Three Studies in Hedge Funds and Credit Default Swaps

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Abstract

This thesis consists of one hedge fund study and two credit default swap (CDS) studies. The first study investigates the relationship between mega hedge funds (the largest 25% of funds) and two bond yields (U.S. Treasury yield and Baa yield). Using a merged sample of 9,725 hedge funds from 1994 to 2012, I find that hedge fund outflow produced a more significant relationship than inflow, and the dollar outflow of large hedge funds can predict the increase in the bond yields. The association is also more pronounced for large funds with a short notice period prior to redemption. The results suggest that hedge fund flows provide predictive information for the movement of bond yields. The second study investigates the systematic and firm-specific credit and liquidity risks of CDS spreads. Using data on CDS spreads of 356 U.S. firms from 2002 to 2011, I find that systematic credit and liquidity risks are important in cross-sectional prediction of CDS spreads. In addition, the importance of systematic liquidity risk becomes substantial since the financial crisis in 2007. This finding challenges the current Basel III procedures for counterparty credit risk regulations, in which only pure default should be used. In addition, the systematic credit and liquidity factors can be used as a proxy for CDS spreads of firms that do not have traded CDSs. The last study extends Carr and Wu (2010), in which deep out-of-the-money (DOOM) put options and CDSs are associated as they both provide credit insurance for credit protection buyers. Using the Nelson-Siegel (1987) model, I obtain the credit and illiquidity components for DOOMs and CDSs over the period from May 2002 to May 2012. I show that, after controlling the factors that explain the difference between the DOOM and CDS markets, the components converge over time in these two markets. Thus, I can exploit the observed convergence pattern by constructing a simple trading strategy, and this benchmark strategy produces a positive return. I further construct two other strategies based on the component information, and these two refined strategies outperform the benchmark strategy by the Sharpe ratio and Carhart alpha. My three studies contribute to the literature in hedge fund systemic risk and CDS credit and liquidity risks.

Declaration

No portion of the work referred to in the thesis has been submitted in support of an application for another degree or qualification of this or any other university or other institute of learning.

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Acknowledge

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Chapter 1

Introduction

This thesis, which consists of three studies in two research areas, has a special focus on liquidity impact. The first area is hedge fund research and the second is credit default swap (CDS) research. A hedge fund is a private investment instrument that, fund managers have claimed, earns high absolute returns. The hedge fund industry has prospered in the last two decades, and its potential impact on financial markets, due to its sheer size, cannot be overstated. Credit products have also become more popular and important in the last ten years. Among all the research on CDSs, the study of liquidity risk is scarce but has been gaining more popularity lately. In this chapter, I describe recent developments in the literature and explain how these developments relate to my studies.

1.1 Hedge Fund Return Characteristics, Liquidity Risk, and Interconnectedness

Hedge funds are popular for investors who look for high returns. These private funds constantly report their success and receive much public attention. The hedge fund industry keeps prospering, and the total amount invested in the U.S. market is nearly US$2.8 trillion according to a Hedge Fund Research Inc. report in 2014. Yet the history of hedge funds is rather short: the first appearance of hedge funds began in the mid-20th century (Caldwell 1995). Hedge funds, at that time, were unorganized and run by a small group of private investors and fund managers. Fund managers, on behalf of their clients, invest in selected assets based on their analytical skills, and earn performance-based fees if the performance is good (Fung and Hsieh 1999). Some banks, restricted by their risk-management policy, are not willing to provide the capital that fund managers need. Fund managers then turn to wealthy private clients or institutional investors to support their capital requirements. Hedge funds sometimes operate as hedge fund families to effectively conduct marketing strategies and attract new investors (Kolokolova 2011).

Hedge funds are different from other investment organizations such as commodity trading agents (CTAs) and mutual funds. Fung and Hsieh (1999) provide comprehensive analyses of these organizations. CTAs are similar to hedge fund managers. They provide investment advice for their clients who are registered with a managed account. Also, CTAs manage clients' asset portfolios and charge performance-based fees and management fees in return. CTAs and hedge funds, despite their similarities, have a few differences: CTAs are regulated and supervised by the federal government and a supervision committee. Hedge funds, on the other hand, were not required to be registered before the 2007–2009 financial crisis. Before the crisis, hedge funds were free from supervision by financial authorities such as the Securities Exchange Commission (SEC), Commodity Futures Trading Commission (CFTC), Federal Reserve, the Office of the Comptroller of the Currency (OCC), and the Office of Thrift Supervision (OTS). By and large, they abide by investment laws designed to protect individual investors. After the 2007–2009 financial crisis, some financial authorities began to address the issue of lack of supervision and paid more attention to the previously less regulated industries such as hedge funds and private equity funds. As a result, hedge funds now have to be registered and supervised if they operate and market in the U.S. according to the Dodd–Frank Act, or in the EU according to the Alternative Investment Fund Managers (AIFM) Directive.

Mutual funds are different from hedge funds in a number of aspects (viz. regulations, return characteristics, and investment strategy). Mutual funds need to follow strict internal and external regulations that discourage moral hazard. Mutual fund investors often come from the general public. To protect these investors, mutual funds are forced to maintain operational transparency by reporting their holding positions and trading activities frequently. Also, the typical size of mutual funds is larger than that of hedge funds; mutual funds rely more on administration fees because they usually perform a buy-and-hold strategy, while hedge funds embrace risk and adopt a more dynamic strategy in order to earn higher performance fees. In other words, hedge funds enjoy greater flexibility in trading strategy than mutual funds.

Hedge fund performance evaluation often includes a high-water mark provision (HWM). A HWM denies the hedge fund manager his performance fee unless the end-of-year net asset value (NAV) exceeds some past maximum NAVs. Therefore, a HWM induces a call option feature into fund managers' compensation. This may induce higher risk taking by fund managers (Hodder and Jackwerth 2007). More recent literature relates a HWM to a short put which could lead to decreased risk taking, especially for funds with a longer investment horizon and for funds with brokerage restrictions (Aragon and Nanda (2011), Buraschi, Kosowski, and Sritrakul (2014), Dai and Sundaresan (2009), Drechsler (2014), Lan, Wang, and Yang (2013), and Panageas and Westerfield (2009)).

1.1.1 Fund Return Characteristics

To characterize hedge fund performance, Fung and Hsieh (2004) propose a seven-factor model to explain fund returns, namely: (i) equity market factor proxied by Standard & Poor's 500 stock return, (ii) size spread factor proxied by the difference between Wilshire Small Cap 1750 and Wilshire Large Cap 750 return,[1] (iii) bond market factor proxied by the month-end to month-end change in the U.S. Federal Reserve 10-year constant-maturity yield, (iv) credit spread factor proxied by the month-end to month-end change in the difference between the Moody's Baa yield

[1]The Wilshire index no longer exists and has been replaced by Russell 2000.

and the Federal Reserve's 10-year constant-maturity yield, and (v) three trend factors proposed in Fung and Hsieh (2001) (return of portfolio of lookback straddles on bond futures, the return of portfolio of lookback straddles on currency futures, and the return of portfolio of lookback straddles on commodity futures). These factors represent the markets in which hedge funds actively participate. The seven-factor model is widely used in the study of hedge funds.

In order to attract potential investors, hedge funds "voluntarily" report on vendors' platforms their performance and other factual information. At the time of writing, five of the most important hedge fund reporting platforms are BarclayHedge, EurekaHedge, Hedge Fund Research (HFR), Morningstar, and TASS Lipper. The information in these platforms is self-reported. Hedge funds, of course, can stop reporting their performance at any time. Hedge fund data, therefore, contain several biases due to this self-reporting mechanism. The biases are:

1. Backfill Bias: A hedge fund can upload its past performance when it starts to advertise. Naturally, it will report its past returns only if they are good. Therefore, the early period of fund performance will be upwardly biased.

2. Survivorship Bias: Some vendors delete hedge funds that stop reporting or are liquidated. Therefore, the information on defunct funds is missing.

3. Selection Bias: Hedge funds might not advertise themselves in all vendor platforms. As a result, no single vendor platform includes all outstanding hedge funds. Joenvaara, Kosowski, and Tolonen (2012) analyze the mainstream hedge fund databases and suggest the use of consolidated hedge fund data to avoid selection bias.

Given these biases, I choose to use a merged sample, and the procedures of eliminating the above-mentioned biases are provided in Section 2.3. In addition to sample bias, Getmansky, Lo, and Makarov (2004) find that hedge fund return is highly auto-correlated and attribute this to high exposure to illiquid asset and smoothed performance. Therefore, they use an auto-regression model to recover the actual return volatility and propose a smoothing-adjusted Sharpe ratio to recover the actual performance. Studies such as Miura, Aoki, and Yokouchi (2009) also find evidence that hedge funds are highly exposed to illiquid assets.

1.1.2 Hedge Fund Liquidity Risk

Brunnermeier and Pedersen (2009) provide a theoretical explanation for the interaction between funding illiquidity and market illiquidity. In their theory, funding illiquidity and market illiquidity might reinforce each other and form a vicious circle. Liquidity shock increases the asset volatility and margin requirement. If market speculators have enough capital at hand, there is no shortage of funding liquidity. However, if the speculators fail to meet the increased margin, they will be forced to unwind their positions to cover the margin call. This fire sale may further produce liquidity shocks to the market, triggering a devastating "loss spiral". Hedge funds are very likely to be involved in the vicious cycle described in Brunnermeier and Pedersen (2009) since hedge funds tend to hold a large amount of illiquid assets. Khandani and Lo (2007) and Khandani and Lo (2011) described the unprecedented losses in the U.S. stock markets among the long-short equity hedge funds during the week of August 6, 2007 as a result of sudden liquidation. Several studies show hedge funds have substantial liquidity risk. Sadka (2010) finds market-wide and fund-specific liquidity risks explain hedge fund performance. Hu, Pan, and Wang (2013) support the findings in Sadka (2010); Hu et al. find that their liquidity factor explains hedge fund returns.

Teo (2011) studies the impact of funding constraints on hedge funds. A longer redemption period provides fund managers with more time to liquidate positions to return clients' money. Therefore, funds with a longer redemption period suffer less from funding shortage. On the other hand, investors prefer to have a short redemption period to protect their investment. Teo's study shows that funds with a short redemption period and high net inflow outperform funds with a short redemption period and low net inflow. The results suggest that hedge funds embrace liquidity risk and earn liquidity premiums.

1.1.3 Interconnectedness with Other Financial Sectors

The hedge fund industry thrived and peaked just before the credit crash in 2007.[2] Hedge funds hold a large amount of assets and may pose systemic risk. Also, large financial institutions, including hedge funds, have become more interconnected in recent decades. In order to capture the level of interconnectedness among these large institutions, Billio, Getmansky, Lo, and Pelizzon (2012) use VAR (vector autoregression) to study the interconnectedness in institutions' returns. They investigate large hedge funds, banks, broker/dealers, and insurance companies, and find evidence that these hedge funds and financial institutions are more connected now than they were previously in terms of their returns. The escalating interconnectedness raises concern about the systemic risk of these organizations. They also find that banks seem to play a more important role in transmitting shocks than other organizations.

1.1.4 Research Motivation and Contribution

Motivated by these studies, I investigate hedge funds' impact on bond yields in my first study. I find that the hedge fund industry is growing rapidly and the growth, interestingly, is rather asymmetric in terms of assets under management (AuM): the largest 25% of funds account for more than 80% of total AuM. With this asymmetric capital concentration in hedge funds, I switch my attention to these mega funds. I choose a relatively illiquid corporate bond market and a highly liquid Treasury bond market to test whether these bond yields are statistically related to fund flows among the mega hedge funds. I study two types of fund flows: dollar flows and percentage flows.

I find that fund flows predict bond yields. Dollar inflow leads to decreases in Treasury bond prices; dollar outflow, in contrast, predicts increases in both government and corporate bond yields. In addition, the predictability is more pronounced since 2003. I also find that the outflow impact is linked to hedge funds with a short notice period prior to redemption. The results suggest that hedge fund flows can

[2] See the general analysis of hedge fund samples in Section 2.3.

predict bond yields. However, since I do not have bond trading information to show that it is the hedge fund trading that changes the bond yields, it is possible that they are both driven by some other common factor(s).

I also observe that a higher percentage outflow is followed by decreasing yields on Treasury bonds but not the Baa bond yields. This result is stronger for funds imposing a short notice period prior to redemption.

1.2 CDS Credit and Liquidity Risks

Credit default swaps (CDSs) have become a popular financial tool for hedging a firm's default risk. A CDS buyer is protected over a pre-determined period from making a loss due to credit events. Once the underlying firm encounters the credit event (usually bankruptcy), the CDS buyer receives a full amount to recover his loss. The buyer, of course, pays a premium for this protection. A CDS seller, on the other hand, receives the premium and is obligated to cover the loss incurred by the CDS buyer. CDSs are often traded over the counter.

Conventionally, the part that the protection buyer pays to the protection seller is called the "premium leg" whereas the part that the protection seller compensates the buyer for the loss caused by the credit event is called the "protection leg". A CDS is traded fairly if the expected payment from the protection buyer is equal to the expected amount of recovery from the seller. The pricing of CDSs is standard and can be found in many textbooks.[3]

1.2.1 CDS Credit Risk

A firm's credit risk is related to debt insolvency and is a key determinant in CDS evaluation. Merton (1974) is among the pioneers to use the Black–Scholes formula to evaluate a firm's debt value under uncertainty. There are several strict assumptions in Merton (1974). One often-criticized assumption is that default happens only

[3]See, for example, Chaplin (2010), Hull (2014), Lipton and Rennie (2011), and O'Kane (2008).

on the maturity date. There are also other restrictive assumptions. For example, a firm can only have one outstanding zero-coupon debt. Nevertheless, based on these simplified assumptions, the payoff of the debt holder can be viewed as a short European call; thus the value of the outstanding debt can be modeled by the classical option pricing theory.

Distance-to-default (DTD) in Merton (1974) is often used to measure a firm's default risk. DTD reflects the required change in the firm's asset value, expressed as asset standard deviations, in order to trigger a default. DTD is widely used for default risk measurement such as the KMV model. Although the Merton (1974) model is easy to implement, the assumptions for default are rather restrictive. Several studies have relaxed the assumptions in Merton (1974) and provide reasonable evaluation for a firm's credit risk. One study that improves Merton (1974) is Leland and Toft (1996). First of all, Leland and Toft (1996) allow firms to default at any time prior to the debt's maturity date. Also, Leland and Toft (1996) allow firms to hold multiple coupon bonds. In their model, the value of the defaultable bond is still option-like, and can be priced as a barrier option. I use the Leland and Toft (1996) model to form credit components in CDSs. Details are provided in Section 3.3.2.

One particular feature in Leland and Toft (1996) is that a firm can have strategic default (optimal default threshold) in order to maximize equity holders' benefits. They shed light on other studies that consider more complex default procedures. For example, Ericsson and Renault (2006) include a negotiation process after the announcement of default. He and Xiong (2012) add a secondary bond market to explain the possible debt rollover risk.

1.2.2 CDS Liquidity Risk

Recent studies have found that liquidity is substantially priced in CDS spreads. Tang and Yan (2007) study CDS quotes and CDS bid-ask spreads, and conclude that short-term changes in CDS spreads are also explained by the CDS illiquidity. Corò, Dufour, and Varotto (2013) construct two bid-ask-spread-based liquidity factors: daily time-weighted average bid-ask spread, and industry average bid-ask spread. They find both liquidity factors dominate CDS spread changes. Credit risk factors, on the other hand, although still statistically significant, have a weaker explanatory power. Their findings suggest that CDS liquidity risk has become increasingly important. Gennotte and Leland (1990) provide an explanation why liquidity is priced in assets. In their theory, asset equilibrium price (such as a CDS spread) is determined by the demand and supply. The supply side, however, is affected by liquidity shocks according to Gennotte and Leland (1990). Gennotte and Leland (1990) argue that some traders such as hedgers, rebalancers, and liquidity traders tend to hold zero net positions, and their participation improves market efficiency in terms of matching the needs between buyers and sellers. However, they leave the market during market turbulence, and their exit brings further liquidity shocks to the market. Gennotte and Leland (1990) provide new insights on how market liquidity impacts on asset pricing.

Cespa and Foucault (2014) extend Gennotte and Leland (1990) by giving a channel of illiquidity spillover across markets. They argue that informed traders learn from other asset prices. Hence, the equilibrium price of one asset should contain price information of the other assets. Such cross-asset "learning" forms a feedback loop between assets according to the level of price informativeness and could lead to illiquidity spillover. The findings in Das and Hanouna (2009) can be seen as empirical supporting evidence for such cross-asset learning. They find a strong connection between stock liquidity (Amihud stock illiquidity measure) and CDSs. Since the stock price also reflects the firm's credit quality, CDS traders could use stock to hedge credit risk. I follow the argument in Cespa and Foucault (2014) and postulate that CDS spread is affected by stock illiquidity.

1.2.3 Research Motivation and Contribution

In my second study, I develop a model relating CDS spread with firm-specific and market aggregate illiquidities based on Gennotte and Leland (1990) and Cespa and Foucault (2014). I argue that illiquidity of other assets is also priced in the CDS spreads. Surprisingly, the current literature focuses only on the asset's own liquidity. For empirical tests, I examine firm-specific and systematic credit and liquidity impacts on CDS spreads.

The test results indicate that the systematic credit and illiquidity components are equally important in explaining changes in individual firms' CDS spreads. These findings fill the gap in the CDS studies of systematic risks. Also, the importance of the systematic liquidity factor has increased since the financial crisis in 2007. These findings suggest that individual CDS spreads consist of a significant proportion of the liquidity component. This means that the probability of "pure" default seems to be lower than the CDS-implied probability of default. The latter, instead of the "pure" default probability, is used in the assessment of counterparty default risk in Basel III.

My last study explores the association between put options and CDSs. Carr and Wu (2010) establish a link between deep out-of-the-money (DOOM) put options and CDSs, since they both provide credit protection contingent on the firm defaulting. Both protection buyers have the right to sell back the security, share (in the case of a put option), or bond (in the case of a CDS). DOOMs and CDSs can be converted into unit recovery claims (URCs), which Carr and Wu (2010) define as securities that allow the holder to receive one unit when the firm defaults and zero otherwise. The payoff of a URC can be related to a fixed-life Arrow and Debreu (1954) security.

Theoretically, a URC on a given firm should have the same price regardless of the market of origin. However, the actual URCs in DOOMs and CDSs are not consistent, due to different market conditions. In addition, URCs may be affected by different factors such as market illiquidity. I use the Nelson and Siegel (1987) model to separate the hazard rate implied in URC into two components: a credit component and an illiquidity component. The former is the "fitted" component from the credit curve and the latter is the "residual" of the fitted credit curve. Such a separation enables me to have a closer look at the effects of credit and illiquidity components separately.

I find evidence that several option-market related factors can explain the difference between the credit components of DOOMs and CDSs. The explanatory power for the difference between the corresponding illiquidity components is not as strong. I also find evidence that these differences diminish over time, which leads to the convergence of URCs. This finding enables me to construct a simple trading strategy based on the difference in the URC-implied hazard rates. The trading strategy consists of longing the security (DOOM or CDS) with a lower URC-implied hazard rate and shorting the other. I use this simple trading strategy as a benchmark to compare two other improved strategies, which are constructed based on the two components. I find that my refined strategies outperform the benchmark strategy. This finding suggests that both credit and illiquidity provide useful information for predicting DOOM-CDS convergence. My research on DOOMs and CDSs gives new insight into the credit and illiquidity pricing patterns in these two markets.

The rest of this thesis is organized as follows: Chapter 2 is "Too Big to Ignore? Hedge Fund Flows and Bond Yields", Chapter 3 is "Systematic and Firm-specific Credit and Liquidity Risks of CDS Spreads", Chapter 4 is "Anatomize DOOM-CDS Linkage", and Chapter 5 concludes.

Chapter 2

Too Big to Ignore? Hedge Fund Flows and Bond Yields

Abstract

This chapter investigates the predictive power of aggregate hedge fund flows on bond yields. Using a sample of 9,725 hedge funds from a combined data set of five hedge fund databases from 1994 to 2012, we find outflow matters more than inflow and the top 25% largest hedge funds are more important than the smaller funds. Dollar outflow of big funds is followed by increases in both government and corporate bond yields. The results for funds with a short notice period prior to redemption are more pronounced from 2003. Our findings suggest that hedge fund flows can help to predict the movements of bond yields.

2.1 Introduction

The first half of the year 2014 saw an inflow of US$59.9 billion into the global hedge fund industry, leading to its new global record size of US$2.8 trillion according to Hedge Fund Research, Inc.[1] This chapter investigates the extent to which hedge fund flows predict bond yields. We consider both a relatively illiquid corporate bond market and a highly liquid Treasury bond market using dollar and percentage hedge fund flows. We find a total dollar inflow to the largest 25% of hedge funds can predict decreases in Treasury bond yields in the next month. A dollar outflow predicts increases in both government and corporate bond yields. This effect is especially pronounced for the largest 25% of hedge funds. The strongest impact is observed after 2003 and is linked to outflows from large hedge funds with a short notice period prior to redemption. Such dollar outflows are followed by substantial increases in yields for both corporate and Treasury bonds. We also find a higher percentage outflow is followed by a decrease in Treasury bond yields, but not in Baa bond yields. This result is partly consistent with the "flight to safety" phenomenon in which investors relocate capital from risky assets to safer Treasury bonds. This phenomenon is particularly strong for funds with a short notice period prior to redemption.

Overall, hedge fund flows help to predict changes in bond yields one month ahead after controlling for other determinants of bond yields. This chapter is related to Kruttli, Patton, and Ramadorai (2013), who show that the aggregate liquidity of hedge funds, proxied by the average hedge fund return serial correlation coefficient, has predictive power for future returns on stock, bond, and currency indices. Several other studies have shown that hedge funds can influence financial markets, and vice versa. Using an equally weighted hedge fund index and a VAR model, Wrampelmeyer (2011) finds some evidence that hedge fund returns affect equity and foreign exchange volatility. Kang, Kondor, and Sadka (2012) link hedge fund trading and stock-idiosyncratic volatility.

[1]https://www.hedgefundresearch.com/index.php?fuse=products-irglo

Choi, Getmansky, Henderson, and Tookes (2010) investigate convertible bond issuance and convertible bond arbitrage hedge funds. These arbitrageurs are primary purchasers on that market and the inflow to funds becomes a funding resource for the purchase. The authors find that the flow of convertible bond arbitrage hedge funds explains the number of the convertible bonds issued. Following their analysis, we investigate on a more general scale whether hedge fund flow has any predictive power for bond yields. This chapter contributes to the discussion on the potential impact of hedge funds on financial markets and provides empirical evidence that hedge fund flow can predict bond yields. The analysis of fund flow and bond yields, however, can only provide evidence on statistical predictability and indirectly suggest potential links between hedge fund trading activity and bond markets. Analysis of a direct impact would require bond holding data, which are not available in this research.

2.2 Other Hedge Fund Literature

Although hedge fund holdings are not available, previous research has analyzed the impact of hedge fund equity holdings on equity markets. Several studies make use of 13F filings to investigate hedge fund cash management in terms of equity securities. Large hedge funds are required to report their large stock holdings on a quarterly basis. Ben-David, Franzoni, and Moussawi (2012) investigate the hedge fund stock trading during 2007–2009. They consider both long (obtained in the 13F report) and short (proxied by short interest) equity positions constructed by hedge funds. They find that there is little overlap between the long and short positions. The correlation between the positions is rather low. The finding suggests that the hedge fund long and short positions cannot be canceled out. Therefore, they shift their focus onto the long positions and investigate what drives the changes in the holdings. They find that the changes in stock holdings are mainly driven by hedge fund flow. Given that there was tremendous sell-off in hedge fund equity holdings during the financial crisis, clients' redemption is likely to be the main reason why hedge funds sold stocks. The authors claim that (institutional) clients of hedge funds fear fund managers may lock up the money if funds have poor performance; therefore, these clients tend to be very sensitive to market turbulence and, as a result, money withdrawal becomes more severe than in other investment vehicles such as mutual funds. In addition, they find some evidence that hedge funds reallocate their positions from stocks to government and corporate bonds since they observe the increased correlation of hedge fund return and the corresponding asset indexes during the financial crisis period.

Jiao (2013) investigates hedge fund holdings in the 13F report during 2000–2009. They find hedge fund holdings are positively related to equity returns one quarter ahead before 2007. Since the boom in the hedge fund industry during 2000–2007, hedge funds have become more important in the equity market and their trading has increased the demand in equity. There is also an alternative explanation for the results: hedge funds have better skill in timing the market. Both explanations, however, can co-exist in the real world. In addition, Jylha, Rinne, and Suominen (2014) find that hedge funds provide liquidity to the stock market. Cella, Ellul, and Giannetti (2013) study the trading behavior of 13F institutional investors, including mutual funds and hedge funds. They use "churn" ratio (a measure of portfolio turnover) to proxy the investing horizon and find that institutional investors with short trading horizons react more strongly to market shocks than investors with long trading horizons. Upon realization of the market shock, short-horizon investors sell large amounts of their stock holdings and the fire sales create price pressure in the stock market. In addition, the fire sales affect the prices of other assets held by the same institutional investors (Coval and Stafford 2007).

Liquidity risk and its impact on hedge fund performance is addressed in Sadka (2010) and Teo (2011). Sadka (2010) finds that systematic liquidity risk, measured by the Sadka illiquidity measure, has a strong explanatory power on hedge fund returns. He finds that the loadings on liquidity risk for fund styles are different, suggesting that liquidity risk varies dramatically from one hedge fund strategy to another. Teo (2011) documents significant illiquidity risk premiums; funds that are highly exposed to liquidity risk outperform those with low liquidity risk exposure.

Hu, Pan, and Wang (2013) propose a new liquidity measure based on the noise of Treasury bond yields. They argue that their noise measure reflects the shortage of arbitrary capital in the economy, thereby capturing the market-wide liquidity risk. Since hedge funds often invest in illiquid assets, they are sensitive to liquidity risk. The authors show that their illiquidity measure can explain hedge funds' return in addition to traditional factors that are not related to liquidity.

Chan, Getmansky, Haas, and Lo (2005) show that returns on the S&P 500 index, a synthetic bank index, a bond index, and several other indices have a significant impact on hedge funds' performance. They show that hedge funds are rather active participants in these markets; therefore, there is potential systemic risk from hedge funds. Boyson, Stahel, and Stulz (2010) apply the Co-movement Box proposed by Cappiello, Manganelli, and Gerard (2005) and find contagion risk between hedge fund returns and market returns in small-cap, mid-cap, and emerging market equities, as well as high-yield and emerging market bonds. They also show that market-wide liquidity shocks are strongly linked to hedge fund contagion. Similarly, Dudley and Nimalendran (2011) find asymmetric correlation between hedge fund returns and returns on the equity index. Funds with low returns are more likely to co-move with the equity market, indicating the possibility of contagion risk among funds that face funding constraints. They also use quantile regression of hedge fund returns on member margins of the Chicago Mercantile Exchange (CME) and find that, in the lower quantile, hedge funds are affected by funding liquidity. The studies of Boyson, Stahel, and Stulz (2010) and Dudley and Nimalendran (2011) suggest that liquidity shock can spread from hedge funds to other markets via a liquidity spiral as discussed in Brunnermeier and Pedersen (2009). These studies, put together, show that hedge funds and the financial markets are linked and affect each other.

In the aftermath of the subprime crisis, the UK Financial Services Authority (FSA) commissioned a series of reports in 2009–2010 to assess the systemic risk posed by hedge funds. The FSA investigation focuses only on defaults of hedge funds and the resulting counterparty risks that systemically important financial institutions (SIFIs) are exposed to. The FSA reports concluded that hedge funds do not pose any systemic risk to the economy and the financial system. This conclusion may have underestimated hedge funds' influence, as it neglected possible contagion effects. In particular, as of 2012, the largest 1% of hedge funds controlled 38% of the assets in the hedge fund industry, with 90% of the assets being controlled by only the top 25% of funds according to the hedge fund database used in this chapter. Large hedge funds are particularly important as they are the alternative investment outlets for institutional investors (Joenvaara, Kosowski, and Tolonen 2014), and they are getting more interwoven with other large financial institutions (Billio, Getmansky, Lo, and Pelizzon 2012). After the collapse of Long Term Capital Management in 1998, there may not be another single fund whose default can generate the same level of impact in the global financial market. Nevertheless, hedge funds as a group can still impact on global financial stability. If a sufficient number of hedge funds experience extreme losses simultaneously, these losses can spill over to other markets. For example, Khandani and Lo (2007) and Khandani and Lo (2011) report that during the week of August 6, 2007, when some multi-strategy funds and proprietary trading desks started to liquidate their equity portfolios to stop further losses, such sudden liquidations had a profound impact on price levels, resulting in margin calls to long-short equity hedge funds. This was then followed by pension funds' decisions to withdraw their investments in hedge funds, which put further pressure on the hedge fund industry and the financial markets. The chain of events finally resulted in unprecedented losses of several high-profile quantitative long-short equity hedge funds.

2.3 Hedge Fund Data

In this chapter, we use a merged hedge fund database, which combines five mainstream hedge fund databases (viz. BarclayHedge, EurekaHedge, Hedge Fund Research (HFR), Morningstar, and TASS Lipper).[2] The sample period covers 19 years

[2] This is an extended database used in Hodder, Jackwerth, and Kolokolova (2013).

from January 1994 to December 2012. It includes time-series data of monthly net-of-fees returns and assets under management (AuM), as well as other fund-related static information (such as fees, notice periods, etc.). For those funds that report to more than one database, we choose the record with the longest reporting history. Moreover, we use only hedge funds that report returns in U.S. dollars. In order to control for a backfill bias,[3] we delete the first 12 observations of each hedge fund. We only use funds with more than 24 remaining observations. We further exclude 21 monthly return data points in our sample that were higher than 200% or less than -100%. Two hedge funds are removed from our sample because of seemingly unrealistic AuM.[4] The final sample contains 9,725 hedge funds.

Table 2.1 reports the descriptive statistics of the hedge funds in our sample. In general, hedge funds produce a positive average monthly return of 0.61% with a standard deviation of 4.29%. The average fund size is around $200 million with a standard deviation of $70 million. The high standard deviation in fund size indicates that funds faced substantial in- and outflows over the sample period. Half of the funds report the usage of leverage. The average management fee is 1.5% and the performance fee is around 17%. The average lock-up period and notice period are both around one month.

Each hedge fund database has its own fund style classification. We compare the definition of the categories across the databases and aggregate hedge funds into nine broad styles: "Directional Equity", "Equity Market Neutral", "Emerging Market", "Event-Driven", "Fixed Income", "Global Macro", "Managed Futures", "Multi-strategy", and "Not Defined". Table 2.2 reports the fund distribution across the nine categories. "Equity Market Neutral" is the largest group among all fund styles, accounting for 25% of all funds. The second largest fund style, excluding "Not Defined", is "Directional Equity". These two large equity-related fund styles

[3]Fund managers can choose to "backfill" their past performance since inception when they join a database. Such "backfilled" returns are normally reported if they reflect good track record. See, for example, Fung and Hsieh (2004).

[4]These two hedge funds are Athena Guaranteed Futures Ltd (TASS number 628) and LG Asian Smaller Companies (TASS number 57686). The single AuM reported for these funds exceeds $300 billion, whereas the total AuM of the rest of the hedge funds is less than $400 billion over the same period.

Table 2.1: Hedge Funds Descriptive Statistics

This table reports the descriptive statistics of hedge funds in our sample from 1994 to 2012. We include fund return (in percent per month), AuM (in million USD), percentage flow, usage of a high-water mark (HWM), usage of leverage (Lev), management fee ($MgmtFee$ in percent), performance fee ($PerfFee$ in percent), lock-up period (in months), and notice period prior to redemption (in months).

