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The Risk Components of Credit Spreads

par

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Sommaire

L'objectif de ce mémoire est d'examiner l'importance relative des risques de liquidité et de défaut sur les écarts de crédits. Nous concentrons notre analyse sur le marché interbancaire Américain et présentons une étude empirique sur l'écart TED ainsi que sur les écarts de crédit des banques du panel USD LIBOR. Nous mesurons le risque de liquidité grâce à l'écart des taux entres les bons du trésor Américain 10 ans appartenant à la plus récente émission et ceux appartenant aux six précédentes émissions. Le risque de défaut est représenté par les primes de risque sur les dérivés sur événement de crédit. Nos résultats montrent que les deux facteurs de risque: liquidité et défaut sont des composantes significatives des écarts de crédit. De surcroît, l'importance du risque de liquidité est dynamique et dépend du niveau de liquidité dans le marché. De plus nous remarquons la présence d'une relation négative entre les écarts de crédit et les primes sur les dérivés sur événements de crédit entre 2004 et 2007. Enfin, la pertinence de la relation entre les écarts de crédit et leurs facteurs de risque dépend de la période de temps sélectionnée.

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Abstract

This paper studies the relative importance of liquidity and default risk in understanding the dynamic behaviour of credit spreads. In particular, I analyse the interbank market by using the TED spread and the credit spread of the USD LIBOR PANEL banks. I measure liquidity risk with on-the-run off-the-run yield spreads and Credit default swap premiums are used to represent default risk. Findings show that both liquidity and default risks are significant components of credit spreads. Furthermore, the importance of liquidity risk is not static, but depends on the level of liquidity risk in the market. In addition, a negative relationship is present between CDS premiums and credit spreads between 2004 and 2007. Lastly, the relationship between credit spreads and the components of credit risk may be distorted by the time period selection used for analysis.

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1 Introduction

During the 2008 global financial crisis, credit spreads increased, surpassing previously recorded highs. The interbank market came to a standstill.[1] The question of which factors were responsible for these drastic changes became a matter of utmost concern to policymakers, central banks, and financial institutions. In principle, multiple explanations can be offered. On the one hand, the spike in credit spreads could be attributed to liquidity risk, which has two forms, market liquidity risk, the inability to rapidly exchange a security near its market price, and firm specific liquidity risk, the lack of access to short-term funding. On the other hand, default risk i.e. the possibility that interest and/or capital will not be repaid, could be the cause of the credit spread dynamics. I verify the relative importance of these two risk factors on the credit spreads of the principle banks within the US dollar interbank market and the TED spread.[2]

The analysis of the dynamic behaviour of credit spreads received considerable attention in the financial literature. While initially researchers neglected the role of liquidity risk in the fluctuations of credit spreads, more recent works have jointly modelled liquidity and default risk. The usual finding in this stream is that default risk is the most important determinant of credit spreads. However, these papers analyse stable time periods in financial markets, and use simple liquidity risk proxies and econometric specifications.

The present paper proposes a new methodology to study the role of liquidity and default risk for credit spreads, using an innovative measure of liquidity risk, that can identify both forms of liquidity risk more robustly and explicitly consider financial crises explicitly. I study a data set that includes a financial crisis, since many financial practitioners believe that liquidity risk is present only during periods of high market volatility.

[1]Interbank spreads are the differences between rates of inter-bank loans and lower risk government security of the same maturity.

[2]See Glossary in Section 9.6 for a detailed description of the various spreads and key variables.

To investigate the credit environment of the interbank market, the TED spread and the credit spreads of the USD LIBOR panel banks are analysed. Given that LIBOR is the one of the primary reference rates in the interbank market, the banks that provide quotes for these rates, namely the USD LIBOR panel banks, are selected for this analysis. I quantify liquidity risk with the maturity adjusted spread between on-the-run and off-the-run treasury notes. This allows comparison of securities with the same default risk to provide a measure of liquidity risk. Default risk is calculated using credit default swap premiums.

I perform a time series analysis of the dynamic behaviour of credit spreads to uncover the role of liquidity and default risks. I consider three alternative econometric models: OLS, regime-switching, and autoregressive moving average models, which are tested on a data set that includes the most recent financial crisis. The OLS model is selected because it is the most commonly used in previous works. The regime-switching model allows one to test if the level of liquidity risk in the market affects the relevant importance of the components of credit risk. Lastly, ARMA models are estimated because they can model the data better.

Understanding the dynamic behaviour credit spreads can be beneficial to market finance, corporate finance, and central banking participants. First, fixed-income products are heavily traded by various types of investors and a better understanding of the relationships between yield spreads and the various components of risk can help investors make more informed decisions. For instance, improvements can be made in forecasting, pricing, and hedging of portfolios containing fixed-income products when quantifiable measures of default and liquidity risk are available.

Second, management's decisions are affected by changes in credit spreads caused by factors such as debt issuance, balance sheet composition, and high-risk project undertaking. For instance, the sign of the relationship between credit spreads and default risk lead a firm to the change the default probability on its debt by altering working capital and liquidity ratios. At the same time, if a positive relationship between credit spreads and liquidity risk is present, firms could lower their cost of capital by strategically issuing debt during low liquidity risk environments.

