, within the industry portfolios, the one with the highest beta estimate (0.20) lies in the mines portfolio. These results suggest that small firms, companies with low book to market or those in the mines industry are the most exposed to the variations in funding liquidity, which is consistent to the results in Table 6.3.

Scatter plots of excess returns versus their dollar volume weighted ΔIFL betas for the 25 portfolios and 30 industry portfolios are displayed in Figures 7.11(a) and 7.11(b), respectively. Similar to Figure 6.1, aside from the small and low BM portfolio ($SMALL\_LoBM$) and smoke industry portfolio ($Smoke$), Figure 7.2 indicates that portfolios with higher IFL innovation betas had larger mean excess returns, which suggests that dollar volume weighted implied funding liquidity still performs well.

Table 7.19 reports the coefficients and Newey-West adjusted *t*-statistics (in parentheses) obtained from the cross-sectional regressions with the dollar volume weighted implied funding liquidity measure. Compare to the results in Table 6.4, the estimates for the dollar volume weighted implied funding liquidity are still positive ($\lambda_{\Delta IFL} > 0$) and significant at the 1% level for the 25 equity, while aside from the univariate model, it is not statistically significant for 30 industry portfolios.

In particular, $\lambda_{\Delta IFL}$ amounts to 0.1246 and 0.1120 per unit of the ΔIFL beta for the stock and industry portfolios, respectively. In addition, the univariate model with the dollar volume weighted implied funding liquidity explains around 3.73% and 2.69% percent of the cross-sectional variations in returns for the 25 size and book-to-market and 30 industry portfolios. This suggests that the dollar volume weighted implied funding liquidity risk alone still a meaningfully explanation of cross-sectional stock portfolio returns, even though this explanation is relatively weaker.

The estimates in Panel A of Table 7.19 for Fama French's three factors (1992) and Carhart's momentum factor (1997) with dollar volume weighted implied funding liquidity are significant, suggesting that they are still important in capturing equity market returns after controlling for the trading activity. The four-factor model with the dollar volume weighted implied funding liquidity measure has

Table 7.19: Cross-Sectional Regressions with the Dollar Volume Weighted Implied Funding Liquidity

Panel A: 25 Portfolios							
Model	λ_0	$\lambda_{\Delta IFL}$	λ_{MKT}	λ_{SMB}	λ_{HML}	λ_{Mom}	R^2
Univariate	0.9896***	0.1246***					3.73%
	(25.43)	(24.94)					
CAPM	0.3892***	0.0090*	1.0371***				69.36%
	(10.30)	(1.74)	(33.55)				
FF	0.2270***	0.0109**	0.9987***	0.5204***	0.2734***		90.35%
	(6.32)	(2.24)	(72.33)	(3.92)	(3.54)		
FF, Mom	0.2435***	0.0108**	0.9893***	0.5235***	0.2647***	-0.0229***	90.49%
	(7.57)	(2.22)	(78.23)	(3.94)	(3.46)	(-3.10)	
Panel B: 30 Industry Portfolios							
Model	λ_0	$\lambda_{\Delta IFL}$	λ_{MKT}	λ_{SMB}	λ_{HML}	λ_{Mom}	R^2
Univariate	0.8928***	0.1120***					2.69%
	(21.34)	(16.17)					
CAPM	0.3350***	0.0046	0.9636***				50.50%
	(8.85)	(0.86)	(17.33)				
FF	0.2249***	0.0048	1.0106***	0.0758**	0.3474***		58.12%
	(5.23)	(0.90)	(19.19)	(2.17)	(5.60)		
FF, Mom	0.2654***	0.0045	0.9875***	0.0835**	0.3259***	-0.0562**	59.04%
	(6.78)	(0.82)	(19.03)	(2.38)	(5.15)	(-2.75)	

This table reports the estimates and Newey-West t-statistics (in bracket) from Fama and MacBeth (1973)□s two-stage regressions for the 25 size and book-to-market (Panel A) and 30 industry equity portfolios (Panel B) over the sample period from 04 January 1996 to 31 August 2015. ΔIFL is the dollar volume weighted funding liquidity innovations; MKT is the excess market return; SMB is the average return on the small stock portfolios minus the average return on the big stock portfolios; HML is the average return on the value portfolios minus the average return on the growth portfolios; MOM is a momentum factor. $*/{*}{*}/{*}{*}{*}$ denotes the significance level at 10%, 5% and 1% level, respectively.

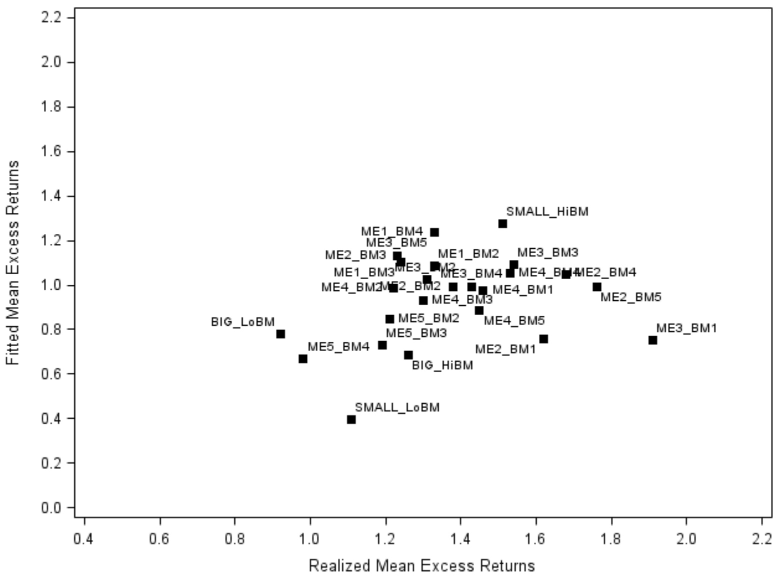
R-square values of 90.35% and 58.12% for the 25 size and book-to-market, and 30 industry portfolios, respectively. $\lambda_{\Delta IFL}$s are smaller but still statistically significant relative to Fama and French's three factors, and Fama and French's three factors plus momentum for the 25 size and book-to-market portolios. For example, the estimated dollar volume weighted implied funding liquidity risk premiums, $\lambda_{\Delta IFL}$, is 0.0109. Moreover, the five-factor model, controlling for MKT, SMB, HML, and MOM, with the dollar volume weighted implied funding liquidity measure does well with R-square value of 90.49% for the 25 size. Consistent with Chordia et al. (2001), equity portfolio with greater exposure to the implied funding liquidity risk performed more poorly after taking the influence of trading activity into consideration.

Figure 7.12(a) and 7.12(b) plots the actual versus predicted average returns from the one-factor model with the dollar volume weighted implied funding liquidity for the 25 size and book-to-market portfolios and 30 industry portfolio, respectively. Similarly, a strong and positive relationship exists between the realised and the predicted average returns for these portfolios. This suggests that funding liquidity matters in explaining the cross-sectional variations in equity portfolio returns, and the sensitivities of equity and industry portfolios to funding liquidity still tend to proportionally explain their risk which is not fully captured by other well-known priced factors after we take the trading activity into account.

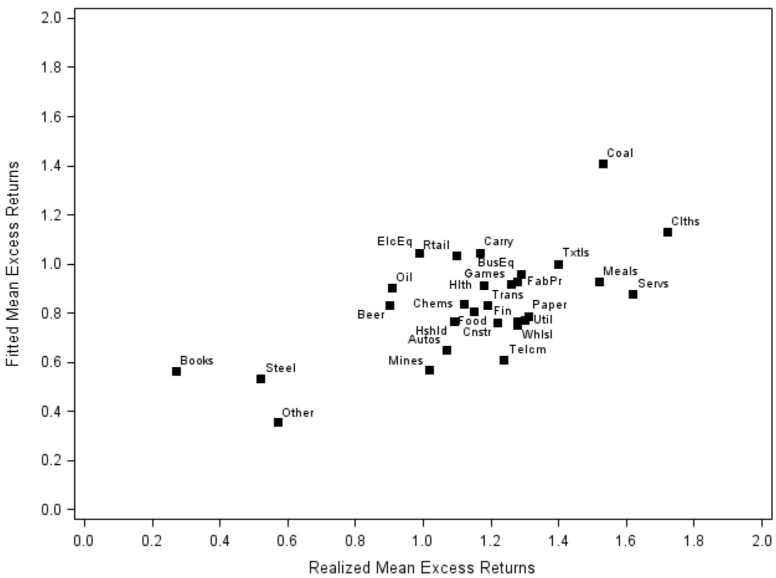
As comparisons, we consider seven existing liquidity measures documented in the literature (Pástor and Stambaugh, 2003; Brunnermeier et al., 2008; Hu et al., 2013; Fontaine et al., 2015; Amihud, 2002; Corwin and Schultz, 2012) in the cross-sectional regressions including the PS measure, the TED spread, and the Noise, FG, Amihud, CS, and Sadka measures, as well as RS in addition to the dollar volume weighted implied funding liquidity measure.

In this comparison analysis, we obtained the CAPM with the dollar volume weighted implied funding liquidity measure as the benchmark. Table 7.20 (Panel A) reports the estimates of the liquidity measures for the 25 size-to-book portfolios, while Panel B shows the estimates of the liquidity measures for the 30 industry portfolios.

The Panel A of Table 7.20 reports that, aside from PS, Noise, RS, and CS measures, other liquidity measures are significant at the one percent level. The dollar volume weighted implied funding liquidity remains positive and significant at the one percent level, which is consistent to Table 6.8. The model with all liquidity



(a) 25 Portfolios



(b) 30 Industry Portfolios

Figure 7.12: Realised vs Predicted Average Returns of Stock Returns: Dollar Volume Weight

This figure presents the average realised versus predicted returns from the one-factor model with the dollar volume weighted implied funding liquidity for the 25 size and book-to-market portfolios (Panel 7.12(a)) and 30 industry portfolio (Panel 7.12(b)). The sample spans January 1996 to August 2015.