	Ret (%)	AuM ($M)	Flow (%)	HWM	Lev	MgmtFee (%)	PerfFee (%)	Lock-up (Months)	Notice (Months)
Mean	0.61	204	0.64	0.74	0.48	1.49	17.43	0.91	0.60
Median	0.57	25	0.57	1.00	0.00	1.50	20.00	0.00	0.00
Std	4.29	70	7.02	0.44	0.50	0.66	6.76	3.88	1.70
Max	12.04	120,866	39.80	1.00	1.00	20.00	65.00	84.00	18.00
Min	-8.76	0	-42.28	0.00	0.00	0.00	0.00	0.00	0.00

Table 2.2: Fund Style Distribution

This table reports the number and the proportion of funds within each hedge fund style. Fund styles across different databases are merged into nine general styles according to the nature of the reported style.

Fund Style	# Funds	Proportion (%)
Directional Equity	1,224	13
Equity Market Neutral	2,479	25
Emerging Market	489	5
Event-Driven	528	5
Fixed Income	732	8
Global Macro	632	6
Managed Futures	641	7
Multi-strategy	910	9
Not Defined	2,090	21
Total	9,725	

account for approximately 40% of the hedge fund industry.

Table 2.3 reports the hedge fund return descriptive statistics for the different fund styles. "Event-Driven" funds exhibit the highest mean return of 0.69% per month; "Global Macro" funds have the lowest mean return of 0.52%. Unlike a relatively low dispersion in mean returns across fund styles, the difference in AuMs is rather pronounced. "Global Macro" funds, on average, are the largest, with an average fund size of $408 million. "Managed Futures" funds are the smallest, with an average size of just $49 million. Similarly, there is considerable size variation for each style. For instance, the mean AuM of "Directional Equity" funds is $119 million with a standard deviation of $57 million.

To understand the distribution of the total assets managed by the hedge fund industry, we split funds in quartiles according to their average size. For each year, we form AuM-sorted portfolios. The fund size statistics for each of the portfolios are reported in Table 2.4. Q1 is the portfolio that includes the 25% of funds with the largest AuM, while Q4 includes the smallest 25% funds. The statistics are reported for each of the 19 years, as well as for the whole sample period.

The first column reports the total number of hedge funds in our sample for each year. The number of funds increases steadily from 568 in 1994 and peaks at 5,357 in 2007. It drops thereafter to the levels of 2003–2004, with 3,246 funds in our database in 2012. The decreased number of the funds was due to investors' withdrawals from hedge funds after substantial losses experienced in the crisis period, with many funds being forced to liquidate due to performance deterioration and the difficulty in maintaining fund operation.

Columns (2) to (5) of Table 2.4 report the mean and standard deviation of the AuM for the four quartile portfolios, Q1 to Q4. There is a substantial difference between the largest and the smallest funds in terms of their AuM. The average size of funds over 1994–2012 is \$851 million for the Q1 portfolio while that of the Q4 portfolio is just \$0.2 million. It indicates that the top 25% of funds are, on average, over 4,000 times larger than the bottom 25% of funds. This difference decreases over time, and this is likely to be driven by the increasing number of funds. Importantly, the portfolio of the top 25% of funds controls as much as 89% of the total AuM as of the end of 2012.

Table 2.3: Hedge Fund Style Descriptive Statistics

This table reports the descriptive statistics for hedge funds by fund style over the period from 1994 to 2012. The fund characteristics reported include returns (in percent per month), AuM (in million USD), flow (in percent), usage of high-water mark (HWM), usage of leverage (Lev), management fee ($MgmtFee$, in percent), performance fee ($PerfFee$ in percent), lock-up period (in months), and notice period (in months).

	EqDir		EqMktNeu		EmgMkt		EvDriv		FixedInc		GlobMac		ManFut		Multi		NotDef	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std
Ret (%)	0.67	4.87	0.58	4.54	0.68	6.05	0.69	3.11	0.55	2.55	0.52	4.41	0.67	5.54	0.56	3.26	0.62	4.18
AuM ($M)	119	57	272	82	93	39	161	56	166	62	408	133	49	23	388	100	131	60
Flow(%)	0.83	8.34	0.48	6.01	0.66	7.97	0.63	5.06	0.83	6.33	0.62	6.47	0.86	7.27	0.46	6.10	0.65	8.44
HWM	0.82	0.39	0.78	0.41	0.64	0.48	0.74	0.44	0.74	0.44	0.73	0.44	0.59	0.49	0.78	0.42	0.69	0.46
Lev	0.49	0.50	0.43	0.50	0.45	0.50	0.44	0.50	0.57	0.49	0.52	0.50	0.39	0.49	0.47	0.50	0.53	0.50
MgmtFee (%)	1.42	0.47	1.42	0.53	1.62	0.49	1.44	0.62	1.38	0.54	1.62	0.81	2.01	1.13	1.49	0.58	1.45	0.68
PerfFee (%)	17.50	6.63	17.94	5.80	15.99	7.29	17.68	6.12	17.19	7.22	17.39	7.09	18.95	6.79	16.93	7.51	16.86	7.20
Lock-up (Mth)	0.86	4.61	0.78	3.68	0.64	3.30	0.59	2.95	0.83	4.05	0.87	3.51	0.50	2.95	0.91	4.56	1.41	3.92
Notice (Mth)	0.63	1.55	0.74	1.92	0.81	1.38	0.71	1.37	0.75	1.89	0.76	2.03	0.72	1.86	0.71	2.00	0.17	1.07

Table 2.4: AuM-sorted Portfolio Fund Size

This table reports the fund sizes of the AuM-sorted portfolios. Each year, we sort the individual hedge funds into four groups according their average AuM in that year. For each year, we report the number of funds included in each group as well as the mean and standard deviation of fund size for the four groups. The last line summarizes the mean and standard deviation of fund sizes in the four groups based on the whole sample period.

	(1)	(2)		(3)		(4)		(5)	
		Q1 Portfolio		Q2 Portfolio		Q3 Portfolio		Q4 Portfolio	
	# HFs	Mean	Std	Mean	Std	Mean	Std	Mean	Std
1994	568	1,223,513,045	68,990,602	1,977,502	158,878	1,202	24	104	4
1995	926	1,210,217,703	89,396,770	12,424,534	862,444	1,885	78	190	6
1996	1,223	1,170,648,271	53,096,383	14,583,655	974,309	3,072	92	224	11
1997	1,520	1,196,099,710	59,221,206	17,496,468	1,530,296	38,083	6,965	251	27
1998	1,851	984,154,683	69,120,522	20,018,866	775,031	295,381	30,021	294	9
1999	2,141	756,004,039	34,032,180	20,041,094	1,707,955	635,555	128,916	345	27
2000	2,437	745,543,933	36,795,969	24,684,867	701,009	1,058,664	51,684	407	7
2001	2,645	629,319,792	16,479,600	23,505,451	935,740	1,334,493	119,176	411	10
2002	2,988	539,148,163	15,299,916	27,113,238	791,127	1,941,527	94,010	447	6
2003	3,408	562,155,086	20,799,422	33,037,156	3,590,002	2,791,081	401,454	494	25
2004	4,217	591,940,387	24,768,790	43,308,295	1,789,890	5,042,767	404,465	659	11
2005	4,851	591,873,126	11,940,639	48,276,361	1,063,586	6,639,631	222,234	764	12
2006	5,226	652,891,424	23,455,859	53,623,011	1,525,327	8,043,559	301,303	879	18
2007	5,357	764,896,976	26,034,751	69,831,116	3,783,954	11,755,587	373,613	22,024	2,511
2008	5,312	720,124,108	78,358,851	68,544,418	8,746,034	13,750,687	1,325,637	261,605	278,589
2009	3,793	684,638,745	37,373,966	71,383,218	3,282,630	22,227,231	1,168,847	4,970,341	219,424
2010	3,770	768,040,815	24,825,794	79,158,017	2,209,869	24,628,344	1,143,087	5,178,496	132,222
2011	3,667	849,632,928	28,955,985	80,477,280	3,518,060	25,426,187	1,370,989	5,202,161	306,285
2012	3,246	876,056,229	12,581,056	80,097,672	1,644,673	23,588,856	830,827	4,709,889	151,768
1994–2012	9,725	851,115,652	282,150,463	52,385,262	8,841,584	11,131,490	924,529	198,704	348,819

We next consider monthly rolling windows for constructing the AuM-sorted portfolios. For each month, we calculate the average AuM over the past 12 months for each fund, and then sort funds into quartile portfolios according to their average past size. We plot the total AuM for the four portfolios in Figure 2.1. There is a substantial difference between the total AuM for all funds and that excluding the top 25%. The huge gap highlights, again, that a small group of the largest funds controls the bulk of the assets in the hedge fund industry. Such a high capital concentration suggests that analyzing a complete sample of hedge funds may be misleading as it dilutes the impact of the top funds that control 90% of the total assets. It also suggests that the top 25% of funds should be given special attention, as they are likely to affect their smaller peers and can potentially drive the global financial market.[5]

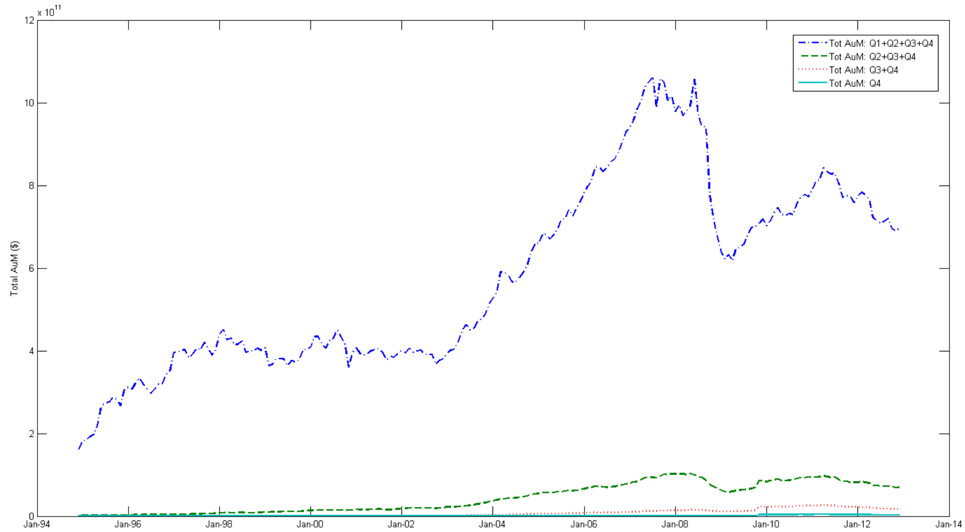
Different types of investors may target certain types of hedge funds. For example, large institutional investors are likely to invest only in large or mega funds (Joenvaara, Kosowski, and Tolonen 2014) whereas smaller and individual investors access smaller funds. Flows to individual funds are driven by both macroeconomic conditions and fund-specific characteristics such as past returns, risks, various redemption restrictions etc.[6] At the aggregate level, when the fund-specific components are averaged out, the flow to funds reflects investors' expectation about the industry's future performance and the availability of free capital for investing. Institutional investors are likely to be better at possessing information about the future prospects of the industry. Smaller investors are likely to be less tolerant, have a lower buffer for outside capital, and, thus, react more promptly to poor fund performance or external liquidity shocks. Based on this conjecture, we test whether there are any lead-lag relations between the in- and outflows of the top 25% of hedge funds and the rest of the hedge fund industry. The results of the VAR regression analysis indicate that, indeed, inflow to the largest funds provides a positive signal and leads

[5]While the top 25% of funds are more important, the results obtained here are qualitatively the same when all funds are considered. The regression results are robust when we use total flow in comparison with the flow to the top 25% funds as shown in Table 2.7 (for total flow) and Table 2.8 (for flow to the top 25% funds).

[6]See, for example, Agarwal, Daniel, and Naik (2004), Goetzmann, Ingersoll, and Ross (2003), Ding, Getmansky, Liang, and Wermers (2009), and Ozik and Sadka (2014).

Figure 2.1: AuM-sorted Portfolios Total AuM

This figure plots the total AuM for four AuM-sorted portfolios from 1994 to 2012. The top curve is the sum of the total AuM across all four portfolios. The next one is the total AuM of all portfolios excluding the top 25% of funds. The third curve represents AuM in the bottom two quantile portfolios, and the last curve is the AuM of the portfolio containing the smallest 25% of funds.



to reducing outflows from all funds. The results and detailed discussion are in Appendix 2.A. In what follows, we will focus on the aggregate flows of the largest 25% of hedge funds only.

As control variables, mutual fund data are obtained from the CRSP database. Since mutual funds have restricted investment subjects according to their reported fund styles, we then narrow our chosen mutual fund styles to fixed income mutual funds only. In particular, we choose corporate (CRSP Category Code: IC), government (CRSP Category Code: IG), and money market (CRSP Category Code: IM) mutual funds, since these three types of mutual funds focus only on U.S. bond markets while the rest focuses on other bond markets such as emerging markets. The sample period is from January 1994 to December 2012.

Table 2.5 reports the descriptive statistics of the mutual funds' returns and flows. The average return is 0.32%, which is smaller than the hedge fund average return of 0.61%. In addition, the average mutual fund flow is 1.98%, which is larger than the average hedge fund flow of 0.64%. The larger average mutual fund flow reflects less restriction of the redemption for investors as well as the overall size of the mutual funds.

Table 2.5: Mutual Fund Descriptive Statistics

This table reports the descriptive statistics of fixed income mutual funds in our sample from 1994 to 2012. Mutual fund excess return (in percent per month) and mutual fund percentage flow are used as control variables.

	Return (%)	Flow (%)
Mean	0.32	1.98
Median	0.26	-0.20
Std	1.26	17.73
Max	391.19	260.37
Min	-64.25	-62.21

2.4 Research Design and Hypothesis

Hedge funds actively participate in the markets of less liquid assets such as corporate bonds (Choi, Getmansky, Henderson, and Tookes 2010). According to the *Financial Times*, hedge funds accounted for one-fifth of all trading volume in the U.S. Treasury bond market in 2010 (`http://www.ft.com/intl/cms/s/0/d7063d32-a554-11dfb734-00144feabdc0.html#axzz3hFVPTDqH`).[7] Given such a large amount of trading volume attributed to hedge funds, the size of mega hedge funds, and their ability to take leverage, the hedge fund industry has the potential to impact on financial market prices, driving prices away from their fundamental values. Such an influence is likely to be more pronounced in smaller and less liquid markets (e.g., corporate bonds), in which hedge funds are responsible for a bigger share of the trading volume.[8] Hedge funds' trading activity can also exert an in-

[7] *Financial Times*, August 11, 2010, "Hedge funds develop taste for U.S. Treasury bonds". Most of the hedge funds involed in bond trading are global macro funds and fixed-income arbitrage funds. Many long-short equity funds do not have the expertise to trade risky bonds, and are not permitted to hold bonds by their investor mandate.

[8] Hedge fund impact might be less visible in large and liquid markets (such as the U.S. equity market), because the proportion of their trading volume to total market trading volume is relatively small. The estimated size of the hedge funds industry is about $3 trillion, whereas the total size of mutual funds was estimated at $24.7 trillion and pension funds at $19.3 trillion as of December 2010.

direct price impact through herding and liquidity spiral. Herding can cause excess price movements on both bull and bear markets if other market participants mimic the trading pattern of hedge funds. A liquidity spiral is likely to cause more damage during a market downturn, especially if market liquidity is low. When hedge funds are faced with massive losses and clients' redemption, they will be forced to sell their holdings quickly, depressing market prices, leading to further losses and fund outflows. Other financial institutions, such as pension funds who have stop-loss provisions in their risk-management systems, might join the run, spreading the fear of possible massive losses and causing a liquidity drain-out. A liquidity spiral (Brunnermeier and Pedersen 2009) is more likely when hedge funds experience fund outflows and are forced to liquidate their assets.

The aforementioned conjecture cannot be proven without information on hedge fund trading activity. Hedge funds' portfolio holdings, unfortunately, are not observable[9] and such a direct inference is not possible. We recognize, however, that upon large fund in- and outflow, hedge funds are more likely to trade, especially when they encounter a large amount of withdrawal from investors (Ben-David, Franzoni, and Moussawi 2012). Moreover, fund outflows may signal a change in the market conditions in general, or the presence of other more favorable investment opportunities.[10] In this section, we attempt to capture the link between hedge fund flows and changes in corporate bond yields (measured by the Moody's Baa yield) and changes in government bond yields (measured as the 10-year Treasury bond yield). Here, we use the fund flow information as a signal for bond and general market conditions.

We denote by $Flow_t$ the average hedge fund percentage flow at time t based on

[9]Large hedge fund investment companies are required to disclose parts of their holdings (long positions in U.S. equities and some option holdings) through SEC 13F filings. Thus, the information is available only for a smaller number of hedge funds. The 13F reporting frequency is quarterly. The assets included in these filings cover largely U.S. equity and do not include bond holdings. Thus, the 13F information is not perfectly suitable for the current analysis.

[10]See, for example, Zheng (1999) and Keswani and Stolin (2008) for smart money effect. At the same time withdrawals may also be related to investors' background risk such as meeting personal liabilities.

individual fund i's flows $Flow_{i,t}$.

$$Flow_{i,t} = DollarFlow_{i,t} \times (AuM_{i,t-1})^{-1}$$

$$DollarFlow_{i,t} = AuM_{i,t} - (1 + R_{i,t}) \times AuM_{i,t-1}$$

where $R_{i,t}$ is the reported return of hedge fund i at time t and $AuM_{i,t}$ is the corresponding assets under management. *Flow* is a percentage flow, and *DollarFlow* is a fund flow in trillions of dollars.

We use superscripts O and I to denote outflow and inflow respectively. Superscript T stands for the top 25% of hedge funds whereas superscript B stands for the rest of the funds. For example, $Flow_{t-1}^{T,I}$ is the average percentage inflow for the top 25% of the largest hedge funds at time $t-1$. To facilitate interpretation of the results, we change the signs and represent outflows as positive values. We control for fund flow outliers and delete 0.5% of the highest and the lowest percentage flows, as suggested by Chan, Getmansky, Haas, and Lo (2005).

When hedge funds face clients' demand for redemption, fund managers may have to sell parts of their portfolios, depressing market prices (and bond price) in the meantime. A lower bond price is translated into a higher bond yield. The reverse effect may be observed upon fund inflows.

H1: [Flow Predictability] Hedge fund dollar flow is negatively related to changes in bond yields.

To test this hypothesis, we regress changes in bond yields on changes in the lagged dollar fund flow.[11] [12] [13] As additional control variables, we include the average ex-

[11] A more widely used percentage fund flow cannot capture the magnitude of a trading activity. Consider a simplified example. One fund has $10 million of assets and the other has $1 million of assets, and both funds need to sell 1% of their bond positions immediately. The large fund will sell $1 million worth of bonds, whereas the small one will sell only $0.1 million worth of bonds. The large fund is more likely to produce a price impact by selling 10 times more than the small fund, despite the same percentage of outflow.

[12] Since the dollar flow is highly autoregressive, we use changes in dollar flow and changes in bond yield in the regression. While the T-bond market trading volume has grown substantially over time, the use of changes in yield would help to prevent the problem due to the change in the scale of the T-bond market volume.

[13] In an earlier version, both contemporaneous and lagged changes in dollar flow were used. Here, we present the test with only the lagged term to highlight the predictive role of the flow information. The two sets of results are qualitatively the same.

cess returns and average percentage flows of bond-oriented mutual funds, as mutual funds also actively participate in bond markets. We also include CBOE VIX index and lagged bond yields as macroeconomic controls, following Choi, Getmansky, Henderson, and Tookes (2010).

Our baseline linear regression is:

$$\begin{aligned}\Delta Yield_t = \beta_0 + \beta_1\, D_{Crisis} + \beta_2\, \Delta Yield_{t-1} + \beta_3\, \Delta VIX_t \\ + \beta_4\, MFExRet_{t-1} + \beta_5\, MFFlow_t + \beta_6\, HFExRet_{t-1} \\ + \gamma\, \Delta DollarFlow_{t-1} + \varepsilon_t\end{aligned} \quad (2.1)$$

where $Yield$ is the Moody's Baa yield or U.S. 10-year Treasury bond yield. D_{Crisis} is a dummy variable capturing the financial crisis. It takes a value of 1 between July 2007 and February 2009. VIX is the value of the CBOE VIX index. $MFExRet$ is the average excess return of bond-oriented mutual funds over the risk-free rate. $MFFlow$ is the average percentage flow to bond-oriented mutual funds. $HFExRet$ is the average excess return of hedge funds over the risk-free rate. $DollarFlow$ is the aggregate hedge fund dollar flow. We use the 10-year U.S. Treasury bond yield obtained from the H.15 Release as the risk-free rate.[14]

Ben-David, Franzoni, and Moussawi (2012) claim that (institutional) clients of hedge funds tend to withdraw their money quickly when the market becomes turbulent, in the fear that fund managers may impose a lock-up whenever they suffer heavy losses. Hence, we conjecture that outflow and inflow will have asymmetric impacts on bond yields.

H1 Corollary 1: *Bond yield change is more pronounced for fund outflow than fund inflow.*

The corresponding regression is:

$$\Delta Yield_t = \beta_0 + \beta\, Ctrls + \gamma^I\, \Delta DollarFlow^I_{t-1} + \gamma^O\, \Delta DollarFlow^O_{t-1} + \varepsilon_t \quad (2.2)$$

[14] http://www.federalreserve.gov/releases/h15/data.htm

where $Ctrls$ are all the control variables used in Equation (2.1), $DollarFlow^I$ is the aggregate dollar inflow to hedge funds, and $DollarFlow^O$ is the aggregate dollar outflow.[15] We expect γ^I to be either negative or insignificant, and γ^O to be positive and larger in magnitude.

As the top 25% of funds are likely to attract institutional investors, their flows are expected to be larger in magnitude. Outflows from such funds might signal a change in market conditions or a shift in investment opportunity set. We use dollar fund outflows from the top 25% of funds and the rests of the industry separately in Equation (2.2) and test the following corollary:

H1 Corollary 2: Price prediction is better for the top 25% of funds.

To avoid potential multicollinearity, we include inflow and outflow as separate variables in the same regression without the (unsigned) flow information as shown below:

$$\Delta Yield_t = \beta_0 + \beta\ Ctrls + \gamma^{I,T}\ \Delta DollarFlow^{I,T}_{t-1} + \gamma^{O,T}\ \Delta DollarFlow^{O,T}_{t-1} + \varepsilon_t \quad (2.3)$$

where $DollarFlow^{I,T}$ is the aggregate dollar inflow to the top 25% of hedge funds, and $DollarFlow^{O,T}$ is the aggregate dollar outflow for these large funds. We repeat the regression for the rest of the hedge funds.

Last, but not least, we expect funds with a longer notice period to be less prone to sudden fund outflows. They have more time to raise funds and to offload their positions if necessary.[16] Thus, their outflow should be less informative. We divide

[15]The aggregate dollar flow is used, instead of the average flow, to capture the magnitude of fund flow in and out of the hedge fund industry. For example, assuming all hedge funds have an outflow of \$1 million. If there are 10 hedge funds, then the aggregate outflow is \$10 million. But if there are 100 hedge funds, then the aggregate outflow is \$100 million, which is ten times larger than the previous case. However, there is no difference in terms of average dollar flow.

[16]Discussion with hedge fund practioners indicates that in pursuing and implementing their investment strategy, hedge funds often hold cash in their portfolio. The use and level of cash varies with investment style and asset market the funds are invested in e.g. long only funds may retain cash out of tactical considerations; other styles have more cash as the instruments used e.g. forwards, contracts for difference (CFD), options, only require partial funding. Any excess cash in a fund is usually held as free cash or deposited in money market accounts with the fund's custodian or prime broker. If cash is invested and not held as free cash, this is usually invested in U.S. Treasuries or money market funds; the focus then is on safety, not yield. For bridging any financing needs, acting as a liquidity buffer, or to leverage the fund, some funds negotiate credit

funds into two groups according to the lengths of their notice periods. A long-notice group contains funds with notice periods longer than 30 days, and a short-notice group includes funds with notice periods less than 30 days. We consider outflows from funds with long and short notice periods in Equation (2.2). This leads to the corollary below:

> *H1 Corollary 3:* *Price prediction is stronger for funds with a short notice period.*

Bernanke, Gertler, and Gilchrist (1994) note that periods of financial turmoil are often characterized by increasing risk aversion of investors and investors' relocation of their capital to safer investments. Such "flight to quality" and related "flight to liquidity" increase the demand for safe and liquid government bonds and push their yields down (Beber, Brandt, and Kavajecz 2009).[17] The relocation between risky and risk-free assets can result in outflow from the hedge fund industry. When rebalancing portfolios, investors often operate in terms of percentages of their portfolio to be relocated. Thus, high percentage outflow from hedge funds may be an indicator for such a relocation exercise. It leads to the following hypothesis:

> *H2:* *[Flight to Safety] Hedge fund percentage outflow is negatively associated with changes in Treasury bond yield.*

To test the *Flight to Safety* hypothesis, we run a regression similar to Equation (2.2) but use percentage flow (instead of dollar flow).

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lines with their prime broker. We would like to thank Stephan Schwill for his helpful discussion.

[17]The hypothesis *H2* below is only partly consistent with the *flight to safety* hypothesis. In *flight to safety*, investors substitute risky assets with assets that are less risky and more liquid such as Treasury bonds. The risky assets are not limited to corporate bonds. But we do not test all other risky assets here.

2.5 Empirical Results

2.5.1 Aggregate Fund Flows

Table 2.6 reports the correlation coefficients between changes in dollar flow, changes in bond yields, and other control factors. In general, changes in flows are negatively correlated with changes in Baa bond yields (-0.22) and positively correlated with changes in Treasury bond yields (+0.18). We find that VIX is highly correlated with fund outflows (0.48 with percentage outflow and 0.57 with change in dollar outflow), suggesting that hedge fund investors are sensitive to market uncertainty. Fund flow itself is highly correlated with inflow and outflow. The corresponding correlation coefficients are 0.85 and -0.89 for changes in dollar flow, and 0.85 and -0.88 for percentage flow. This raises the concern regarding multicollinearity. Therefore, when we include outflow and inflow in the regression, we do not mix them with flow itself.

We first test our *Hypothesis H1*. Table 2.7 reports the estimation results for Equation (2.1) for changes in the Treasury bond yield (Panel A) and for changes in the Baa yield (Panel B). The regression coefficients are not standardized. The change in the dollar flow is used instead of dollar flow itself in order to remove the trending problem in dollar flow. Model (1) uses only control variables, and Model (2) includes hedge fund flow in addition. The explanatory power of the regressions is rather low, and marginally improved after the inclusion of hedge fund flows. The adjusted R-square for Treasury yields increases from 0.03 to 0.08, whereas the adjusted R-square for Baa yields increases from 0.06 to 0.08. Changes in hedge fund flow are negatively related to changes in bond yields. The loadings for Treasury yields and Baa yields are both -0.03, and statistically significant at the 5% level.[18] We do not find statistical evidence that bond-oriented mutual fund percentage flows are related to the changes in bond yields.

[18]Note that the change in yield is in decimal, whereas the change in dollar flow is in trillions of dollars. If $\beta = -0.03$, this means that a one standard deviation increase in $\Delta DollarFlow$ will reduce $\Delta yield$ by $\beta \times \sigma_{\Delta DollarFlow} = 0.03 \times 0.0189 = 0.006$ or 60 basis points. An increase of one trillion dollars in dollar flow will reduce bond yield by $\beta \times 100\%$ or 3%.

We then test our *Corollary 1* in *H1*, which hypothesizes that outflow has a greater impact than inflow.[19] We now include in- and outflows as separate variables in the regression. Table 2.8 starts with the base case of fund outflow, then Model (3) includes total dollar inflow, Model (4) considers inflow to large funds, and Model (5) uses inflow to small funds. Although the overall impact of fund flow is similar for Treasury bond yields and Baa yields (as shown in Table 2.7), the results for in- and outflows are not the same. The changes in Treasury bond yields are negatively related to fund inflow, especially the inflow to the top 25% of funds. The loading of -0.05 has a p-value of 0.07. The aggregate outflow is positively related to changes in Treasury bond yields, but not statistically significant. In contrast, aggregate fund outflow is positively related to changes in Baa yields, with the loadings varying from 0.03 to 0.04 depending on the specification, and are significant at the 5% level. The loadings on inflow are not statistically significant but still exhibit negative signs. These results suggest that at an aggregate level, hedge fund outflow predicts the increase in corporate bond yields.

We now investigate the impact of fund outflow in more detail to test our *Corollaries 2* and *3* in *H1*. We consider outflow from top and bottom funds, as well as the outflow from the funds with short and long notice periods prior to redemption. Table 2.9 reports the estimation results. Together with fund inflow, Model (6) and Model (7) consider outflows for top and bottom funds respectively (tests for *Corollary 2*). Models (8) and (9) use outflows from top funds with long and short notice, and Models (10) and (11) include outflow from bottom funds with long and short notice (tests for *Corollary 3*).

[19]Note that from here onwards, all fund flow regressions are tested using their first difference because of the trending problem.

Table 2.6: Factor Correlations

This table reports the correlation coefficients over the sample period from 1994 to 2012 between various variables for explaining bond yields. Δ indicates monthly changes. Baa is the Moody's Baa yield, $TB10Y$ is the U.S. 10-year Treasury yield. VIX is the CBOE VIX index, $MFExRet$ is the excess return of bond-oriented mutual funds, $MFFlow$ is the percentage fund flow of bond-oriented mutual funds, $HFExRet$ is the excess return of hedge funds, $\Delta DollarFlow$ is the change in hedge fund flow in trillions of dollars, and $Flow$ is percentage fund flow. Superscript I stands for hedge fund inflow, and superscript O stands for hedge fund outflow.

	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) ΔBaa	0.64	0.24	-0.29	0.11	-0.31	-0.22	-0.13	0.25	-0.18	-0.08	0.22
(2) $\Delta TB10Y$		-0.16	-0.26	-0.16	0.06	0.18	0.14	-0.16	0.01	0.06	0.03
(3) ΔVIX			-0.10	0.30	-0.46	-0.48	-0.33	0.48	-0.54	-0.35	0.57
(4) $MFExRet$				-0.42	0.56	-0.14	-0.03	0.21	0.08	0.05	-0.09
(5) $MFFlow$					-0.51	-0.26	-0.22	0.23	-0.21	-0.14	0.22
(6) $HFExRet$						0.63	0.65	-0.45	0.53	0.53	-0.40
(7) $Flow$							0.85	-0.88	0.44	0.44	-0.33
(8) $Flow^I$								-0.49	0.40	0.51	-0.21
(9) $Flow^O$									-0.36	-0.26	0.36
(10) $\Delta DollarFlow$										0.85	-0.89
(11) $\Delta DollarFlow^I$											-0.51
(12) $\Delta DollarFlow^O$											

Table 2.7: HF Dollar Flow and Bond Yields

This table reports the results based on total hedge fund flow from 1994 to 2012. D_{Crisis} is a dummy variable, taking a value of 1 from July 2007 to February 2009 and 0 for the rest of the sample. Lag1 is the previous value of the corresponding dependent variable. Δ indicates monthly changes in the corresponding variable. Baa is the Moody's Baa yield, $TB10Y$ is the U.S. 10-year Treasury yield. VIX is the CBOE VIX index, $MFExRet$ is the excess return of bond-oriented mutual funds, $MFFlow$ is the percentage fund flow of bond-oriented mutual funds, $HFExRet$ is the excess return of hedge funds, and $\Delta DollarFlow$ is hedge fund flow in trillions of dollars.