Finally, the relative contribution of the different components of credit risk would allow for more informed policy interventions. For instance, if liquidity risk is responsible for spikes in credit spreads, central bankers could inject liquidity through the use of quantitative easing. If large increases in credit spreads are due to default risk, central bankers could decrease the default risk within the interbank market by insuring the banking industry's obligations.

The findings of this paper are: first both default and liquidity risk are components of credit spreads. Second, the relative importance of liquidity risk increases during periods of financial crisis. Third, the relationship between the default and liquidity risk and credit spreads can be distorted due to the selection of the range and time frame of the data. Fourth, a puzzling negative relationship is present between CDS premiums and credit spreads between 2004 and 2007. Lastly, a discrepancy exists between the relative importance of the default and liquidity risk. While the credit spreads of the USD LIBOR panel banks are more strongly related to default risk, the interbank spread, the TED, is influenced to a greater extent by liquidity risk.

The remainder of the article is organized as follows. Section 2 reviews the literature. Section 3 provides the information on the data set and the key variables used in the analysis. Section 4 presents both the methodology and results of the TED spread analysis. Section 5 includes both the methodology and results of the US LIBOR panel bank credit spreads. Section 6 describes and reports the estimated GARCH models. Section 7 provides a brief conclusion. Section 8 is the acknowledgments section. Lastly, Section 9 contains the appendices.

2 Literature Review

The separation of risk premia on bonds into default and liquidity was introduced by Fisher (1959). However, academic research on liquidity risk was not on the forefront until recently, due to the popularity of measuring default risk with a contingent claim model theorized by Merton (1974). Within these types of analyses, liquidity risk is assumed to be null and default risk is the only factor responsible for credit spread fluctuations. This leads to what researchers have called the credit puzzle, where models that focus solely on default risk underestimate credit spreads. Hence, including a liquidity risk factor might help correct this shortcoming. Another reason for the lesser amount of research on liquidity risk is due to the difficulty in its quantification. This is a direct result of the unobservable nature of liquidity.

The reintroduction of liquidity as a research topic within the academic literature began after the seminal work of Amihud and Mendelson (1986), who demonstrated that illiquidity demands a premium. Moreover, the collapse of Long-Term Capital Management due to their inability to correctly manage liquidity risk, exhibited by Edwards (1999), increased the necessity and attractiveness of research on liquidity risk.

Various measures for liquidity risk have been suggested within academic literature. One widely accepted measure of security-specific liquidity is the bid-ask spread. Also, Roll (1984) created a measure that replicates the percentage bid-ask spread when the data are readily available. Furthermore, proxies such as frequency of trades and volatility of bond prices have been suggested by Shulman (1993). In addition, Amihud (2002) suggests a liquidity risk measure that is constructed using a ratio of return to volume price data.

Regarding credit spreads, Amihud and Mendelson (1991) finds that fixed-income securities also price liquidity and Amihud (2002) obtains that liquidity is time varying. Furthermore, several studies have been conducted on the relationship between credit spreads and liquidity risk. For instance, Bao, Pan, and Wang (2011) create bond-specific and aggregate measures of liquidity risk that follow random processes. They argue that liquidity risk explains a substantial proportion of credit spreads. In addition, Chen, Lesmond, and Wei (2007) find that a positive relationship between bond-specific liquidity risk measures and credit spreads. Similarly, de Jong and Driessen (2006) note a positive and significant relationship between bond returns and both treasury and equity market illiquidity.

Studies have also sought to verify if market sector, time period and credit quality are factors that influence the importance of liquidity risk within credit spreads. For instance, Friewald, Jankowitsch, and Subrahmanyam (2008) test various liquidity risk measures on a large set of bonds while controlling for credit risk with credit ratings during the subprime crisis. Their findings show that liquidity risk is a significant indicator of credit spreads, and that the level of liquidity risk depends on the bond's market sector and credit rating of the bond. Further, they conclude that the lower the credit quality of the bond the higher its exposure to liquidity risk. Acharya, Amihud, and Bharath (2010) use a Markov regime switching model to determine that the importance of liquidity risk in the measuring of credit spreads depends on macroeconomic and financial market conditions. Furthermore, they affirm the flight to quality phenomenon by showing that junk bond returns decrease during a liquidity shock, while investment grade bonds increase during a liquidity shock. Lastly, the Dick-Nielsen, Feldhutter, and Lando (2012) create a new measure of bond-specific liquidity risk based on four previously suggested proxies, and find a positive relationship between illiquidity and credit spreads. The paper also asserts that the importance of liquidity risk increased during the most recent financial crisis, and that AAA-rated bonds have an inverse relationship with illiquidity during the financial crisis. This can also be attributed to the flight to quality phenomenon.