Table 7.20: Cross-sectional Regressions with Liquidity Measures: Dollar Volume Weight

Model	λ_0	$\lambda_{\Delta IFL}$	λ_{MKT}	λ_{PS}	λ_{TED}	λ_{FG}	λ_{Noise}	λ_{Amihud}	λ_{RS}	λ_{CS}	λ_{Sadka}	R^2
Panel A: 25 Portfolios												
+PS	0.4587***	0.0126**	1.0335***	0.6130								69.53%
	(11.09)	(2.79)	(30.44)	(0.62)								
+TED	0.7951***	0.0091*	1.0272***		-0.6150***							69.91%
	(8.48)	(2.03)	(31.66)		(-4.12)							
+FG	0.4565***	0.0102**	1.0384***			-0.2892***						69.84%
	(11.19)	(2.13)	(32.90)			(-5.83)						
+NOISE	0.5781***	0.0139***	1.0317***				-0.0363					69.84%
	(5.26)	(2.83)	(29.98)				(-1.08)					
+Amihud	0.6370***	0.0143***	1.0302***					-0.0530***				69.58%
	(12.74)	(2.98)	(32.20)					(-4.64)				
+RS	0.6086***	0.0130**	1.0319***						-4.0083			69.53%
	(7.08)	(2.76)	(32.24)						(-1.58)			
+CS	0.4461***	0.0131**	1.0357***							0.7031		69.45%
	(6.00)	(2.78)	(33.12)							(0.15)		
+Sadka	0.4131***	0.0119**	1.0415***								3.3061***	70.26%
	(9.57)	(2.55)	(33.26)								(7.72)	
+ALL	-0.1727	0.0066	1.0443***	-0.6069	-0.6114***	-0.4199***	0.0714	-0.1925***	10.4376	61.2945***	2.8146***	72.14%
	(-1.58)	(1.41)	(30.34)	(-0.73)	(-3.89)	(-6.21)	(1.18)	(-9.74)	(1.67)	(6.88)	(6.84)	
Panel B: 30 Industry Portfolios												
+PS	0.4303***	0.0004	0.9527***	2.8999**								50.91%
	(6.99)	(0.07)	(17.42)	(2.13)								
+TED	0.8645***	-0.0021	0.9517***		-0.8049***							50.95%
	(7.64)	(-0.38)	(16.55)		(-5.05)							
+FG	0.4215***	0.0006	0.9652***			-0.2649***						50.81%
	(6.99)	(0.10)	(16.84)			(-4.92)						
+NOISE	0.6734***	0.0047	0.9545***				-0.0754***					50.78%
	(7.62)	(0.81)	(16.46)				(-3.65)					
+Amihud	0.6190***	0.0045	0.9567***					-0.0580***				50.71%
	(7.03)	(0.77)	(16.61)					(-3.60)				
+RS	0.6127***	0.0031	0.9579***						-5.0396*			50.49%
	(4.92)	(0.54)	(16.54)						(-1.78)			
+CS	0.4588***	0.0033	0.9623***							-2.3871		50.54%
	(2.91)	(0.57)	(16.61)							(-0.22)		
+Sadka	0.3834***	0.0022	0.9678***								2.9064***	51.01%
	(6.56)	(0.38)	(16.80)								(4.82)	
+ALL	-0.1798	-0.0045	0.9606***	1.5891	-0.8097***	-0.3077***	0.0021	-0.1673***	17.2447***	60.0584***	2.3904***	53.70%
	(-1.08)	(-0.81)	(17.34)	(1.20)	(-4.50)	(-5.21)	(0.06)	(-5.45)	(3.06)	(3.60)	(4.56)	

This table reports the estimates and the Newey West t-statistics (in the bracket) from the cross-sectional regressions with other liquidity measures. Let ΔIFL denotes the innovations in the dollar volume weighted implied funding liquidity measure, and MKT the excess market return. We considered the Pastor and Stambaugh's (PS) measure (2003), Brunnermeier et al.'s Treasury-LIBOR (TED) spread (2008), Hu et al.'s Noise (Noise) measure (2013), Fontaine and Garcia's (FG) measure (2012), Amihud's il-liquidity (Amihud) measure (2002), Corwin and Schultz's (CS) measure (2012), the relative spread (RS), and Sadka's (Sadka) measure (2006). The significance level is written in $*/**/***$ for 10%, 5% and 1% level, respectively.

measures reports an R-square of 72.14%. However, Table 7.5 (Panel B), we could observe our measure is not significant. The R-square with all liquidity variables and the market return is about 72.23%.

We observe that the dollar volume weighted implied funding liquidity remains significant in explaining stock return variations even controlling for established liquidity measures.

Table 5.7 reports that the implied funding liquidity measure is associated with some existing investor sentiment indexes, and the coefficients for implied funding liquidity remain positive and significant after controlling for established investor sentiment measures as shown in Table 6.11. Now, we investigate whether our dollar volume weighted liquidity measure still matters after controlling for the investor sentiment indexes.

Following the literature documented before, we considered seven existing investor sentiment measures documented in section 5.5. We included these indexes in the cross-sectional regressions with the implied funding liquidity measure. For performance comparison purpose, we use the univariate model with the dollar volume weighted implied funding liquidity measure as a benchmark.

Panel A of Table 7.21 reports the estimates of the investor sentiment measures for the 25 size-to-book portfolios. We observe that the dollar volume weighted implied funding liquidity remains positive and significant at the one percent level in both the bivariate models and the model including all measures. After we consider all the seven investor sentiment measures with our implied funding liquidity measure together, the model registers an R-square of 36.65%, which is similar to the results summarised in Table 6.11.

Table 7.21 (Panel B) presents the estimates for the 30 industry portfolios, and we observe similar patterns for the industry portfolios. That is, our dollar weighted implied funding liquidity measure is still statistically significant when controlling for alternative investor sentiment proxies in the bivariate regressions. In the regression with all measure, the R-square is about 32.10%, similar to the one in Table 6.11.

Table 7.21: Cross-sectional Regressions with Investor Sentiment Measures: Dollar Volume Weight

	λ_0	$\lambda_{\Delta IFL}$	$\lambda_{\Delta BW}$	$\lambda_{\Delta HJTZ}$	$\lambda_{\Delta UMC}$	$\lambda_{\Delta CB}$	$\lambda_{\Delta DEG}$	$\lambda_{\Delta JLMZ}$	$\lambda_{\Delta PCR}$	R^2
Panel A: 25 Portfolios										
+BW	0.4780***	0.1530***	4.5633***							07.34%
	(5.21)	(21.53)	(7.05)							
+HJTZ	0.3638***	0.1170***		-6.5028***						10.81%
	(3.91)	(19.36)		(-20.44)						
+UMC	0.5313***	0.1363***			0.3301***					11.44%
	(5.75)	(18.24)			(14.54)					
+CB	0.5737***	0.1051***				6.3111***				15.20%
	(6.36)	(13.50)				(21.34)				
+DEG	0.4309***	0.1523***					0.1351**			7.04%
	(4.60)	(21.11)					(2.57)			
+JLMZ	0.4569***	0.1749***						6.0462***		16.58%
	(4.91)	(26.20)						(23.48)		
+PCR	0.3872***	0.0767***							-18.010***	11.81%
	(4.18)	(9.68)							(-35.75)	
+ALL	0.6240***	0.0265***	13.8330***	-9.6070***	0.0607**	4.7359***	0.3454***	5.8842***	-12.654***	34.81%
	(7.05)	(3.89)	(17.59)	(-35.41)	(2.37)	(13.43)	(7.47)	(26.76)	(-22.45)	
Panel B: 30 Industry Portfolios										
+BW	0.6629***	0.1573***	3.9294***							7.58%
	(10.14)	(11.00)	(3.31)							
+HJTZ	0.5326***	0.1082***		-8.8566***						12.19%
	(8.73)	(8.74)		(-16.42)						
+UMC	0.6972***	0.1447***			0.2473***					10.37%
	(12.39)	(9.58)			(8.14)					
+CB	0.7505***	0.1143***				5.6576***				13.38%
	(13.10)	(7.60)				(12.80)				
+DEG	0.6168***	0.1578***					-0.1039			7.27%
	(9.97)	(11.11)					(-1.63)			
+JLMZ	0.6458***	0.1769***						5.4392***		14.19%
	(10.47)	(12.07)						(16.96)		
+PCR	0.5827***	0.0879***							-16.363***	10.50%
	(9.43)	(7.28)							(-13.74)	
+ALL	0.7671***	0.0307**	13.8063***	-11.885***	-0.0295	4.8188***	0.2109**	5.6868***	-10.625***	32.10%
	(13.35)	(2.41)	(9.73)	(-15.20)	(-0.85)	(10.65)	(2.68)	(16.92)	(-10.00)	

This table reports the estimates and Newey West t-statistics (in the bracket) from the cross-sectional regressions. IFL denotes the dollar volume weighted implied funding liquidity measure. We considered seven investor sentiment indexes, including Baker and Wurgler's (2006) investor sentiment measure, BW, the aligned investor sentiment index of Huang et al. (2015), HJTZ, the consumer sentiment index of University of Michigan, UMC, the Conference Board consumer confidence index, CB, the Financial and Economics Attitudes Revealed by Search (FEARS), the investor sentiment index of Da et al. (2015), DEG, the Jiang et al. manager sentiment index (2018), JLMZ, and CBOE Put-Call ratios, PCR. +All indicates regressions with all of the relevant variables in the model. The significance level is written in $*/**/***$ for 10%, 5% and 1% level, respectively.

7.6 Equal Weight

In the previous chapter, we calculated implied funding liquidity with value weight or dollar volume weight across all call and put options with various exercise prices and maturity dates. In this section, we seek to perform further robustness check with equally weighted implied funding liquidity measure.