Panel A: Dependent Variable: $\Delta TB10Y$

	Model (1)			Model (2)		
	Coef.	t-stat	p-value	Coef.	t-stat	p-value
Const.	0.00	1.00	0.32	0.00	0.45	0.65
D_{Crisis}	-0.00	-1.07	0.28	-0.00	-0.15	0.88
Lag1	0.11	1.59	0.11	0.07	0.92	0.36
ΔVIX	-0.00	-1.92	0.06	-0.00	-2.69	0.01
$MFExRet_{t-1}$	0.01	0.67	0.50	-0.03	-1.36	0.17
$MFFlow_t$	-0.01	-0.94	0.35	-0.00	-0.33	0.75
$HFExRet_{t-1}$				0.04	3.35	0.00
$\Delta DollarFlow_{t-1}$				-0.03	-2.29	0.02
R-square	0.06			0.11		
R-adjust	0.03			0.08		

Panel B: Dependent Variable: ΔBaa

	Model (1)			Model (2)		
	Coef.	t-stat	p-value	Coef.	t-stat	p-value
Const.	-0.00	-0.28	0.78	-0.00	-0.24	0.81
D_{Crisis}	0.00	1.09	0.28	0.00	1.25	0.21
Lag1	0.13	1.88	0.06	0.13	1.81	0.07
ΔVIX	0.00	3.01	0.00	0.00	2.57	0.01
$MFExRet_{t-1}$	0.00	0.30	0.76	-0.00	-0.20	0.84
$MFFlow_t$	0.01	0.71	0.48	0.01	1.12	0.26
$HFExRet_{t-1}$				0.01	1.21	0.23
$\Delta DollarFlow_{t-1}$				-0.03	-2.54	0.01
R-square	0.08			0.11		
R-adjust	0.06			0.08		

Table 2.8: HF Dollar Inflow and Bond Yields

This table reports the results based on hedge fund inflow from 1994 to 2012. Δ indicates monthly changes in the corresponding variable. Baa is the Moody's Baa yield, $TB10Y$ is the U.S. 10-year Treasury yield, and $\Delta DollarFlow$ is the change in hedge fund flow in trillions of dollars. Superscript I stands for inflow, superscript O stands for outflow. Superscript T stands for the top 25% of hedge funds, and superscript B stands for the rest of the hedge funds.

Panel A: Dependent Variable: $\Delta TB10Y$

	Model (3)			Model (4)			Model (5)		
	Coef.	t-stat	p-value	Coef.	t-stat	p-value	Coef.	t-stat	p-value
$\Delta DollarFlow^{I}_{t-1}$	-0.04	-1.65	0.10						
$\Delta DollarFlow^{T,I}_{t-1}$				-0.05	-1.79	0.07			
$\Delta DollarFlow^{B,I}_{t-1}$							-0.33	-0.93	0.35
$\Delta DollarFlow^{O}_{t-1}$	0.02	1.07	0.29	0.02	1.11	0.27	0.02	1.28	0.20
Controls	Included			Included			Included		
R-square	0.11			0.11			0.10		
R-adjust	0.07			0.08			0.07		

Panel B: Dependent Variable: ΔBaa

	Model (3)			Model (4)			Model (5)		
	Coef.	t-stat	p-value	Coef.	t-stat	p-value	Coef.	t-stat	p-value
$\Delta DollarFlow^{I}_{t-1}$	-0.02	-0.72	0.47						
$\Delta DollarFlow^{T,I}_{t-1}$				-0.02	-0.67	0.51			
$\Delta DollarFlow^{B,I}_{t-1}$							-0.08	-0.25	0.80
$\Delta DollarFlow^{O}_{t-1}$	0.03	2.11	0.04	0.03	2.18	0.03	0.04	2.26	0.02
Controls	Included			Included			Included		
R-square	0.11			0.11			0.11		
R-adjust	0.08			0.08			0.08		

Table 2.9 shows that large funds' outflow is positively related to changes in Treasury yield. The corresponding loading of 0.05 is significant at the 10% level. The impact is strong for funds with a long notice period, but not those with a short notice period. It is clear that the top 25% fund flows can help to predict changes in Treasury bond yields. We do not find any evidence of significant impact of outflows from small funds, disregarding the length of their notice periods.

The lower panel of Table 2.9 reports the results for changes in Baa yields. Consistent with the results in Table 2.8, outflows from both large and small funds and with long and short notice periods are positively related to changes in Baa yields. The loading for large funds is 0.06 which is significant at the 1% level (Model (6)), and that for small funds is 0.58 which is significant at the 5% level. The loading on small funds is much larger than that for large funds as the scale of fund flow is much smaller for the small funds. The only specification in which dollar outflow is not statistically significant is that of small funds with a long notice period.

Furthermore, we find that the loadings of $\Delta DollarFlow^O$ on ΔBaa (somewhere between 0.03 and 0.40) are, in general, slightly higher than those for $\Delta TB10Y$ (somewhere between 0.02 and 0.05). It is generally believed that illiquid assets are more sensitive to market shocks than liquid assets. Therefore, when the hedge fund industry experiences a large outflow of funds, it may be a signal of market shock, with corporate bonds experiencing a larger price drop than the Treasury bonds. However, since we do not have the actual bond trading data, it is possible that both hedge fund flow and bond yields are driven by some other common factor(s).

Table 2.9: HF Dollar Outflow and Bond Yields

This table reports the results based on hedge fund outflow from 1994 to 2012. Δ indicates monthly changes in the corresponding variable. Baa is the Moody's Baa yield, $TB10Y$ is the U.S. 10-year Treasury yield, and $\Delta DollarFlow$ is the change in hedge fund flow in trillions of dollars. Superscript I stands for inflow, superscript O stands for outflow. Superscript T stands for the top 25% of hedge funds, and superscript B stands for the rest of the hedge funds. Superscript S stands for funds with a notice period shorter than 30 days, and superscript L stands for funds with a longer notice period.

Panel A: Dependent Variable: $\Delta TB10Y$

	Model (6)			Model (7)			Model (8)			Model (9)			Model (10)			Model (11)		
	Coef.	t-stat	p-value	Coef.	t-stat	p-value	Coef.	t-stat	p-value	Coef.	t-stat	p-value	Coef.	t-stat	p-value	Coef.	t-stat	p-value
$\Delta DollarFlow^{I}_{t-1}$	-0.03	-1.30	0.19	-0.04	-1.76	0.08	-0.03	-1.30	0.20	-0.04	-1.66	0.10	-0.04	-1.69	0.09	-0.04	-1.67	0.10
$\Delta DollarFlow^{T,O}_{t-1}$	0.05	1.87	0.06															
$\Delta DollarFlow^{T,O,L}_{t-1}$							0.05	1.87	0.06									
$\Delta DollarFlow^{T,O,S}_{t-1}$										0.29	1.08	0.28						
$\Delta DollarFlow^{B,O}_{t-1}$				0.40	1.26	0.21												
$\Delta DollarFlow^{B,O,L}_{t-1}$													2.63	1.00	0.32			
$\Delta DollarFlow^{B,O,S}_{t-1}$																0.32	1.07	0.29
Controls	Included			Included			Included			Included			Included			Included		
R-square	0.12			0.11			0.12			0.11			0.11			0.11		
R-adjust	0.08			0.08			0.08			0.07			0.07			0.07		

Panel B: Dependent Variable: ΔBaa

	Model (6)			Model (7)			Model (8)			Model (9)			Model (10)			Model (11)		
	Coef.	t-stat	p-value	Coef.	t-stat	p-value	Coef.	t-stat	p-value	Coef.	t-stat	p-value	Coef.	t-stat	p-value	Coef.	t-stat	p-value
$\Delta DollarFlow^{I}_{t-1}$	-0.01	-0.44	0.66	-0.02	-0.96	0.34	-0.01	-0.45	0.65	-0.02	-0.90	0.37	-0.02	-1.04	0.30	-0.02	-0.90	0.37
$\Delta DollarFlow^{T,O}_{t-1}$	0.06	2.65	0.01															
$\Delta DollarFlow^{T,O,L}_{t-1}$							0.06	2.63	0.01									
$\Delta DollarFlow^{T,O,S}_{t-1}$										0.40	1.64	0.10						
$\Delta DollarFlow^{B,O}_{t-1}$				0.58	2.03	0.04												
$\Delta DollarFlow^{B,O,L}_{t-1}$													3.02	1.30	0.20			
$\Delta DollarFlow^{B,O,S}_{t-1}$																0.44	1.65	0.10
Controls	Included			Included			Included			Included			Included			Included		
R-square	0.12			0.11			0.12			0.10			0.10			0.10		
R-adjust	0.09			0.08			0.09			0.07			0.07			0.07		

The loadings on the outflows from top and bottom funds with short notice periods are positive (0.40 and 0.44 respectively), but only marginally significant. In order to assess the stability of these results, we repeat the analysis for the two sub-periods. The size of the hedge fund industry has grown substantially since 2003 (see Figure 2.1), thus we may expect more pronounced results in the later part of our sample period. Table 2.10 reports the results for fund outflow for two sub-periods: from January 1994 to June 2003, and from July 2003 to December 2012. The sub-period is chosen by separating the complete sample period into two sub-sample periods of equal length. We find that the outflow from large funds with a short notice period is positively related to changes in the yields of both government and corporate bonds in the second sub-period. The loadings of 0.09 and 0.07 are significant at the 1% and 5% levels respectively. The outflow from small funds is not statistically significant in both sub-samples. These findings provide support for *Corollaries 2* and *3* from the *Flow Predictability* hypothesis and suggest that the bond yields are explained by top funds with short notice periods.[20]

[20] These results suggest that some hedge funds may have sold bonds in response to fund outflows. We performed a limited check using the reported equity holdings of hedge fund investment companies to the Securities and Exchange Commission (SEC) though 13F filings. We matched 1,050 hedge fund firms from our sample to the ones reporting to the SEC. This sample was previously used in Mattes (2011). We then compared the net quarterly outflows and the changes in reported equity holdings. We found that, for a median HF company, its net quarterly outflow is $25 million larger than its changes in reported long equity positions. This means that apart from equity liquidation, hedge funds have to find other channels to fund the cash outflows by selling bonds or otherwise.

Table 2.10: Sub-period Analysis for HF Dollar Outflow

This table reports the results based on hedge fund outflow for two sub-periods from January 1994 to June 2003, and from July 2003 to December 2012. Δ indicates monthly changes in the corresponding variable. Baa is the Moody's Baa yield, $TB10Y$ is the U.S. 10-year Treasury yield, and $\Delta DollarFlow$ is the change in hedge fund flow in trillions of dollars. Superscript I stands for inflow, superscript O stands for outflow, superscript T stands for the top 25% of hedge funds, and superscript B stands for the rest of the hedge funds. Superscript S stands for funds with a notice period shorter than 30 days, and superscript L stands for funds with a longer notice period.

Panel A: Dependent Variable: $\Delta TB10Y$

	1994.1-2003.6						2003.7-2012.12					
	Coef.	t-stat	p-value	Coef.	t-stat	p-value	Coef.	t-stat	p-value	Coef.	t-stat	p-value
$\Delta DollarFlow^{I}_{t-1}$	-0.03	-0.67	0.51	-0.02	-0.55	0.59	-0.03	-1.17	0.24	-0.05	-1.53	0.13
$\Delta DollarFlow^{T,O,S}_{t-1}$	-0.02	-0.39	0.70				0.09	2.68	0.01			
$\Delta DollarFlow^{B,O,S}_{t-1}$				-0.04	-0.02	0.99				0.47	1.44	0.15
Controls	Included			Included			Included			Included		
R-square	0.09			0.09			0.20			0.16		
R-adjust	0.03			0.03			0.14			0.10		

Panel B: Dependent Variable: ΔBaa

	1994.1-2003.6						2003.7-2012.12					
	Coef.	t-stat	p-value	Coef.	t-stat	p-value	Coef.	t-stat	p-value	Coef.	t-stat	p-value
$\Delta DollarFlow^{I}_{t-1}$	-0.01	-0.41	0.68	-0.03	-1.02	0.31	-0.00	-0.16	0.87	-0.02	-0.52	0.61
$\Delta DollarFlow^{T,O,S}_{t-1}$	0.04	1.11	0.27				0.07	2.05	0.04			
$\Delta DollarFlow^{B,O,S}_{t-1}$				-0.81	-0.45	0.66				0.31	0.99	0.32
Controls	Included			Included			Included			Included		
R-square	0.05			0.04			0.24			0.21		
R-adjust	-0.01			-0.02			0.19			0.16		

2.5.2 Hedge Fund Percentage Flows

Table 2.11 reports the results for $\Delta TB10Y$ and ΔBaa when the changes in yields are related to control variables and the average percentage flow across all funds. At such an aggregate level, we cannot detect any significant relation between percentage flow and changes in bond yields.

Table 2.12 disaggregates inflows and outflows and considers inflows to top and bottom funds separately. We do not find any significant relation between bond yields and percentage fund inflow. The percentage outflow however is negatively related to changes in Treasury bond yields with the loading being -0.04 significant at the 10% level, and there is no significant relation to changes in Baa yields.[21]

In Table 2.13 we take a closer look at different types of fund outflow and confirm that percentage outflow from all types of hedge funds is negatively related to changes in Treasury bond yields. In addition, Table 2.14 shows that the negative relationship between percentage fund outflow and Treasury bond yield is stable across different sub-periods.[22]

We also consider the flows to funds with different fund styles. In particular, we aggregate in- and outflows across top funds following equity-related strategies and fixed income strategies and include them separately in the regression. Table 2.15 reports the results for the changes in Treasury bond yields and the Baa yields. We find that significant results are most likely to be associated with Treasury yields. We find that the loadings for the inflow and outflow of equity-related funds are significant. A scatter plot (not presented here) of Treasury yields and equity fund percentage flows reveals that there were some big common movements during the

[21] Note that the change in yield is in decimal, whereas percentage flow used in the regression is also in decimal. If $\beta = 0.03$, this means that a one standard deviation increase in $Flow$ will increase $\Delta yield$ by $\beta \times \sigma_{Flow} = 0.03 \times 0.0201 = 0.00603$ or 60 basis points. From Table 2.1, the mean Flow(%) is 0.64% or 0.0064. So an average Flow increase will increase yield by $0.03 \times 0.0064 = 0.000192$ or 0.0192% or 1.92 basis points.

[22] The examiners pointed out that hedge fund AuM has more than tripled in a decade. If the price impact hypothesis is correct, then hedge fund flows should have a larger impact in the latter period. The percentage flow is basically adjusting flows by AuM, and has the effect of keeping the impact comparable across time. In Table 2.9, the fund's dollar flow analyses were performed over two sub-periods from 1994 to 2003 and from 2003 to 2012. The results are indeed significant only in the second period.

Table 2.11: HF Percentage Flow and Bond Yields

This table reports the results based on the average percentage hedge fund flow from 1994 to 2012. D_{Crisis} is a dummy variable, taking a value of 1 from July 2007 to February 2009 and 0 for the rest of the sample. Lag1 is the previous value of the corresponding dependent variable. Δ indicates monthly changes in the corresponding variable. Baa is the Moody's Baa yield, $TB10Y$ is the U.S. 10-year Treasury yield. VIX is the CBOE VIX index, $MFExRet$ is the excess return of bond-oriented mutual funds, $MFFlow$ is the percentage fund flow of bond-oriented mutual funds, $HFExRet$ is the excess return of hedge funds, and $Flow$ is the average percentage hedge fund flow.

Panel A: Dependent Variable: $\Delta TB10Y$

	Model (1)			Model (2)		
	Coef.	t-stat	p-value	Coef.	t-stat	p-value
Const.	0.00	1.00	0.32	0.00	0.64	0.52
D_{Crisis}	-0.00	-1.07	0.28	-0.00	-0.04	0.97
Lag1	0.11	1.59	0.11	0.10	1.36	0.18
ΔVIX	-0.00	-1.92	0.06	-0.00	-2.52	0.01
$MFExRet_{t-1}$	0.01	0.67	0.50	0.01	0.54	0.59
$MFFlow_t$	-0.01	-0.94	0.35	-0.01	-0.76	0.45
$HFExRet_{t-1}$				0.00	0.00	1.00
$Flow_{t-1}$				0.03	1.43	0.15
R-square	0.06			0.09		
R-adjust	0.03			0.06		

Panel B: Dependent Variable: ΔBaa

	Model (1)			Model (2)		
	Coef.	t-stat	p-value	Coef.	t-stat	p-value
Const.	-0.00	-0.28	0.78	-0.00	-0.14	0.89
D_{Crisis}	0.00	1.09	0.28	0.00	1.10	0.27
Lag1	0.13	1.88	0.06	0.14	1.95	0.05
ΔVIX	0.00	3.01	0.00	0.00	2.85	0.00
$MFExRet_{t-1}$	0.00	0.30	0.76	0.02	0.81	0.42
$MFFlow_t$	0.01	0.71	0.48	0.01	0.59	0.56
$HFExRet_{t-1}$				-0.01	-0.77	0.44
$Flow_{t-1}$				0.01	0.64	0.52
R-square	0.08			0.08		
R-adjust	0.06			0.05		

Table 2.12: HF Percentage Inflow and Bond Yields

This table reports the results based on hedge fund inflow from 1994 to 2012. Δ indicates monthly changes in the corresponding variable. Baa is the Moody's Baa yield, $TB10Y$ is the U.S. 10-year Treasury yield, and $Flow$ is the average hedge fund percentage flow. Superscript I stands for inflow, superscript O stands for outflow. Superscript T stands for the top 25% of hedge funds, and superscript B stands for the rest of the hedge funds.

Panel A: Dependent Variable: $\Delta TB10Y$

	Model (3)			Model (4)			Model (5)		
	Coef.	t-stat	p-value	Coef.	t-stat	p-value	Coef.	t-stat	p-value
$Flow^{I}_{t-1}$	0.01	0.31	0.75						
$Flow^{T,I}_{t-1}$				-0.07	-0.78	0.43			
$Flow^{B,I}_{t-1}$							-0.02	-0.77	0.44
$Flow^{O}_{t-1}$	-0.04	-1.69	0.09	-0.04	-1.64	0.10	-0.04	-1.56	0.12
Controls	Included			Included			Included		
R-square	0.10			0.10			0.10		
R-adjust	0.06			0.07			0.07		

Panel B: Dependent Variable: ΔBaa

	Model (3)			Model (4)			Model (5)		
	Coef.	t-stat	p-value	Coef.	t-stat	p-value	Coef.	t-stat	p-value
$Flow^{I}_{t-1}$	0.01	0.27	0.79						
$Flow^{T,I}_{t-1}$				-0.05	-0.63	0.53			
$Flow^{B,I}_{t-1}$							-0.01	-0.48	0.63
$Flow^{O}_{t-1}$	-0.01	-0.67	0.50	-0.01	-0.62	0.54	-0.01	-0.58	0.56
Controls	Included			Included			Included		
R-square	0.08			0.09			0.08		
R-adjust	0.05			0.05			0.05		

crisis period. Therefore, the statistically significant results might be driven by these big common movements. Interestingly, we find negative loadings of fixed income funds on Treasury and corporate yields. This result suggests possible connection between bond trading and bond fund percentage inflow, and the possible use of the latter to help predict movements in Treasury and corporate bond yields.

2.6 Conclusion

The hedge fund industry is characterized by extreme capital concentration, with the largest 25% of funds controlling some 90% of the total assets in the industry. Compared with the smaller funds, these mega funds are likely to attract different types of investors such as large pension funds. Flows into different-sized funds may thus reflect information, liquidity, and preferences of different types of investors.

We find that fund flow is negatively related to next-period changes in Treasury bond yields and Moody's Baa yields. An inflow to the large funds predicts a decrease in Treasury bond yields, whereas an outflow predicts an increase in corporate bond yields. Outflow from large funds also has a negative relationship with Treasury bond yields. The results of outflows are more pronounced after 2003, and are strongest for large funds with short notice periods.

We also find that an increase in the fund percentage outflow predicts a decline in Treasury bond yields. This finding is partly consistent with the *flight to safety* hypothesis. There is no significant link between percentage outflows and changes in corporate bond yields.

Since we do not have hedge funds' bond holding data, it is not possible to conclude that hedge fund bond trading has an impact on bond yields. We can only conclude that hedge fund flow, conditional on the flow direction and fund size, indeed can help to predict bond yield movements. However, it is also possible that both bond yields and hedge fund flows are driven by other common factor(s).

Table 2.13: HF Percentage Outflow and Bond Yields

This table reports the results based on hedge fund outflow from 1994 to 2012. Δ indicates monthly changes in the corresponding variable. Baa is the Moody's Baa yield, $TB10Y$ is the U.S. 10-year Treasury yield, and $Flow$ is the average percentage hedge fund flow. Superscript I stands for inflow, superscript O stands for outflow. Superscript T stands for the top 25% of hedge funds, and superscript B stands for the rest of the hedge funds. Superscript S stands for funds with a notice period shorter than 30 days, and superscript L stands for funds with a longer notice period.

Panel A: Dependent Variable: $\Delta TB10Y$

	Model (6)			Model (7)			Model (8)			Model (9)			Model (10)			Model (11)		
	Coef.	t-stat	p-value	Coef.	t-stat	p-value	Coef.	t-stat	p-value	Coef.	t-stat	p-value	Coef.	t-stat	p-value	Coef.	t-stat	p-value
$Flow^{I}_{t-1}$	0.02	0.65	0.52	0.01	0.50	0.62	0.02	0.63	0.53	0.03	1.08	0.28	0.02	0.71	0.48	0.03	1.10	0.27
$Flow^{T,O}_{t-1}$	-0.15	-2.16	0.03															
$Flow^{T,O,L}_{t-1}$							-0.15	-2.08	0.04									
$Flow^{T,O,S}_{t-1}$										-0.11	-3.32	0.00						
$Flow^{B,O}_{t-1}$				-1.82	-2.35	0.02												
$Flow^{B,O,L}_{t-1}$													-0.44	-2.36	0.02			
$Flow^{B,O,S}_{t-1}$																-0.13	-3.41	0.00
Controls	Included			Included			Included			Included			Included			Included		
R-square	0.10			0.11			0.10			0.13			0.11			0.13		
R-adjust	0.07			0.07			0.07			0.10			0.07			0.10		

Panel B: Dependent Variable: ΔBaa

	Model (6)			Model (7)			Model (8)			Model (9)			Model (10)			Model (11)		
	Coef.	t-stat	p-value	Coef.	t-stat	p-value	Coef.	t-stat	p-value	Coef.	t-stat	p-value	Coef.	t-stat	p-value	Coef.	t-stat	p-value
$Flow^{I}_{t-1}$	0.01	0.57	0.57	0.01	0.44	0.66	0.01	0.56	0.58	0.02	0.68	0.50	0.01	0.44	0.66	0.02	0.71	0.48
$Flow^{T,O}_{t-1}$	-0.09	-1.45	0.15															
$Flow^{T,O,L}_{t-1}$							-0.09	-1.41	0.16									
$Flow^{T,O,S}_{t-1}$										-0.05	-1.65	0.10						
$Flow^{B,O}_{t-1}$				-1.04	-1.45	0.15												
$Flow^{B,O,L}_{t-1}$													-0.16	-0.95	0.34			
$Flow^{B,O,S}_{t-1}$																-0.06	-1.74	0.08
Controls	Included			Included			Included			Included			Included			Included		
R-square	0.09			0.09			0.09			0.09			0.09			0.09		
R-adjust	0.06			0.06			0.06			0.06			0.05			0.06		

Table 2.14: Sub-period Analysis for HF Percentage Flow

This table reports the results based on hedge fund outflow for two sub-periods, from January 1994 to June 2003, and from July 2003 to December 2012. Δ indicates monthly changes in the corresponding variable. Baa is the Moody's Baa yield, $TB10Y$ is the U.S. 10-year Treasury yield, and $Flow$ is hedge fund percentage flow. Superscript I stands for inflow, superscript O stands for outflow, superscript T stands for the top 25% of hedge funds, and superscript B stands for the rest of the hedge funds. Superscript S stands for funds with a notice period shorter than 30 days, and superscript L stands for funds with a longer notice period.

Panel A: Dependent Variable: $\Delta TB10Y$

	1994.1-2003.6						2003.7-2012.12					
	Coef.	t-stat	p-value	Coef.	t-stat	p-value	Coef.	t-stat	p-value	Coef.	t-stat	p-value
$Flow^{I}_{t-1}$	0.06	1.51	0.13	0.05	1.26	0.21	0.00	0.07	0.95	0.04	0.70	0.49
$Flow^{T,O,S}_{t-1}$	-0.40	-2.72	0.01				-0.05	-0.67	0.50			
$Flow^{B,O,S}_{t-1}$				-0.16	-2.53	0.01				-0.12	-2.30	0.02
Controls	Included			Included			Included			Included		
R-square	0.15			0.14			0.11			0.15		
R-adjust	0.09			0.09			0.05			0.09		

Panel B: Dependent Variable: ΔBaa

	1994.1-2003.6						2003.7-2012.12					
	Coef.	t-stat	p-value	Coef.	t-stat	p-value	Coef.	t-stat	p-value	Coef.	t-stat	p-value
$Flow^{I}_{t-1}$	0.05	1.59	0.11	0.04	1.48	0.14	0.01	0.10	0.92	0.02	0.41	0.68
$Flow^{T,O,S}_{t-1}$	-0.21	-1.86	0.07				-0.06	-0.76	0.45			
$Flow^{B,O,S}_{t-1}$				-0.09	-1.83	0.07				-0.08	-1.54	0.13
Controls	Included			Included			Included			Included		
R-square	0.07			0.07			0.20			0.22		
R-adjust	0.01			0.01			0.15			0.17		

Table 2.15: HF Percentage Flow: Fund Style

This table reports the results based on in- and outflow to/from hedge funds following equity-oriented and bond-oriented styles from 1994 to 2012. Δ indicates monthly changes in the corresponding variable. Baa is the Moody's Baa yield, $TB10Y$ is the U.S. 10-year Treasury yield, and $Flow$ is the average hedge fund percentage flow. Superscript I stands for inflow, superscript O stands for outflow. Superscript T stands for the top 25% of hedge funds, and superscript B stands for the rest of the hedge funds. Subscript $Eqty$ stands for equity-oriented funds and subscript $Bond$ stands for bond-oriented funds. The control variables are the CBOE VIX index (VIX), the excess return on the bond-oriented mutual funds ($MFExRet$), the fund percentage flow of bond-oriented mutual funds ($MFFlow$), and the average excess return on hedge funds ($HFExRet$).

	Dependent: $\Delta TB10Y$			Dependent: ΔBaa		
	Coef.	t-stat	p-value	Coef.	t-stat	p-value
Const.	0.00	1.85	0.07	0.00	0.84	0.40
D_{Crisis}	0.00	0.37	0.71	0.00	0.91	0.36
Lag1	-0.11	-1.17	0.24	0.07	0.79	0.43
ΔVIX	-0.00	-0.28	0.78	0.00	3.27	0.00
$MFExRet_{t-1}$	0.00	0.21	0.84	0.00	0.27	0.79
$MFFlow_t$	-0.00	-0.12	0.91	0.00	0.38	0.70
$HFExRet_{t-1}$	0.02	1.55	0.12	-0.00	-0.15	0.88
$Flow_{t-1}^{T,I,Bond}$	-0.89	-3.28	0.00	-0.78	-3.23	0.00
$Flow_{t-1}^{T,I,Eqty}$	0.29	1.89	0.06	0.22	1.58	0.11
$Flow_{t-1}^{T,O,Bond}$	0.48	1.34	0.18	0.29	0.90	0.37
$Flow_{t-1}^{T,O,Eqty}$	-0.48	-2.53	0.01	-0.16	-0.92	0.36
R-square	0.16			0.13		
R-adjust	0.12			0.09		

Appendix

2.A Lag-Lead Relation in Fund Flows by Fund Size

In this appendix, we address the possible lead-lag relation between flows to funds from different size groups. Flows to large funds can reveal the expectations of large institutional investors and serve as a signal for other smaller investors, inducing herding behavior in the hedge fund industry.[23] Furthermore, if the inflow to top funds reflects a shift in preferences or investor composition, a higher inflow to top funds may lead to lower inflow to other funds. We estimate the VAR regression below to capture the interaction between in- and outflows to/from funds of different sizes:

$$\begin{bmatrix} Flow_t^{T,I} \\ Flow_t^{B,I} \\ Flow_t^{T,O} \\ Flow_t^{B,O} \end{bmatrix} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1} \cdot Ctrls + \boldsymbol{\Gamma} \cdot \begin{bmatrix} Flow_{t-1}^{T,I} \\ Flow_{t-1}^{B,I} \\ Flow_{t-1}^{T,O} \\ Flow_{t-1}^{B,O} \end{bmatrix} + \boldsymbol{\varepsilon_t} \tag{2.4}$$

Here $Ctrls$ are the seven hedge fund risk factors from Fung and Hsieh (2004) that control for the general macroeconomic conditions. $\boldsymbol{\beta_1}$ and $\boldsymbol{\Gamma}$ are matrices of factor loadings, and $\boldsymbol{\beta_0}$ and $\boldsymbol{\varepsilon_t}$ are vectors of constants and error terms respectively.

The matrix $\boldsymbol{\Gamma}$ captures flow herding, investment choice, and flow substitutions effects:

$$\boldsymbol{\Gamma} = \begin{bmatrix} \gamma_{11} & \gamma_{12} & \gamma_{13} & \gamma_{14} \\ \gamma_{21} & \gamma_{22} & \gamma_{23} & \gamma_{24} \\ \gamma_{31} & \gamma_{32} & \gamma_{33} & \gamma_{34} \\ \gamma_{41} & \gamma_{42} & \gamma_{43} & \gamma_{44} \end{bmatrix}$$

For example, a positive and significant γ_{34} would indicate that an outflow from smaller funds precedes one from big funds.

As a preliminary step, we estimate a reduced version of Equation (2.4) including only average percentage flows to the top 25% of funds and the bottom 75% of funds ($Flow^T$ and $Flow^B$). Table 2.16 shows that the macroeconomic control variables are significant determinants of the flow patterns, producing a similar impact on flows to top and bottom funds. The loadings of $SNP500$ for large fund flow and small fund flow are 0.27 and 0.29 respectively; both are significant at the 1% level. Similarly, the corresponding loadings of SML (0.14 and 0.15 respectively) are also

[23] There is much evidence on herding among both institutional and individual investors. See, for example, Nofsinger and Sias (1999), and Sias (2004), among others.

Table 2.16: Hedge Fund Flow Determinants

This table reports the VAR results of hedge fund flow from 1994 to 2012. $Flow$ is hedge fund flow. The superscript T stands for the top 25% of funds, and B stands for the rest of the hedge funds. $SNP500$ is the return on S&P 500, SML is the difference between the returns on the Russell 2000 index and the returns on the S&P 500 index. $TB10Y$ is the U.S. 10-year T-bill yield. $CredSpr$ is credit spread, defined as the difference between the Moody's Baa yield and the U.S. 10-year T-bill yield. $PTFSBD$ is the bond trend-following factor, $PTFSFX$ is the FX trend-following factor, and $PTFSCOM$ is the commodity trend-following factor.

	Dependent: $Flow^T$			Dependent: $Flow^B$		
	Coef.	t-stat	p-value	Coef.	t-stat	p-value
$Flow^T$	0.40	3.02	0.00	-0.02	-0.21	0.84
$Flow^B$	0.00	-0.03	0.98	0.34	2.65	0.01
$SNP500$	0.27	12.89	0.00	0.29	15.10	0.00
SML	0.14	5.35	0.00	0.15	6.70	0.00
$TB10Y$	-0.86	-2.24	0.03	-0.73	-2.13	0.03
$CredSpr$	-1.48	-2.85	0.00	-1.20	-2.60	0.01
$PTFSBD$	-0.01	-1.08	0.28	0.00	-0.73	0.47
$PTFSFX$	0.00	0.53	0.60	0.01	1.49	0.14
$PTFSCOM$	0.01	2.14	0.03	0.01	2.43	0.02
Const.	0.00	2.37	0.02	0.00	4.98	0.00
R-square	0.68			0.71		
R-adjust	0.67			0.70		

highly significant. When stock markets are booming, hedge funds are more likely to gain new capital from investors. The loadings on $TB10Y$ and $CredSpr$ are also significant, but negative, suggesting lower flows to hedge funds during the periods of high bond yields.