As can be seen from the extensive research mentioned above, liquidity risk is significantly related to credit spreads, and its importance increases during periods of financial turbulence. However, these studies do not attempt to verify if liquidity or default risk explains a greater proportion of credit spreads. I attempt to answer this question in light of recent research that has displayed conflicting results on the relative importance of liquidity and default in the modelling of credit spreads. For Instance, recent studies like (Longstaff, Mithal, and Neis 2005) and (Covitz and Downing 2007) have shown default risk explaining the majority of spread fluctuations. Longstaff, Mithal, and Neis (2005) use CDS premiums to model default risk and find that after removing it from credit spreads, the remainder of the bond spread can be attributed to liquidity risk. Covitz and Downing (2007) conduct an empirical analysis on credit spreads of commercial paper and find that liquidity risk is a relevant factor, but contrary to the general belief that liquidity risk is the prevalent factor in short-term credit spreads, default risk is more explanatory even for such short-term instruments. On the other hand, (Schwarz 2010) finds that liquidity risk is the more prevalent factor by constructing a new measure of systematic liquidity risk using the spread between German government bonds and Kreditanstalt fur Wiederaufbau agency bonds. One possible explanation for these conflicting conclusions is that the time series are selected from different periods. Schwarz (2010) uses data from January 2007 to April 2008, which includes the financial crisis. On the other hand, Longstaff, Mithal, and Neis (2005) use March 2001 to October 2002, which is a much more stable period. To alleviate this problem, I analyse a time series that spans from January 2004 to October 2010, which includes both a stable period and financial crisis.

In this paper, I build an aggregate liquidity risk proxy based on the yield spreads between off-the-run and on-the-run treasury securities. I do so becasue various studies have shown that on-the-run treasury notes and bonds are more liquid than their off-the-run counterparts. For example, Krishnamurthy (2002) compares the on-the-run 30-year treasury bond yield with the yield of the nearest off-the-run 30-year treasury bond. He finds that the on-the-run bonds have lower yields, and explains that this difference by the higher liquidity of the on-the-run bond. Goldreich, Hanke, and Nath (2005) conduct similar research, but analyse 2-year treasury notes. They also find that the on-the-run notes are more liquid than the off-the-run counterparts. However, to reach this conclusion, they make simple adjustments to the yields of the off-the-run notes for maturity and coupon rate differences. Other studies like (Collin-Dufresne, Goldstein, and Martin 2001), use the on-the-run and off-the-run spreads of treasury notes and bonds as an indicator of liquidity risk.

To measure default risk, I follow Longstaff, Mithal, and Neis (2005) and use credit default swap premiums. I assume that the premiums less a risk-free yield are representative of the default risk of the underlying firm. This assumption is supported by Blanco, Brennan, and Marsh (2005), who demonstrates, using an arbitrage relationship, that CDS premiums adequately price credit risk. However, the recent study by Chen, Fabozzi, and Sverdlove (2010) illustrates that CDS premiums are also affected by liquidity risk. Therefore, the use of CDS premiums as proxies for credit risk suffers from the potential limitation of overestimating default risk. However, it is still common practice to proxy credit risk with CDS premiums, such as in (Schwarz 2010).

To investigate the credit spreads of the interbank market I conduct an in-depth analysis of the risk factors affecting the TED spread and the credit spread of the USD LIBOR panel banks. While such an analysis on the TED spread has yet to be conducted, previous studies have used the TED spread as an indicator of general market conditions. For example, Melvin and Taylor (2009) consider the TED spread to be a proxy for credit risk. Bianchi, Drew, and Wijeratne (2010) display the TED spread as a measure of systematic market risk used by hedge fund managers for implementing investment decisions. Lashgari (2000) assumes the TED spread to be a measure of investor confidence.

In contrast, I study which factors affect the dynamics of the TED spread. This is in line with papers such as (Schwarz 2010), (Nobili 2009), (Eisnschmidt and Tapking 2009), and (DeSocio 2009), which analyse the credit risk components of interbank spreads. One of the challenges of this type of analysis is measuring default risk, because there are no credit default swap contracts on

LIBOR. Although credit default swap contracts on financial institutions that provide quotes for LIBOR, i.e. the USD LIBOR panel banks, are available. Therefore, I assume that the average default risk of the USD LIBOR panel banks is representative of the default risk of the TED spread. This stems from the works of Nobili (2009) and DeSocio (2009), which use credit default swap premiums of the EURIBOR panel banks to measure the default risk of interbank spreads.

Lastly, in contrast with articles such as (Nobili 2009), (Eisnschmidt and Tapking 2009), (DeSocio 2009), and (Longstaff, Mithal, and Neis 2005) remove the default component of the credit spreads and assume that residuals are attributed to liquidity risk, I jointly model default and liquidity risk within credit spreads. This follows the work of Schwarz (2010) that creates a liquidity risk proxy and a default risk proxy to jointly test the significance of the various components.

3 Data Set and Key Variables

This section provides the data set used for the empirical analysis, the methodology for the construction of the on-the-run off-the-run liquidity risk proxy and credit spreads and the statistics and correlation matrices of the key variables.