More specifically, the implied funding liquidity measure, IFL_t, is obtained as follows:

$$IFL_t = \frac{\sum_{i=1}^{N} |IV_{i,t}^C - IV_{i,t}^P|}{N} \tag{7.6}$$

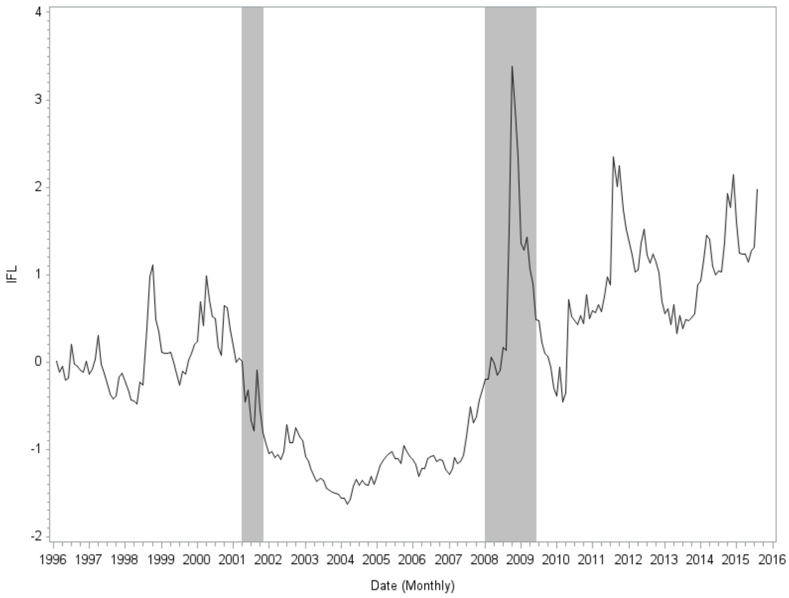
Where $IV_{i,t}^C$ and $IV_{i,t}^P$ are the implied volatilities obtained from the call and put options of the same stock i with the same strike price and maturity date; N is the number of stock at that time.

Then, we calculate the equally weighted ΔIFL with the function 4.4.

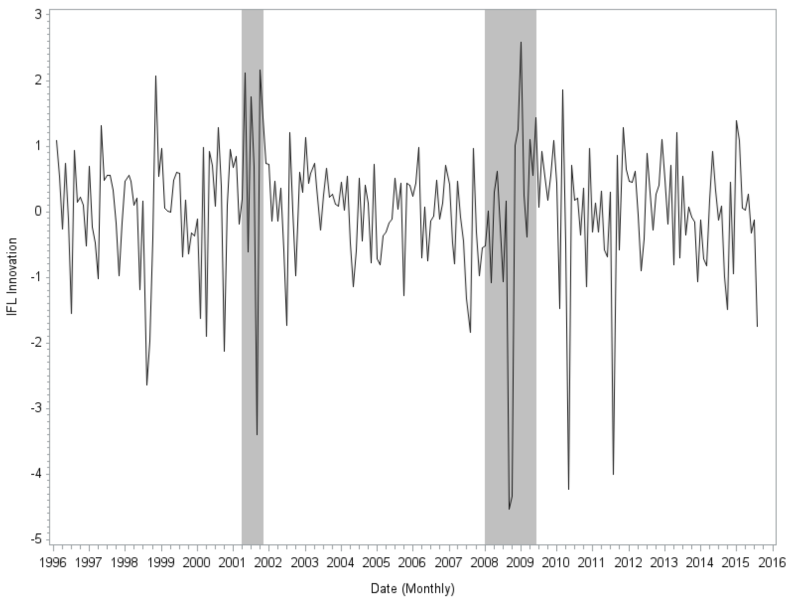
The monthly level and innovations of the standardised equally weighted implied funding liquidity measure from January 1996 to August 2015 are shown in Panel (a) and Panel (b) of Figure 7.13 separately. We still see significant increases in the liquidity measure during the previously mentioned episodes of financial stress. We observe that the largest decrease still occurred in October 2008 which coincided with the collapse of Lehman Brothers and the funding squeezes in interbank lending markets.

Now, we estimate the return predictability power of the equally weighted implied funding liquidity measure, using monthly returns of the $S\&P500$ index and the value-weighted average returns provided by CRSP as market return measures. Consistent with the method in the main chapter, we control for variables that are found to predict market returns, including the dividend yield on the $S\&P500$ index, the real GNP growth rate, the long-term government bond return, and the past market excess returns. We still use the predictive regression model 4.13.

Table 7.22 shows the results of the return predictive regressions for the equally weighted implied funding liquidity measure with horizons of one month, three months, and six months for CRSP value-weighted Returns (Panel A) and S&P 500 returns (Panel B), respectively. We observe that the coefficients for the equally



(a) Monthly Level



(b) Monthly Innovations

Figure 7.13: Equally Weighted Implied Funding Liquidity

This figure presents the time series of the monthly level (Panel a) and innovations (Panel b) of the standardised dollar volume weighted implied funding liquidity measure over the sample from January 1996 to August 2015. The shaded area contains the NBER's business cycle dates.

Table 7.22: Market Return Predictability with Equally Weighted Implied Funding Liquidity

Panel A: CRSP Value-Weighted Market Returns						
	$\triangle IFL_{t-1}$	r_{t-1}	DIV_{t-1}	GNP_{t-1}	LTG_{t-1}	Adj R^2
1	0.0013***	-0.0726	-0.0006	5.7503***	0.0318**	15.66%
(t-stat)	(3.06)	(-0.98)	(-0.07)	(3.76)	(2.27)	
3	0.0019***	0.9140***	0.0288***	12.7513***	0.0328*	57.38%
(t-stat)	(3.38)	(9.37)	(2.60)	(6.35)	(1.78)	
6	0.0026***	0.8431***	0.0905***	21.4075***	0.0004	35.84%
(t-stat)	(2.61)	(4.78)	(4.52)	(5.89)	(0.01)	
Panel B: S&P 500 Returns						
	$\triangle IFL_{t-1}$	r_{t-1}	DIV_{t-1}	GNP_{t-1}	LTG_{t-1}	Adj R^2
1	0.0012***	-0.1121	0.0006	6.4191***	0.0242*	16.47%
(t-stat)	(3.13)	(-1.52)	(0.07)	(4.38)	(1.81)	
3	0.0016***	0.8544***	0.0275**	13.2244***	0.0209	55.50%
(t-stat)	(3.12)	(8.76)	(2.58)	(6.80)	(1.18)	
6	0.0024**	0.8179***	0.0840***	21.6079***	-0.0081	35.41%
(t-stat)	(2.52)	(4.62)	(4.34)	(6.12)	(-0.25)	

This table shows the predictability of equally weighted implied funding liquidity with horizons of one month, three months, and six months for CRSP value-weighted returns (Panel A) and S&P 500 returns (Panel B). Dependent variables are the cumulative growth rates of each variable calculated over one, three and six months. IFL_{t-1} is the equally weighted implied funding liquidity at $t-1$, and $MKTEX_{t-1}$ is the market excess returns. The full sample period spans January 1996 to August 2015, and the significance levels are presented as $*/{*}{*}/{*}{*}{*}$ for 10%, 5% and 1%, respectively.

weighted liquidity measure remains positive and significant for horizons of three and six months. The predictive power of the equally weighted implied funding liquidity remains robust after controlling for other forecasting variables including dividend yield, the GNP growth rate and long-term government bond returns.

Having estimating the predictive power of the equally weighted implied funding liquidity, and we now examine whether the innovations in this equally weighted implied funding liquidity measure could explain the cross-sectional differences in stock returns. With Fama and MacBeth's (1973) two-stage approach, we obtained 25 size and book-to-market portfolios and 30 industry portfolios for the asset pricing tests. In addition, we considered the pricing effects of the equally weighted implied funding liquidity innovations controlling for other factors including Fama and French's (1992) three factors and Carhart's (1997) momentum factor.

Table 7.23 presents the exposures to equally weighted implied funding liquidity innovations for 25 size and book-to-market and 30 industry stock portfolio returns. Accordingly, we observe that the beta estimates are positive and significant for both the equity and industry portfolios; this means that the excess returns of the portfolios tend to be higher corresponding with abnormally larger implied funding liquidity. This evidence is consistent with the results in Table 6.3.

Among the 25 Fama and French's stock portfolios, the small and low book-to-market has the highest exposure (0.36) to the equally weighted implied funding liquidity innovations, and it is economically and statistically significant at the 1 percent level. Among the industry portfolios, the one with the highest beta estimate (0.41) lies in the coal portfolio. These results suggest that small firms, companies with low book to market or those in the coal industry are the most exposed to the variations in funding liquidity, which has the pattern as that in Table 6.3.

Figures 7.14(a) and 7.14(b) present scatter plots of excess returns versus their equally weighted ΔIFL betas for the 25 portfolios and 30 industry portfolios, respectively. Aside from the small and low BM portfolio ($SMALL\_LoBM$) and smoke industry portfolio ($Smoke$), Figure 7.2 indicates that portfolios with higher IFL innovation betas had larger mean excess returns. This pattern is consistent with Figure 6.1.