The fund flow itself seems to be persistent. Higher flow to top funds in the current month leads to higher flow to the same group of funds in the following month. The same holds for bottom funds. The corresponding loadings of 0.40 and 0.34 are highly significant. We find no evidence, at the aggregate level, of any links between flows across top and bottom funds. As we expect, the relations between in- and outflows are not the same. We now turn to the full regression specification in Equation (2.4).

Table 2.17 reports the results for interaction of in- and outflows. The loadings on the control variables are consistent with those reported in Table 2.16 and are not reported here to conserve space.[24] Consistent with the previous results, both in- and outflows are persistent within each group of funds. For example, outflow from the bottom funds ($Flow_{t-1}^{B,O}$) leads to future outflows from bottom funds ($Flow_{t}^{B,O}$) with the corresponding coefficient of 0.45 being highly statistically significant.

Higher inflow into top funds reduces the next-period outflows from both top and bottom funds. The corresponding coefficients of -0.44 and -0.31, respectively, are highly significant. At the same time, higher inflow to top funds leads to lower inflow to bottom funds. The loading of -0.23 is significant at the 5% level, reflecting a substitution effect between the top and bottom funds. Here past outflow is positively related to future inflow, suggesting that investors relocate capital across different-sized funds.

In short, we find an asymmetric lead-lag relation between in- and outflows to top and bottom funds. If top funds attract higher inflow, the ability of smaller funds to attract new investment is reduced. At the same time, higher inflow to top funds is a positive signal, which reduces outflow from both top and bottom funds in the next period.

[24]The full results are available from the authors on request.

Table 2.17: Lead-Lag Relation in Fund Flow

This table reports the VAR results for flows to hedge funds with different notice periods from 1994 to 2012. *Flow* is hedge fund percentage flow. The superscript T stands for the top 25% of funds, and B stands for the rest of the funds. I stands for inflow and O stands for outflow.

	Dependent: $Flow^{T,I}$			Dependent: $Flow^{B,I}$			Dependent: $Flow^{T,O}$			Dependent: $Flow^{B,O}$		
	Coef.	t-stat	p-value	Coef.	t-stat	p-value	Coef.	t-stat	p-value	Coef.	t-stat	p-value
$Flow^{T,I}$	0.20	1.91	0.06	-0.23	-2.29	0.02	-0.44	-3.13	0.00	-0.31	-3.01	0.00
$Flow^{B,I}$	0.12	1.17	0.24	0.52	5.37	0.00	0.32	2.33	0.02	0.29	2.85	0.00
$Flow^{T,O}$	-0.02	-0.26	0.80	-0.06	-0.71	0.48	0.23	1.97	0.05	-0.04	-0.50	0.62
$Flow^{B,O}$	0.04	0.43	0.67	0.18	1.79	0.08	0.20	1.44	0.15	0.45	4.32	0.00
Controls	Included			Included			Included			Included		
R-square	0.30			0.43			0.43			0.56		
R-adjust	0.26			0.40			0.40			0.54		

Chapter 3

Systematic and Firm-specific Credit and Liquidity Risks of CDS Spreads

Abstract

In this chapter we develop a theoretical model for pricing assets with illiquidity and test it empirically using the CDS spreads of 356 U.S. non-financial firms from 2002 to 2011. We find that systematic credit risk, systematic illiquidity, individual firm default risks and stock illiquidity are significant predictors for changes in CDS spreads. The illiquidity impact is asymmetric and is particularly strong when stock becomes more illiquid. Our model performs well for cross-sectional predictions and can be used to approximate spreads for firms that do not have CDSs. Our findings challenge Basel III's adoption of CDS-implied probability of default in the assessment of counterparty default risk, because apart from firm default risk, systematic factors have important impacts on CDS spreads, and the spreads contain a significant liquidity risk in addition to the firm's default risk.

3.1 Introduction

Basel III stipulates that CDS-implied default probability must be used in the calculation of risk capital attributed to counterparty credit risk.[1] In this chapter, we argue that CDS spread reflects much more than just the credit worthiness of an underlying entity. It is also driven by CDSs' illiquidity, as well as market-wide and industry-based credit and illiquidity factors.

Corò, Dufour, and Varotto (2013) show recently that changes in CDS spreads are largely explained by the bid-ask spreads of CDSs. The credit risk of the firm, on the other hand, has little explanatory power. CDS bid-ask spread is a popular measure for CDS liquidity.[2] Nevertheless, Das and Hanouna (2009) show that stock-based Amihud illiquidity measure (Amihud 2002) can proxy for CDS illiquidity since CDS traders can also use equity to hedge their risk exposure.[3] Their finding provides evidence for the connection between equity and CDS market liquidity.

A number of studies investigate default risk spill-over across markets. For example, Longstaff, Mithal, and Neis (2005) explore the link between a bond's default risk and CDS spread, whereas Huang and Huang (2012) consider the relationship between a bond's default risk and the firm's asset value. CDSs have a potential impact on corporate finance; Saretto and Tookes (2013) find that firms with traded CDS contracts have higher leverage ratios and longer debt maturities. They argue that banks hold single-name CDSs to reduce capital requirement, and, as a result, are able to provide more loans to firms with traded CDS contracts. These studies, however, have omitted correlated liquidities between markets.

In this chapter, we develop a model relating CDS spread with firm-specific and systematic aggregate credit and illiquidities. We use an equity-based model to sepa-

[1] ["When computing CVA (Credit Valuation Adjustment) risk capital charge,] s is the credit spread of the counterparty [...]. Whenever the CDS spread of the counterparty is available, this must be used. Whenever such a CDS spread is not available, the bank must use a proxy spread that is appropriate based on the rating, industry and region of the counterparty." *Basel III: A global regulatory framework for more resilient banks and banking systems*, p.32, http://www.bis.org/publ/bcbs189.pdf.

[2] See, e.g., Tang and Yan (2007), Das and Hanouna (2009), and Corò, Dufour, and Varotto (2013).

[3] See Cespa and Foucault (2014) for theory of liquidity spillover due to asset informativeness.

rate the credit and illiquidity components of CDSs and examine their individual and systematic impacts on individual CDS spreads. As we test the impact of four groups of factors on individual CDS spreads—firm-specific credit, firm-specific illiquidity, systematic credit, and systematic illiquidity—it is important that the firm-specific factors are not obtained from the CDS calibration, to prevent a spurious relationship. Hence we use equity information to construct firm-specific factors. The decomposed CDS components are aggregated to produce the systematic factors, each time with a specific target firm excluded to avoid spurious results. With this procedure, we find a substantial difference among factors. We study CDS spreads of 356 U.S. non-financial firms for the period from 2002 to 2011 and find evidence that firm-specific, industry-related, and market-wide credit and illiquidity risk factors are significant predictors of changes in individual firms' CDS spreads.

Following Das and Hanouna (2009), we use Amihud stock illiquidity measure as a proxy for CDS illiquidity, because CDS bid-ask spreads are not widely available.[4] As in Das and Hanouna (2009), we find changes in stock illiquidity are positively associated with changes in CDS spreads. However, unlike Das and Hanouna (2009), we find that this impact is asymmetric and is statistically significant only when stock becomes more illiquid. Our finding is similar to the Brennan, Huh, and Subrahmanyam (2013) finding of asymmetric liquidity impact on stock returns. Our finding suggests possible liquidity contagion between CDS and stock markets with stock illiquidity as the common driver.

When the spreads are decomposed into their credit and illiquidity components following Forte (2011) and Forte and Lovreta (2012), our test results indicate that the systematic credit and illiquidity components are equally important in explaining changes in individual firms' CDS spreads. Similar findings are documented in Longstaff, Pan, Pedersen, and Singleton (2007), where global factors are found to be more important than individual country measures in explaining changes in sovereign

[4]We use Markit, one of the largest CDS data vendors, containing thousands of entities worldwide, as our CDS data source. Our Markit database does not contain bid-ask information because the CDS spreads are expressed as composite prices. Other mainstream CDS databases—Reuters EOD, and Credit Market Analysis (CMA)—also provide composite prices for CDSs, and CDS bid-ask spreads are not available in these databases either. See Mayordomo, Peña, and Schwartz (2013) for a comprehensive comparison of the five main CDS databases.

CDSs. Here, we find that changes in industry and market credit and illiquidity factors are just as important as firm-specific information in affecting changes in individual firms' CDS spreads. Recently, Galil, Shapir, Amiram, and Ben-Zion (2014) find that the median CDS spreads of mixed credit quality have a cross-sectional explanatory power for individual firms' CDS spreads. Their finding suggests the existence of a systematic risk factor in CDS spreads. Here, we consider both credit and liquidity systematic risks, and study their separate effects on CDS spreads.

Since our model for corporate CDS spreads does not rely on the firms having traded CDSs, our model can be used to approximate CDS spreads for regulatory counterparty risk management. Our model has a good cross-sectional predictive power with an average out-of-sample R-square of 27%.

3.2 Related Literature

Our study is related to several strands of credit risk literature, the first of which links the credit and equity markets. Friewald, Wagner, and Zechner (2014), for example, study credit risk premiums extracted from CDS spread and find that CDS premiums are strongly and positively related to Merton's equity risk premiums. Schneider, Wagner, and Zechner (2014) find CDS spread is related to equity option-implied volatility, ex ante variance and skewness. Together with option-implied moments, CDS spread has predictive power for stock returns. Berndt, Douglas, Duffie, Ferguson, and Schranz (2008) analyze default intensities derived from Moody's KMV Expected Default Frequency (EDF) and CDS spreads in four U.S. industries. They find a strong relation between physical and risk-neutral probabilities of default (PD) extracted, respectively, from EDF and CDS spreads. Galil, Shapir, Amiram, and Ben-Zion (2014) find that stock return, stock return volatility, and the median of CDS spreads obtained in a mixture of rating classes can explain the cross-sectional variations in CDS spreads. Their finding concerning median CDS spreads implies the existence of CDS systematic risk.

The second strand of literature focuses on the liquidity risk of CDSs and finds changes in CDS spreads are dominated by changes in liquidity of CDSs rather than changes in the credit risk of the underlying entity. Corò, Dufour, and Varotto (2013) construct two bid-ask-spread based liquidity factors: daily time-weighted average bid-ask spread, and industry average bid-ask spread. They find both liquidity factors dominate CDS spread changes, while other factors, such as changes in credit rating and macroeconomic conditions, have a weak (albeit still statistically significant) explanatory power. Tang and Yan (2007) study CDS quotes and CDS bid-ask spreads, and conclude that short-term changes in CDS spreads are explained by their illiquidities. Buhler and Trapp (2010) use CDSs to separate bond spreads into their credit and liquidity components, and find that the illiquidity component is important in explaining bond spreads. In addition, they document an illiquidity co-movement between the bond and CDS markets. Bedendo, Cathcart, and El-Jahel (2011) use the CreditGrade model to derive model-implied CDS spreads from put options, and find that the difference between market and option-implied CDS spreads can be explained by the individual CDS bid-ask spreads and stock-based Amihud illiquidity measure. They find, however, that some of the difference cannot be explained by the individual illiquidity, and conclude that the equity and CDS markets have become less connected. Das and Hanouna (2009), a paper that is closely related to this chapter, find a strong connection between stock liquidity and the liquidity risk of CDSs. They compare the Amihud illiquidity measure, the LOT (Lesmond, Ogden, and Trzcinka 1999) measure, and CDS bid-ask spread, and find that the Amihud stock illiquidity measure predicts quarterly changes of CDS spreads. (Following the findings of their paper, we also use the Amihud stock illiquidity measure in our empirical tests later.) Brunnermeier and Pedersen (2009) argue that liquidity drain-out is due to a vicious cycle of market and funding liquidity interactions. Subsequently, Brennan, Chordia, Subrahmanyam, and Tong (2012) show that stock liquidity premium arises mainly from the sell side. Furthermore, Brennan, Huh, and Subrahmanyam (2013) condition the Amihud stock illiquidity based on the sign of stock returns, and find Amihud illiquidity has a stronger explanatory power for negative stock returns.

CDSs, on the other hand, also have an impact on stock illiquidity. Boehmer, Chava, and Tookes (2013) find firms with traded CDSs have less liquid and less efficient stock prices. They argue that stock liquidity is reduced because speculators can now use the CDS market to hedge their equity risk, resulting in equity becoming less liquid. This finding corresponds to the theoretical prediction below, made by Cespa and Foucault (2014).

The third strand of CDS literature focuses on systematic drivers. Conrad, Dittmar, and Hameed (2011) calibrate CDS-implied PD to equity option-implied PD and find the change of CDS spreads of systemically important financial institutions (SIFIs) to be a leading indicator for the changes in other CDS spreads. Their findings suggest the existence of a systematic risk factor driving all CDS spread changes. This chapter shows, later, that the systematic drives are just as important as firm-specific information.

Finally, our theoretical model for CDS spread is based on Gennotte and Leland (1990) and Cespa and Foucault (2014). Gennotte and Leland (1990) provide a general equilibrium asset pricing model that includes illiquidity. In Cespa and Foucault (2014), illiquidity interacts between assets in the same and different markets. They argue that informed traders learn from other asset prices. Hence, the equilibrium price of one asset should contain prices of other assets. Such cross-asset "learning" forms a feedback loop between assets according to the level of price informativeness and could lead to illiquidity spillover.

3.3 Model Specification

3.3.1 Asset Price and Illiquidity

Following Gennotte and Leland (1990) and Cespa and Foucault (2014), we provide, in this section, a simple economic explanation of how asset price is driven by its own illiquidity and the illiquidity of other assets. Assume an economy consists of M assets[5] and two types of agents, viz. investors and liquidity providers. *Investors* hold (long or short) positions in assets and maximize their expected utility of wealth according to their individual risk tolerance. These investors are assumed to be fully informed. *Liquidity providers* are market makers whose aim is to provide market liquidity to accelerate investors' matching process but strive to have zero net position. Their active participation in the market increases trading volume and liquidity.

The payoff of asset m, v_m, is:

$$v_m = \delta_m + d_m \delta_{-m} + \varepsilon_m \tag{3.1}$$

where δ_m is the expected return of asset m, δ_{-m} is the (average) expected return of other assets, d_m is the loading for δ_{-m}, and $\varepsilon_m \sim N(0, \sigma^2_{\varepsilon_m})$ is the idiosyncratic noise. The assets are correlated with variance-covariance matrix Ω_v.

Investor j has a CRRA (constant relative risk aversion) utility function with risk aversion parameter γ_j ($\gamma_j \leq 1$ and $\gamma_j \neq 0$):

$$U(W_j) = \frac{W_j^{\gamma_j}}{\gamma_j}. \tag{3.2}$$

The optimal investment can be solved through mean-variance optimization. Then, the demand function for asset m is

[5]The assets here are not restricted to equities; they may include bonds, CDSs, and other tradable assets.

$$x_{jm}(p_m|\delta_m, \delta_{-m}, p_{-m}) = (1-\gamma_j)^{-1} \sum_{l=1}^{M} \eta_{ml}[E(v_l|\delta_l, \delta_{-l}, p_l, p_{-l}) - p_l] \tag{3.3}$$

where η_{ml} is the m-th row's elements of the inverse variance-covariance matrix (Ω_v^{-1}) and p_m is today's asset price for m. Writing $E(v_l|\delta_l, \delta_{-l}, p_l, p_{-l}) = \delta_l + d_l\delta_{-l}$, Equation (3.3) becomes

$$x_{jm}(p_m|\delta_m, \delta_{-m}, p_{-m}) = (1-\gamma_j)^{-1} \sum_{l=1}^{M} \eta_{ml}[\delta_l + d_l\delta_{-l} - p_l]. \tag{3.4}$$

Now we turn to the market maker whose supply function for asset m is assumed to be

$$u_m \sim N(0, \sigma_{u_m}). \tag{3.5}$$

Liquidity providers maintain zero net positions on balance. Without the loss of generality, we assume there is only one liquidity provider for each asset. At any time, the market clearance price for asset m at equilibrium is

$$\sum_{j=1}^{J} x_{jm}(p_m|\delta_m, \delta_{-m}, p_{-m}) + u_m = 0 \tag{3.6}$$

where there are J investors wanting to hold asset m in their portfolios. Now replacing x_{jm} with Equation (3.4), and separating the summation term for asset m and for the other assets, we get:

$$0 = \sum_{j=1}^{J} \frac{1}{1-\gamma_j} \eta_{mm}[\delta_m + d_m\delta_{-m} - p_m] + \sum_{j=1}^{J} \frac{1}{1-\gamma_j} \sum_{l=1, l\neq m}^{M} \eta_{ml}[\delta_l + d_l\delta_{-l} - p_l] + u_m. \tag{3.7}$$

After some re-arrangements, we obtain the market equilibrium price for asset m, conditional on all the other information:

$$p_m(\delta_m, \delta_{-m}, p_{-m})$$
$$= (\delta_m + d_m\delta_{-m}) + \eta_{mm}^{-1} \sum_{l=1, l\neq m}^{M} \eta_{ml}[\delta_l + d_l\delta_{-l} - p_l] + \eta_{mm}^{-1}[\sum_{j=1}^{J}(1-\gamma_j)^{-1}]^{-1}u_m. \tag{3.8}$$

Equation (3.8) implies that, apart from its own fundamental value δ_m, the equilibrium price of asset m depends on the fundamental values and prices of other assets as well as the liquidity of asset m. The illiquidity of asset m can be derived as the sensitivity of its price to liquidity provision:

$$L_m \equiv \frac{\partial p_m}{\partial u_m} = \eta_{mm}^{-1}[\sum_{j=1}^{J}(1-\gamma_j)^{-1}]^{-1}. \tag{3.9}$$

The greater the value of L_m, the more illiquid is asset m. Since the price of other assets p_{-m} is affected by their liquidity, u_{-m} and L_{-m}, the price of asset m will be affected by the liquidity of other assets through p_{-m}, which we called the peer liquidity effect. The liquidity of asset m: $\frac{\partial p_m}{\partial u_m}$; the liquidity due to other assets: $\frac{\partial p_m}{\partial u_{-m}}$. Surprisingly, at the time of writing, the current literature focuses only on the individual asset's own liquidity, disregarding the peer liquidity effect altogether.

Here we consider the case of CDSs and include two sources of the cross-asset/market link. The first source is from the underlying asset of the CDSs. Since the underlying asset can be used to hedge CDS risks, the liquidity of the underlying asset can, of course, affect the CDS price. The other source is the peer information. CDSs are usually traded over the counter and are less liquid. The peer CDS prices (asset $-m$) are likely to contain unobservable market information that may also affect the CDS spread (asset m). Therefore, the liquidity of the peer CDSs represents the level of the price informativeness of the market (Cespa and Foucault 2014).

There are also some examples about the cross-asset link in demand. Bongaerts, Jong, and Driessen (2011) provide some information about the buyers and sellers in the CDS market (2006 Survey of the British Bankers' Association). The survey shows that banks are net protection buyers while insurers are net protection sellers. In addition, hedge funds are active participants, contributing to 28% of the buyers of the CDS contracts and 32% of the sellers. Therefore, hedge funds have the need to trade underlying bonds or equities for hedging purposes. Given our model rationale, the cross-asset linkage in liquidity is likely to happen because hedge funds need to include information about the underlying asset to hedge their risk. However, we do not have available hedge fund data in CDS to test whether the cross-asset linkage in liquidity can be driven by hedge funds.

3.3.2 Separating CDS Spread into Credit and Liquidity Components

In this section, we describe the procedure for decomposing each CDS spread into its credit (λ_t) and liquidity (θ_t) components as follows:

$$CDS_t = \lambda_t \times \theta_t. \tag{3.10}$$

The multiplicative connection of the credit and liquidity components implies that the determinants of the CDS are in exponential form. Therefore, the credit and liquidity determinants of the CDS can be expressed as $\log CDS = \log \lambda + \log \theta$. We consider a structural model described by Leland and Toft (1996) to estimate the credit component λ_t. Leland and Toft (1996) model firms with debts of different maturities, which leads more naturally to a complete term structure of CDS spreads. We adapt the calibration steps described in Forte (2011) to extract the credit and liquidity components. Forte (2011) uses both CDS and stock information (whereas the classical Merton (1974) model relies solely on stock information) and, thus, delivers more robust estimates of CDS spreads.

Forte (2011), however, does not separate the CDS spread into the credit and liquidity components because that would involve a joint estimation of the recovery rate, and these three pieces of information are generally not jointly identifiable. Here, we benefit from having recovery rate information provided in the Markit database, and this allows us to separate the CDS spread into the credit and liquidity components. To achieve this separation, first we calibrate the λ_t parameter to the reported recovery rate. We then derive the θ_t parameter from the CDS spread conditional on the estimated value of λ_t. Note that θ_t may contain not only the liquidity component but also all other model mis-specification errors. However, we provide evidence in Section 3.6.1 that θ_t is indeed related to liquidity.

Calibration Procedure

First, the firm's asset dynamics are assumed to follow a geometric Brownian motion. According to Leland and Toft (1996), the value of debt with maturity τ, given the firm's asset value V_t, is

$$\begin{aligned}\mathbf{d}(V_t,\tau) =& \frac{c(\tau)}{r} + \left\{ e^{-r\tau}[k(\tau) - \frac{c(\tau)}{r}][1 - F_t(\tau)] \right\} \\ &+ \left\{ [R(\tau)V_B - \frac{c(\tau)}{r}]G_t(\tau) \right\}\end{aligned} \tag{3.11}$$

where $c(\tau)$ is the bond coupon payment, $k(\tau)$ is the bond principle, r is the risk-free rate, V_B is the default barrier, $R(\tau)$ is the recovery rate in the case of default, $1-F(\tau)$ is the probability in the case of the firm's survival and $G(\tau)$ is the probability in the case of default.[6] Intuitively, the debt value in Equation (3.11) consists of three terms; $c(\tau)/r$ is the present coupon value. The term in the first set of curly brackets expresses the present bond value if default does not occur, and the term in the second set of curly brackets expresses the present bond value in the case of default. Since a firm may have bonds with different times to maturity, the total debt value of the firm is the summation of all outstanding debts:

$$D(V_t) = \sum_{i=1}^{N} \mathbf{d}(V_t, \tau_i). \tag{3.12}$$

[6]See Leland and Toft (1996) for the detailed discussion. The expressions of $F(\tau)$ and $G(\tau)$ are provided in Appendix 3.A.

In Equation (3.11), $R(\tau)V_B$ is the residual value of a firm, or default barrier, in the case of default. We can relate CDS information to the default barrier:

$$R(\tau)V_B = (1-\alpha)\beta k(\tau) \tag{3.13}$$

where α is the bankruptcy cost and β is the default point expressed as a percentage of the face value of debt, $k(\tau)$. We follow the argument in Forte (2011) and set $(1-\alpha)\beta$ as the recovery rate in the case of default. Since the Markit database provides the market recovery rate, β is calculated as $\beta = \frac{R}{1-\alpha}$, with α being set equal to 0.3 (following the suggestion of Leland (2004)). With the new default barrier, $\mathbf{d}(V_t, \tau)$ can be re-expressed as

$$\begin{aligned} \mathbf{d}(V_t,\tau) =& \frac{c(\tau)}{r} + e^{-r\tau}[k(\tau) - \frac{c(\tau)}{r}][1 - F_t(\tau)] \\ &+ [(1-\alpha)\beta k(\tau) - \frac{c(\tau)}{r}]G_t(\tau). \end{aligned} \tag{3.14}$$

Therefore, the bond yield for τ-year debt is

$$y(V_t,\tau) = \frac{c(\tau)}{\mathbf{d}(V_t,\tau)} \tag{3.15}$$

and the implied credit spread, λ_t, is

$$\lambda_t = y(V_t,\tau) - r_t. \tag{3.16}$$

Following Forte (2011), we use λ_t as the credit component of the CDS spread.

We also need asset price V_t to calculate $F_t(\tau)$ and $G_t(\tau)$ in Equation (3.14). Unfortunately, V_t is unobservable in practice, and has to be calibrated using equity. We use the firm's capital structure to obtain the implicit asset value. We denote the equity value by $S(V_t)$, and the firm's capital structure satisfies

$$V_t = S(V_t) + D(V_t) + BC(V_t) \tag{3.17}$$

$$S(V_t) = V_t - D(V_t) - BC(V_t) \tag{3.18}$$

where $BC(V_t)$ represents the bankruptcy cost, defined as $D(V_t|\alpha = 0) - D(V_t)$, according to Forte (2011). Therefore, the firm's equity value is

$$S(V_t) = V_t - D(V_t|\alpha = 0) \tag{3.19}$$

We first use Equation (3.19) to calibrate V_t to the observed stock price S_t, and then use the calibrated V_t to calculate the bond yield $y(V_t, \tau)$ and credit component λ_t.

Given the credit component λ_t, the liquidity component θ_t is obtained by minimizing the mean square error using Equation (3.10):

$$\underset{\theta}{\operatorname{argmin}} \frac{1}{N} \sum_{i=1}^{N} [\log CDS_{t_i} - \log \lambda_{t_i} - \log \theta]^2. \tag{3.20}$$

We use a rolling-window estimation for the liquidity component θ in order to reduce the noise in the market-quoted CDS spreads. Equation (3.20) and θ are estimated using the past 12-month daily data. We use calibrated θ and the 1-year λ of the individual firms to compile the systematic credit and illiquidity factors.

3.4 Empirical Framework

Recall in Section 3.3.1, we show that asset price (CDS spread in our case) depends on its own and peer group fundamental values and illiquidity. In the case of CDS, we relate fundamental value to credit risk. Moreover, we argue that CDS spread will be driven by factors that are firm-specific as well as systematic. Next, we separate the CDS spread into the credit and liquidity components according to Section 3.3.2. Then we compile the aggregate systematic credit and liquidity risk factors, each time excluding the referenced firm that is being tested. As a result, four types of factors are tested in the empirical section: firm-specific credit and liquidity factors, and systematic credit and liquidity factors. For the systematic factors, we compile market-wide and industry-based measures and find they are both important in driving CDS spreads.

In the empirical test, we examine the extent to which each of these factors affects CDS spreads by running a panel regression of quarterly changes in CDS spreads of non-financial firms.[7]

3.4.1 Firm-specific Credit Risk and Illiquidity

As discussed, to avoid spurious results, CDSs' calibrated components cannot be used directly as firm-specific credit and illiquidity factors. Hence, equity market information is used to form firm-specific factors instead. In particular, the firm's distance-to-default (DTD) from Merton (1974) is used to measure individual credit risk.[8] DTD is defined as

$$DTD = \frac{\log(V/D) + (\mu_V - \sigma_V^2/2)T]}{\sigma_V \sqrt{T}} \tag{3.21}$$

where V is the firm's asset value, which follows a geometric Brownian motion, T and D are, respectively, the time to maturity and value of the outstanding debt, and μ_V and σ_V are, respectively, the mean and volatility of the return on the asset. DTD reflects the required change in the firm's asset value, expressed as the number of standard deviations, in order to trigger a default. In this chapter, a 1-year distance-to-default is estimated using the past 12 months of daily equity data.[9] We expect DTD to be negatively related to CDS spreads.

The individual illiquidity of a CDS contract will be reflected in its bid-ask spread

[7]As a robustness check we perform the analysis twice, once based on monthly changes and once for financial firms (80 financial firms in our sample), and find that the results do not change qualitatively. We treat financial and non-financial firms differently for two reasons. First, financial firms have very different debt structures than non-financial firms. Second, the liquidity extraction procedure discussed later can be used only for non-financial firms' CDSs. These results are available on request.

[8]Despite the presence of many other measures for credit quality, e.g., Moody's credit rating, Altman Z-score, physical PDs estimated from a reduced-form model such that in Duan, Sun, and Wang (2012), DTD remains one of the most widely used measures. We do not use a PD-based credit quality indicator, such as that in Campbell, Hilscher, and Szilagyi (2008), as we do not have information on real defaults. We do not feel comfortable in applying Campbell et al.'s results directly, since their sample ends in 2003, whereas our sample period is from 2002 to 2011, which includes a crisis-induced structural change in 2007.

[9]For the steps for estimation please see, for example, (Vassalou and Xing 2004) for the iteration method and Duan (1994) and Duan (2000) for the likelihood method, among others.

(Corò, Dufour, and Varotto 2013). Unfortunately, CDS bid-ask spread information is not available in our database. Das and Hanouna (2009) show that equity market liquidity (measured by the Amihud (2002) stock illiquidity measure) is linked to CDS market liquidity. Das and Hanouna (2009) argue that the seller of a CDS hedges credit risk by taking a short equity position, viz. selling stocks or buying put options. The implementation of hedging, including changes in the hedge ration and the closeout of the hedging position, results in hedging cost. As a result, liquidity in equity markets should have an impact on CDS spreads. Following their argument, we use the Amihud (2002) stock-based illiquidity measure below, to proxy for CDS illiquidity:

$$Amihud = \frac{1}{Days} \sum_{Days} \frac{|Return_t|}{Price_t \times Volume_t} \times 10^6 \tag{3.22}$$

where $Return$ is the daily stock return, $Price$ is the daily closing share price, and $Volume$ is the number of shares traded on that day. Amihud captures the underlying stock illiquidity and we calculate the Amihud illiquidity measure for each stock using the past 5 months of daily data. We expect the illiquidity measure to be positively related to CDS spreads.

We recognize that the illiquidity's impact on asset prices may be asymmetric.[10] To control for potential asymmetry, we also consider the Amihud measure conditional on the sign of its changes:

$$\begin{aligned} \Delta \log Amihud^{+}_{it} &= \Delta \log Amihud_{it} \times I_{\{\Delta \log Amihud_{it} \geq 0\}} \\ \Delta \log Amihud^{-}_{it} &= \Delta \log Amihud_{it} \times I_{\{\Delta \log Amihud_{it} \leq 0\}}. \end{aligned} \tag{3.23}$$

3.4.2 Systematic Credit and Liquidity Factors

As mentioned in Section 3.3.2, we use a structural model to decompose individual CDSs into the individual credit (λ_{it}) and liquidity (θ_{it}) components. To avoid spurious results in the panel regression, we exclude the referenced firm when calculating

[10]See Brennan, Huh, and Subrahmanyam (2013).

the industry average. Similarly, we exclude the referenced industry when calculating the market average. Therefore, the industry CDS liquidity risk factor at time t, denoted as $\log \theta_{it}^{IND}$, is the average of $\log \theta_{it}$ within the same industry. $\log \theta_{it}^{MKT}$ is the average of $\log \theta_{it}$ excluding firms from the same industry:

$$\log \theta_{it}^{IND} \equiv \frac{1}{N_k - 1} \sum_{j \neq i, j \in k,} \log \theta_{jt} \tag{3.24}$$

$$\log \theta_{it}^{MKT} \equiv \frac{1}{N - N_k} \sum_{j \neq i, j \notin k} \log \theta_{jt}. \tag{3.25}$$

Similarly, the industry CDS credit risk factor (denoted as $\log \lambda_{it}^{IND}$), and market CDS credit risk factor (denoted as $\log \lambda_{it}^{MKT}$) are obtained by excluding the corresponding referenced firm(s).