3.1 Data

The data set for the analysis has a period range of daily frequencies from January 1, 2004 to September 30, 2010 and includes 1760 observations per series. The data includes CDS premiums, interest rates, corporate bond yields, and 10-year treasury note yields. All the data, except the 10-year treasury note yields, are obtained from Thomson Reuters Datastream. The credit default swap and corporate bond yield data include Bank of America, Credit Suisse, Deutsche Bank, HSBC, JP Morgan Chase, Lloyds, Rabobank, RBS, UBS, and HBOS. The credit default swaps are based on 5-year senior debt and the corporate bonds are fixed rate, non callable, US dollar denominated bonds with original maturities above 10 years issued between 1996 and 2002. The interest rates are the 3 month US LIBOR, 90-day US treasury bill yield and constant maturity treasury yields of 1, 3, and 6 month, and 1, 2, 3, 5, 7, 10, 20, 30 years. Finally, the Bloomberg terminal is used to acquire daily 10-year treasury note yields. The data set includes 34 different notes with varying maturities and coupon yields, as the 10-year treasury notes are auctioned on a quarterly basis.

3.2 Liquidity Risk Proxies

Many articles that estimate liquidity risk focus on security specific liquidity components. In contrast, I estimate an aggregate liquidity risk factor consistent with Schwarz (2010). Therefore, I construct measures based on the liquidity differences between on-the-run and off-the-run treasury securities. The on-the-run treasury note is the most recently auctioned note, whereas, off-the-run securities are all the previously issued notes with the same maturity as on-the-run at issuance. For this paper, the six most recent off-the-run treasury notes are used, because their maturities are somewhat near the on-the-run counterpart and there is a lower likelihood of stale prices/yields. The Appendix includes the various coupon rates, issuance and maturity dates of the on and off-the-run notes by time period, (*see Section 9.1).

The on-the-run security is more liquid, because it is more actively traded than off-the-run security. Also, treasury securities are considered to be default risk-free instruments due to the credit worthiness of the United States of America. This leads to the conclusion that the differences between yields among the various notes are due to liquidity risk.

3.2.1 Bid-Ask Spread

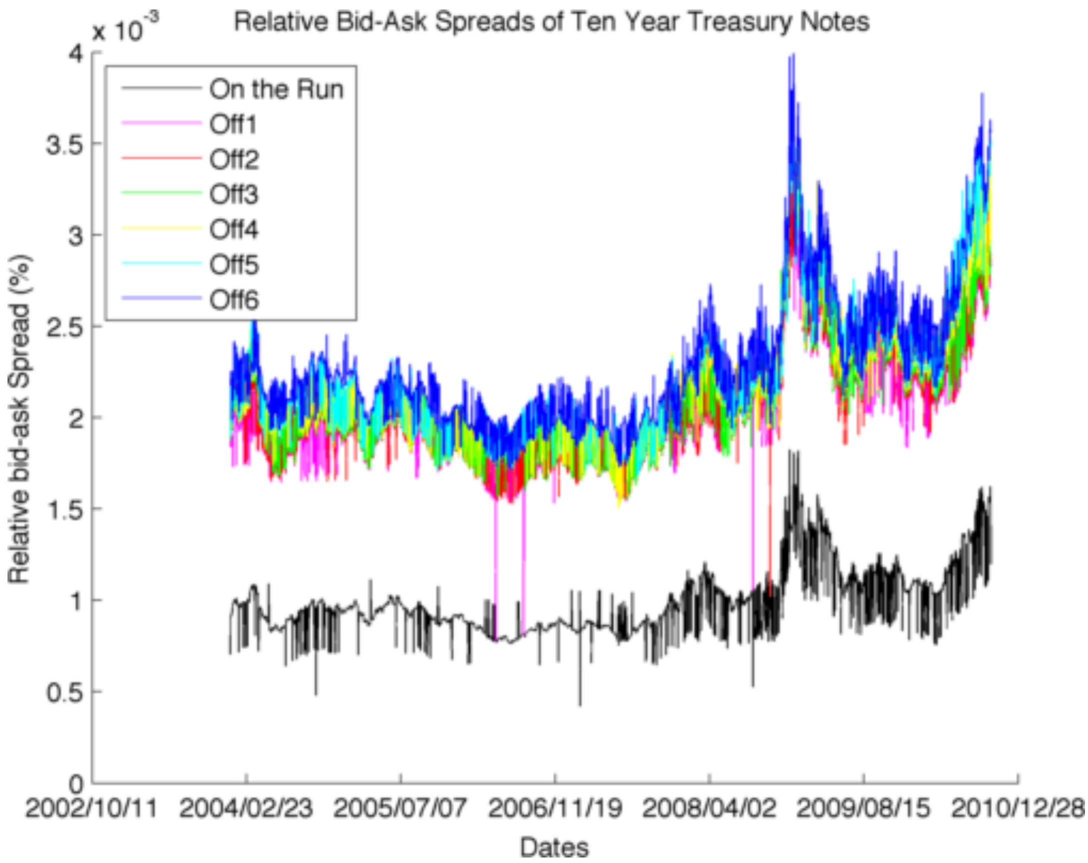
In this subsection, I demonstrate that the on-the-run notes are more liquid than their off-the-run counterparts. This is achieved through the comparison of the bid-ask spread of the on and off-the-run securities. In addition, I show that the liquidity risk of all the treasury notes are correlated, which provides evidence of market liquidity.