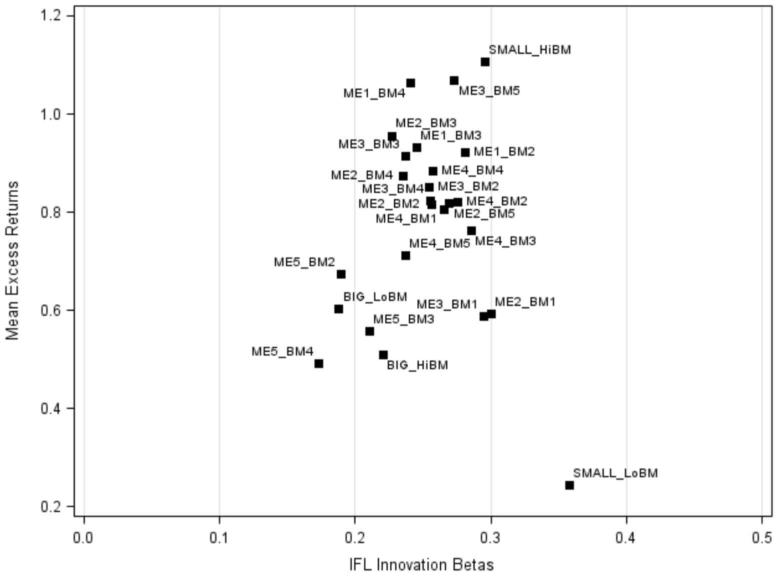
Table 7.24 presents the coefficients and Newey-West adjusted *t*-statistics (in parentheses) obtained from the cross-sectional regressions with the equally weighted implied funding liquidity measure. The estimates for the equally weighted implied funding liquidity are positive ($\lambda_{\Delta IFL} > 0$) and significant at the 5% level for both

Table 7.23: Exposures to Equally Weighted Implied Funding Liquidity

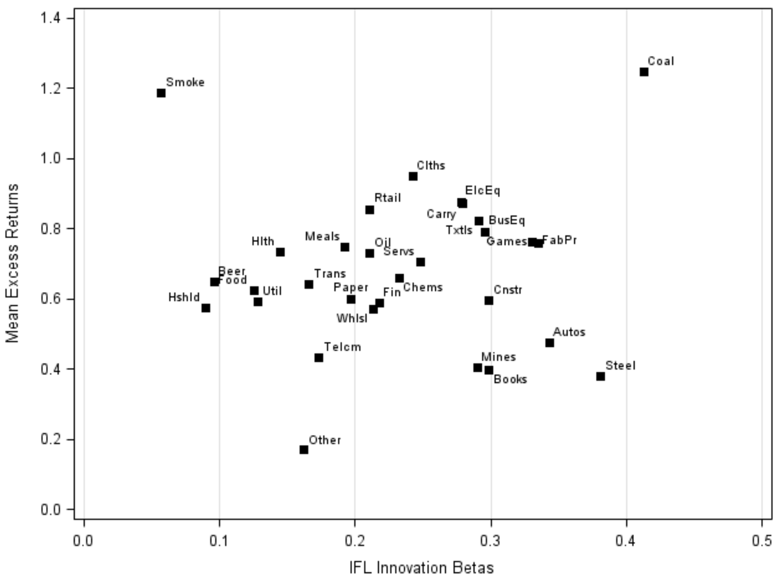
Panel A: 25 Size and Book-to-Market Portfolios					
Betas	Low B/M	2	3	4	High B/M
Small	0.36***	0.30***	0.30***	0.27***	0.19***
	(5.31)	(5.18)	(5.51)	(5.49)	(5.19)
2	0.28***	0.26***	0.25***	0.28***	0.19***
	(4.87)	(5.62)	(6.02)	(7.20)	(5.69)
3	0.25***	0.23***	0.24***	0.29***	0.21***
	(5.24)	(5.41)	(6.04)	(7.10)	(5.96)
4	0.24***	0.24***	0.26***	0.26***	0.17***
	(5.55)	(5.46)	(6.42)	(6.82)	(4.77)
Big	0.30***	0.27***	0.27***	0.24***	0.22***
	(6.37)	(5.47)	(6.49)	(5.49)	(5.15)

Panel B: 30 Industry Portfolios					
Industry	Betas	Industry	Betas	Industry	Betas
Autos	0.34***	FabPr	0.33***	Paper	0.20***
	(5.37)		(6.11)		(4.81)
Beer	0.10**	Fin	0.22***	Rtail	0.21***
	(2.40)		(4.76)		(5.38)
Books	0.30***	Food	0.13***	Servs	0.25***
	(6.65)		(4.07)		(4.61)
BusEq	0.30***	Games	0.34***	Smoke	0.06
	(4.46)		(5.98)		(0.98)
Carry	0.28***	Hlth	0.14***	Steel	0.38***
	(5.86)		(4.33)		(5.48)
Chems	0.23***	Hshld	0.09**	Telcm	0.17***
	(5.01)		(2.54)		(3.95)
Clths	0.24***	Meals	0.19***	Trans	0.17***
	(4.77)		(5.15)		(4.00)
Cnstr	0.30***	Mines	0.29***	Txtls	0.29***
	(6.04)		(4.37)		(4.23)
Coal	0.41***	Oil	0.21***	Util	0.13***
	(3.90)		(4.65)		(3.80)
ElcEq	0.28***	Other	0.16***	Whlsl	0.21***
	(5.37)		(3.41)		(5.71)

This table reports OLS estimates of the equally weighted implied funding liquidity ΔIFL betas $\beta_{i,\Delta IFL}$ which is the slope coefficients from the time-series regressions on ΔIFL for the sample period from January 1996 to August 2015. Panel A shows the estimates for the 25 size and book-to-market portfolios while Panel B reports the coefficients for the 30 industry portfolios. The full sample period spans January 1996 to August 2015. Newey West t-statistics are shown in bracket and $*$, $**$, $***$ denote significant levels at 10%, 5% and 1% level, respectively.



(a) Monthly Level



(b) Monthly Innovations

Figure 7.14: Equally Weighted ΔIFL Betas and Portfolio Excess Returns

This figure shows the scattered average portfolio excess returns versus their equally weighted implied funding liquidity risk betas ($\beta_{\Delta IFL}$). Figure 7.14(a) is based on 25 size and book-to-market equity portfolios, and Figure 7.14(b) is based on 30 industry stock portfolios. IFL Innovation betas and mean excess returns were estimated for each equity portfolio and the sample spans January 1996 to August 2015.

Table 7.24: Cross-Sectional Regressions with the Equally Weighted Implied Funding Liquidity

Model	λ_0	$\lambda_{\Delta IFL}$	λ_{MKT}	λ_{SMB}	λ_{HML}	λ_{Mom}	R^2
Panel A: 25 Portfolios							
Univariate	1.0179***	0.2533***					12.50%
	(25.80)	(30.30)					
CAPM	0.4093***	0.0440***	1.0133***				69.72%
	(10.61)	(7.60)	(33.72)				
FF	0.2341***	0.0180**	0.9921***	0.5161***	0.2705***		90.41%
	(6.38)	(2.54)	(81.69)	(3.85)	(3.53)		
FF, Mom	0.2495***	0.0173**	0.9835***	0.5193***	0.2622***	-0.0219***	90.54%
	(7.53)	(2.47)	(88.16)	(3.88)	(3.45)	(-3.02)	
Panel B: 30 Industry Portfolios							
Model	λ_0	$\lambda_{\Delta IFL}$	λ_{MKT}	λ_{SMB}	λ_{HML}	λ_{Mom}	R^2
Univariate	0.9190***	0.2315***					8.71%
	(21.35)	(14.75)					
CAPM	0.3529***	0.0368***	0.9424***				50.68%
	(9.13)	(3.96)	(17.57)				
FF	0.2390***	0.0258***	0.9966***	0.0700*	0.3432***		58.16%
	(5.55)	(3.21)	(19.63)	(2.03)	(5.58)		
FF, Mom	0.2775***	0.0242***	0.9750***	0.0778**	0.3226***	-0.0547**	59.08%
	(7.15)	(2.90)	(19.54)	(2.25)	(5.15)	(-2.65)	

This table reports the estimates and Newey-West t-statistics (in bracket) from Fama and MacBeth (1973)□s two-stage regressions for the 25 size and book-to-market (Panel A) and 30 industry equity portfolios (Panel B) over the sample period from January 1996 to August 2015. ΔIFL is the equally weighted funding liquidity innovations; MKT is the excess market return; SMB is the average return on the small stock portfolios minus the average return on the big stock portfolios; HML is the average return on the value portfolios minus the average return on the growth portfolios; MOM is a momentum factor. $*/**/***$ denotes the significance level at 10%, 5% and 1% level, respectively.

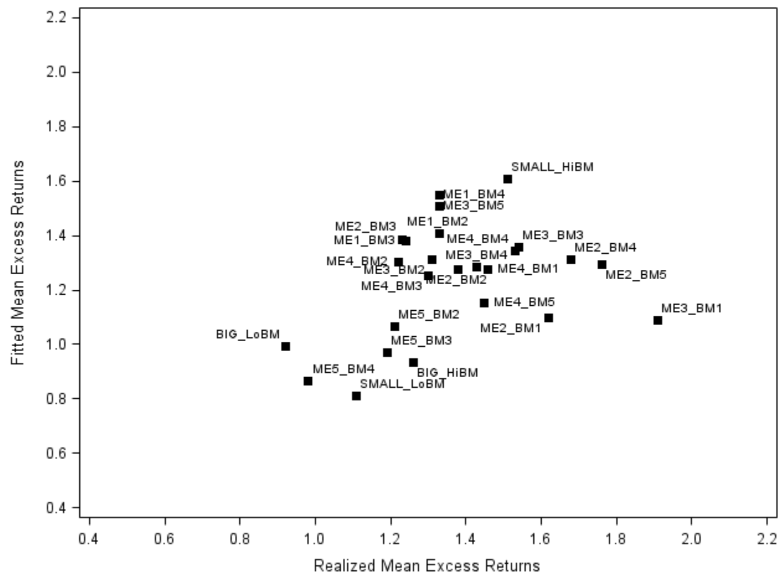
of the 25 equity and 30 industry portfolios.

Compared with their counterparts in Table 6.4, the $\lambda_{\Delta IFL}$s are larger. For instance, $\lambda_{\Delta IFL}$ amounts to 0.2533 and 0.2315 per unit of ΔIFL beta for equity and industry portfolios in the univariate model, respectively. Furthermore, the univariate model with the equally weighted implied funding liquidity explains approximately 12.50% and 8.71% of the cross-sectional variations in returns for the 25 size and book-to-market and 30 industry portfolios. This shows that the equally weighted implied funding liquidity risk alone could explain cross-sectional stock portfolio returns, and this explanation power is stronger compared to the results in Table 6.4.