3.4.3 Panel Regression

The final panel regression specification has the following form:

$$\begin{aligned} \Delta \log CDS_{it} = \beta_0 &+ \beta_1^{+} \Delta \log Amihud_{it}^{+} \\ &+ \beta_1^{-} \Delta \log Amihud_{it}^{-} \\ &+ \beta_2 \Delta DTD_{it} \\ &+ \beta_3^{L} \Delta \log \theta_{it}^{IND} + \beta_3^{C} \Delta \log \lambda_{it}^{IND} \\ &+ \beta_4^{L} \Delta \log \theta_{it}^{MKT} + \beta_4^{C} \Delta \log \lambda_{it}^{MKT} + \varepsilon_{it}. \end{aligned} \tag{3.26}$$

The changes in variables are used to obtain stationary time-series variables. We expect both default and liquidity risks to drive the changes in CDS spreads. The evidence of both liquidity and default risk to drive (quarterly) CDS changes can also be referred to other literature such as Tang and Yan (2007), Das and Hanouna (2009), and Corò, Dufour, and Varotto (2013).

3.5 Data

We obtain daily CDS spreads from the Markit database and the corresponding equity information from Bloomberg. The Markit database provides daily information of CDS contracts with maturities from 6 months to 30 years. For 2011, our Markit database provides global, corporate, municipal, and sovereign single-name CDS data of approximately 2,650 individual entities and 3,000 entity-tiers. It contains the average of daily CDS spreads reported by different contributors, underlying debt seniority and the associated recovery rates. Our sample covers U.S. firms from January 2001 to May 2012. Further description of the Markit data can be found in Appendix 3.B.

CDS spreads for the same firm may have different quoted prices due to the contract tier, which is related to the payback priority of the underlying bond. For example, secured debt has a higher priority in the payback order than subordinate debt. In our sample, there are in total 2.7 million data points of individual CDS quotes. Most of these data points belong to Senior Unsecured Debt (SNRFOR), accounting for 75% of all data points. Subordinated Debt (SUBLT) accounts for 20% of the data points. Junior Subordinated Debt (JRSUBUT2) and Preference Shares (PREFT1) account for only 0.02% and less than 0.01%, respectively, of total data points. Table 3.1 reports the proportion of CDS quotes for the different tiers. We use CDS quotes for senior unsecured debt. If this senior tier is not available for a given firm, the subordinated debt is chosen instead. The descriptive statistics of our initial sample are reported in Table 3.2.

Table 3.2 shows that the 10-year CDS spreads have the highest mean of 232.51 basis points (bp), while 6-month CDS spreads have the lowest mean of 163.63 bp. The average recovery rate is 40% across all maturities. Being particularly interested in the impact of liquidity risk on prices, we choose to use 1-year CDS contracts in this chapter instead of the more liquid 5-year CDSs. 21% of the observations for the 1-year contracts are missing in the database.[11] For the 1-year CDS contracts, the

[11] We drop the year 2001 in our sample, as our Markit database covers fewer than 100 companies in that year.

mean spread is 176.20 bp, and its standard deviation is 688.62 bp. The maximum spread is 40,175.46 bp while the minimum spread is 0.81 bp.[12]

Table 3.3 reports the summary statistics of the daily changes in 1-year CDS spreads. The average change in CDS spread is rather small (0.21 bp) but the change is comparatively volatile (the standard deviation is 100.92 bp). Interestingly, we observe some extreme daily changes in CDS spreads (larger than 10,000 bp). These extreme changes indicate that these CDS spreads were stale and remained at a low level, but they were traded again to reflect the possible immediate credit event, leading to a dramatic jump in CDS spreads. Likewise, the CDS spreads might fall back to the previous price level if the event is resolved.

The market value of equity and book values of short- and long-term debt for the firms in our sample are retrieved from Bloomberg. Their descriptive statistics are reported in Table 3.4. Our sample includes 436 individual firms, for which we have a complete set of data as required for the analysis. Table 3.5 reports firms' industry sectors as categorized in Bloomberg. Among the 436 firms in our sample, "Financial" is the largest group with 80 firms. "Consumer, Cyclical" is the second largest with 74 firms. The smallest group is "Technology" with 18 firms. We drop financial firms in our main analyses; therefore, there are 356 firms remaining in our final sample.

We need the following data to estimate the credit and liquidity components. We use daily CDS spreads (CDS_t) and their corresponding recovery rates (R_t) from the Markit database and daily stock information obtained from Bloomberg. We use stock market capitalization as each firm's equity value. Short-term liability (STL_t) and long-term liability (LTL_t) are used to decide the firm's solvency ability.[13] The firm's interest expenses (IE_t) and cash dividend (CD_t) are used to calculate the payout rate. We choose the daily 12-month cumulated values for interest expenses

[12]The maximum spread was reached just before Smurfit-Stone Container defaulted. The company was ranked as one of the largest forest, paper, and packaging companies in the world. Its CDS spread was highest on January 22, 2009, and the company filed for bankruptcy on January 27, 2009. The large value of CDSs is due to the procedure used to annualize CDS spreads.

[13]The corresponding field names in Bloomberg are "BS_CUR_LIAB" (short-term liability) and "BS_LT_BORROW"(long-term liability).

Table 3.1: CDS Tier Ratio

This table reports the percentages of CDS quotes in different tier contracts in our Markit database. SNRFOR is Senior Unsecured Debt, SUBLT is Subordinated Debt, JRSUBUT2 is Junior Subordinated Debt, and PREFT1 denotes Preference Shares. The sample period is from January 2001 to May 2012.

Tier	SNRFOR	SUBLT2	SECDOM	JRSUBUT2	PREFT1
Ratio	74.61%	20.01%	5.35%	0.02%	$\leq$ 0.01%

and cash dividends.[14]

[14] The corresponding field names are "Trail_12M_INT_EXP" for interest expenses and "Trail_12M_COM_DVD" for cash dividends.

Table 3.2: CDS Spreads Descriptive Statistics

This table reports the descriptive statistics of daily CDS spreads (in basis points) from our sample of 436 firms (356 non-financial and 80 financial firms) over the period from January 2002 to December 2011. It contains sample averages, standard deviations (Std), and maximum and minimum values. “Missing Rate (%)” indicates the percentage of missing data points. The last row reports the total number of observations for a given maturity. “R. Rate” stands for reported recovery rate.

	CDS spread (bp)								R. Rate
	6m	1y	2y	3y	4y	5y	7y	10y	(in %)
Mean	163.63	176.20	186.53	204.15	227.01	233.08	230.93	232.51	40.02
Median	30.50	40.88	55.15	72.59	92.73	103.48	107.27	115.89	40.00
Std	762.28	688.62	597.33	564.91	546.86	510.48	499.83	477.80	5.91
Max	48,355.65	40,175.46	29,701.04	33,899.01	21,782.97	25,340.71	24,222.70	23,791.63	80.75
Min	0.58	0.81	0.79	1.28	1.45	1.00	3.27	4.34	0.50
Missing Rate (%)	42.41	21.00	22.90	16.21	42.99	9.52	17.87	19.60	1.31
# of Obs	617,562	847,133	826,767	898,531	611,363	970,260	880,696	862,142	1,058,357

Table 3.3: Descriptive Statistics for Daily Changes of 1-year CDS Spreads

This table reports the descriptive statistics of daily changes of 1-year CDS spreads (in basis points) from our sample over the period from January 2002 to December 2011. It contains sample average, standard deviations (Std), maximum and minimum values. “Missing Rate (%)” indicates the percentage of missing data points.

	Δ Spread (bp)
Mean	0.21
Median	0.00
Std	100.92
Max	21,955.91
Min	-29,294.46
Missing Rate (%)	22
# of Obs	838,874

To implement Equation (3.14), we assume that all firms have 10 different maturities of bonds, ranging from 1 to 10 years (following Forte (2011)). The nominal value of total debt is equal to $STL_t + LTL_t$. For the individual nominal value of debt ($k_t(\tau)$), the short-term debt (ie. $k_t(1)$) is set equal to STL_t, while the long-term debts (i.e. $k_t(\tau), \tau = 2, ..., 10$) are equal to $\frac{1}{9} \times LTL_t$. Coupon ($c_t(\tau)$) of the different bonds is set equal to the proportion of $k_t(\tau)$ to total debt, that is $c_t(\tau) = \frac{k_t(\tau)}{STL_t+LTL_t} \times IE_t$.

The payout rate (δ_t in Equation (3.30)) is calculated as $\frac{IE_t+CD_t}{V_t}$. The firm's asset value (V_t) is needed to determine the payout rate. We apply an iterative procedure to Equation (3.19) to calibrate the firm's asset value as well as its asset volatility in the spirit of Vassalou and Xing (2004).

3.6 Empirical Results

In Section 3.6.1, we analyze the market liquidity component extracted from the CDS spreads. Next, we examine the impact of systematic and firm-specific credit and liquidity factors on CDS spreads in a panel regression. We then report the main results for the changes in CDS spreads without separating the systematic credit and liquidity factors for comparison. Finally, we perform an out-of-sample test of the cross-sectional prediction power of our model. All the analyses reported here are

Table 3.4: Firm Equity and Debt Values Descriptive Statistics

This table reports the descriptive statistics of firms' daily data retrieved from Bloomberg for our sample of 436 firms (356 non-financial and 80 financial firms) over the period from 2002 to 2011. It includes total market equity value, short-term debt (S-T Debt) and long-term debt (L-T Debt). "Missing Rate (%)" indicates the percentage of missing daily observations.

	Values in $Mn		
	Equity Value	S-T Debt	L-T Debt
Mean	8,945.77	4,503.06	5,300.48
Median	3,026.38	97.25	1,142.89
Std	22,232.12	35,418.49	20,529.26
Max	527,172.20	831,211.00	439,274.00
Min	0.00	0.00	0.00
Missing Rate (%)	19	6	6
# of Obs	2,838,420	3,314,565	3,320,307

Table 3.5: Firm Sector Distribution

This table reports the number of firms in our sample categorized in each of the nine sectors as reported in Bloomberg.

Firm Sector	# of Firms
Basic Materials	31
Communications	32
Consumer, Cyclical	74
Consumer, Non-cyclical	68
Energy	45
Financial	80
Industrial	58
Technology	18
Utilities	30
Total	436

based on quarterly changes. In addition, the results for monthly changes in variables are consistent with the results for quarterly changes. Quarterly results are reported because they have higher goodness-to-fit.

3.6.1 CDS Market Illiquidity

In this section, we examine the extent to which the liquidity component θ extracted from the CDS spread is indeed associated with liquidity. We obtain individual CDS liquidity parameters (θ_{it}) as discussed in Section 3.3.2, and then average $\log \theta_{it}$ to obtain an overall market liquidity measure of $\log \theta_t^{MKT}$.

Figure 3.1i plots the time series of quarterly changes of CDS market illiquidity θ_t^{MKT}. Higher θ indicates less liquidity. In the year 2002, $\Delta \log \theta_t^{MKT}$ fluctuates considerably. This may be partially due to the small sample size in the early years. From 2003 to 2007, $\Delta \log \theta_t^{MKT}$ is quite stable and, most of the time, negative as CDS liquidity improves steadily over time. However, in 2007–2009, $\Delta \log \theta_t^{MKT}$ increases substantially, reflecting the deterioration of the liquidity during the financial crisis. After the financial crisis, $\Delta \log \theta_t^{MKT}$ recovers but remains more volatile than in the pre-crisis period.

Figure 3.1ii plots the ratio, $\log \theta_t^{MKT} / \log CDS_t^{MKT}$. It indicates that the relative importance of the liquidity factor generally increases over time until before the start of financial crisis in 2007. During the crisis, the credit component dominates and the ratio drops from 35% to below zero in 2009. The ratio becomes negative due to several CDSs with spreads of over 10,000 bps. The liquidity component gains relative importance again after the crisis.

Figure 3.1iii plots the time series of quarterly changes in CDS market credit component λ_t^{MKT}. We find the change in the credit component is more random than the change in the CDS liquidity component, and it may have become slightly more volatile after the financial crisis. But the CDS credit component does not appear to have experienced structural change over time.

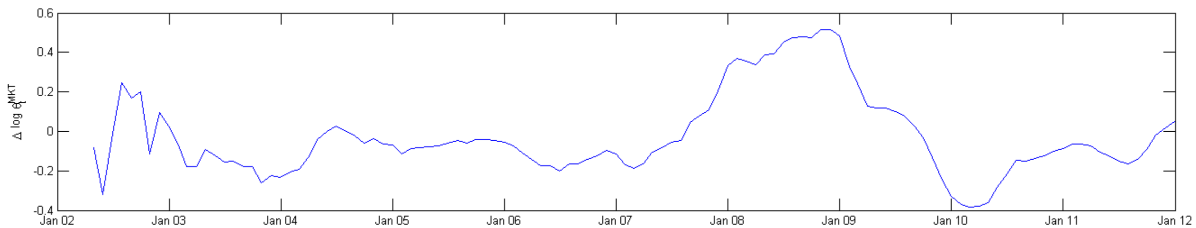
We want to show that the decomposition is meaningful and that the liquidity factor, $\log\theta_t = \sum_{i=1}^{N}\log\theta_{it}/N$, does contain liquidity information, and is not merely a collection of random errors. To perform this sanity check, we choose the determinants of liquidity (viz. VIX, $30DHistVol$, $\log Amihud$, and $BaaMinusAaa$) as suggested in Bedendo, Cathcart, and El-Jahel (2011). In addition, as the liquidity component of CDS spreads may be related to equity correlation risk ($StockPairCorr$), we include the average pairwise correlation of the underlying stock returns as well.

The difference between Baa and Aaa yields provides information regarding overall CDS market illiquidity. Hu, Pan, and Wang (2013) argue that market illiquidity can be of two kinds—'local' market illiquidity and 'overall' market illiquidity. Local illiquidity, which may be proxied by individual asset bid-ask spread, is related to the trading constraints of market makers; overall illiquidity, which may be proxied by the spread of Baa and Aaa bond yields, reflects the general level of arbitrage capital. Ideally, we should include CDS bid-ask spreads; however, this information is not available in our CDS sample. Instead we use the Amihud (2002) measure to proxy for individual CDS illiquidity, and use the average of individual stock log-Amihud as a global illiquidity systematic factor. VIX is known as the investors' "fear gauge" in the stock market. High volatility and high uncertainty are associated with illiquidity. Correlation of stock returns is proxy for the correlation risk. Contagion and correlation risk tend to increase when the market is on the downside and highly illiquid.

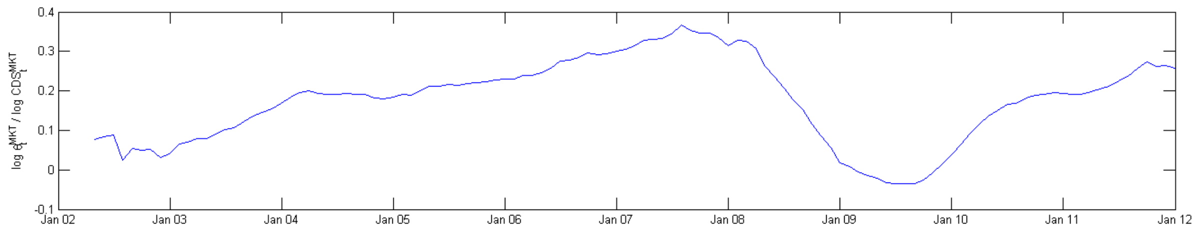
Figure 3.1: Changes in Market CDS Credit and Liquidity Components, and Ratio of Illiquidity to Spread

Note: $\log \theta_t^{MKT} = \sum_i \log \theta_{it}/N$; $\log CDS_t^{MKT} = \sum_i \log CDS_{it}/N$; $\log \lambda_t^{MKT} = \sum_i \log \lambda_{it}/N$; and N is the total number of firms in our CDS sample at time t.

(i) Changes in CDS Market Illiquidity, $\Delta \log \theta_t^{MKT}$



(ii) Ratio of $\log \theta_t^{MKT}$ to $\log CDS_t^{MKT}$



(iii) Changes in CDS Market Credit Component, $\Delta \log \lambda_t^{MKT}$

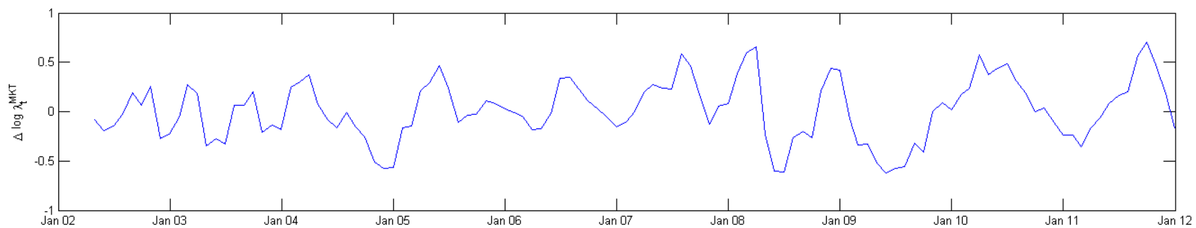


Figure 3.2 provides time-series plots for the liquidity determinants used in the sanity test. We find all determinants share a similar trend. In particular, all variables responded to the financial crisis from 2007 to 2009.

Figure 3.3 provides the scatter plots for all liquidity determinants against our market liquidity component $\Delta \log \theta_t^{MKT}$. The strongest association is noted with the cross-sectional average Amihud stock illiquidity measure. Interestingly, we observe a non-linear relationship between $\Delta \log \theta_t^{MKT}$ and the other four liquidity determinants in the plots. A positive association is observed only when $\Delta \log \theta_t^{MKT}$ is positive, implying an asymmetric association.

Finally, we estimate the following regression specification based on quarterly changes:

$$\begin{aligned}\Delta \log \theta_t^{MKT} =& \beta_0 + \beta_1 \Delta \log Amihud_t + \beta_2 \Delta VIX_t + \beta_3 \Delta BaaMinusAaa \\ &+ \beta_4 \Delta 30DHistVol_t + \beta_5 \Delta StockPairCorr_t + \varepsilon_t \qquad (3.27)\end{aligned}$$

where $\log Amihud_t$ is the average of individual stock log-Amihud (2002) measures, VIX_t is the CBOE VIX spot index, $BaaMinusAaa_t$ is the difference between Moody's Baa and Aaa yields, $30DHistVol_t$ is the average of individual firms' 30-day historical stock volatility, and $StockPairCorr_t$ is the average of pairwise correlation on stock returns for all firms in our sample.

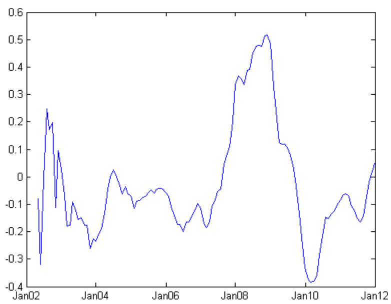
Panel A of Table 3.6 reports the correlation among $\Delta \log \theta_t^{MKT}$ and the five illiquidity determinants. Consistent with the previous analysis, $\Delta \log \theta_t^{MKT}$ has a positive correlation with all the illiquidity determinants. The highest correlation appears in $\log Amihud$, the aggregate stock illiquidity, with a correlation coefficient of 0.52. In addition, $\Delta \log \theta_t^{MKT}$ is also correlated with $BaaMinusAaa$ and $30DHistVol$ (0.34 and 0.36, respectively) whereas $\Delta \log \theta_t^{MKT}$ is least correlated with $StockPairCorr$ (0.18).

Panel B reports the estimation results. In Column (1), only the loading of Amihud measure is significant at the 1% level. The adjusted R-square is 25%. The

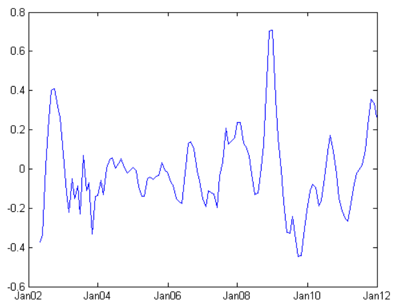
Figure 3.2: Time Series Plots of Sanity Test Variables

This figure presents the time series of the CDS illiquidity θ and five market stress variables used in Equation (3.27). The sample period is from 2002 to 2011. Δ represents the quarterly changes in the variables. $\log \theta$ is the market average of individual log-liquidity components obtained by our CDS credit and liquidity decomposition. $\log Amihud$ is the average of individual stock log-Amihud measures, VIX is the CBOE VIX spot index, $BaaMinusAaa$ is the difference between the Moody's Baa and Aaa yields, $30DHistVol$ is the average of individual firms' 30-day historical stock volatility, and $StockPairCorr$ is the average of pairwise correlation on stock returns for all firms in our sample.

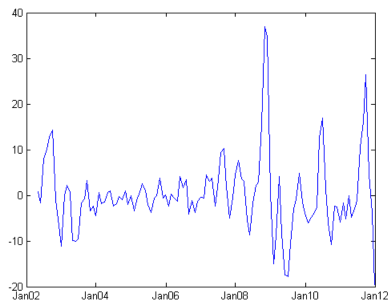
(i) $\Delta \log \theta$



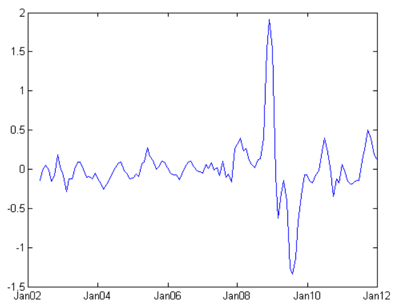
(ii) $\Delta \log Amihud$



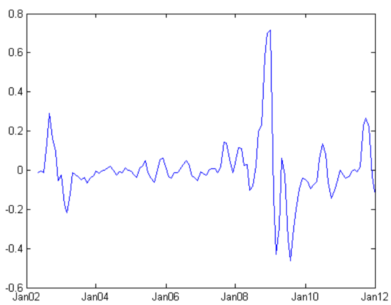
(iii) ΔVIX



(iv) $\Delta BaaNinusAaa$



(v) $\Delta 30DHistVol$



(vi) $\Delta StockPairCorr$

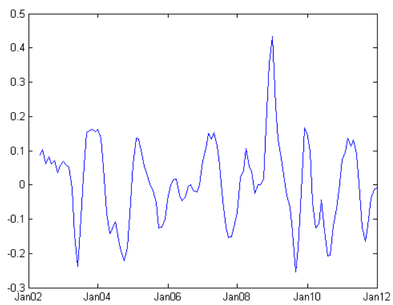


Figure 3.3: Scatter Plots of Liquidity Determinants

This figure presents the scatter plots of five market stress variables used in Equation (3.27) to regress against CDS market liquidity components. The sample period is from 2002 to 2011. Δ represents the quarterly changes in the variables. $\log \theta$ is the market average of individual log-liquidity components obtained by our CDS credit and liquidity decomposition. $\log Amihud$ is the average of individual stock log-Amihud measures, VIX is the CBOE VIX spot index, $BaaMinusAaa$ is the difference between the Moody's Baa and Aaa yields, $30DHistVol$ is the average of individual firms' 30-day historical stock volatility, and $StockPairCorr$ is the average of pairwise correlation on stock returns for all firms in our sample.

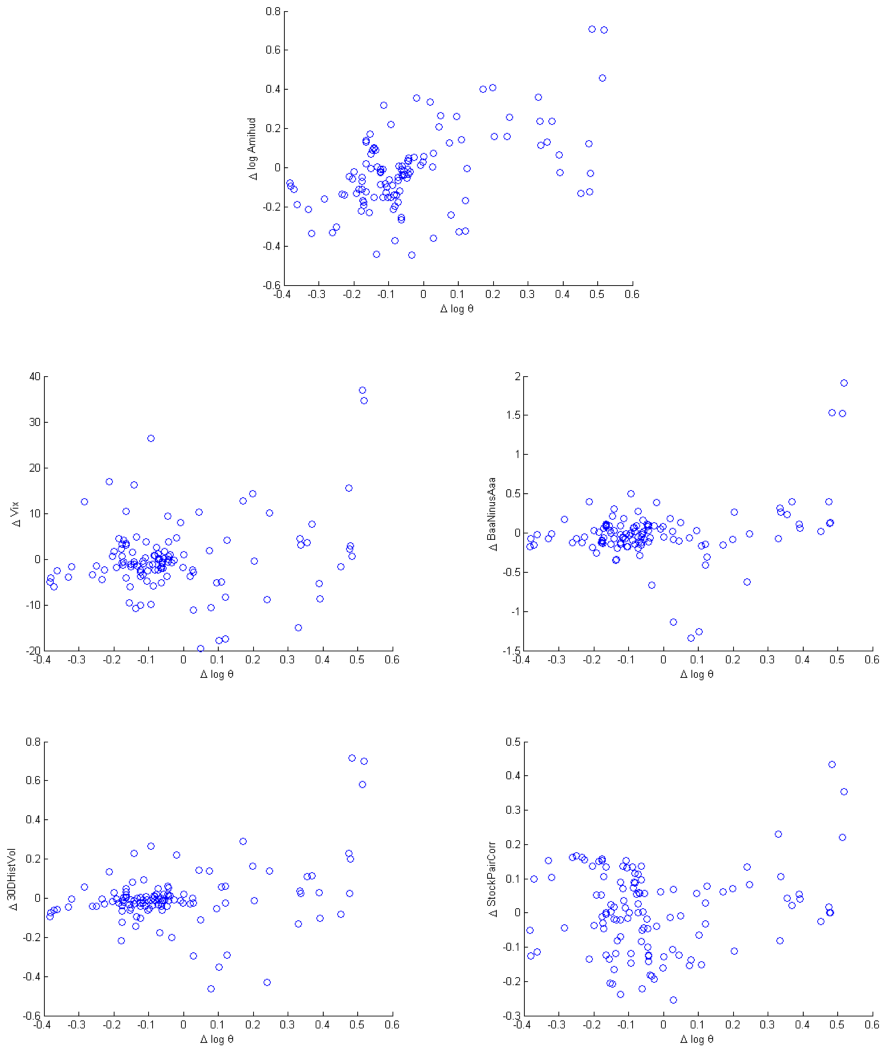


Table 3.6: CDS Market Illiquidity Component

This table reports the regression results for the determinants of the quarterly changes in the logarithm of the average liquidity component $\Delta \log \theta$ over a period from 2002 to 2011. $\log Amihud$ is the log-Amihud illiquidity measure; VIX is VIX index; $BaaMinusAaa$ is the difference between the Moody's Baa and Moody's Aaa bond yields; $30DHistVol$ is 30-day historical stock volatility; $StockPairCorr$ is the pairwise stock correlation over the 12-month horizon; $D_{2007-2011}$ is dummy variable taking a value of 1 between 2007 and 2011. In the asymmetric analysis, we flip the sign of negative $\Delta \log \theta^{MKT}$ to be positive in order to interpret the results. when Panel A reports correlation and Panels B and C report regression results.

Panel A: Correlation

	(1)	(2)	(3)	(4)	(5)
(1) $\Delta \log \theta^{MKT}$					
(2) $\Delta \log Amihud$	0.52				
(3) ΔVIX	0.23	0.40			
(4) $\Delta BaaMinusAaa$	0.34	0.64	0.61		
(5) $\Delta 30DHistVol$	0.36	0.62	0.67	0.87	
(6) $\Delta StockPairCorr$	0.18	0.16	0.14	0.34	0.29

Panel B: Regression Results

		(1)			(2)	
	Coef.	t-stat	p-value	Coef.	t-stat	p-value
Const	-0.02	-1.21	0.23	-0.07	-3.30	0.00
$\Delta \log Amihud$	0.50	4.68	0.00	0.49	4.76	0.00
ΔVIX	0.00	0.03	0.98	0.00	-0.16	0.87
$\Delta BaaMinusAaa$	-0.06	-0.64	0.52	-0.06	-0.68	0.50
$\Delta 30DHistVol$	0.15	0.64	0.52	0.17	0.74	0.46
$\Delta StockPairCorr$	0.18	1.25	0.22	0.16	1.18	0.24
$D_{2007-2011}$				0.11	3.37	0.00
R-square	0.28			0.35		
R-adjust	0.25			0.31		

Panel C: Asymmetric Effect

	$\Delta \log \theta^{MKT} \geq 0$			$\Delta \log \theta^{MTK} < 0$		
	Coef.	t-stat	p-value	Coef.	t-stat	p-value
Const.	0.27	10.72	0.00	0.12	11.34	0.00
$\Delta \log Amihud$	-0.42	-3.09	0.00	-0.13	-1.59	0.12
ΔVIX	0.00	1.88	0.07	-0.00	-0.31	0.76
$\Delta BaaMinusAaa$	0.18	2.26	0.03	0.09	0.92	0.36
$\Delta 30DHistVol$	-0.11	-0.64	0.53	-0.15	-0.66	0.51
$\Delta StockPairCorr$	0.68	3.16	0.00	0.11	1.22	0.23
R-square	0.61			0.09		
R-adjust	0.54			0.03		

result does not change when an additional dummy variable for the post-crisis period is included (Column 2). The loading on the dummy variable is positive and significant, supporting potential structural break after the financial crisis, but the Amihud measure remains significant at the 1% level.

Since we observe non-linear association in our previous scatter plot, we separate the CDS market illiquidity into positive and negative changes and repeat the same regression in Equation (3.27). Panel C reports the regression results. Interestingly, we find that all the liquidity determinants, except for $30DHistVol$, become significant at least at the 10% level when we include only the positive changes in $\log \theta^{MKT}$. This indicates that CDS market illiquidity is related to the liquidity determinants when the CDS market becomes more illiquid. And the R-square improves dramatically to 54%. On the contrary, we do not find significance in the case of negative changes in $\log \theta_t^{MKT}$. This finding provides evidence of asymmetric association between CDS market illiquidity and liquidity determinants. Since we choose liquidity determinants from the bond and equity markets, the results suggest a possible liquidity contagion among these and CDS markets.

The observed association in Panel C also signals the asymmetric impact on investors' risk aversion. As one market becomes more illiquid, investors becomes more cautious regarding the risks in other related markets, and are more likely to respond to the uncertainty. The same does not apply when the market becomes more liquid.

Since we observe a sign flip in the loading of Amihud measure due to multicollinearity in our chosen factors, we rerun the regression by using principal component analysis (PCA) and choose only the first principal component (PC) to check our results. We include all determinants ($\log Amihud$, VIX, $BaaMinusAaa$, $30DHistVol$, and $StockPairCorr$) to construct our PC, since all factors are directly or indirectly linked to liquidity shocks. The first PC can be still considered as a liquidity component. Table 3.7 reports the PCA results. The results show an asymmetric effect on CDS market liquidity components. Consistent with our previous results, the R-square improves substantially when the CDS market becomes illiquid whereas the explanatory power is rather marginal when the CDS market becomes liquid. In addition, there is a positive association between CDS market liquidity components and the first principal component for the set of liquidity determinants.

Table 3.7: CDS Market Illiquidity Component (PCA)

This table reports the principal component analysis (PCA) results for the determinants of the quarterly changes in the logarithm of the average liquidity component $\Delta \log \theta$ over a period from 2002 to 2011. "Explain" reports the level of the explained variation by the first component. In the asymmetric analysis, we flip the sign of negative $\Delta \log \theta^{MKT}$ to be positive in order to interpret the results.