The bid-ask spread is widely considered to be a measure of liquidity. A narrow spread indicates a period of high liquidity, whereas a wide spread indicates a period of illiquidity. However, an adjustment must be made for the comparison of bid-ask spreads of varying securities and time frames. This is due to the size of the spread being relative to the price/yield level. For example, a 20 basis spread might be a tight spread for a yield near 8 percent, but is a wide spread for a 1 percent yield. To overcome this issue, I focus on the relative bid-ask yield spread, which is calculated as follows.

$$RBA_t = (bid\, yield_t - ask\, yield_t)/ask\, yield_t \tag{1}$$

The following figure plots the daily relative bid-ask spread of the on-the-run 10-year treasury note and the six most recent off-the-run 10-year treasury notes. The on-the-run security has a much lower relative bid-ask spread throughout the series, indicating that it is much more liquid than the off-the-run notes. A relationship between the liquidity of the notes and the length of time since issuance is also clearly visible. Hence, the older the note, the higher its relative bid-ask spread and illiquidity. Finally, the plot displays that liquidity of the varying notes are highly correlated. This supports the view that liquidity risk is systematic, but affects differing fixed income products by different amounts based on their individual liquidity risk profiles.

Figure 1: Daily Relative Bid-Ask Spreads: On and off-the-run Treasury Notes



This figure shows the daily relative bid-ask spread of the on-the-run security and the six off-the-run notes. The on-the-run note has a much lower relative bid-ask spread than the off-the-run notes for the entire time series. Furthermore, the figure displays that the greater the time span from issuance date, the more illiquid the treasury security will be. This can be seen from the 6^{th} off-the-run note having the greatest spread throughout the series.

3.2.2 Yield Differences

In the bid-ask spread analysis, I display that the on-the-run 10-year treasury note is more liquid than the off-the-run treasury notes. In addition, studies such as (Krishnamurthy 2002), (Goldreich, Hanke, and Nath 2005) explain that the difference in yields between the on and off-the-run are due to liquidity differences. Moreover, (Collin-Dufresne, Goldstein, and Martin 2001), and (Longstaff, Mithal, and Neis 2005) use these yield spreads as measures of liquidity risk. Hence, this justifies calculation of an aggregate liquidity risk proxy based on the differences in yields between on and off-the-run treasury notes.

In this subsection, I illustrate that a simple on-the-run/off-the-run treasury note analysis cannot ascertain the difference in liquidity risk due to the varying maturities of the notes. Instead, a new method for the analysis of liquidity differences between on-the-run and off-the-run treasury notes is proposed. This is achieved by assuming that the on-the-run note yields are equal to that of a par yield curve estimated from the constant maturity treasury yields, and by calculating the differences between the curve and the off-the-run yields.

A simple liquidity risk proxy is built by taking the difference between the mean yield of the nearest 6 off-the-run securities and the yield of the on-the-run security.

$$Liquidity\,Risk_t = mean(yield_{1t\,Off}, yield_{2t\,Off}, \ldots, yield_{6t\,Off}) - yield_{t\,On} \quad (2)$$

However, the liquidity risk proxy is comprised of mostly negative values, due to the different maturities of the treasury notes. As a result, the aggregate liquidity risk proxy does not seem to hold substantial information. The following table displays the maturity ranges of the on-the-run and off-the-run securities and the maturity differences between the on and off-the-run notes. As shown, the maturity of the on-the-run treasury note is between 0.25 to 1.5 years greater than the off-the-run security. This leads to inaccurate comparisons of yields.

Table 1: Maturity of The On-the-run and Off-the-run 10-Year Treasury Notes

	On The Run	Off 1	Off 2	Off 3	Off 4	Off 5	Off 6
Min Maturity	9 3/4	9 1/2	9 1/4	9	8 3/4	8 1/2	8 1/4
Max Maturity	10	9 3/4	9 1/2	9 1/4	9	8 3/4	8 1/2
Maturity Difference with On the run		1/4	1/2	3/4	1	1 1/4	1 1/2

The table reports the maturity ranges of the on and off-the-run treasury notes, represented by OFF_n. Also, the maturity differences between the on-the-run security and all other notes are presented. As can be seen, the maturity of the on-the-run treasury note is between 0.25 to 1.5 years greater than the off-the-run.