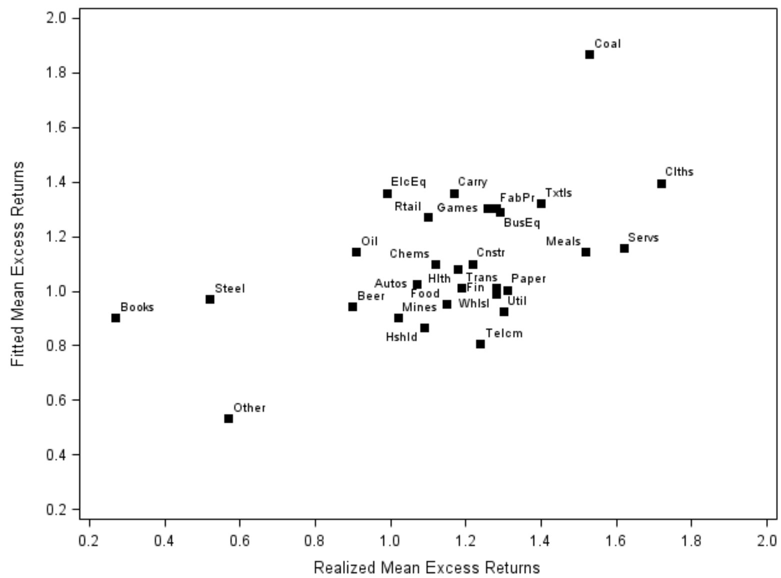
In addition, the estimates in Table 7.24 for Fama French's (1992) three factors and Carhart's (1997) momentum factor with equally weighted implied funding liquidity are significant at the 5% level, and this means that the implied funding liquidity measure is important in capturing equity market returns. The four-factor model with implied funding liquidity measure registers R-square values of 90.41% and 58.16% for the 25 size and book-to-market, and 30 industry portfolios, respectively. In particular, $\lambda_{\Delta IFL}$s are larger but still statistically significant relative to Fama and French's three factors, and Fama and French's three factors plus momentum. For instance, the estimated equally weighted implied funding liquidity risk premiums, $\lambda_{\Delta IFL}$, are 0.0180 and 0.0258, respectively. Moreover, the five-factor model, controlling for MKT, SMB, HML, and MOM, with the equally weighted implied funding liquidity measure does well with R-square values of 90.54% and 59.08% for the 25 size and book-to-market and 30 industry portfolios, respectively.

Figure 7.15(a) and 7.15(b) plots the actual versus predicted average returns from the one-factor model with the equally weighted implied funding liquidity for the 25 size and book-to-market portfolios (Panel a) and 30 industry portfolio (Panel b). We observe that there is a strong and positive relationship between the realised and the predicted average returns for these portfolios. Consistent with the estimates in Table 7.24, this pattern suggests that funding liquidity matters in explaining the cross-sectional variations in equity portfolio returns.

Next, we estimate whether the equally weighted implied funding liquidity measure includes information about stock returns beyond what is captured in the previous liquidity measures (Pástor and Stambaugh, 2003; Brunnermeier et al., 2008; Hu et al., 2013; Fontaine et al., 2015; Amihud, 2002; Corwin and Schultz,



(a) 25 Portfolios



(b) 30 Industry Portfolios

Figure 7.15: Realised vs Predicted Average Returns of Stock Returns: Equal Weight

This figure presents the average realised versus predicted returns from the one-factor model with equally weighted implied funding liquidity for the 25 size and book-to-market portfolios (Panel 7.15(a)) and 30 industry portfolio (Panel 7.15(b)). The sample spans January 1996 to August 2015.

2012). As comparisons, we considered seven existing liquidity measures documented in the literature in the cross-sectional regressions including the PS measure, the TED spread, and the Noise, FG, Amihud, CS, and Sadka measures, as well as RS in addition to the equally weighted implied funding liquidity measure.

We obtained the CAPM plus the equally weighted implied funding liquidity measure as the benchmark for performance comparison. Table 7.25 (Panel A) shows the estimates of the liquidity measures for the 25 size-to-book portfolios, whilst Panel B reports the estimates of the liquidity measures for the 30 industry portfolios.

Similar to Table 6.8, Panel A of Table 7.25 shows that the TED, FG , Amihud, and Sadka measures are significant at the one percent level while PS, Noise, and CS measures are insignificant. The equally weighted implied funding liquidity remains positive and significant at the one percent level after controlling for these existing liquidity measures. For instance, after we control all the existing liquidity measures, the regression slop on ΔIFL is 0.0359 and is statitisticaly at the one percent level, with a Newey West t statistic of 8.32. The model including the market return factor and all of the liquidity variables reports an R-square of 72.32%.

In Panel B of Table 7.25, which presents the regression results for the industry portfolios, we observe similar patterns. The TED, FG, Amihud, and Sadka measures register the same signs as above and are significant at one percent level while the impacts of the PS, Noise, and CS measures are not always significant. The R-square of all liquidity variables and the market return is about 53.68%.

In short, we observe that the equally weighted implied funding liquidity remains significant after controlling for established liquidity measures in the equity market, and our measure potentially provides more information about asset returns beyond what is captured in the previous liquidity measures.

As shown in Section 6.4, the implied funding liquidity measure contains additional information beyond what is captured by the exiting investor sentiment indexes. Now, we investigate whether the equally weighted liquidity measure still capture extra information controlling for the investor sentiment indexes.

We still include seven existing investor sentiment measures discussed in Section 5.5. We included these indexes in the cross-sectional regressions with the implied funding liquidity measure. For comparison purpose, we obtain the univariate model with the equally weighted implied funding liquidity factor as a benchmark.

Table 7.25: Cross-sectional Regressions with Liquidity Measures: Equal Weight

Model	λ_0	$\lambda_{\Delta IFL}$	λ_{MKT}	λ_{PS}	λ_{TED}	λ_{FG}	λ_{Noise}	λ_{Amihud}	λ_{RS}	λ_{CS}	λ_{Sadka}	R^2
Panel A: 25 Portfolios												
+PS	0.4705***	0.0483***	1.0117***	-0.3555								69.91%
	(11.29)	(9.12)	(30.68)	(-0.36)								
+TED	0.7432***	0.0427***	1.0059***		-0.4967***							70.22%
	(8.14)	(8.52)	(31.72)		(-3.41)							
+FG	0.4700***	0.0438***	1.0147***			-0.2551***						70.17%
	(11.41)	(8.15)	(32.75)			(-5.40)						
+NOISE	0.6323***	0.0492***	1.0050***				-0.0482					70.28%
	(5.69)	(8.48)	(29.38)				(-1.42)					
+Amihud	0.6625***	0.0488***	1.0048***					-0.0562***				70.00%
	(12.82)	(8.54)	(31.94)					(-4.91)				
+RS	0.5874***	0.0474***	1.0080***						-3.0704			69.93%
	(6.84)	(8.41)	(32.10)						(-1.20)			
+CS	0.4697***	0.0476***	1.0108***							0.1047		69.86%
	(6.14)	(8.45)	(32.92)							(0.02)		
+Sadka	0.4297***	0.0393***	1.0209***								293.513***	70.51%
	(9.75)	(6.79)	(33.39)								(6.66)	
+ALL	-0.1894*	0.0359***	1.0279***	-1.3493	-0.4389***	-0.4155***	0.0262	-0.1908***	13.9335**	57.8910***	251.814***	72.32%
	(-1.74)	(8.32)	(30.01)	(-1.68)	(-2.97)	(-6.17)	(0.44)	(-9.70)	(2.21)	(6.51)	(6.11)	
Panel B: 30 Industry Portfolios												
+PS	0.4394***	0.0339***	0.9347***	2.0830								51.05%
	(7.01)	(4.02)	(17.36)	(1.63)								
+TED	0.8140***	0.0309***	0.9333***		-0.6935***							51.03%
	(7.67)	(3.52)	(16.70)		(-4.71)							
+FG	0.4333***	0.0344***	0.9437***			-0.2317***						50.95%
	(7.01)	(3.79)	(16.99)			(-4.69)						
+NOISE	0.7248***	0.0406***	0.9297***				-0.0869***					51.01%
	(7.70)	(4.17)	(16.50)				(-4.08)					
+Amihud	0.6443***	0.0391***	0.9336***					-0.0617***				50.91%
	(7.11)	(4.04)	(16.70)					(-3.80)				
+RS	0.5940***	0.0375***	0.9364***						-4.2180			50.68%
	(4.85)	(3.96)	(16.63)						(-1.51)			
+CS	0.4825***	0.0379***	0.9397***							-3.1091		50.74%
	(3.06)	(3.99)	(16.72)							(-0.29)		
+Sadka	0.3975***	0.0304***	0.9491***								260.693***	51.10%
	(6.61)	(3.63)	(16.95)								(4.77)	
+ALL	-0.1965	0.0245***	0.9468***	0.9382	-0.6453***	-0.3037***	-0.0386	-0.1663***	20.3568***	56.8606***	218.558***	53.68%
	(-1.18)	(3.90)	(17.24)	(0.73)	(-3.89)	(-5.19)	(-1.07)	(-5.46)	(3.62)	(3.49)	(4.45)	

This table reports the estimates and the Newey West t-statistics (in the bracket) from the cross-sectional regressions with other liquidity measures. Let ΔIFL denotes the innovations in the at-the-money option adjusted implied funding liquidity measure, and MKT the excess market return. We considered the Pastor and Stambaugh's (PS) measure (2003), Brunnermeier et al.'s Treasury-LIBOR (TED) spread (2008), Hu et al.'s Noise (Noise) measure (2013), Fontaine and Garcia's (FG) measure (2012), Amihud's il-liquidity (Amihud) measure (2002), Corwin and Schultz's (CS) measure (2012), the relative spread (RS), and Sadka's (Sadka) measure (2006). The significance level is written in $*/**/***$ for 10%, 5% and 1% level, respectively.