	All Sample			$\Delta \log \theta^{MKT} \geq 0$			$\Delta \log \theta^{MKT} < 0$		
	Coef.	t-stat	p-value	Coef.	t-stat	p-value	Coef.	t-stat	p-value
Const.	-0.03	-1.55	0.12	0.23	9.67	0.00	0.13	14.17	0.00
1st Comp.	0.05	5.06	0.00	0.05	4.24	0.00	0.01	1.90	0.06
R-square	0.18			0.36			0.04		
R-adjust	0.18			0.34			0.03		
Explain	0.61			0.73			0.54		

3.6.2 Panel Regression

In this section, we examine the impact of industry- and market-wide credit and liquidity systematic factors. Table 3.8 reports the correlation coefficients for all the variables in Panel A and the panel regression (Equation (3.26)) results in Panel B. From Panel A, it is clear that industry illiquidity and market illiquidity are highly correlated. Similarly, industry credit and market credit are also highly correlated. So for the interpretation of results, we will treat industry and market factors as almost identical. Next, we note that credit and liquidity are negatively correlated, and such a negative correlation is slightly stronger at the firm-specific level. With these relationships in the background, it is clear from Panel A that the factors that drive firms' CDS spreads are, in the decreasing order of explanatory power, systematic credit risk (measured by λ^{MKT} or λ^{IND}), firm-specific credit risk (measured by DTD), and increase in firm-specific illiquidity (measured by $Amihud^{+}$).[15]

The full and sub-sample panel regression results in Panel B support the above findings. The overall R^2 of 40% is largely due to the second sub-period, which includes the financial crisis. All the factors except for $\Delta \log Amihud^{-}$ are highly significant. The loadings on $\Delta \log \theta^{IND}$ and $\Delta \log \lambda^{IND}$ are 0.31 and 0.36 respectively; the loadings on $\Delta \log \theta^{MKT}$ and $\Delta \log \lambda^{MKT}$ are 0.58 and 0.51 respectively. These results indicate that indeed both systematic credit and liquidity risks are priced in CDS spreads, and they have comparable impacts on quarterly changes in CDS spreads. Similarly, firm-specific credit and liquidity affect CDS spreads. However, the firm-specific liquidity results are driven by an increase in illiquidity, but not when the liquidity improves.

[15] We also test whether there is any asymmetry in our CDS-based liquidity component, θ. We test $\Delta \log \theta^{IND}$ and $\Delta \log \theta^{MKT}$ separated by their signs. We do not find any asymmetry in this case as the loadings for the sign-separated factors are all significant. The results are available on request.

Table 3.8: Systematic and Firm-specific Credit and Illiquidity Impact on CDS Spreads

This table reports correlation coefficients across and regression results for quarterly changes in individual log-CDS spreads ($\Delta \log CDS$) for different sample periods. $\Delta \log Amihud^{+}$ is a quarterly change in the log-Amihud illiquidity measure, if positive; $\Delta \log Amihud^{-}$ is a quarterly change in the log-Amihud illiquidity measure, if negative; DTD is the individual firm's distance-to-default calibrated using the Merton (1974) model; $\log \theta$ is the logarithm of a CDS liquidity component; and $\log \lambda$ is the logarithm of a CDS credit component. IND stands for the industry-wide average and MKT stands for market-wide average. Panel A reports correlations and Panel B reports panel regression results.

Panel A: Correlation

	2002–2011						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) $\Delta \log CDS$							
(2) $\Delta \log Amihud^{+}$	0.32						
(3) $\Delta \log Amihud^{-}$	0.20	0.35					
(4) ΔDTD	-0.35	-0.35	-0.27				
(5) $\Delta \log \theta^{IND}$	0.27	0.39	0.19	-0.35			
(6) $\Delta \log \lambda^{IND}$	0.42	0.13	0.12	-0.16	-0.25		
(7) $\Delta \log \theta^{MKT}$	0.30	0.42	0.21	-0.38	0.80	-0.18	
(8) $\Delta \log \lambda^{MKT}$	0.44	0.15	0.14	-0.18	-0.17	0.81	-0.21

	2002–2006						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)							
(2)	0.13						
(3)	0.09	0.34					
(4)	-0.21	-0.15	-0.17				
(5)	0.05	0.08	0.11	-0.13			
(6)	0.36	-0.01	-0.02	-0.05	-0.22		
(7)	0.05	0.18	0.17	-0.18	-0.01	-0.09	
(8)	0.40	-0.02	-0.02	-0.08	-0.05	0.68	-0.17

	2007–2011						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)							
(2)	0.35						
(3)	0.26	0.37					
(4)	-0.40	-0.40	-0.31				
(5)	0.29	0.41	0.22	-0.41			
(6)	0.45	0.15	0.19	-0.20	-0.30		
(7)	0.31	0.41	0.24	-0.44	0.91	-0.24	
(8)	0.45	0.18	0.21	-0.21	-0.24	0.86	-0.27

Panel B: Panel Regression

	2002–2011			2002–2006			2007–2011		
	Coef.	t-stat	p-value	Coef.	t-stat	p-value	Coef.	t-stat	p-value
Const	-0.02	-4.41	0.00	-0.08	-8.97	0.00	0.00	-0.18	0.86
$\Delta \log Amihud^{+}$	0.17	8.95	0.00	0.36	8.11	0.00	0.11	5.33	0.00
$\Delta \log Amihud^{-}$	0.03	1.74	0.08	0.05	1.84	0.07	0.02	0.68	0.50
ΔDTD	-0.03	-15.47	0.00	-0.04	-12.73	0.00	-0.03	-10.03	0.00
$\Delta \log \theta^{IND}$	0.31	13.84	0.00	0.21	6.87	0.00	0.34	8.93	0.00
$\Delta \log \lambda^{IND}$	0.36	23.03	0.00	0.27	12.85	0.00	0.42	18.96	0.00
$\Delta \log \theta^{MKT}$	0.58	22.51	0.00	0.36	6.75	0.00	0.58	13.98	0.00
$\Delta \log \lambda^{MKT}$	0.51	28.89	0.00	0.51	19.24	0.00	0.47	19.23	0.00
R-square	0.40			0.23			0.44		
R-adjust	0.40			0.23			0.44		

3.6.3 Out-of-Sample Prediction

One potential application of our model is to approximate (changes in) CDS spreads for firms that do not have (actively) traded CDSs. One can choose, for example, the last CDS quote available or the industry/rating average CDS as the initial value as suggested by Basel III, and then apply our model to refine the spread estimate.

We use an out-of-sample test for cross-sectional predictions and consider two benchmark cases: (i) a simple average CDS spread, where $\bar{y}_i = \frac{1}{T}\sum_t y_{it}$ is the average of past CDS changes, and (ii) CDS spread predicted using Merton's DTD, where $\bar{y}$ now is the fitted value of the regression below when only the firm's DTD is used as a factor:

$$\Delta \log CDS_{it} = \beta_0 + \beta_1 \Delta DTD_{it} + \varepsilon_{it}. \tag{3.28}$$

The out-of-sample performance of the two benchmark cases is compared with the complete model specification in Equation (3.21).

Following Welch and Goyal (2008), our adjusted out-of-sample R-square is defined as:

$$\overline{R}^2_{OOS} = 1 - \frac{\sum_i \sum_t (y_{it} - \hat{y}_{it})^2 \;/\; DF_A}{\sum_i \sum_t (y_{it} - \bar{y}_i)^2 \;/\; DF_N} \tag{3.29}$$

where y_{it} is the actual change in log-CDS spreads, $\hat{y}_{it}$ is the predicted change based on our model with parameters estimated using a training sub-sample, and DF is the degree of freedom for the corresponding hypothesis. The null hypothesis here is that our proposed model ($\hat{y}$) does not perform better than that benchmark ($\bar{y}$).

In addition, we consider the rolling-window analysis. The initial sample period is from January 2002 to January 2005, and then we roll the whole sample period forward to the next month. Here, we consider two out-of-sample analyses. In the first analysis, we consider a general time-series out-of-sample prediction. We use the entire cross-sectional sample as the training sample and test their time-series predictability in one quarter. In the second analysis, we turn our interest to the cross-sectional prediction. We randomly choose 100 firms as a test sample with the remaining firms constituting a training sample, and perform the procedure 1,000 times. The purpose is to understand whether the traded CDSs can provide contemporaneous information for firms that do not have traded CDSs.

The average $\overline{R}^2_{OOS}$ and the descriptive statistics are reported in Table 3.9. The results show that our model provides only good cross-sectional prediction. In the time-series out-of-sample analysis, the average $\overline{R}^2_{OOS}$ is negative in both cases. It indicates that our model cannot be used for predicting future changes in CDSs. In the cross-sectional out-of-sample analysis, our model, however, improves the mean square error by 27% compared with a simple average (Case 1) and by 26% when compared with the prediction based on DTD only. It indicates that although DTD is an important factor in explaining the changes in CDS spreads, individual stock liquidity and systematic factors substantially improve the forecasting performance. Overall, the out-of-sample results suggest that cross-sectionally our model produces good predictability and stable outcomes across time, with systematic credit and liquidity factors being especially important since the financial crisis.

3.7 Conclusion

In this chapter, we develop a simple model to explain how systematic and firm-specific credit and liquidity factors affect asset prices. When applied to CDS spreads, the model consists of four groups of factors: individual firms' credit and liquidity factors, and systematic credit and liquidity factors. We use CDSs' calibrated components to compile the systematic factors. But the firm-specific factors are not obtained from calibration in order to avoid spurious results. They are obtained using equity information instead. This application can resolve the potential endogeneity, as there are substantial differences among factors. We empirically investigate the extent to which these factors explain the quarterly changes in 1-year CDS spreads for 356 U.S. non-financial firms over the sample period from 2002 to 2011.

Our results show that CDS spreads are driven by individual firms' credit risk

Table 3.9: Out-of-sample Predictability

This table reports the descriptive statistics of the adjusted out-of-sample R-squared ($\overline{R}^2_{OOS}$) for quarterly changes in CDS spreads for non-financial firms. The initial sample period is from January 2002 to January 2005, and then we roll the sample period forward to the next month to construct a rolling-window analysis. We consider both time series and cross-sectional predictability. In the time-series analysis, we use the entire cross-sectional sample as the training sample and test their time-series predictability in one quarter. In the cross-sectional analysis, we randomly choose 100 firms as a testing sample and use the remaining firms as a training sample. The procedure is performed 1,000 times. Case 1 is based on the null hypothesis that our model does not outperform simple average prediction. Case 2 is based on the null hypothesis that our model does not outperform the predictions based on the firm's DTD. The results are reported for the complete sample period from 2002 to 2011.

	Time Series		Cross-Sectional	
	Case 1	Case 2	Case 1	Case 2
Mean	-56.49	-17.45	0.27	0.26
Std	21.12	2.64	0.12	0.07
Max	-17.39	-12.94	0.58	0.45
Min	-99.04	-42.17	-0.05	0.03

(measured by Merton's distance-to-default), and the Amihud stock illiquidity measure. Unlike Das and Hanouna (2009), who find a monotonic relation between changes in stock illiquidity and changes in CDS spreads, we find this happens only when stock becomes more illiquid, and there is no significant relation if the stock becomes more liquid. We argue that hedging demand across equity and CDS markets increases when the stock market experiences liquidity shocks, and this further increases illiquidity premium.

Following Forte (2011) and Forte and Lovreta (2012), we split CDS spread into its credit and liquidity components and use them to construct market and industry credit and liquidity factors. We also find changes in the industry- and market-wide credit and liquidity factors strongly influence the changes in CDS spreads. The market factors, however, have a slightly stronger impact than industry factors for non-financial CDSs. The impact is especially pronounced after the start of the financial crisis in 2007, but is less strong in the pre-crisis period.

In our sanity test, we choose well-known liquidity determinants from bond and equity markets to compare with our market CDS illiquidity. We find there is a non-linear association between our CDS illiquidity and other liquidity determinants. Only increases in the CDS market illiquidity have a positive relationship with the determinants whereas the negative changes in the CDS market illiquidity do not. This finding suggests a possible liquidity contagion among these markets. As one market becomes more illiquid, investors tend to respond to the uncertainty quickly. But this is not the case when one market becomes more liquid.

As our model does not use individual firms' CDS information, such as CDS bid-ask spread, it can be used for cross-sectional prediction of CDS spreads for firms that do not have (actively traded) CDSs. Our model reduces the mean squared error of the out-of-sample predictions by 27% when compared with the simple average prediction, and by 26% when compared with predictions based on firms' distance-to-default only.

Financial regulations, such as Basel III, stipulate that CDS spreads must be used to produce a market estimate of the default probability of a counterparty. Our findings challenge this approach as individual firms' CDS spreads are driven by many factors other than the firm's default risk. They are significantly influenced by the overall market credit and liquidity conditions as well as the firm's stock illiquidity.

Appendix

3.A The Expression of $F_t(\tau)$ and $G_t(\tau)$

Leland and Toft (1996) assume the asset dynamics follows a geometric Brownian Motion:

$$dV_t = (\mu - \delta)V_t dt + \sigma V_t dW_t \tag{3.30}$$

where μ is the asset's expected growth, δ is the payout rate, and σ^2 is the asset volatility. The value of debt is shown in Equation (3.11) with

$$F_t(\tau) = N[h_{1,t}(\tau)] + \left(\frac{V_t}{V_B}\right)^{-2a} N[h_{2,t}(\tau)] \tag{3.31}$$

$$G_t(\tau) = \left(\frac{V_t}{V_B}\right)^{-a+z} N[q_{1,t}(\tau)] + \left(\frac{V_t}{V_B}\right)^{-a-z} N[q_{2,t}(\tau)] \tag{3.32}$$

where

$$\begin{aligned}
q_{1,t}(\tau) &= \frac{-b_t - z\sigma^2\tau}{\sigma\sqrt{\tau}}, \quad q_{2,t}(\tau) = \frac{-b_t + z\sigma^2\tau}{\sigma\sqrt{\tau}} \\
h_{1,t}(\tau) &= \frac{-b_t - a\sigma^2\tau}{\sigma\sqrt{\tau}}, \quad h_{2,t}(\tau) = \frac{-b_t + a\sigma^2\tau}{\sigma\sqrt{\tau}} \\
a &= \frac{r - \delta - \sigma^2/2}{\sigma^2}, \quad b_t = \ln(V_t/V_B), \quad z = \frac{\sqrt{(a\sigma^2)^2 + 2r\sigma^2}}{\sigma^2}.
\end{aligned}$$

3.B Markit Database

Markit was founded in 2001. It has been collecting and compiling CDS spreads worldwide since 2001 and also constructs CDS indices such as the Markit iTraxx index. The database contains the legal entity of the underlying bonds, seniority tier, documentation clause (DocClause), CDS recovery rate, and CDS tenors. In what follows, we briefly summarize the database based on the Markit user guides of 2011 and 2012 and its descriptive statistics.

DocClause

The type of credit event trigger determines the payment of CDS contracts. Most CDS contracts follow the definition set by the ISDA (International Swaps and Derivatives Association). The ISDA defines six broad types of credit events: bankruptcy, failure to pay, repudiation/moratorium, obligation acceleration, obligation default, and restructuring. However, of these events, restructuring is the most complex credit event, and there is a potential arbitrage opportunity for CDS buyers. When a firm is under a restructuring process, restructuring may not lead to an obvious or immediate loss to the debt owner; however, there is a chance for CDS buyers to create a profit opportunity unrelated to changes in credit quality, because protection buyers may exploit the cheapest-to-delivery rule and deliver the most illiquid bond (see, for example, Packer and Zhu (2005), Collender (2008)). There are four types of restructuring defined by the ISDA:

1. *Full restructuring (CR)*: This clause is the most favorable for CDS buyers. It classifies any form of restructuring as a credit event and a bond of any maturity can be used as a deliverable bond.

2. *Modified restructuring (MR)*: Modified restructuring classifies restructuring as a credit event, but limits deliverable bonds to those that mature within 30 months of the termination date of the CDS contract.

3. *Modified-modified restructuring (MM)*: The modified-modified restructuring clause is less strict than modified restructuring. It classifies deliverable bonds as those within 60 months of the termination date of the CDS contract.

4. *No restructuring (XR)*: The no restructuring clause does not consider restructuring as a credit event in a CDS contract. This is the most favorable term for CDS sellers.

Tier

Payback seniority is another important attribute of the CDS contracts, which has an impact on CDS spreads. CDS spreads are lower for secured debt but higher for subordinate debt. CDSs could be traded on debts with different debt seniorities of the same entity at any time. In Markit, there are four debt seniority levels: Junior, Subordinate, Senior, and Preferred.

Markit Data Screening Procedure

The Markit database provides corporate, municipal, and sovereign single-name CDS data of approximately 2,650 individual entities and 3,000 entity-tiers. The data source is from multiple market makers (primary banks). As for data input, each contributor is required to upload their CDS spreads[16] and the recovery rate of the trade. Then Markit will check the data's credibility. The average CDS spread (entity-tier-tenor) is calculated only if there are at least three distinct quote contributors and at least two of these contributors pass the data credibility tests. The tests consist of a Curve Buildability Test, a Backwardation Test, a Stale Data Test, and an Outlier Test. The first two tests ensure that data follow standard pricing mechanisms and the last two tests ensure data are not outdated.

1. *Curve Buildability Test*: Markit uses the ISDA's CDS standard model to calculate the survival probability for each contributor's credit curve. The contributor's curve is rejected if unreasonable values appear.

2. *Backwardation Test*: A different DocClause allows a different quality of bond to be included as a deliverable. The reasonable relationship of CDS spread according to its DocClause is

$$CDS_{CR} \geq CDS_{MM} \geq CDS_{MR} \geq CDS_{XR}.$$

If the contributor's credit curve fails to conform to this rule, the curve is rejected.

3. *Stale Data Test*: The 5-year CDS contracts are the most liquid contracts. Markit makes use of the liquid contract to adjust the potential stale data problem. For each contributed curve, Markit calculates the number of days the 5-year CDS spread has remained unchanged. Curves from all dealers are ranked in terms of their number of days of no change and Markit generally uses the top 50% of curves for

[16]CDS spreads can be of two types: a par spread and an up-front spread. In the case of a par spread, CDS buyers do not need to pay up-front, while in the case of an up-front spread they do. The quoted premiums are different for these two types of spreads. Markit uses the ISDA's CDS standard model to convert up-front spread to par spread. The CDS spreads in Markit are all par spread.

illiquid entities and top 67% of curves for liquid entities. An entity is defined to be illiquid if it receives contributions from 13 or fewer contributing banks; otherwise it is defined to be liquid. The curves that fail the stale data test are not used in the composite calculation.

4. *Outlier Test*: The outlier test works by first calculating a provisional median curve based on all contributions that passed the previous three tests. The test then computes a weighted sum of squared deviations across tenors and the recovery rate of each contributed curve from the provisional median curve. It then ranks the curves and rejects the ones with the highest deviations.

Markit only includes CDS spreads that pass the above-mentioned tests, and reports the average of the spreads by entity, tier, and tenor.

Chapter 4

Anatomize DOOM-CDS Linkage

Abstract

In this chapter, we exploit the divergence of the implied hazard rates derived from deep out-of-the-money put options (DOOMs) and credit default swaps (CDSs) to produce profitable trading strategies. We extend Carr and Wu (2010) by decomposing the implied hazard rates into credit and illiquidity components. We find that the information about the components refines the prediction of the convergence and better trading performance. We show that, after controlling for factors explaining the structural difference between the markets, both components converge over time in these two markets. While the Carr-Wu "Benchmark" strategy produces the largest total returns due to the large amount of trades, our component-refined strategies lead to greater mean return (by 1.81%) and beat the "Benchmark" strategy by the Sharpe ratio and Carhart alpha.

4.1 Introduction

Both deep out-of-the-money (DOOM) put options and credit default swaps (CDSs) provide protection against firms' defaults. Protection buyers have the right to sell the security (a share or a bond) at a pre-specified price if the specific default event occurs. DOOMs and CDSs can be converted into a unit recovery claim (URC) that pays one unit if the firm defaults and zero otherwise (Carr and Wu 2010).

Theoretically, a URC on a given firm should have the same price regardless of the market of origin. However, URCs may be affected by different factors such as market illiquidity. In this chapter, we use the Nelson and Siegel (1987) model to separate the URC into two components: a credit component "fitted" from the credit curve and an illiquidity component as the "residual" from the fitted credit curve. We extend Carr and Wu (2010) by examining the difference in the credit and illiquidity components between DOOMs and CDSs, explicitly accounting for factors that drive illiquidity, firms' characteristics, and market conditions. The component separation in this chapter follows Hu, Pan, and Wang (2013), who use the difference between the theoretical and actual Treasury yield curves to capture the overall market illiquidity. There are several studies relating residual components to illiquidity. For example, Bedendo, Cathcart, and El-Jahel (2011) study the difference between actual CDS spreads and theoretical CDS spreads derived from CreditGrade model and find that the difference contains illiquidity. In the same spirit, Hu, Pan, and Wang (2013) use the Nelson-Siegel-Svosson model to extract liquidity information. Therefore, we expect the residual term from our decomposition should contain illiquidity information for DOOMs and CDSs, in addition to firm-specific credit risk.

In this chapter, we find evidence that some option-market related factors, including option moneyness, option-implied volatility, and open interest, can explain the difference in the credit components between DOOMs and CDSs. However, their explanatory power for the difference in the illiquidity components is not as strong. We also find evidence that the deviations in the credit components and the illiquidity components both diminish over time, and this convergence leads to the convergence of the URCs. Using VAR regressions on the two components, we find evidence that the DOOM market leads the CDS market in the valuation of the credit components; however, the opposite lead-lag relationship is observed for the illiquidity components.

Finally, we exploit the observed URC convergence pattern by constructing a simple trading strategy that consists of longing the security (DOOM or CDS) that has a lower URC-implied hazard rate and shorting the other. We use this simple trading strategy as a benchmark to compare two other more refined strategies, based on more information about the two components. Using the sample from May 2002 to May 2012, we find our benchmark strategy produced the highest total return due to the much larger number of trades. Our refined strategies, however, outperform the benchmark strategy by 1.81% on average, and beat the benchmark strategy by the Sharpe ratio and Carhart alpha. Given the round-trip transaction costs for puts and CDSs, it is most likely that our trading strategies will remain profitable.

4.2 Relative Literature

This chapter builds upon several strands of literature. The first one relates to the credit and equity markets. There are several studies that explore the cross-market association. For example, Berndt, Douglas, Duffie, Ferguson, and Schranz (2008) analyze hazard rates based on the Moody's KMV Expected Default Frequency (EDF) and CDS spreads in four industries in the U.S. They find a strong relation between real and risk-neutral probabilities of default.Friewald, Wagner, and Zechner (2014) study credit risk premiums extracted from CDS spreads and find that excess CDS premiums are strongly positively related to Merton's equity risk premiums. Schneider, Wagner, and Zechner (2014) estimated the credit risk premiums following Friewald, Wagner, and Zechner (2014) and show that they are related to higher moments of equity returns such as volatility and skewness. Bedendo, Cathcart, and El-Jahel (2011) compare the option-implied CDS spread and actual CDS spread and find that there exists a persistent difference between these two spreads that could be due to illiquidity. These studies motivate us to separate the credit and illiquidity components in DOOMs and CDSs, so that we can test whether the interactions of the two components between the two markets are different.

Carr and Wu (2010) build a theoretical model to explain the connection between deep out-of-the-money put options (DOOMs) and CDSs. [1] This chapter is closely related to Carr and Wu (2010). The authors argue that both DOOMs and CDSs contain the firm's default information, and both types of instruments can hedge default risk. Using a sample of 121 companies and weekly data from January 2005 to August 2008, the authors find that the unit recovery claims (URCs) estimated from put options and CDSs are of similar magnitudes, and any deviations will converge and can be used to predict future market movements. This chapter enriches the literature on DOOMs and CDSs. Kim, Park, and Noh (2013) study DOOMs and CDSs around the subprime mortgage crisis period, and find that the association is not as tight in that period. They thus propose a modified URC to provide a tighter linkage. Fonseca and Gottschalk (2014) study the term structure of CDSs and the implied volatility surface for five European countries from 2007 to 2012. They find that, during that period, the cross-hedging strategy between credit risk and equity volatility may be jeopardized as there is a significant deviation between credit risk and equity volatility. Angelopoulos, Giamouridis, and Nikolakakis (2013) study the market integration among stock, DOOMs and CDSs. They find that the magnitude of deviation between DOOMs and CDSs can predict the future stock movement;

[1] Merton (1974), among other literature, shows how the possibility of default is related to the pricing of equity options. Therefore, equity options can be used to hedge default risk. But, such implementation of hedging default risk by normal options can be less effective since the option price is not driven merely by the default risk. Carr and Wu (2010) provide a theory that if a put option is extremely out-of-the-money, the underlying stock process becomes irrelevant for the pricing of the put and the put reflects only the possibility of default. Such deep out-of-the-money put options (DOOMs) provide credit protection because protection buyers have the right to sell a share at a pre-specified price. Of course, a DOOM put as credit protection depends on the level of the option moneyness and the option expiry. Carr and Wu (2010) assume that there exists a default corridor that the underlying stock should not enter. Once the underlying price has entered the default corridor, it will never recover. The specification of the default corridor is to mimic a credit event. In reality, the evidence of the existence of default corridor can be found in some credit events such as the bankruptcy of Lehman Brothers, when the asset value jumped before the default occurred and fell to a much lower value afterward. Therefore, if the strike prices of the DOOM put options are located within the default corridor, these DOOM puts, similar to CDSs, become a credit insurance.

larger deviation is positively associated with the stock return. This chapter has two contributions. We separate DOOMs and CDSs into their credit and illiquidity components, and study their deviation and reversion. Such separation is not done in these studies. We also provide profitable trading strategies based on the information about the components.

Several recent papers have established connections between CDSs and various other non-equity markets. Della Corte, Sarno, Schmeling, and Wagner (2014), for example, find that sovereign CDSs explain the performance of currency options better than traditional factors such as the Treasury rates. Subrahmanyam, Tang, and Wang (2014) find that the existence of CDSs affects corporate decisions such as the level of cash holdings. Firms tend to increase cash holdings after the introduction of the traded CDSs on their bonds. They argue that some firms become more cautious because CDS-protected creditors can be tougher in debt renegotiations and less willing to support distressed borrowers. Consequently, firms hold more cash after the inception of CDS trading on their debt.

The second strand of literature investigates the impact of liquidity (and liquidity risk) on CDS spreads. They find that CDS liquidity risk seems to matter more than pure credit risk in explaining the changes in CDS spreads. Corò, Dufour, and Varotto (2013) construct two bid-ask-spread based liquidity factors: daily time-weighted average bid-ask spread, and industry average bid-ask spread. Both liquidity factors dominate CDS changes, while other factors, such as changes in credit rating and macroeconomic conditions, have a significant but much weaker explanatory power. Tang and Yan (2007) study a range of liquidity factors related to trading quotes and bid-ask spread, and conclude that the short-term changes in CDS spread are driven by the trading illiquidity. Buhler and Trapp (2010) develop a reduced-form model for pure credit risk and pure liquidity risk by calibrating CDS and bond data. They find that the illiquidity component is important in explaining bond spreads. They also find an illiquidity co-movement between the bond and CDS markets.

CDS liquidity risk can spill over across markets. Das and Hanouna (2009) find that underlying equity liquidity is related to the liquidity risk of CDS. The authors compare the Amihud (2002) illiquidity measure, the LOT (Lesmond-Ogden-Trzcinka) measure of Lesmond, Ogden, and Trzcinka (1999), and the CDS bid-ask spread, and conclude that the Amihud stock illiquidity measure is important in explaining the quarterly change in CDS spreads.

Liquidity risk is asymmetric and exhibits a stronger market impact during liquidity drain-out. Brunnermeier and Pedersen (2009) describe a liquidity drain-out as a vicious circle of market and funding liquidity interactions. This is supported by several recent empirical studies. Brennan, Chordia, Subrahmanyam, and Tong (2012) analyze the impact of sell-side liquidity on stock returns, and show that liquidity premium arises mainly from the sell order. Brennan, Huh, and Subrahmanyam (2013) decompose the Amihud (2002) illiquidity measure into two half-Amihud measures, and find negative Amihud illiquidity (with negative stock returns) has a higher explanatory power for stock returns. Kolokolova, Lin, and Poon (2014) find that Amihud stock illiquidity widens CDS spreads, but this impact is asymmetric and is observed only when stock becomes more illiquid.

4.3 Research Design

In this section, we first describe the procedure for extracting risk-neutral hazard rates from put option prices and CDS spreads. Next, we describe the separation of the implied hazard rate into credit and illiquidity components, and investigate the information spillover between the DOOM and CDS markets.

4.3.1 URC-implied Hazard Rate

Carr and Wu (2010) define a unit recovery claim (URC) as a security that pays one unit if a firm defaults before time T. In other words, a URC represents a risk-neutral default probability as follows:

$$URC(t,T) = \mathbb{E}^{Q}\left[e^{-r\tau} I_{\{\tau<T\}}\right] \tag{4.1}$$

where r is the risk-free interest rate, τ is the default time, and I is an indicator function taking the value of 1 if default happens before T and zero otherwise.

If default events follow a Poisson distribution with constant hazard rate λ, then

$$URC(t, T) = \lambda \frac{1 - e^{-(r+\lambda)(T-t)}}{r + \lambda}. \tag{4.2}$$

Given the default arrival rate has a flat term structure with $\lambda = k/(1 - R^b)$, where k is the CDS spread and R^b is the bond recovery rate, Carr and Wu (2010) show that the CDS-implied URC can be written as

$$URC^C(t, T) = \zeta k \frac{1 - e^{-(r+\zeta k)(T-t)}}{r + \zeta k} \tag{4.3}$$

where ζ is the inverse of loss-given-default.

Next consider the put-implied URC. An American put option allows investors to sell the underlying stock at the pre-determined strike price. In terms of credit protection, the protection buyer will exercise the put option when a certain threshold value, R_τ, is reached:

$$P(K, T) = \mathbb{E}^Q \left[e^{-r\tau}(K - R_\tau) I_{\{\tau < T\}} \right] \tag{4.4}$$

where K is the strike price and R_τ is the asset value at the time when the firm defaults.

Carr and Wu (2010) claim that, apart from firms that are "too big to fail", the price of a DOOM put is entirely driven by the default probability and not by the stock price or the stock volatility. The authors prove that as long as the stock price is bounded below by a strictly positive barrier $B > 0$ before default, but drops below a lower barrier $A < B$ at default, and stays below A thereafter, then any two co-terminal American puts struck within the default corridor $[A, B]$ replicate a pure credit insurance that pays off if and only if the company defaults prior to the option expiry. In particular, the DOOM put option has analytical value

$$P(t,T) = K\left[\lambda\frac{1-e^{-(r+\lambda)(T-t)}}{r+\lambda}\right] - Ae^{-rT}\left[1-e^{-\lambda(T-t)}\right]. \quad (4.5)$$

Combining Equations (4.2) and (4.5), the put-implied URC can be valued as a scaled difference between two put option prices:

$$URC^P = \frac{P(K_2,T)-P(K_1,T)}{K_2-K_1}. \quad (4.6)$$

For the special case in which stock price falls to zero at default time (i.e. $A = 0$), $K_1 = 0$, Equation (4.6) can be rewritten as

$$URC^P = P(K,T)/K. \quad (4.7)$$

Based on the aforementioned specification, we obtain the URC-implied hazard rates for put options and CDS spreads. We extract the put-implied hazard rate (denoted as λ^P) based on Equations (4.2) and (4.7). The CDS-implied hazard rate (denoted as λ^C) is computed as $\lambda^C = k/(1-R^b)$.

4.3.2 Credit Curve Fitting

When there are shortages of arbitrage capital, assets may keep being traded at prices significantly different from their fundamental values (Hu, Pan, and Wang 2013). The authors measure the “noise” in U.S. Treasury bonds as the difference between the fitted and the observed yields, and use it as a measure for the shortage of arbitrage capital in the economy. Following the same spirit, we estimate the residual term in the URC-implied hazard rates as the difference between the observed hazard rates and their fitted values as follows:

$$\lambda(\tau) = y(\tau) + \theta(\tau) \quad (4.8)$$

where λ is the URC-implied hazard rate obtained from a DOOM/CDS with maturity τ, y is the fitted value specific to the credit rating class, and θ is the residual.[2]

Following Hu et al., we obtain the daily fitted values $y(\tau)$ for each rating class based on the Nelson-Siegel model below, which allows for a hump-shaped term structure:

$$y(\tau|\beta_0, \beta_1, \beta_2, m) = \beta_0 + \beta_1 \left(\frac{1 - e^{-\tau/m}}{\tau/m} \right) + \beta_2 \left(\frac{1 - e^{-\tau/m}}{\tau/m} - e^{-\tau/m} \right) \tag{4.9}$$

where β_0 and β_1 are the long-term and short-term hazard rates, β_2 captures a hump at the medium term, and m determines the shape and the position of the hump. Equation (4.9) is estimated separately for DOOMs and CDSs. Following Hu et al., we set $\beta_0 > 0$, $\beta_0 + \beta_1 > 0$, $\beta_0 + \beta_1 + \beta_2 > 0$ and $m > 0$ to avoid negative hazard rates. Since $y(\tau)$ is fitted to a group of put options (or CDSs) with the same rating, $y(\tau)$ will be the same if these put options (or CDSs) have the same maturity and belong to the same rating class.