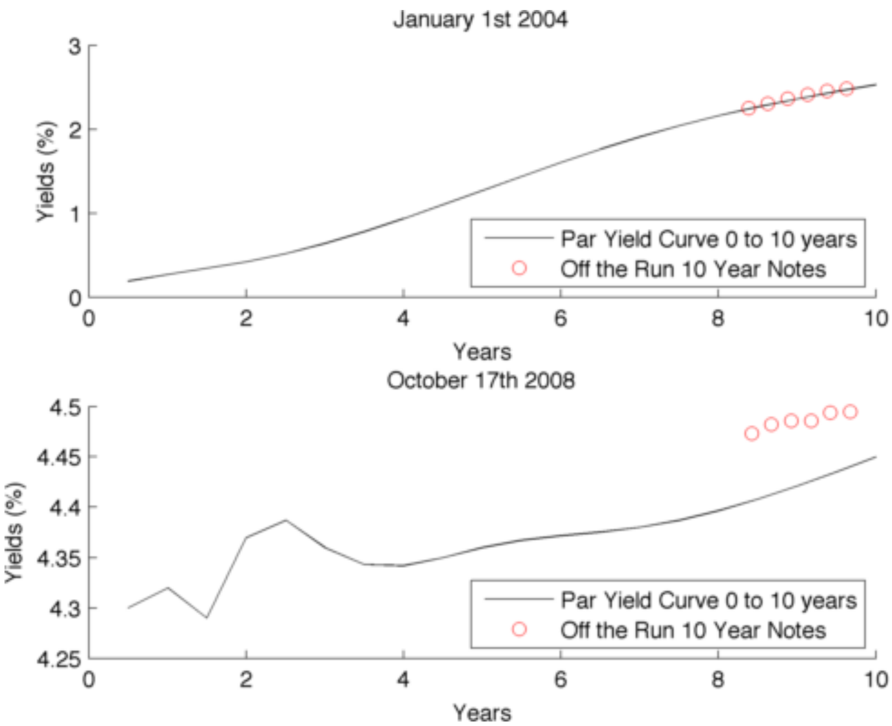
I introduce a more robust method for comparing on and off-the-run US treasury securities. As a first step, I use constant maturity treasury yields to estimate daily 0 to 10-year par yield curves with a cubic spline interpolation with nodes set at half-year intervals. Because these yields are calculated using the most actively traded treasury securities, I assume that the yield curves represent the on-the-run treasury term structure. Then I take the mean of the differences between the six off-the-run 10-year note yields and the corresponding yield curve estimates.

$$Liquidity\,Risk_t = mean(yield_{1tOff} - yield_{tOn},\, yield_{2tOff} - yield_{tOn},\, \ldots,\, yield_{6tOff} - yield_{tOn}) \tag{3}$$

The following figure provides a visual explanation of the comparison of the on and off-the-run treasuries. The top graph displays a low liquidity risk day with only a slight dispersion between the off-the-run data points and the curve. The bottom graph displays a high liquidity risk day, with a large dispersion between the off-the-run data points and the yield curve.

As can be seen in the plot below, estimated aggregate liquidity risk proxy is quite noisy, so the series is smoothed with a 3 period moving average. In the unadjusted version, the liquidity risk proxy has 149 negative observations, which is 8.5% of the total sample. The smoothed version has 105 negative observations, which is 6% of the total sample. The majority of these negative values that are between March and June 2009 coincides with the announce-

Figure 2: Off-the-run 10-Year yields vs. 0 to 10 Par Year Treasury Yield Curve



This figure is included to give a visual explanation of the on-the-run and off-the-run yield difference analysis. The circles on the graphs denote the six off-the-run treasury securities and the lines displays the par yield curves, which are estimated by using a cubic spline interpolation on the constant maturity treasury yields. The constant maturity treasury yields are assumed to be equivalent to on-the-run securities, as they are estimated using the on-the-run issues where possible. To calculate the liquidity risk proxy, I take the difference from the off-the-run points, circles, and the equivalent interpolated data points on the estimated yield curve. The top graph displays the January 1^{st} 2004 analysis, where there is low liquidity risk due to the off-the-run notes that are near the on-the-run par yield curve. The bottom graph displays the October 17^{th} 2008 analysis, where there is high liquidity risk due to the off-the-run notes that are much further away from the on-the-run par yield curve.

ment of the expansion of the quantitative easing program in the treasury market. I assume that these negative values are due to an excess liquidity environment provided by the government intervention into the treasury market. For the completion of the analysis, the smoothed liquidity risk proxy is used.