Table 7.26: Cross-sectional Regressions with Investor Sentiment Measures: Equal Weight

Panel A: 25 Portfolios										
	λ_0	$\lambda_{\Delta IFL}$	$\lambda_{\Delta BW}$	$\lambda_{\Delta HJTZ}$	$\lambda_{\Delta UMC}$	$\lambda_{\Delta CB}$	$\lambda_{\Delta DEG}$	$\lambda_{\Delta JLMZ}$	$\lambda_{\Delta PCR}$	R^2
+BW	0.6748***	0.2315***	5.6086***							14.43%
	(7.17)	(26.57)	(8.59)							
+HJTZ	0.5474***	0.1976***		-3.7477***						15.18%
	(5.72)	(24.41)		(-11.87)						
+UMC	0.6634***	0.2033***			0.2511***					16.31%
	(7.02)	(20.81)			(10.26)					
+CB	0.6866***	0.1733***				5.1677***				19.04%
	(7.38)	(17.06)				(16.02)				
+DEG	0.6180***	0.2305***					0.2201***			14.08%
	(6.43)	(26.74)					(4.28)			
+JLMZ	0.6755***	0.2686***						6.8637***		25.94%
	(7.11)	(32.26)						(26.62)		
+PCR	0.5472***	0.1709***							-11.640***	15.63%
	(5.78)	(16.80)							(-23.01)	
+ALL	0.7229***	0.1159***	12.6168***	-8.1025***	0.0520*	3.9644***	0.3253***	6.4265***	-7.8077***	36.29%
	(7.92)	(11.60)	(16.13)	(-34.10)	(1.97)	(11.25)	(7.20)	(29.53)	(-14.21)	
Panel B: 30 Industry Portfolios										
+BW	0.8632***	0.2366***	4.9978***							13.24%
	(12.61)	(13.57)	(4.24)							
+HJTZ	0.6994***	0.1808***		-6.3539***						14.85%
	(11.26)	(11.77)		(-15.57)						
+UMC	0.8399***	0.2179***			0.1622***					14.67%
	(13.96)	(11.27)			(4.86)					
+CB	0.8712***	0.1865***				4.4368***				16.57%
	(14.16)	(10.14)				(10.27)				
+DEG	0.8046***	0.2347***					-0.0166			12.75%
	(12.43)	(13.32)					(-0.25)			
+JLMZ	0.8652***	0.2705***						6.2595***		21.61%
	(13.42)	(14.58)						(17.74)		
+PCR	0.7533***	0.1861***							-9.6711***	13.67%
	(11.88)	(12.30)							(-11.61)	
+ALL	0.8659***	0.1182***	12.6205***	-10.390***	-0.0391	4.0602***	0.1929**	6.2239***	-5.8651***	33.06%
	(14.54)	(7.12)	(9.28)	(-15.65)	(-1.09)	(9.57)	(2.48)	(16.93)	(-7.18)	

This table reports the estimates and Newey West t-statistics (in the bracket) from the cross-sectional regressions. IFL denotes the equally weighted implied funding liquidity measure. We considered seven investor sentiment indexes, including Baker and Wurgler's (2006) investor sentiment measure, BW, the aligned investor sentiment index of Huang et al. (2015), HJTZ, the consumer sentiment index of University of Michigan, UMC, the Conference Board consumer confidence index, CB, the Financial and Economics Attitudes Revealed by Search (FEARS), the investor sentiment index of Da et al. (2015), DEG, the Jiang et al. manager sentiment index (2018), JLMZ, and CBOE Put-Call ratios, PCR. +All indicates regressions with all of the relevant variables in the model. The significance level is written in $*/**/***$ for 10%, 5% and 1% level, respectively.

Panel A of Table 6.11 presents the estimates of the investor sentiment measures for the 25 size-to-book portfolios. Overall, we find that the dollar volume weighted implied funding liquidity remains positive and significant at the one percent level. For example, when we include all the indices in one regression, the coefficient of our measure is 0.1159 with an R-square of 36.29%.

Panel B reports the estimates for the 30 industry portfolios, and we see similar patterns, except for UMC, which is not significant in the bivariate regression. Most importantly, our equally weighted implied funding liquidity measure is still statistically significant. The R-square with all investor sentiment variables is about 33.06%.

7.7 Summary

In summary, we first examined the influence of the presence of informed trading for our implied funding liquidity and then perform various checks to assess the robustness of influence of implied funding liquidity on stock returns. Consistent with the findings in empirical literature on liquidity, we demonstrated that our implied funding liquidity innovations have a strong positive relationship with the portfolio returns. Following Brown and Hillegeist (2007), we used the PIN measure to control for the level of information asymmetry in the stock markets. The results show that implied funding liquidity remains significant in explaining the variations of stock returns after controlling for the differences in level of information asymmetry across stocks.

In subsection 7.2, we considered the influence of moneyness in the construction of our implied funding liquidity measure. Following Pan (2002), we obtained only at-the-money option pairs, which are call and put options with the strike prices between 0.95 and 1.05 times the underlying spot prices, to compute an at-the-money adjusted implied funding liquidity measure. Second, deviations of Put-Call parity may result from the non-synchronicity in reporting of the closing stock prices in the option and in the underlying stock markets (Battalio and Schultz, 2006). Therefore, we used the delta-gamma approximation method to compute the implied volatility for each option, and then the adjusted implied funding liquidity measure based on this underlying price in section 7.3. Third, as most regulators of stock exchanges around the world imposed restrictions or bans on short selling in the financial crisis, we constructed an alternative implied funding liquidity measure with the samples extracting underlying stocks with short-selling constrictions in section 7.4. Finally, we form a dollar volume weighted implied funding liquidity measure in section 7.5, and a equally weighted implied funding liquidity measure in section 7.6. Our findings suggest that the implied funding liquidity measure incorporates the forward-looking nature of the option markets, and our measure potentially provides incremental information about asset returns beyond what is captured in the previous liquidity measures after taking the these robustness restrictions into account.

Chapter 8. Conclusion

Prior studies (Cremers and Weinbaum, 2010; An et al., 2014) show that the differences between call and put option prices of the same underlying asset can help predict future variations of the individual stock returns. The return-predictive power of option prices can arise when informed investors choose to trade options ahead of the underlying asset because the option markets are more liquid or facilitate higher leverage (Black, 1972; Easley et al., 1998).

This study has examined the effects of funding constraints on a cross-section of US stock returns and macroeconomic developments. We constructed the implied funding liquidity measure based on the systematic deviations from Put-Call parity in the US equity option markets. The Put-Call parity is a no-arbitrage relationship that links the prices of European call and put options without any explicit assumption regarding the underlying return distribution or the behaviour of investors. During normal periods, traders, including hedge funds and proprietary trading desks at investment banks, take advantage of the abundant supply of capital to exploit price deviations across markets. In these conditions, option prices move closer to their parity condition due to the presence of arbitrageurs. However, as Brunnermeier and Pedersen (2009) assert, the ability of market participants to absorb shocks is significantly reduced when they face funding shortages. Tighter funding constraints force traders to liquidate their positions early, and consequently prices move away from their fundamental values. We have argued that systematic deviations from Put-Call parity, implied funding liquidity, can provide useful information about liquidity conditions that help explain asset returns. We investigated the predictive power of the liquidity measure for future excess market returns and future developments of macroeconomic variables. We examined whether the innovations in implied funding liquidity can explain the cross-section of stock returns and developed a portfolio strategy to exploit the pricing signals from the funding liquidity measure.

Using stock and option data over the sample from 4 January 1996 to 31 August 2015, we found that the implied funding liquidity measure significantly forecasts the future returns of the S&P500 index and CRSP value-weighted index over a horizon of six months. The implied funding liquidity can also predict future changes in a wide range of macroeconomic variables over the horizon of one year. This result shows that tighter funding constraints observed via the deviations from Put-Call parity in option markets lead to future market declines and predict future macroeconomic conditions.

Our empirical findings show that the innovations of implied funding liquidity significantly explain the returns of 25 size and book-to-market portfolios and 30 industry portfolios. Their importance in stock returns is not due to established equity market factors and is not affected by other liquidity measures mentioned in the literature. We then assessed the economic value of the pricing effects of implied funding liquidity by sorting stocks into portfolios based on their exposure to the innovations in implied funding liquidity. Our results have shown that investing in the portfolio of stocks with the largest exposure to implied funding liquidity innovations, and shorting those with the smallest generates an excess return of about 7.3% per annum. These strategy returns remain statistically and economically significant after controlling for transaction costs and various effects that might affect stock returns.

Our findings show that implied funding liquidity significantly predicts market returns and its innovations explains a large cross-section of US stock returns. In particular, the implied funding liquidity measure can predict future changes in the S&P500 index and CRSP's value-weighted index over a horizon of three months. That is, tighter funding constraints that cause greater deviations in Put-Call parity in option prices are negatively related to future market returns. We have also shown that funding liquidity is priced. Innovations in implied funding liquidity significantly explain the cross-sectional variations in returns of 25 size and book-to-market portfolio and 30 industry portfolios. Their results remain robust after controlling for standard factors in equity markets including Fama and French's (1992) three factors and Carhart's (1997) momentum factor.

In this study, we also examined the economic value of the asset-pricing effect by constructing a portfolio strategy based on innovations in implied funding liquidity. Following the literature explaining the cross-section of equity returns (Fama and French, 1992), we formed ten portfolios of stocks according to their sensitivity, or beta, to the innovations in implied funding liquidity. Using a sample of daily US stock data obtained from the CRSP from 4 January 1996 to 31 August 2015, we find that investing in stocks with the largest exposure to the implied funding measure and shorting the ones of the lowest provides a US investor significant excess returns of about 6% per annum. We find that the returns remain significant even after adjusting for transaction costs.