4.3.3 Information Spillover

There exists abundant evidence that information is impounded into asset prices in different markets at different speeds. Using a general VECM (vector error correction model) approach, Forte and Pena (2009) show that stock market often leads the CDS and bond markets. In this section, we investigate the information spillover between the option and CDS markets. We perform a VAR analysis of the changes in λ, y and θ.

For example, for the changes in λ, the VAR regression specification has the

[2] There may be other factors in addition to the shortage of arbitrage capital that affect the sign and/or the magnitude of θ. Some of the factors are market-specific (since bonds are the underlying assets for CDSs and stocks are the underlying assets for put options); others are firm-specific or are related to the general market conditions. Carr and Wu (2010) find, for example, that URC^P is greater than URC^C. Empirically, URC^P increases as stock price moves closer to the strike price and as stock volatility increases, but it decreases as put open interest increases.

following form:

$$\begin{bmatrix} \Delta\lambda_t^P \\ \Delta\lambda_t^C \end{bmatrix} = \begin{bmatrix} \alpha_0^P \\ \alpha_0^C \end{bmatrix} + \begin{bmatrix} \beta^{PP} & \beta^{PC} \\ \beta^{CP} & \beta^{CC} \end{bmatrix} \cdot \begin{bmatrix} \Delta\lambda_{t-1}^P \\ \Delta\lambda_{t-1}^C \end{bmatrix} + \begin{bmatrix} \varepsilon_t^P \\ \varepsilon_t^C \end{bmatrix} \tag{4.10}$$

Positive and significant β^{PC} would imply that past changes of CDS-implied hazard rate predict future changes of put-implied hazard rate. Similar regressions are run separately for y and θ.

4.4 Cross-Market Divergence and Reversion

In this section, we examine the divergence between DOOMs and CDSs implied URC documented in Carr and Wu (2010). We calculate the implied hazard rates λ from DOOMs and CDSs. Equation (4.8) suggests that the discrepancy between λ^P and λ^C could be due to the divergence between the two credit components y^P and y^C or between the two residual components θ^P and θ^C. Thus, we consider three divergence measures, D^λ, D^y, and D^θ, as defined below:

$$D^\lambda = \lambda^P - \lambda^C \tag{4.11}$$

$$D^y = y^P - y^C \tag{4.12}$$

$$D^\theta = \theta^P - \theta^C \tag{4.13}$$

Unlike Hu et al., we keep the sign of the residual (θ) in this chapter, as the sign provides location information (above or below the fitted values). The additional information can prevent erroneous comparison in cross-market analysis.[3]

[3]For example, a firm has the following information: $\lambda^P = 0.05$, $y^P = 0.03$, and $\theta^P = 0.02$, while $\lambda^C = 0.01$, $y^C = 0.03$, and $\theta^C = -0.02$. Then $D^\theta = 0.04$ if their signs of residuals are included, but $D^\theta = 0$ if the signs are dropped, which is wrong.

4.4.1 Divergence Determinants

In theory, DOOMs should reflect only pure default risk and the pricing of DOOMs is irrelevant to the underlying stock process. In practice, DOOMs, however, might still contain information about option pricing. Therefore, we choose several candidate factors that are related to option pricing to explain why the pricing of DOOMs is different from the pricing of CDSs. Specifically, the average URC-implied hazard rate ($(\lambda^P + \lambda^C)/2$) reflects the average credit quality in the option and CDS markets; option moneyness ($|Delta|$ and $\ln(K/S)$) is also likely to explain why DOOMs are different from CDSs; option-implied volatility (IV_P) reflects investors' expectation regarding underlying stock process; and option open interest (OI) reflects the demand in the option market. Significant results suggest that the pricing of DOOMs contains other information as well as default risk. We test for any systematic discrepancies between the two markets by estimating the following contemporaneous pooled panel regressions:

$$D_{it} = \beta_0 + \beta_1 X_{it} + e_{it} \tag{4.14}$$

where D_{it} is one of the three divergence measures (D^{λ}_{it}, D^{y}_{it}, or D^{θ}_{it}) for firm i at time t, and X_{it} are the corresponding explanatory factors. As some of the factors mentioned above capture similar information, we include one factor at a time as suggested by Carr and Wu (2010).

4.4.2 Reversion Tests

In theory, λ^P and λ^C should be the same, and any discrepancies between them should vanish eventually. However, since market-specific factors might have caused the deviation between λ^P and λ^C, D^{λ} might be persistent and the theoretical convergence might never occur. Similarly, the convergence between y^P and y^C, and between θ^P and θ^C, might be prevented by the structural difference between the two markets. To empirically test whether the convergence in y and θ does occur, we include the estimated residuals (e_{it}) from Equation (4.14) as explanatory variables for future changes in y and θ.

For the credit components, a pooled panel regression specification is

$$\Delta y^P_{it+\Delta t} = \beta^P_0 + \beta^P_1 e^y_t + \eta_t \tag{4.15}$$

$$\Delta y^C_{it+\Delta t} = \beta^C_0 + \beta^C_1 e^y_t + \zeta_t \tag{4.16}$$

and a similar regression is run for the illiquidity component, θ. A negative β^P_1 and a positive β^C_1 would suggest a reduction in differences between components over time, after controlling the market-specific factors in Equation (4.14).

Finally, we relate the potential convergence in the implied hazard rates to the residuals from the regressions of the credit and illiquidity components:

$$\Delta \lambda^P_{it+\Delta t} = \beta^P_0 + \beta^P_1 e^y_t + \beta^P_2 e^\theta_t + \eta_t \tag{4.17}$$

$$\Delta \lambda^C_{it+\Delta t} = \beta^C_0 + \beta^C_1 e^y_t + \beta^C_2 e^\theta_t + \zeta_t \tag{4.18}$$

Again, a negative β^P_1 (β^P_2) and a positive β^C_1 (β^C_2) would suggest a convergence in λ over time.[4]

4.4.3 Long-Short Portfolio Performance

If λ^P and λ^C converge over time, the prices of DOOMs and CDSs should move conversely. Then one could trade at time t on the signal of the λs, taking a long position in the security with a lower λ and a short position in the security (written on the same firm) with a higher λ. The positions are to be unwound after the two λs have converged at time T. The return on this strategy is given as

$$r = \mu^{Long} - \mu^{Short}, \tag{4.19}$$

$$\mu = \frac{\log Price_T - \log Price_t}{T - t} \tag{4.20}$$

[4]See Carr and Wu (2010) for details of convergence in λ.

where $Price$ is the traded price of the instrument of interest. Here, we simplify the strategy by fixing $(T-t)$ to be 7 and 30 days.

We construct three strategies based on our previous discussions and compare their performance. The first strategy (*Benchmark* strategy, hereafter) is to trade according to D^{λ}. If D^{λ} is positive, we long CDSs and short puts as we expect $D^{\lambda} \to 0$ over time. Since $D^{\lambda} = D^{y} + D^{\theta}$, the strength of the convergence in λ is weakened if D^{y} and D^{θ} have different signs and move in different directions. Therefore, we construct a stricter strategy (*Decomposition* strategy, hereafter) to include both y and θ information. We trade on the D^{λ} only when D^{y} and D^{θ} have the same sign. We expect the additional information to enhance the prediction in the convergence in λ. The last, and the most stringent, strategy (*Past Change* strategy, hereafter) is constructed based on the past changes in y_t and θ_t. We make use of the loadings in the VAR regression to predict the time-series innovation in y and θ in (4.10). For example, if β^{CC} (ie. the loading on Δy^{C}) is negative, and Δy_t^{C} is positive, we expect y_{t+1}^{C} to decrease since Δy_{t+1}^{C} is expected to be negative. We therefore check the past change of the components in addition to the contemporaneous information regarding D^{λ}, D^{y}, and D^{θ}. The "Past Change" strategy, again, is expected to enhance the precision of the λ convergence prediction.

Here we provide a "Benchmark" example to present how our proposed trading strategies are carried out. If one observes positive D^{λ}, he should expect the DOOM put price will decrease and the CDS price will increase in the future, given the expectation that λ^{P} and λ^{C} will converge to the same value. Therefore, he should short the put and buy the CDS at the same time and unwind the positions when the convergence happens. Since we do not know exactly when the convergence will happen, we simply fix the trading period for 7 or 30 days as we expect the convergence will happen in a short time. The convergence can disappear if market conditions change during the proposed trading period, and the portfolio may start to lose money if the positions are not unwound. Advanced methodology such as a dynamic trading strategy may be used in order to achieve a higher return; however, such implementation makes it difficult to compare the performance among trading strategies if the holding periods are different for every trade.

Since put option and CDS prices are not in a linear relation, we compute the hedge ratio for put options and CDSs for the long-short strategy. From Equations (4.3) and (4.6) (i.e. $URC^C = URC^P$), the price of a put option and the CDS spread for the same underlying firm are linked by the following relation:

$$P = K\zeta k \frac{1 - e^{-(r+\zeta k)\tau^C}}{r + \zeta k} \tag{4.21}$$

where P is the put option price, k is the CDS spread, and τ^C is the time to maturity of the CDS. Differentiating the put option price with respect to the CDS spread, we obtain the following hedge ratio:

$$\begin{aligned}\frac{dP}{dk} =& K\zeta \frac{1 - e^{-(r+\zeta k)\tau^C}}{r + \zeta k} \\ &+ K\zeta^2 \tau^C k \frac{1 - e^{-(r+\zeta k)\tau^C}}{r + \zeta k} \\ &- K\zeta^2 k \frac{1 - e^{-(r+\zeta k)\tau^C}}{(r + \zeta k)^2} \\ =& K \left[k^{-1} + \zeta\tau^C - \zeta(r + \zeta k)^{-1}\right] URC^C. \end{aligned} \tag{4.22}$$

In constructing the portfolio, we long (short) a CDS, while we simultaneously short (long) dP/dk units of put options.

In implementing this trading strategy, we make several additional assumptions. We assume put options and CDSs are traded at the quoted prices with zero transaction cost. The securities are perfectly divisible and there are no trading limits. Since we consider short trading periods ($(T - t)$ are 7 and 30 days), we exclude CDS accruals, and assume that the premium needs to be paid in full, not in quarterly installments. That is, CDS buyers (sellers) pay (receive) the annual CDS spread at the time of a transaction.

4.5 Data

We use CDS information from the Markit database, and put option information from OptionMetrices. We describe in detail these two sources of data below.

4.5.1 Markit Sample

The Markit database provides daily information on CDS quotes with maturities from 6 months to 30 years. For each CDS contract, our Markit database contains the daily truncated mean of CDS spreads reported by various contributors, underlying debt seniority and the associated recovery rates. Because there are insufficient CDS quotes for earlier years, we select CDS data points from May 2002 to May 2012.

CDS spreads for the same firm may have different quoted prices due to the contract tier and the payback priority of the underlying bond. For example, secured debt has a higher priority in the payback order than subordinate debt. Table 4.1 summarizes the CDS tier distribution in our Markit database. Our sample consists of 1.4 million CDS tier-entity contracts, 89% of which are associated with senior unsecured debt (SNRFOR). Hence, we choose only the CDS quotes with SNRFOR in our sample. In addition, since long-maturity CDSs are very illiquid, we do not use CDSs with a maturity longer than 10 years.

Figure 4.1 plots the number of CDS contracts for firms with different ratings. BBB-rated firms are the most popular, whereas AAA-rated firms are the least popular. AA-rated firms are also under-represented in the sample, which is consistent with lower demand for credit protection for high-quality firms. Interestingly, CDSs on CCC-rated firms are also rarely traded. Such a result is rather expected because firms that are very likely to default would require nearly 100% of the principal to protect the default risk.

Table 4.2 reports the summary statistics for our sample. From Table 4.2, a 5-year CDS contract, which are the most liquid in the CDS market, has 1.1 million data points whereas a 4-year CDS contract has just 0.74 million data points. The largest

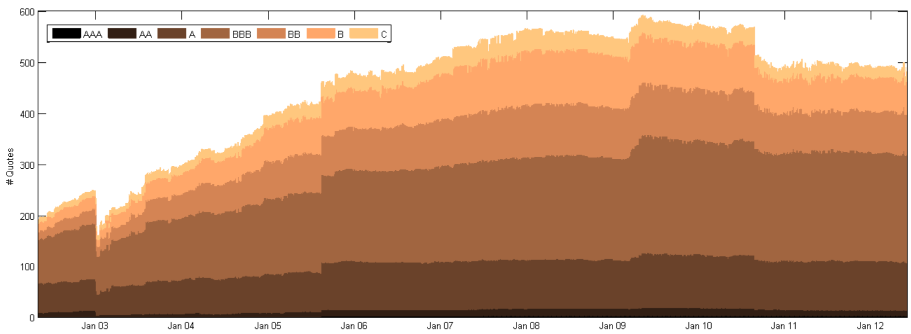
Table 4.1: Summary of CDS Tiers

This table reports the number of CDS contracts according to tiers in our Markit database over the period from January 2001 to May 2012. We count only once if CDS quotes with different maturities belong to the same entity and tier each day. The contract tiers are presented in the order of seniority. JRSUBUT2 stands for junior subordinated debt, SUBLT2 stands for subordinated debt, SNRFOR stands for senior unsecured debt, SECDOM stands for secured debt, and PREFT1 stands for preference shares.

Tier	Count	%
JRSUBUT2	150	0.01%
SUBLT2	93,851	6.79%
SNRFOR	1,232,356	89.13%
SECDOM	56,229	4.07%
PREFT1	4	$< 0.01\%$
Total	1,382,590	

Figure 4.1: Distribution of CDS Quotes

This figure plots the number of CDS quotes in our Markit database based on the credit ratings of the underlying. The sample period is from May 2002 to May 2012.



CDS spread of 47,216 bp belongs to a particular 6-month contract.[5] A 6-month CDS contract has the smallest average spread of 181.12 bp, whereas a 10-year CDS has the largest average spread of 249.83 bp. The average recovery rate is 39.22%.

[5]If a company is almost certain to default immediately, the CDS spreads may be more than 10,000 bp due to the annualization of the CDS spreads. For more details see Hull, Predescu, and White (2004), footnote 11, p. 2794.

Table 4.2: Summary Statistics for CDSs and DOOMs

This table reports the descriptive statistics for CDS spread and DOOM put option prices in our sample. The sample period is from May 2002 to May 2012. The statistics reported are sample mean, standard deviation (Std), and maximum and minimum values. The table also reports the data missing rate and the number of observations (#Obs). "Recovery" stands for recovery rate.

	CDS Spread (in Basis Point)									Put	
	6m	1y	2y	3y	4y	5y	7y	10y	Recovery (%)	Bid ($)	Ask ($)
Mean	181.12	189.91	203.53	216.49	250.28	243.97	245.60	249.83	39.22	0.28	0.43
Std	862.31	770.14	674.46	621.83	632.27	559.85	553.08	528.97	4.02	0.31	0.36
Max	47,216.26	40,175.46	38,116.27	36,934.43	33,497.83	27,913.98	24,503.77	23,791.63	75.50	3.40	5.00
Min	0.58	0.81	0.79	1.28	1.45	1.00	3.27	4.34	1.25	0.01	0.05
Miss Rate	0.39	0.18	0.20	0.14	0.39	0.09	0.15	0.16	0.01	0.92	0.92
#Obs	743,961	989,061	969,224	1,037,031	739,021	1,106,054	1,022,364	1,013,555	1,202,489	98,250	98,250

4.5.2 OptionMetrics Sample

OptionMetrics provides historical prices and implied volatility for U.S. equity and index options markets. It contains bid and ask prices as well as implied volatilities and option Greeks. We follow Carr and Wu (2010) to filter the put option data. To be included in the sample, the put options must satisfy the following conditions: (i) the bid price is greater than zero, (ii) the open interest is greater than zero, (iii) the time to maturity is greater than 6 months and less than 10 years, (iv) the strike price is \$5 or less, (v) the absolute value of the put's delta is not larger than 15%, (vi) the open interest is the highest if multiple put options on the same underlying are available. [6]

Figure 4.2 plots the histogram for put maturities. The near-month contracts are rather popular in the option market. The 6-month contract is the most common, whereas there are very few options with maturities that are longer than two years. There are no put options with maturity longer than three years, but the most popular CDS contract is one with a 5-year tenor.

We use the aforementioned steps to select out-of-money (-15% delta and below) put options from OptionMetrics and match them to CDS contracts from Markit. For each firm-date we pick a single-pair put-CDS with the nearest matching maturity. Figure 4.3 reports the difference in time to maturity. The majority of the mismatches in time to maturity are less than a year.

The last two columns of Table 4.2 report the descriptive statistics of DOOM put options in our sample. The average bid and ask prices are 0.28 and 0.43 respectively with standard deviations of 0.31 and 0.36 respectively.

[6] Theoretically, if the strike prices of the put options are located within the default corridor, the put prices are linear in the strike price, viz. $P(K_1)/K_1 = P(K_2)/K_2 = ...P(K_n)/K_n$, if $K_1, K_2, ..., K_N \in [A, B]$. Otherwise, the put will act like a general option. However, we do not have sufficient information about the exact range of the default corridor because the number of DOOM put strikes is finite and few. Therefore, the combined criteria of low delta and low strike are to help to identify the DOOMs that act like a CDS. Carr and Wu (2010) show that put options with delta between -15% and 0% is a reasonable guess. However, these DOOMs still contain other information as well as default risk.

Figure 4.2: DOOM Time-to-maturity Histogram

This figure plots the histogram of times to maturity for DOOM (deep out-of-money) put options in our sample. The sample period is from May 2002 to May 2012.

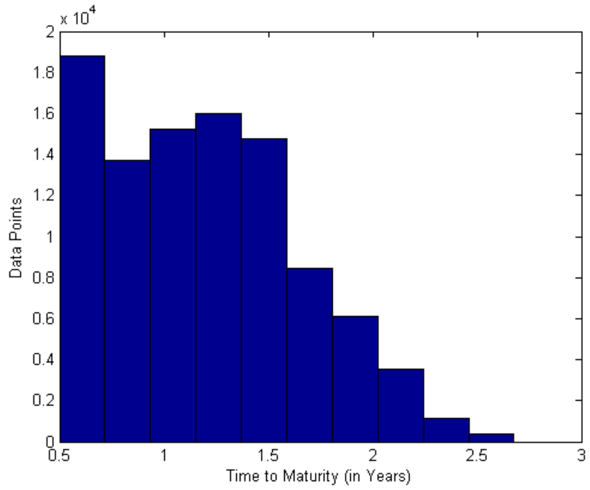
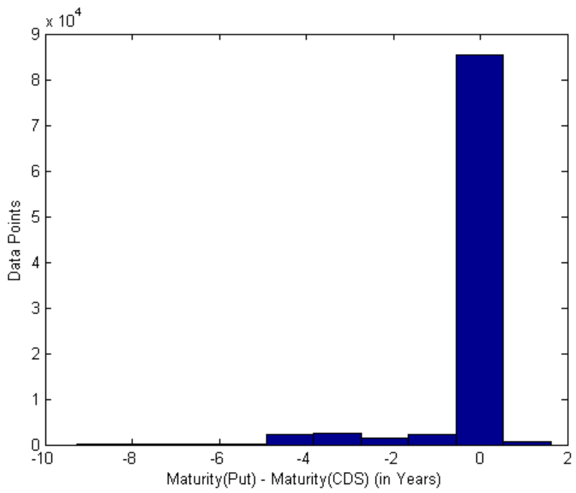


Figure 4.3: DOOM-CDS Mismatches in Time to Maturity

This figure plots the histogram of mismatches in times to maturity between DOOM put options and CDS spreads. The sample period is from May 2002 to May 2012.



4.6 Empirical Results

In this section, we first provide general analysis on the decomposed components obtained from fitting the Nelson-Siegel model, then report the test results for their divergence, reversion, and information spillover. Finally, we discuss the performance of the long-short trading strategies.

4.6.1 Credit Curves Analysis

Figure 4.4 presents the examples of credit curves for CDSs and DOOMs on May 17, 2004 and December 12, 2008. The implied hazard rates are also plotted in the same graph. First of all, we note that the CDS credit curves, in general, show apparent "layers". In addition, the term structures of the CDS credit curves are rather flat. The hazard rate for DOOMs (λ^P) is calculated by using the put option mid-prices. The credit curves for DOOMs are rather different from those for CDSs. Although DOOM credit curves also have "layers", they have more complicated term structures. During the calm period in May 2004, the short maturity credit component is higher than that for the long maturity. This pattern is the same for all rating classes and the difference (or term spread) is larger for the lower-quality rating classes. In December 2008, the term structures of the credit components have very different shapes for the different rating classes: for CCC it is steeply upward sloping, for B it is hump-shaped, and for BBB it is downward sloping. This suggests the credit component of a put option can be very volatile and possibly has more scope for arbitrage if any deviation will converge over time. In short, the term structures of the DOOM-implied hazard rates seem to reflect investors' expectations in different times to maturity. But their expectations also vary over time, according to the corresponding put market conditions.

Figure 4.4: Credit Curve Examples

This figure presents examples of the credit curves for CDSs and put options.

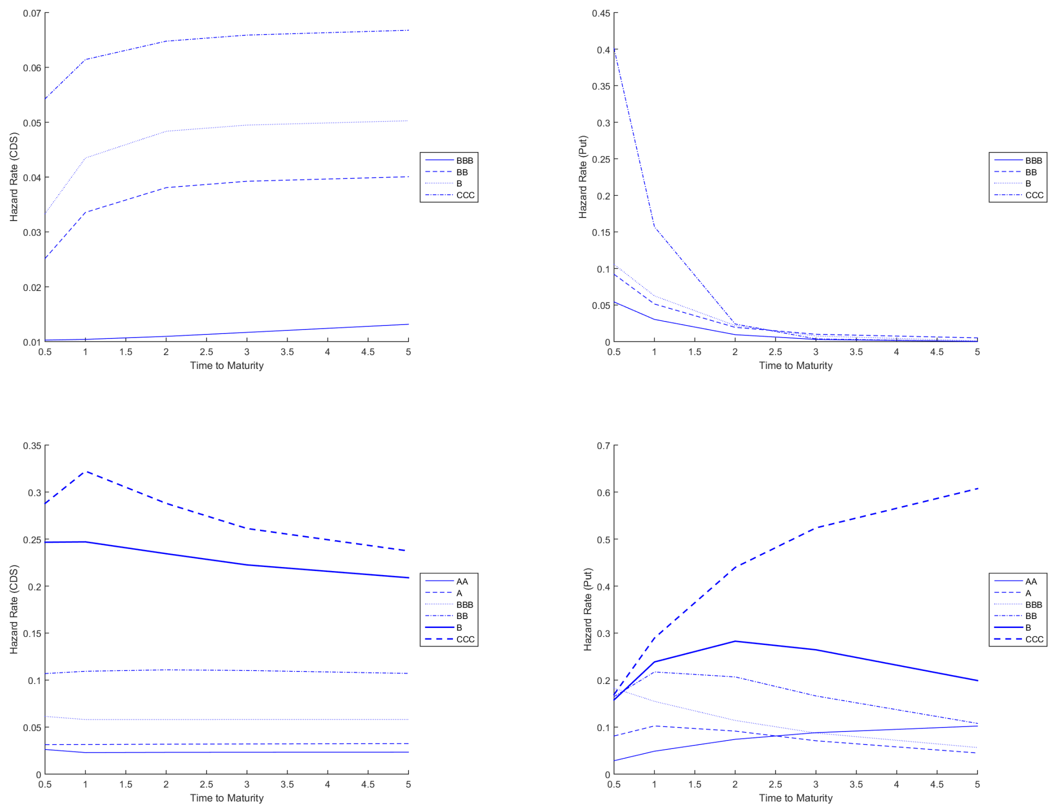


Table 4.3: Descriptive Statistics of λ, y, and θ

This table reports the descriptive statistics for default intensity, λ, credit curve fitted component, y, and residual noise, θ. The superscript indicates whether the value is extracted from CDSs, C, or put options, P. The credit curve fit is performed using the Nelson-Siegel model. The sample period is from May 2002 to May 2012. The statistics reported are sample mean, standard deviation (Std), and maximum and minimum values.

	λ^C	y^C	θ^C	λ^P	y^P	θ^P
Mean	.0720	.0576	.0144	.0945	.0952	-.0007
Std	.0964	.0581	.0919	.0978	.0703	.0670
Max	1.4905	.5982	1.3148	1.8973	1.6667	.9923
Min	.0002	.0011	-.4069	.0043	.0046	-.6508

Table 4.3 reports the descriptive statistics for λ, y, and θ, implied by CDS and DOOM respectively. The credit component y^C reflects the majority part of λ^C. However, y^C has less variation (with a standard deviation of 0.06) than θ^C (with a standard deviation of 0.09), suggesting that y^C is slightly more stable than θ^C. We observe a similar relationship for λ^P, y^P, and θ^P.

Christoffersen, Goyenko, Jacobs, and Karoui (2014) study the illiquidity premiums in put options. They argue that some liquidity indicators, such as dollar-quoted bid-ask spreads, are not a good alternative, since they are mainly driven by the maturity and the level of the moneyness. Here, we test whether the information content of the liquidity component (θ^P) is driven by time to maturity.

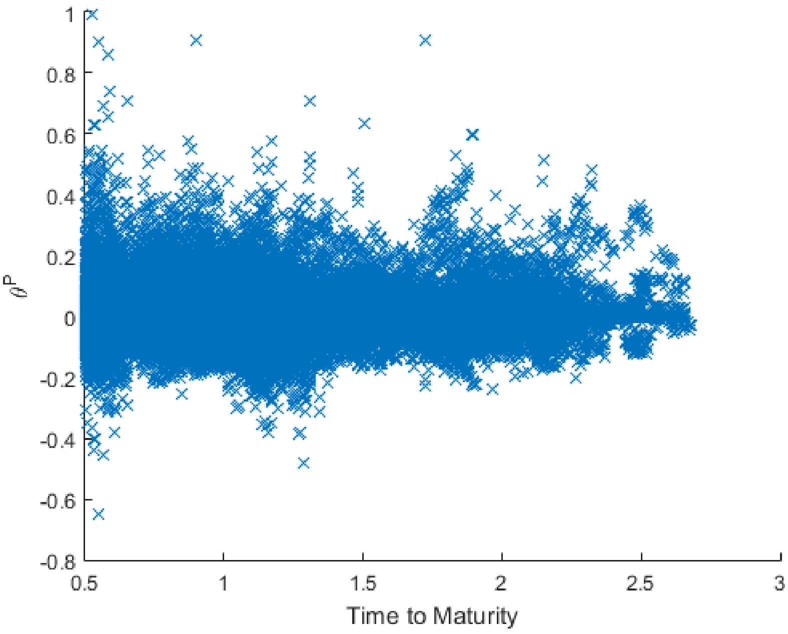
Figure 4.5 plots the scatter plot for the θ^P and its corresponding time to maturity. The figure shows that there is a random relationship between the level of illiquidity and time to maturity. In addition, the correlation coefficient between θ^P and maturity is just 1.95%. The general analysis suggests that our put-implied illiquidity component is irrelevant to time to maturity.

4.6.2 Determinants for Divergence

Table 4.4 reports the regression results for the DOOM-CDS divergence measures (Equation (4.14)). The results reported here refer to univariate regressions. Panels A, B and C report the results for D^λ, D^y, and D^θ, respectively, where the decompo-

Figure 4.5: DOOM Illiquidity and Maturity

This figure presents the scatter plot for the put-implied illiquidity components (θ^P) and their corresponding time to maturity.



sition, $\lambda = y + \theta$, is based on the Nelson-Siegel model. The results reported in the three panels show consistently that D^λ, D^y, and D^θ are all significantly related to the factors suggested in Carr and Wu (2010). The R-squares for D^λ (in Panel A) are similar to those reported in Carr and Wu (2010). Furthermore, we find that these factors capture better divergence in D^y compared with D^θ, since the R-squares in general are higher for D^y (in Panel B) than for D^θ (in Panel C).

In three cases, the Carr-Wu factors have a different impact on D^y compared with D^θ. The average hazard rate $(\lambda^P + \lambda^C)/2$, option-implied volatility, IV_P, and option open interest, OI, have a positive impact on D^y but a negative impact on D^θ. The average hazard rate is a measure of credit quality. As the credit quality worsens, the credit component of a put option is higher than that of a CDS. But the CDS has a greater illiquidity component than the put option. As CDSs are often traded on the Over-the-Counter market and put options are traded on the exchange market, one would expect CDS illiquidity might be more sensitive to credit quality. On the other hand, being exchange traded, put options might reflect the credit quality more accurately. The implied volatility of the put options is derived directly from the put option prices and it indirectly reflects firm risk. If we equate firm risk with credit quality then the aforementioned explanations continue to apply here. The negative impact of OI on D^{θ} is to be expected since a greater open interest reflects a greater trading activity and that would bring down the put option illiquidity component. One possible explanation for the positive impact on D^{y} is the increase in hedge demand for put options. In such a scenario, the put option OI rises, and the put option price increases due to the stronger demand. At the same time, if the put is used to hedge CDS credit risk, the credit risk of the CDS drops due to the hedging effect. As a result, y^{P} increases and y^{C} decreases, leading to larger D^{y}. Despite the different signs for β in Panel B and Panel C, the net impact on D^{λ} and the signs for β^{λ} are the same as those reported in Carr and Wu (2010). As Carr and Wu concluded, put options might have more credit information than CDS spreads.

4.6.3 Reversion Tests

In this section, we analyze whether the divergence between the DOOMs and CDSs will be reversed eventually. First, we examine the credit and illiquidity components individually. Then, we look at how the implied hazard rates (and hence the prices of the securities) of the two markets converge.

Table 4.5 and 4.6 report the results for the reversion tests in Equations (4.15) and (4.16) for the credit and illiquidity components separately using 7-day and 30-day horizons. Table 4.7 reports the results for the reversion tests in Equations (4.17) and (4.18) for the implied hazard rates for the 7-day and 30-day horizons. In all three tables, all the $\beta^{P,y}$ and $\beta^{P,\theta}$ coefficients are negative, and all the $\beta^{C,y}$ and $\beta^{C,\theta}$ coefficients are positive. All the regression coefficients are statistically significant for both time horizons. Given the definitions of divergence in Equations (4.11), (4.12), and (4.13), this means that, after controlling for the permanent difference due to the factors identified in (4.14), a positive error will decrease future values derived from puts and increase future values derived from CDSs, and vice versa for a negative error term. In other words, we expect reversion in the credit and illiquidity components as well as the implied hazard rates. Carr and Wu (2010) show that

Table 4.4: Factor Analysis of DOOM and CDS Divergence

This table reports the estimation results for the determinants of DOOM-CDS divergence. The sample period is from May 2002 to May 2012. λ is the URC-implied hazard rate, which is decomposed into credit (y) and illiquidity (θ) components based on the Nelson-Siegel model. Superscript C stands for CDS and P stands for DOOM put. $|Delta|$, K, IV_P, and OI are, respectively, moneyness, strike, implied volatility, and open interest of the DOOM put.