Figure 3: On-the-run vs. Off-the-run Liquidity Risk Proxy

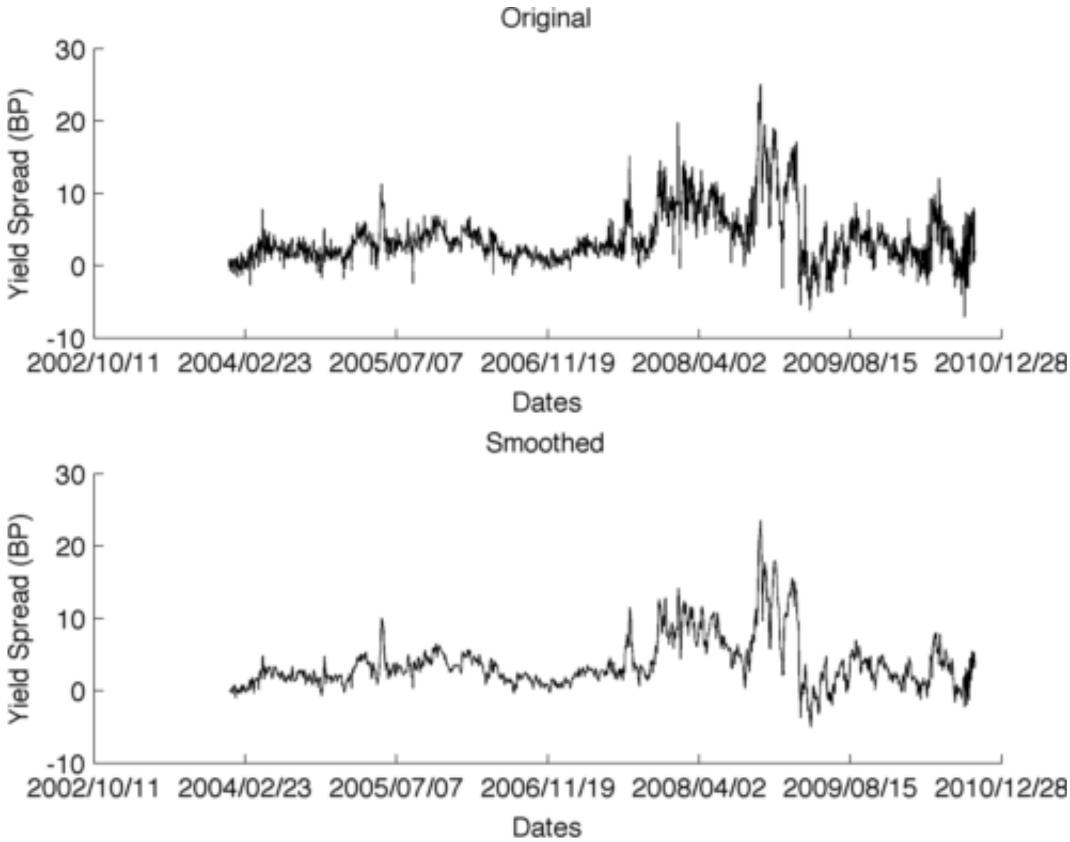
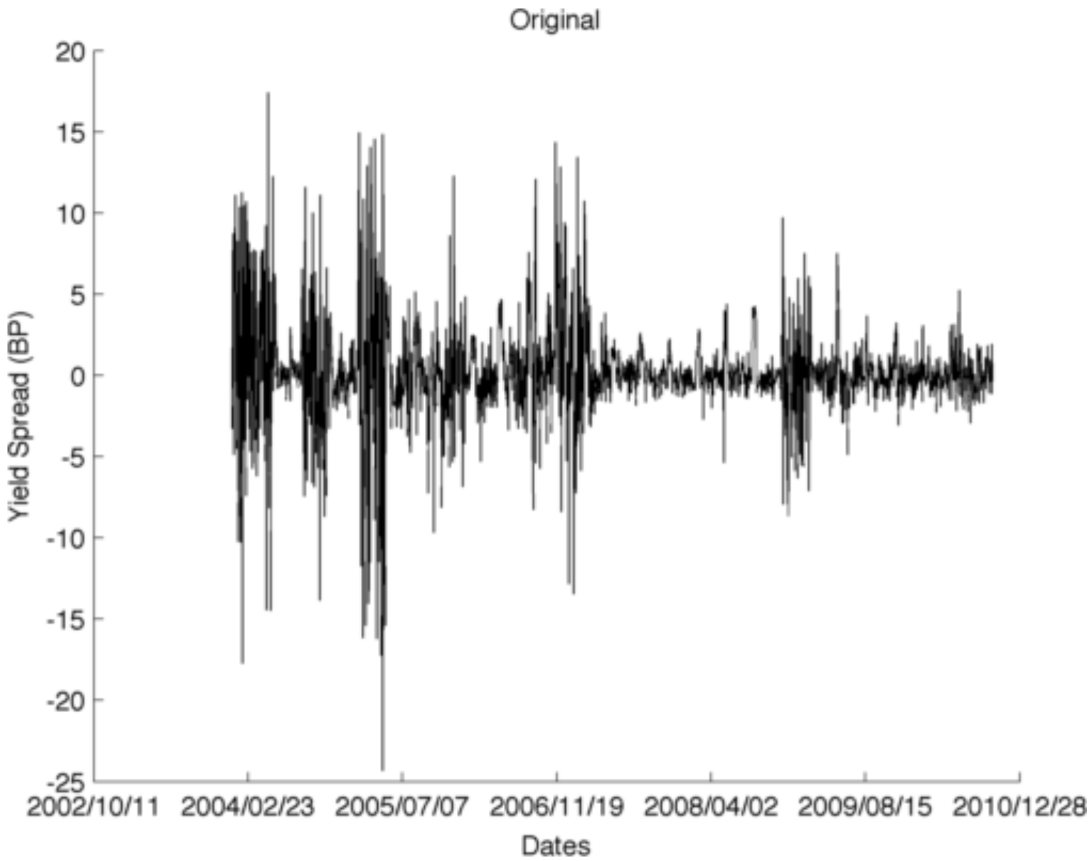


Figure 1 has 2 plots. The top graph displays the liquidity risk proxy estimated by calculating the mean of the differences between the six off-the-run notes and the estimated on-the-run par yield curve. $Liquidity\,Risk_t = mean(yield_{1t\ Off}, yield_{2t\ Off}, \ldots, yield_{6t\ Off}) - yield_{t\ On}$. The bottom graph shows the top series that is smoothed with a 3 period moving average. The smoothed measure will be used as the proxy for liquidity risk.