Our paper is related to the vast and growing literature on market liquidity and funding liquidity measures. In particular, Amihud and Mendelson (1986) considered the bid-ask spread to capture market illiquidity and the cost of trading. Pástor and Stambaugh (2003) measured the market liquidity of an individual stock based on the impacts of orders on stock returns and showed that the innovations in the liquidity average across all the stocks can explain variations in stock returns. Brunnermeier et al. (2008) used the TED spread to capture funding constraints in financial markets and showed that it can affect currency returns. In the Treasury markets, Fontaine and Garcia (2012) developed a liquidity variable obtained from the new and old bond spread, while Hu et al. (2013) obtained the noise measure from the deviations between the observed bond yields and the predicted yields calibrated from Nelson and Siegel's (1987) model. We have argued that our implied funding liquidity has incremental power to explain stock returns against these liquidity measures. Unlike those based on past trading behaviours, implied funding liquidity incorporates forward-looking information from the option markets due to the presence of informed traders (Easley et al., 1998) or future hedging demand (Gârleanu et al., 2009). Therefore, our liquidity measure might carry additional information about asset returns other than those characterised in the previous literature. Our study has shown that the asset-pricing effects associated with implied funding liquidity remain significant even after including a wide range of liquidity measures suggested in the previous studies.

This study mainly contributes to the literature on funding liquidity and its role in asset pricing. Mitchell et al. (2007) showed that liquidity spirals lead to drop and rebound of prices, as new capital arrives slowly. Moreover, Moinas et al. (2016) found that shocks to funding liquidity influences market liquidity in the bond market, and that there is also weaker simultaneous feedback influence of market liquidity on funding liquidity. Hu et al. (2013) proposed a proxy of the illiquidity of the aggregate market using the average pricing errors in the US Treasuries. Chen and Lu (2017) constructed a funding liquidity shock using the return spread between two beta-neutral portfolios formed using stocks with high and low margins. In contrast, this study proposed a new funding liquidity measure based on the deviations of Put-Call parity, and it contains unique and incremental information beyond the well-known existing liquidity proxies, for example, Hu et al.'s (2013) Noise measure, Brunnermeier et al.'s (2008) Treasury-LIBOR (TED) spread, and Fontaine and Gracia's (2012) measure.

Moreover, we estimated the relationship between implied funding liquidity and the cross section of the excess returns arising from the carry trades strategy, which borrows in currencies with low interest rates and invests in currencies with high interest rates. Our another contribution relative to the existing literature is that we have shown that implied funding liquidity, ΔIFL, is an important driver of risk premiums in the cross-sectional carry trade returns. This study examined the effects of funding constraints on the currency market with carry trade strategies. Our results have shown that returns to speculation in foreign exchange markets reflect their sensitivity to the implied funding liquidity. Furthermore, we obtain the monthly hedge fund indices from the Hedge Fund Research, Inc. (HFRI) in order to investigate whether implied funding liquidity influences aggregate hedge fund performance. These results show that implied funding liquidity contains information which has not been fully explained by other risk factors, and that implied funding liquidity matters in explaining cross-sectional variations in hedge fund portfolio returns. This result is consistent with Sadka (2010), Kessler and Scherer (2011), and Chen and Lu (2017).

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Appendix A. Data

A.1 Stock Portfolios

In Chapter 6.2, we obtain the 25 size and book-to-market portfolios and 30 industry portfolios for the asset pricing tests over the period from 04 January 1996 to 31 August 2015, and data for these portfolios are obtained from Kenneth French's data library[1]. In this section, we first discuss the detail for the construction of the 25 size and book-to-market portfolios, and then a detailed list of the 30 industry portfolios will be presented in Table A.1.

At the end of each June, portfolios are built by intersecting of five size formed portfolios based on market equity, and five profitability (OP) formed portfolios. In particular, with regards to the size breakpoints for year t, we obtain the NYSE market stock quintiles at the end of June of year t. In order to calculate OP for June of year t, use annual revenues minus cost of goods sold, interest expense, and selling, general, and administrative expenses divided by book equity for the last fiscal year end in $t-1$. Still use NYSE quintiles as the OP breakpoints.

For July of year t to the next June, the portfolios include all the stocks from NYSE, AMEX, and NASDAQ . In particular, the following data are used: market stock data for June of t, (positive) book equity data for $t-1$, non-missing revenues data for $t-1$, and non-missing data for at least one of the following: cost of goods sold, selling, general and administrative expenses, or interest expense for $t-1$.

NYSE, AMEX, and NASDAQ stocks are grouped into an industry portfolio at the end of June of year t based on its four-digit SIC code at that time. (Compustat SIC codes are obtained for the fiscal year ending in calendar year $t-1$. If Compustat SIC codes are not available, CRSP SIC codes are used instead for June of year t.) Then, returns from from July of t to June of $t+1$ are calculated. Table A.1 reports the Detail for 30 Industry Portfolios presented in the Kenneth R. French Data Library.

[1]We thank Kenneth French for providing the data, which is available at: `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`

Table A.1: List of 30 Industries

Abbreviations	Industries
Food	Food Products
Beer	Beer & Liquor
Smoke	Tobacco Products
Games	Recreation
Books	Printing and Publishing
Hshld	Consumer Goods
Clths	Apparel
Hlth	Healthcare, Medical Equipment, Pharmaceutical Products
Chems	Chemicals
Txtls	Textiles
Cnstr	Construction and Construction Materials
Steel	Steel Works Etc
FabPr	Fabricated Products and Machinery
ElcEq	Electrical Equipment
Autos	Automobiles and Trucks
Carry	Aircraft, ships, and railroad equipment
Mines	Precious Metals, Non-Metallic, and Industrial Metal Mining
Coal	Coal
Oil	Petroleum and Natural Gas
Util	Utilities
Telcm	Communication
Servs	Personal and Business Services
BusEq	Business Equipment
Paper	Business Supplies and Shipping Containers
Trans	Transportation
Whlsl	Wholesale
Rtail	Retail
Meals	Restaraunts, Hotels, Motels
Fin	Banking, Insurance, Real Estate, Trading
Other	Everything Else

This table reports the detail for 30 industry portfolios presented in the Kenneth R. French Data library and it is available at `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_30_ind_port_old.html`

A.2 Currency Samples

Table A.2 reports the entity and currency lists for both the all countries and developed countries samples.

Table A.2: Currency Samples

Panel A: All Countries			
Entity	Currency	Entity	Currency
Australia	Australian Dollar	Japan	Japanese Yen
Austria	Austrian Schilling	Kuwait	Kuwaiti Dinar
Belgium	Belgian Franc	Malaysia	Malaysian Ringgit
Brazil	Brazilian Real	Mexico	Mexican Peso
Bulgaria	Bulgarian Lev	Netherlands	Dutch Guilder
Canada	Canadian Dollar	New Zealand	New Zealand Dollar
Croatia	Croatian Kuna	Norway	Norwegian Krone
Cyprus	Cypriot Pound	Philippines	Philippine Peso
Czech Republic	Czech Koruna	Poland	Polish Zloty
Denmark	Danish Krone	Portugal	Portuguese Escudo
Egypt	Egyptian Pound	Russia	Russian Ruble
Euro Areas	Euro	Saudi Arabia	Saudi Arabian Riyal
Finland	Finish Markka	Singapore	Singapore Dollar
France	French Franc	Slovakia	Slovakian Koruna
Germany	Deutsch Mark	Slovenia	Slovenian Tolar
Greece	Greek Drachma	South Africa	South African Rand
Hong Kong	Hong Kong Dollar	South Korea	South Korean Won
Hungary	Hungarian Forint	Spain	Spanish Peseta
Iceland	Iceland Krona	Sweden	Swedish Krona
India	Indian Rupee	Switzerland	Swiss Franc
Indonesia	Indonesian Rupiah	Taiwan	Taiwan Dollar
Ireland	Irish Punt	Thailand	Thai Baht
Israel	Israeli Shekel	Ukraine	Ukraine Hryvnia
Italy	Italian Lira	The United Kingdom	the British Pound
Panel B: Developed Countries			
Entity	Currency	Entity	Currency
Australia	Australian Dollar	Japan	Japanese Yen
Belgium	Belgian Franc	Netherlands	Dutch Guilder
Canada	Canadian Dollar	New Zealand	New Zealand Dollar
Denmark	Danish Krone	Norway	Norwegian Krone
Euro Areas	Euro	Sweden	Swedish Krona
France	French Franc	Switzerland	Swiss Franc
Germany	Deutsch Mark	The United Kingdom	the British Pound
Italy	Italian Lira		

This table reports the entity and currency lists for both the all countries and developed countries samples.

A.3 Controlled Risk Factors

In Chapters 6 and 7, we controlled Fama-French three factors (Fama and French, 1993), Small minus Big (SMB), High minus Low (HML), and the Excess Return on the Market (MKT) and Momentum factor (MOM) (Carhart, 1997). The six value-weighted portfolios formed on size and book-to-market are used to construct the Fama-French three factors, MKT, SMB and HML include all companies listed at NYSE, AMEX, and NASDAQ. Six valued-weighted portfolios constructed by size and prior (2-12) returns to form the MOM factor. Two portfolios formed on size, and three portfolios construced on prior (2-12) returns, and then the intersections of these portfolios form the six portfolios. The median NYSE market equity is the size breakpoint, whilst the 30th and 70th NYSE percentiles are the breakpoints for the prior (2-12) returns.

MKT is the value-weight return of all CRSP U.S. companies listed on the NYSE, AMEX, or NASDAQ minus the one-month Treasury bill rate.