Panel A: Hazard Rate

	$D^{\lambda} = \lambda^P - \lambda^C$				
	β^{λ}	t-stat	p-value	R-sqr	R-adj
$(\lambda^P + \lambda^C)/2$	-.1131	-34.8646	.0000	.1828	.1544
$\|Delta\|$	.4923	74.3910	.0000	.2282	.2013
$\ln(K/S)$	.0430	70.0431	.0000	.2219	.1948
IV_P	.0206	15.6724	.0000	.1719	.1431
OI	.0000	2.0310	.0423	.1691	.1402

Panel B: Credit Component

	$D^{y} = y^P - y^C$				
	β^{y}	t-stat	p-value	R-sqr	R-adj
$(\lambda^P + \lambda^C)/2$	.1296	63.3848	.0000	.3968	.3758
$\|Delta\|$	.1458	33.3057	.0000	.3729	.3511
$\ln(K/S)$	.0121	29.9219	.0000	.3711	.3492
IV_P	.0558	68.1547	.0000	.4017	.3809
OI	.0000	18.2496	.0000	.3662	.3441

Panel C: Illiquidity Component

	$D^{\theta} = \theta^P - \theta^C$				
	β^{θ}	t-stat	p-value	R-sqr	R-adj
$(\lambda^P + \lambda^C)/2$	-.2430	-70.7898	.0000	.1453	.1155
$\|Delta\|$	.3428	46.6631	.0000	.1127	.0819
$\ln(K/S)$	.0304	44.7285	.0000	.1106	.0797
IV_P	-.0357	-25.0966	.0000	.0939	.0624
OI	-.0000	-9.2535	.0000	.0871	.0553

the URC-implied hazard rates in the DOOM and CDS markets converge in sample period from February 2, 2005 to August 27, 2008. Our findings confirm this result using data from May 2002 to May 2012. Furthermore, we provide evidence that convergence happens in both credit and illiquidity components of the two markets as well. The magnitudes of the regression coefficients and R-square are all very similar, suggesting that both credit and illiquidity components play an equally important role in the convergence of λ^P and λ^C, and hence URC^P and URC^C.

Table 4.5: Reversion of the Credit Components (y)

This table reports the reversion results for the credit component of URCs (unit recover claims) implied by CDS spreads and DOOM put option prices, after controlling for the permanent difference due to option-related factors. The sample period is from May 2002 to May 2012. λ is the URC-implied hazard rate, y and θ are the credit and residual components of the URC-implied hazard rate. The components are extracted by the Nelson-Siegel model. Superscript C stands for CDS and P stands for DOOM put. $|Delta|$, K, IV_P, and OI are, respectively, moneyness, strike, implied volatility, and open interest of the DOOM put.

Panel A: 7-day Prediction

	Put					CDS				
	$\beta^{P,y}$	t-stat	p-value	R-sqr	R-adj	$\beta^{C,y}$	t-stat	p-value	R-sqr	R-adj
$e_{(\lambda^P+\lambda^C)/2}$	-.3043	-35.5295	.0000	.0638	.0638	.0588	14.4389	.0000	.0111	.0111
$e_{\|Delta\|}$	-.2882	-37.1056	.0000	.0692	.0691	.0566	15.2991	.0000	.0125	.0124
$e_{\ln(K/S)}$	-.2924	-36.6997	.0000	.0678	.0677	.0579	15.2581	.0000	.0124	.0124
e_{IV_P}	-.3038	-35.5497	.0000	.0639	.0638	.0623	15.3437	.0000	.0126	.0125
e_{OI}	-.2660	-32.3435	.0000	.0535	.0534	.0531	13.6326	.0000	.0099	.0099

Panel B: 30-day Prediction

	Put					CDS				
	$\beta^{P,y}$	t-stat	p-value	R-sqr	R-adj	$\beta^{C,y}$	t-stat	p-value	R-sqr	R-adj
$e_{(\lambda^P+\lambda^C)/2}$	-.4412	-30.6525	.0000	.0483	.0482	.0923	12.1097	.0000	.0079	.0078
$e_{\|Delta\|}$	-.4452	-34.2152	.0000	.0595	.0594	.0706	10.1775	.0000	.0056	.0055
$e_{\ln(K/S)}$	-.4534	-33.9781	.0000	.0587	.0586	.0616	8.6597	.0000	.0040	.0040
e_{IV_P}	-.4614	-32.2043	.0000	.0530	.0530	.0853	11.2116	.0000	.0067	.0067
e_{OI}	-.4005	-29.0679	.0000	.0436	.0436	.0635	8.7129	.0000	.0041	.0040

Table 4.6: Reversion of the Illiquidity Components (θ)

This table reports the reversion results for the illiquidity component of URCs (unit recover claims) implied by CDS spreads and DOOM put option prices, after controlling for the permanent difference due to option-related factors. The sample period is from May 2002 to May 2012. λ is the URC-implied hazard rate, y and θ are the credit and residual components of the URC-implied hazard rate. The components are extracted by the Nelson-Siegel model. Superscript C stands for CDS and P stands for DOOM put. $|Delta|$, K, IV_P, and OI are, respectively, moneyness, strike, implied volatility, and open interest of the DOOM put.

Panel A: 7-day Prediction

	Put					CDS				
	$\beta^{P,\theta}$	t-stat	p-value	R-sqr	R-adj	$\beta^{C,\theta}$	t-stat	p-value	R-sqr	R-adj
$e_{(\lambda^P+\lambda^C)/2}$	-.2892	-36.1622	.0000	.0660	.0659	.0463	7.2510	.0000	.0028	.0028
$e_{\|Delta\|}$	-.2309	-31.1654	.0000	.0498	.0498	.1104	18.9850	.0000	.0191	.0190
$e_{\ln(K/S)}$	-.2368	-32.3141	.0000	.0534	.0533	.0946	16.3774	.0000	.0143	.0142
e_{IV_P}	-.2246	-31.1936	.0000	.0499	.0499	.0901	15.8982	.0000	.0135	.0134
e_{OI}	-.2446	-33.2378	.0000	.0563	.0562	.0753	12.9394	.0000	.0090	.0089

Panel B: 30-day Prediction

	Put					CDS				
	$\beta^{P,\theta}$	t-stat	p-value	R-sqr	R-adj	$\beta^{C,\theta}$	t-stat	p-value	R-sqr	R-adj
$e_{(\lambda^P+\lambda^C)/2}$	-.4134	-32.8699	.0000	.0551	.0551	.1374	11.6701	.0000	.0073	.0072
$e_{\|Delta\|}$	-.3363	-28.9361	.0000	.0433	.0432	.2075	19.3126	.0000	.0197	.0197
$e_{\ln(K/S)}$	-.3480	-30.2719	.0000	.0471	.0471	.1940	18.2033	.0000	.0176	.0175
e_{IV_P}	-.3313	-29.3458	.0000	.0444	.0444	.1851	17.6928	.0000	.0166	.0166
e_{OI}	-.3633	-31.4907	.0000	.0508	.0508	.1494	13.8834	.0000	.0103	.0102

Table 4.7: Reversion of the Hazard Rates (λ)

This table reports the reversion results for the hazard rates implied by CDS spreads and DOOM put option prices, after controlling for the permanent difference due to option-related factors. The sample period is from May 2002 to May 2012. λ is the URC-implied hazard rate, y and θ are the credit and residual components of the URC-implied hazard rate. The components are extracted by the Nelson-Siegel model. Superscript C stands for CDS and P stands for DOOM put. $|Delta|$, K, IV_P, and OI are, respectively, moneyness, strike, implied volatility, and open interest of the DOOM put.

Panel A: 7-day Prediction

	Put						CDS					
	$\beta^{P,y}$	p-value	$\beta^{P,\theta}$	p-value	R-sqr	R-adj	$\beta^{C,y}$	p-value	$\beta^{P,\theta}$	p-value	R-sqr	R-adj
$e_{(\lambda^P+\lambda^C)/2}$	-.2341	.0000	-.2708	.0000	.0377	.0376	.0710	.0000	.0558	.0000	.0034	.0033
$e_{\vert Delta\vert}$	-.2090	.0000	-.2178	.0000	.0345	.0343	.1168	.0000	.1385	.0000	.0244	.0243
$e_{\ln(K/S)}$	-.2048	.0000	-.2146	.0000	.0337	.0336	.1045	.0000	.1189	.0000	.0184	.0183
e_{IV_P}	-.1375	.0000	-.1707	.0000	.0219	.0218	.0929	.0000	.1123	.0000	.0171	.0170
e_{OI}	-.2106	.0000	-.2135	.0000	.0392	.0391	.0737	.0000	.0911	.0000	.0122	.0121

Panel B: 30-day Prediction

	Put						CDS					
	$\beta^{P,y}$	p-value	$\beta^{P,\theta}$	p-value	R-sqr	R-adj	$\beta^{C,y}$	p-value	$\beta^{P,\theta}$	p-value	R-sqr	R-adj
$e_{(\lambda^P+\lambda^C)/2}$	-.3449	.0000	-.3805	.0000	.0239	.0238	.1933	.0000	.1811	.0000	.0087	.0086
$e_{\vert Delta\vert}$	-.3285	.0000	-.2859	.0000	.0207	.0206	.1757	.0000	.2370	.0000	.0194	.0193
$e_{\ln(K/S)}$	-.3252	.0000	-.2815	.0000	.0202	.0201	.1778	.0000	.2361	.0000	.0196	.0195
e_{IV_P}	-.2266	.0000	-.2210	.0000	.0121	.0120	.1829	.0000	.2367	.0000	.0209	.0208
e_{OI}	-.3046	.0000	-.2899	.0000	.0238	.0237	.1542	.0000	.1971	.0000	.0156	.0155

4.6.4 Information Spillover Tests

In this section, we report the results for the VAR regressions in Equation (4.10) on the information spillover between the put option and CDS markets. We use the first differences of the variables to prevent serial correlation from influencing the results. We include firm and time dummies to control for cross-sectional and time effects. Table 4.8 reports the VAR result for the 7-day change whereas Table 4.9 reports the VAR result for the 30-day change. Panel A reports the result for the URC-implied hazard rates (λ), panel B reports the result for the credit component (y), and panel C reports the result for the illiquidity component (θ).

First note that for both Tables 4.8 and 4.9 and all the panels in the tables, the regression coefficients for the lagged values of the dependent variables are all negative and strongly statistically significant at 7-day and 30-day intervals. This suggests that all variables are stationary and mean reverting. A first difference might have been over differencing, resulting in a negative coefficient with the lagged value.

In contrast, the coefficients for the lagged value of the complimentary variables (e.g. $\Delta\lambda^C_{t-1}$ for $\Delta\lambda^P_t$ and Δy^P_{t-1} for Δy^C_t) are much smaller and positive (with the exception of Δy^P and Δy^C in the 7-day horizon tests). Overall, there is *weak* evidence that there is information spillover between the two markets, with the put option market marginally leading the CDS market on credit changes, while the CDS market marginally leads the put option market on changes in illiquidity.

4.6.5 Long-Short Portfolio Performance

Based on the DOOM and CDS divergence and convergence behavior observed in the previous sections, here we test the profitability of three long-short portfolio trading strategies with a 7-day holding period. The three strategies are named "Benchmark", "Decomposition", and "Past Change", in increasing order of stringency of trading signals. For the "Benchmark" strategy, each day we simply long the security

Table 4.8: 7-day Information Spillover Test

This table reports the VAR results for the information spillover between the CDS and put option markets over a 7-day horizon. The sample period is from May 2002 to May 2012. λ is the URC-implied hazard rate. y and θ are, respectively, the credit and illiquidity components using the Nelson-Siegel model. Superscript C stands for CDS, and P stands for DOOM put.

Panel A: Hazard Rate

	$\Delta\lambda^C$			$\Delta\lambda^P$		
	Coef.	t-stat	p-value	Coef.	t-stat	p-value
Const.	0.00	0.16	0.88	-0.01	-0.21	0.83
$\Delta\lambda^C$ (Lag1)	-0.16	-26.20	0.00	0.08	8.13	0.00
$\Delta\lambda^P$ (Lag1)	0.01	2.82	0.00	-0.31	-55.01	0.00
Firm Dummy	Yes			Yes		
Time Dummy	Yes			Yes		
R-square	0.15			0.30		
R-adjust	0.10			0.26		

Panel B: Credit Component

	Δy^C			Δy^P		
	Coef.	t-stat	p-value	Coef.	t-stat	p-value
Const.	0.00	0.14	0.89	-0.01	-0.85	0.40
Δy^C (Lag1)	-0.15	-25.68	0.00	-0.01	-0.63	0.53
Δy^P (Lag1)	-0.01	-3.76	0.00	-0.34	-59.11	0.00
Firm Dummy	Yes			Yes		
Time Dummy	Yes			Yes		
R-square	0.33			0.38		
R-adjust	0.29			0.35		

Panel C: Liquidity Component

	$\Delta\theta^C$			$\Delta\theta^P$		
	Coef.	t-stat	p-value	Coef.	t-stat	p-value
Const.	0.00	0.06	0.95	0.01	0.33	0.74
$\Delta\theta^C$ (Lag1)	-0.15	-25.06	0.00	0.03	3.07	0.00
$\Delta\theta^P$ (Lag1)	0.00	0.77	0.44	-0.32	-58.48	0.00
Firm Dummy	Yes			Yes		
Time Dummy	Yes			Yes		
R-square	0.10			0.17		
R-adjust	0.05			0.12		

Table 4.9: 30-day Information Spillover Test

This table reports the VAR results for the information spillover between the CDS and put option markets over a 30-day horizon. The sample period is from May 2002 to May 2012. λ is the URC-implied hazard rate. y and θ are, respectively, the credit and illiquidity components using the Nelson-Siegel model. Superscript C stands for CDS, and P stands for DOOM put.

Panel A: Hazard Rate

	$\Delta\lambda^C$			$\Delta\lambda^P$		
	Coef.	t-stat	p-value	Coef.	t-stat	p-value
Const.	-0.01	-0.28	0.78	0.00	0.00	1.00
$\Delta\lambda^C$ (Lag1)	-0.20	-12.24	0.00	0.10	4.92	0.00
$\Delta\lambda^P$ (Lag1)	0.04	3.03	0.00	-0.27	-16.19	0.00
Firm Dummy	Yes			Yes		
Time Dummy	Yes			Yes		
R-square	0.22			0.39		
R-adjust	0.13			0.32		

Panel B: Credit Component

	Δy^C			Δy^P		
	Coef.	t-stat	p-value	Coef.	t-stat	p-value
Const.	0.01	0.73	0.47	0.00	0.19	0.85
Δy^C (Lag1)	-0.15	-8.74	0.00	0.00	0.09	0.93
Δy^P (Lag1)	0.04	5.32	0.00	-0.35	-22.88	0.00
Firm Dummy	Yes			Yes		
Time Dummy	Yes			Yes		
R-square	0.46			0.53		
R-adjust	0.39			0.48		

Panel C: Liquidity Component

	$\Delta\theta^C$			$\Delta\theta^P$		
	Coef.	t-stat	p-value	Coef.	t-stat	p-value
Const.	-0.02	-0.52	0.61	-0.01	-0.22	0.82
$\Delta\theta^C$ (Lag1)	-0.20	-12.51	0.00	0.06	3.51	0.00
$\Delta\theta^P$ (Lag1)	0.04	2.71	0.01	-0.29	-18.68	0.00
Firm Dummy	Yes			Yes		
Time Dummy	Yes			Yes		
R-square	0.15			0.21		
R-adjust	0.05			0.12		

(one CDS or delta amount of put) with the lower implied λ and short the matching security with the higher implied λ. The long-short portfolio is automatically unwound after 7 days.

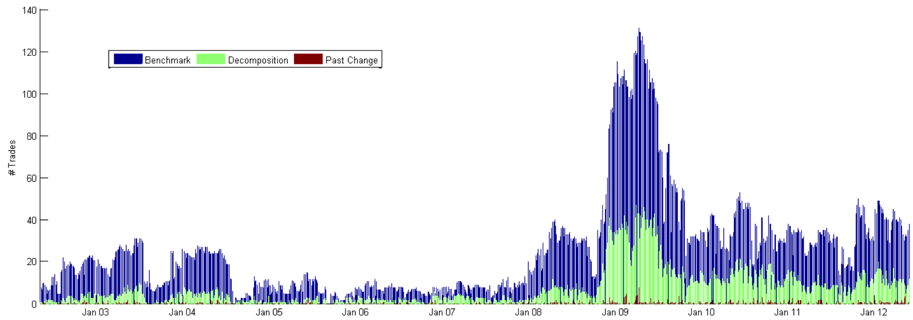
For the "Decomposition" strategy, we perform the same trade as for "Benchmark", but only if D^y and D^θ have the same sign. The argument is that if D^y and D^θ are of different signs, there is a conflict in the prediction of price movement direction. The "Past Change" strategy is even more stringent than the "Decomposition" strategy. Since we notice a weak evidence of information spillover between the two markets, we would long the CDS and short the put option if and only if $\Delta y_t^C < 0$ and $\Delta\theta_t^C < 0$, and Δy_t^P and $\Delta\theta_t^P > 0$; vice versa for the portfolio with a short position in the CDS and a long position in the put option.[7]

For each trading strategy, we report the performance in Table 4.10 for the full and two sub-sample periods. We also report the full period results separately for junk-grade and investment-grade underlying. Although the long-short position is supposed to be delta neutral, the portfolio returns still have large standard deviations. To account for the portfolio risks, we also report the Sharpe ratio (i.e. return in excess of the risk-free interest rate and divided by the standard deviation of the trades, $\frac{r-r_f}{\sigma}$) in Table 4.11 and the Carhart four-factor alpha in Table 4.12. The reported mean return is calculated based on a 7-day trading period. Although the horizon for convergence may be different, all trades are performed within a fixed holding period. Therefore we can compare the returns for these trades. The reported mean returns are on a daily basis. Since the convergence between DOOMs and CDSs is likely to occur within a short time (Angelopoulos, Giamouridis, and Nikolakakis 2013), the actual return may be much deteriorated for a longer holding period. In addition, in the 30-day holding period, the reported daily returns are smaller than in the 7-day holding period. (The outperformance drops from 1.81% to 0.08% for the 30-day holding period.) Given that the average daily return is decreased dramatically for the longer holding period, the actual outperformance for the 1-year holding period will be much smaller than 200%. Therefore, in order not

[7]The results for the 30-day holding period are qualitatively the same. Details are available on request.

Figure 4.6: Number of Trades

This figure plots the daily number of trades for the three trading strategies ("Benchmark", "Decomposition", and "Past Change"). The sample period is from May 2002 to May 2012.



to exaggerate the outperformance, it is reasonable to report the returns on a daily basis.

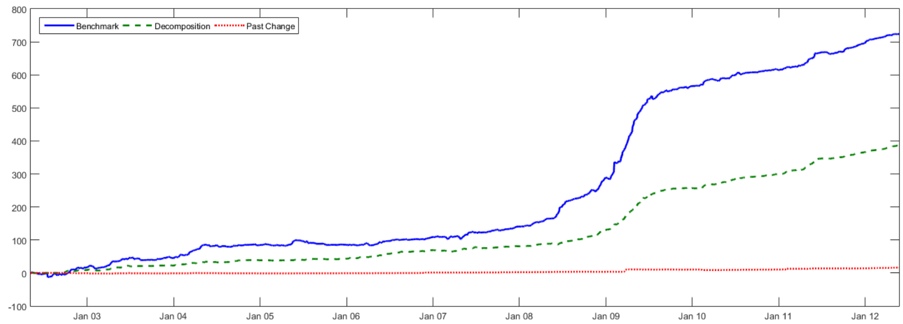
The total numbers of trades are 35,984 for "Benchmark", 10,125 for "Decomposition", and 327 for "Past Change" over 1,434 available days from May 2002 to May 2012. Figure 4.6 provides the daily number of trades for the three strategies. There was a significant increase in the number of trades since 2008, and the number of trades peaked in 2009, highlighting the impact of the financial crisis on these two markets and the divergence between DOOM put and CDS prices. Overall, the number of trades for the "Benchmark" strategy is a lot of higher than for the other two strategies, with an average of 25 trades per day. In contrast, the number of trades for "Past Change" is the fewest, with an average of just 0.7 trades per day.

Figure 4.7 plots the cumulative total return for the three strategies over time. All three cumulative total returns increase steadily over time and experience a steep increase in 2009, reflecting the increase in the number of trades noted above. The cumulative profit of the three strategies generally reflects the number of trades under each strategy. The "Benchmark" strategy is the most profitable, possibly due to the sheer volume of trades.

Tables 4.10, 4.11, and 4.12 show generally that all three strategies are profitable but most of the profit and trades were derived in the second half of the sample period after 2007. There are more trades associated with the junk grade, but the

Figure 4.7: Cumulative Total Return

This figure plots the cumulative returns for the three trading strategies ("Benchmark", "Decomposition", and "Past Change"). The sample period is from May 2002 to May 2012.



trades associated with the investment grade are generally more profitable. While the "Benchmark" strategy produced the largest amount of total profit due to a much larger amount of transactions, it is not as good as the other strategies in terms of the Sharpe ratio (reported in Table 4.11) and Carhart four-factor alpha (reported in Table 4.12). The "Decomposition" strategy beats the "Past Change" strategy based on the Sharpe ratio and Carhart alpha, but with the exception of investment-grade trading. For investment-grade trading, "Past Change" outperformed the other two strategies. Assuming that the round-trip transaction costs are 17 bp and 12 bp for put options and CDSs respectively, it is most likely that our trading strategies will remain profitable after taking the transaction costs into consideration. The mid-price is used in the three implemented strategies. The round-trip transaction cost of 17 bp is estimated according to general option trading. The cost is underestimated for the DOOM case. [8]

4.7 Conclusion

In this chapter, we study the divergence and reversion of the hazard rates implied from DOOM (deep out-of-the-money) put prices and CDS (credit default swap) spreads. Using the Nelson-Siegel model, we decompose the implied hazard rate into

[8]The transaction cost information for put options and CDSs can be referred to Li and Abdullah (2012) and Biswas, Nikolova, and Stahel (2015).

Table 4.10: Long-Short Portfolio Return

This table reports the sample statistics for the returns (in percent) on the three long-short portfolios. In our trading strategies, all trades are performed within a fixed holding period. The mean return is reported for a 7-day trading period. The sample period is from May 2002 to May 2012. The three portfolio strategies are [1] Benchmark strategy, [2] Decomposition strategy, and [3] Past Change strategy.

Panel A: All Samples

		t-test				F-test	
	[1]	[2]	[3]	[1]-[2]	[1]-[3]	[1]-[2]	[1]-[3]
Mean	2.01	3.83	4.99	-1.81	-2.98	1.74	-13.34
Std	25.63	23.89	38.97				
t-stat/F-stat	14.88	16.11	2.32	-6.38	-2.08	1.15	0.43
p-val	0.00	0.00	0.02	0.00	0.04	0.00	0.00
# of Trades	35,984	10,125	327				

Panel B: Before 2006

		t-test				F-test	
	[1]	[2]	[3]	[1]-[2]	[1]-[3]	[1]-[2]	[1]-[3]
Mean	1.37	4.68	2.06	-3.30	-0.69	-1.72	-0.03
Std	27.24	28.96	27.27				
t-stat/F-stat	4.48	6.21	0.66	-4.24	-0.22	0.88	1.00
p-val	0.00	0.00	0.51	0.00	0.82	0.00	0.95
# of Trades	7,915	1,478	77				

Panel C: After 2007

		t-test				F-test	
	[1]	[2]	[3]	[1]-[2]	[1]-[3]	[1]-[2]	[1]-[3]
Mean	2.19	3.68	5.89	-1.49	-3.70	2.25	-16.77
Std	25.16	22.91	41.93				
t-stat/F-stat	14.59	14.94	2.22	-4.91	-2.30	1.21	0.36
p-val	0.00	0.00	0.03	0.00	0.02	0.00	0.00
# of Trades	28,069	8,647	250				

Panel D: Junk Grade

		t-test				F-test	
	[1]	[2]	[3]	[1]-[2]	[1]-[3]	[1]-[2]	[1]-[3]
Mean	1.89	2.94	5.11	-1.06	-3.22	3.34	-18.88
Std	27.46	24.12	46.34				
t-stat/F-stat	10.36	10.07	1.63	-2.86	-1.71	1.30	0.35
p-val	0.00	0.00	0.11	0.00	0.09	0.00	0.00
# of Trades	22,724	6,804	218				

Panel E: Investment Grade

		t-test				F-test	
	[1]	[2]	[3]	[1]-[2]	[1]-[3]	[1]-[2]	[1]-[3]
Mean	2.22	5.63	4.75	-3.41	-2.53	-1.17	5.76
Std	22.14	23.30	16.38				
t-stat/F-stat	11.56	13.93	3.03	-7.85	-1.19	0.90	1.83
p-val	0.00	0.00	0.00	0.00	0.23	0.00	0.00
# of Trades	13,260	3,321	109				

Table 4.11: Long-Short Portfolio Sharpe Ratio

This table reports the sample statistics for the Sharpe ratio on the three long-short portfolios. In our trading strategies, all trades are performed with fixed holding period. The mean return is reported for a 7-day trading period. The sample period is from May 2002 to May 2012. The three portfolio strategies are [1] Benchmark strategy, [2] Decomposition strategy, and [3] Past Change strategy.

Panel A: All Samples

	[1]	[2]	[3]	[1]-[2]	[1]-[3]
Mean	0.08	0.16	0.13	-0.08	-0.05
t-stat	14.88	16.11	2.32	-7.26	-0.89
p-val	0.00	0.00	0.02	0.00	0.37

Panel B: Before 2006

	[1]	[2]	[3]	[1]-[2]	[1]-[3]
Mean	0.05	0.16	0.08	-0.11	-0.03
t-stat	4.48	6.21	0.66	-3.92	-0.22
p-val	0.00	0.00	0.51	0.00	0.82

Panel C: After 2007

	[1]	[2]	[3]	[1]-[2]	[1]-[3]
Mean	0.09	0.16	0.14	-0.07	-0.05
t-stat	14.59	14.94	2.22	-5.98	-0.84
p-val	0.00	0.00	0.03	0.00	0.40

Panel D: Junk Grade

	[1]	[2]	[3]	[1]-[2]	[1]-[3]
Mean	0.07	0.12	0.11	-0.05	-0.04
t-stat	10.36	10.07	1.63	-3.85	-0.61
p-val	0.00	0.00	0.11	0.00	0.54

Panel E: Investment Grade

	[1]	[2]	[3]	[1]-[2]	[1]-[3]
Mean	0.10	0.24	0.29	-0.14	-0.19
t-stat	11.56	13.93	3.03	-7.28	-1.97
p-val	0.00	0.00	0.00	0.00	0.05

Table 4.12: Long-Short Portfolio Carhart Four-Factor Alpha

This table reports the Carhart four-factor alpha (in percent) for the three long-short portfolios. The sample period is from May 2002 to May 2012. We use the Carhart four-factor model to control the market conditions, and then report the constant term. The three portfolio strategies are [1] Benchmark strategy, [2] Decomposition strategy, and [3] Past Change strategy.

Panel A: All Samples

	α	t-stat	p-value
[1]	1.47	4.32	0.00
[2]	3.59	4.58	0.00
[3]	3.75	1.63	0.10

Panel B: Before 2006

	α	t-stat	p-value
[1]	0.69	0.86	0.39
[2]	2.23	1.21	0.23
[3]	-8.08	-1.36	0.18

Panel C: After 2007

	α	t-stat	p-value
[1]	1.79	5.54	0.00
[2]	3.81	4.86	0.00
[3]	5.21	2.04	0.04

Panel D: Junk Grade

	α	t-stat	p-value
[1]	1.47	3.48	0.00
[2]	2.58	2.61	0.01
[3]	5.07	1.14	0.26

Panel E: Investment Grade

	α	t-stat	p-value
[1]	2.04	3.90	0.00
[2]	7.15	6.35	0.00
[3]	4.79	2.05	0.04

the rating-class related fitted credit component and the residual illiquidity component.

The results of the VAR (vector autoregression) tests indicate that the hazard rates and all sub components are stationary over time, with the same spillover relationship in both markets. However, there is weak evidence to indicate that the DOOM put option market seems to react faster to credit deterioration whereas the CDS market is quicker in reacting to liquidity deterioration.

Similar to Carr and Wu (2010), we find the average hazard rate, option moneyness, delta, implied volatility, and option open interest drive the difference between the price structures of the two markets. In addition, we find the same set of factors can also explain the difference in the illiquidity components and the difference in the credit components of the two markets. Carr and Wu (2010) show that, after controlling for these structural factors, the residual is related to the future implied hazard rate and hence can be used to predict future price changes. Again, we find the residual can also be used to predict how the subcomponents will move.

To exploit the divergence and reversion behavior in the two markets, we test three trading strategies with increasingly stringent trading conditions. The first strategy, "Benchmark", simply trades on the divergence of implied hazard rates. The second strategy, "Decomposition", adds an extra condition, by requiring both subcomponents to be over- or under-valued in the same direction. The third strategy, "Past Change", which is also the toughest, takes the previous values and spillover pattern into consideration. We find all three strategies produce positive returns. While the Carr-Wu hazard rate-driven "Benchmark" strategy produced the highest total return due to the much larger number of trades, our more refined strategies outperformed "Benchmark" when evaluated based on the Sharpe ratio and Carhart four-factor alpha. In terms of mean return, the "Decomposition" strategy outperformed "Benchmark" by 1.06–3.41%, while the "Past Change" strategy outperformed "Benchmark" by 0.69–3.70%. Given that the round-trip transactions are 17 bp and 12 bp for put options and CDSs respectively, it is most likely that our trading strategies will remain profitable after taking transaction costs into consideration.

Chapter 5

Conclusion

In this thesis, I conducted three studies in hedge fund and CDS research. The first study investigates the predictability of hedge fund flow on bond yields. I find fund flows predict the movement of bond yields in the next month. In addition, the outflow prediction is rather pronounced for large funds with a short notice period prior to redemption.

The second study investigates the systematic and firm-specific credit and liquidity risks in CDS spreads. I find that the systematic risks are as important as the firm-specific risks. In particular, I documented a pronounced systematic liquidity risk impact in CDS spreads since 2007. This finding supports several previous studies, in which the authors find individual liquidity risk has a (greater) explanatory power for the changes in CDS spreads. In addition, I find an asymmetric association between stock-based Amihud illiquidity and CDS spread: CDS spread increases when the underlying stock becomes illiquid but not vice versa. This new evidence extends the findings in Das and Hanouna (2009). Overall, the evidence of systematic liquidity risks in CDS spreads challenges the current Basel III procedures for counterparty credit risk regulations. Since there is a significant proportion of liquidity risk in the individual CDS spreads on top of the credit risk, the capital charge for counterparty credit risk that is based on CDS spread will be overestimated. More importantly, my proposed model can be used to provide CDS proxy for firms that do not have traded CDSs.

The last study extends Carr and Wu (2010), who establish a theoretical linkage between DOOM (deep out-of-the-money) put options and CDSs. I use the Nelson and Siegel (1987) model to obtain the credit and illiquidity components for DOOMs and CDSs, and investigate the association between these four components (credit and illiquidity components for DOOMs and for CDSs). I find that the difference between DOOM and CDS credit components can be explained by option-related factors, but the difference vanishes over time, after controlling for these factors. I find similar results for the DOOM and CDS illiquidity components as well, but the explanatory power is weak.

To exploit the convergence pattern, I test a trading strategy by longing a security (DOOM or CDS) with a low hazard rate and, at the same time, shorting the other. I find such a simple trading strategy generates a positive average return. I then further consider two other more stringent strategies based on component information. The two refined strategies outperform the benchmark strategies by the Sharpe ratio and Carhart alpha.

My three studies enrich the relevant literature on hedge funds and on CDSs. As a suggestion for future research, one may explore the flow impact on other financial markets, such as commodity or emerging markets. Hedge funds have started to hold large positions in these markets and their holdings might have an impact on these markets. Another suggestion is that one may study the deviation between DOOMs and CDSs due to CDS-related factors.

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