SMB is the the mean return of the three small portfolios subtract that of the three big portfolios.

$$\begin{aligned} SMB =& \frac{1}{3}(SmallValue + SmallNeutral + SmallGrowth) \\ &- \frac{1}{3}(BigValue + BigNeutral + BigGrowth) \end{aligned}$$

HML is the mean return of the two value portfolios subtract that of the growth portfolios.

$$HML = \frac{1}{2}(SmallValue + BigValue) - \frac{1}{2}(SmallGrowth + BigGrowth)$$

MOM is the difference of the mean return of the two high prior return portfolios and the mean return of the two low prior return portfolios:

$$MOM = \frac{1}{2}(SmallHigh + BighHigh) - \frac{1}{2}(SmallLow + BigLow)$$

A.4 Hedge Fund

This section presents the construction of the Fung Hsieh seven factors, the hedge fund strategies, and hedge fund index characteristics.

Table A.3: Fung and Hsieh Seven Factors

Factors	Construction
Bond Trend-Following Factor (PTFSBD)	Return of PTFS Bond lookback straddle
Currency Trend-Following Factor (PTFSFX)	Return of PTFS Currency Lookback Straddle
Commodity Trend-Following Factor (PTFSCOM)	Return of PTFS Commodity Lookback Straddle
Equity Market Factor (EMF)	The Standard & Poors 500 index monthly total return
Size Spread Factor (SSF)	Russell 2000 index monthly total return - Standard & Poors 500 monthly total return
Bond Market Factor (BMF)	The monthly change in the 10-year treasury constant maturity yield (month end-to-month end)
Credit Spread Factor (CSF)	The monthly change in the Moody’s Baa yield less 10-year treasury constant maturity yield (month end-to-month end)

This table reports the Fung and Hsieh seven factors and the construction methods.

Table A.4: Hedge Fund Strategies

Primary Strategy	Sub-Strategy
Equity Hedge	Equity Market Neutral
	Fundamental Growth
	Fundamental Value
	Quantitative Directional
	Sector - Energy/Basic Materials
	Sector - Technology/Healthcare
	Short-Biased
	Multi-Strategy
Event-Driven	Activist
	Credit Arbitrage
	Distressed/Restructuring
	Merger Arbitrage
	Private Issue/Regulation D
	Special Situations
	Multi-Strategy
Macro	Active Trading
	Commodity - Agriculture
	Commodity - Energy
	Commodity - Metals
	Commodity - Multi
	Currency Discretionary
	Currency Systematic
	Discretionary Thematic
	Systematic Diversified
	Multi-Strategy
Relative Value	Fixed Income-Asset Backed
	Fixed Income - Convertible Arbitrage
	Fixed Income - Corporate
	Fixed Income - Sovereign
	Volatility
	Yield Alternatives - Energy Infrastructure
	Real Estate
	Multi-Strategies
Fund of Funds	Conservative
	Diversified
	Market
	Strategic
Emerging Markets	Total
	Asia ex-Japan
	Global
	Russia/Eastern Europe
	Latin America

This table reports the hedge fund Strategy Classification System for all investment managers present in the HFR Database by Hedge Fund Research, Inc. and it is available at `https://www.hedgefundresearch.com/hfri-index-methodology`

Table A.5: Hedge Fund Index Ticker and Characteristics

Ticker	Index Characteristics	Strategy	Substrategy	Region
HFRIAWJ	HFRI Asia with Japan Index	Composite	Composite	Asia
HFRIAWC	HFRI Asset Weighted Composite Index	Composite	Composite	Global
HFRICRDT	HFRI Credit Index	Composite	Composite	Global
HFRIDVRS	HFRI Diversity Index	Composite	Composite	Global
HFRIEM	HFRI Emerging Markets (Total) Index	Composite	Composite	Global
HFRIEMA	HFRI Emerging Markets: Asia ex-Japan Index	Composite	Composite	Asia
HFRICHN	HFRI Emerging Markets: China Index	Composite	Composite	China
HFRIEMG	HFRI Emerging Markets: Global Index	Composite	Composite	Global
HFRIIND	HFRI Emerging Markets: India Index	Composite	Composite	India
HFRIEMLA	HFRI Emerging Markets: Latin America Index	Composite	Composite	Americas
HFRIMENA	HFRI Emerging Markets: MENA Index	Composite	Composite	MENA
HFRICIS	HFRI Emerging Markets: Russia/Eastern Europe Index	Composite	Composite	Europe
HFRIFWI	HFRI Fund Weighted Composite Index	Composite	Composite	Global
HFRIFWIC	HFRI Fund Weighted Composite Index - CHF	Composite	Composite	Global
HFRIFWIE	HFRI Fund Weighted Composite Index - EUR	Composite	Composite	Global
HFRIFWIG	HFRI Fund Weighted Composite Index - GBP	Composite	Composite	Global
HFRIFWIJ	HFRI Fund Weighted Composite Index - JPY	Composite	Composite	Global
HFRIJPN	HFRI Japan Index	Composite	Composite	Asia
HFRINA	HFRI North America Index	Composite	Composite	Americas
HFRIWEU	HFRI Western/Pan Europe Index	Composite	Composite	Europe
HFRIWOMN	HFRI Women Index	Composite	Composite	Global
HFRIWRLD	HFRI World Index	Composite	Composite	Global
HFRIEMNI	HFRI EH: Equity Market Neutral Index	Equity Hedge	Equity Market Neutral	Global
HFRIEHFG	HFRI EH: Fundamental Growth Index	Equity Hedge	Fundamental Growth	Global
HFRIEHFV	HFRI EH: Fundamental Value Index	Equity Hedge	Fundamental Value	Global
HFRIEHMS	HFRI EH: Multi-Strategy Index	Equity Hedge	Multi-Strategy	Global
HFRIENHI	HFRI EH: Quantitative Directional Index	Equity Hedge	Quantitative Directional	Global
HFRISEN	HFRI EH: Sector - Energy/Basic Materials Index	Equity Hedge	Sector - Energy/Basic Materials	Global
HFRIHLTH	HFRI EH: Sector - Healthcare Index	Equity Hedge	Sector - Healthcare	Global
HFRITECH	HFRI EH: Sector - Technology Index	Equity Hedge	Sector - Technology	Global
HFRISTI	HFRI EH: Sector - Technology/Healthcare Index	Equity Hedge	Sector - Technology/Healthcare	Global
HFRISHSE	HFRI EH: Short Bias Index	Equity Hedge	Short Bias	Global
HFRIEHI	HFRI Equity Hedge (Total) Index	Equity Hedge	Composite	Global
HFRIAWEH	HFRI Equity Hedge (Total) Index - Asset Weighted	Equity Hedge	Composite	Global
HFRIACT	HFRI ED: Activist Index	Event-Driven	Activist	Global
HFRICRED	HFRI ED: Credit Arbitrage Index	Event-Driven	Credit Arbitrage	Global
HFRIDSI	HFRI ED: Distressed/Restructuring Index	Event-Driven	Distressed/Restructuring	Global
HFRIMAI	HFRI ED: Merger Arbitrage Index	Event-Driven	Merger Arbitrage	Global
HFRIEDMS	HFRI ED: Multi-Strategy Index	Event-Driven	Multi-Strategy	Global
HFRIEDSS	HFRI ED: Special Situations Index	Event-Driven	Special Situations	Global
HFRIEDI	HFRI Event-Driven (Total) Index	Event-Driven	Composite	Global
HFRIAWED	HFRI Event-Driven (Total) Index - Asset Weighted	Event-Driven	Composite	Global
HFRIFOFC	HFRI FOF: Conservative Index	Fund of Funds	Conservative	Global
HFRIFOFD	HFRI FOF: Diversified Index	Fund of Funds	Diversified	Global
HFRIFOFM	HFRI FOF: Market Defensive Index	Fund of Funds	Market Defensive	Global
HFRIFOFS	HFRI FOF: Strategic Index	Fund of Funds	Strategic	Global
HFRIFOF	HFRI Fund of Funds Composite Index	Fund of Funds	Composite	Global
HFRIMI	HFRI Macro (Total) Index	Macro	Composite	Global
HFRIAWM	HFRI Macro (Total) Index - Asset Weighted	Macro	Composite	Global
HFRIMACT	HFRI Macro: Active Trading Index	Macro	Active Trading	Global
HFRIMCOM	HFRI Macro: Commodity Index	Macro	Commodity	Global
HFRIMCUR	HFRI Macro: Currency Index	Macro	Currency	Global
HFRIMDT	HFRI Macro: Discretionary Thematic Index	Macro	Discretionary Thematic	Global
HFRIMMS	HFRI Macro: Multi-Strategy Index	Macro	Multi-Strategy	Global
HFRIMTI	HFRI Macro: Systematic Diversified Index	Macro	Systematic Diversified	Global
HFRIRVA	HFRI Relative Value (Total) Index	Relative Value	Composite	Global
HFRIAWRV	HFRI Relative Value (Total) Index - Asset Weighted	Relative Value	Composite	Global
HFRIFIMB	HFRI RV: Fixed Income-Asset Backed Index	Relative Value	Fixed Income-Asset Backed	Global
HFRICAI	HFRI RV: Fixed Income-Convertible Arbitrage Index	Relative Value	Convertible Arbitrage	Global
HFRIFIHY	HFRI RV: Fixed Income-Corporate Index	Relative Value	Fixed Income-Corporate	Global
HFRIFISV	HFRI RV: Fixed Income-Sovereign Index	Relative Value	Fixed Income-Sovereign	Global
HFRIFI	HFRI RV: Multi-Strategy Index	Relative Value	Multi-Strategy	Global
HFRIVOL	HFRI RV: Volatility Index	Relative Value	Volatility	Global
HFRISRE	HFRI RV: Yield Alternatives Index	Relative Value	Yield Alternatives	Global

This table reports the hedge fund indices tickers and characteristics present in the HFR Database by Hedge Fund Research, Inc. and it is available at `https://www.hedgefundresearch.com/hfri-index-characteristics`