For robustness, the differences between the on-the-run notes and the on-the-run par yield curve are calculated. The following figure indicates that there are substantial yield differences between the on-the-run notes and the estimated curve. However, these differences do not follow a trend and seem to be random in nature.

Figure 4: On-the-run vs. On-the-run Par Yield Curve



This graph displays the spread between the on-the-run notes and the estimated on-the-run par yield curve. There are no discernible trend, even though they are differences between the actual on-the-run 10-year treasury notes and the estimated on-the-run yield curve.

3.3 Credit Spreads

For the comparison of yield movements of various bonds, the calculation of the credit spreads are necessary. The credit spread of a bond is its yield less a risk-free rate of equivalent maturity. Within this analysis, the corporate bond spreads of the USD LIBOR panel banks are calculated by taking the differences between the yields to maturity of the bonds and the equivalent zero coupon rates. Constant maturity treasury yields are used to estimate daily zero coupon yield curves, as they are considered to be default free. The methodology follows that of Longstaff, Mithal, and Neis (2005) and Bolder and Streliski (1999).

The constant maturity treasury yields are par yields, which are the rates that would make the price of the bond equal to its face value. These yields are used to estimate a par yield curve using a cubic spline interpolation with nodes at half-year intervals. The choice of nodes is related to the semiannual coupon payments of treasury notes and bonds. The semiannual frequency of the nodes are also used by Longstaff, Mithal, and Neis (2005) and Bolder and Streliski (1999). Once the par yield curve is obtained, the zero coupon rates are bootstrapped, assuming that there is a cash flow at every half-year node.

The Bootstrapping procedure begins by solving for the first zero coupon rate with a maturity equal to 0.5-years, $Z(0, 0.5)$.

$$100 = \frac{0.5(Par(0,\ 0.5) * 100) + 100}{(1 + Z(0,\ 0.5))^{0.5}} \tag{4}$$

Once the 0.5-year zero coupon rate, $Z(0, 0.5)$, is obtained, it is used to discount the cash flow at the 0.5-year. The formula will only have one unknown value $Z(0, 1)$, the 1-year zero coupon rate, which can be solved algebraically.

$$100 = \frac{0.5(Par(0,\ 1) * 100)}{(1 + Z(0,\ 0.5))^{0.5}} + \frac{0.5(Par(0,\ 1) * 100) + 100}{(1 + Z(0,\ 1))^{1}} \tag{5}$$

Then the 1.5-year zero coupon rate, $Z(0, 1.5)$, is solved by discounting the cash flows with the previously estimated zero coupon rates and isolating $Z(0, 1.5)$.

$$100 = \frac{0.5(Par(0,\ 1.5) * 100)}{(1 + Z(0,\ 0.5))^{0.5}} + \frac{0.5(Par(0,\ 1.5) * 100)}{(1 + Z(0,\ 1))^{1}} + \frac{0.5(Par(0,\ 1.5) * 100) + 100}{(1 + Z(0,\ 1.5))^{1.5}} \tag{6}$$

The procedure continues until an estimate for a 30-year zero coupon rate, $Z(0, 30)$, is obtained. For a more complete description of the bootstrapping method using par yield curves, see (Bolder and Streliski 1999).

3.4 Correlation Matrices and Statistics

Correlation matrices and statistics of the independent and dependant variables of each credit spread model are shown below.

Table 2: Bank Credit Spread Correlation Matrices

		January 1, 2004 to September 30, 2010			January 1, 2004 to May 17, 2007			May 18, 2007 to September 30, 2010		
		Spread	CDS	Liquidity Risk	Spread	CDS	Liquidity Risk	Spread	CDS	Liquidity Risk
TED	Spread	1.0000	0.3007	0.6239	1.0000	-0.6210	0.1919	1.0000	-0.0781	0.5885
	CDS	0.3007	1.0000	0.2399	-0.6210	1.0000	0.0694	-0.0781	1.0000	-0.0830
	Liquidity Risk	0.6239	0.2399	1.0000	0.1919	0.0694	1.0000	0.5885	-0.0830	1.0000
Bank of America	Spread	1.0000	0.9047	0.1498	1.0000	-0.7809	0.2770	1.0000	0.8450	-0.1469
	CDS	0.9047	1.0000	0.1632	-0.7809	1.0000	0.0656	0.8450	1.0000	-0.1837
	Liquidity Risk	0.1498	0.1632	1.0000	0.2770	0.0656	1.0000	-0.1469	-0.1837	1.0000
Credit Suisse	Spread	1.0000	0.7717	0.6122	1.0000	-0.4438	0.3898	1.0000	0.6675	0.5503
	CDS	0.7717	1.0000	0.3627	-0.4438	1.0000	0.1072	0.6675	1.0000	0.1614
	Liquidity Risk	0.6122	0.3627	1.0000	0.3898	0.1072	1.0000	0.5503	0.1614	1.0000
Deutsche Bank	Spread	1.0000	0.7935	0.3190	1.0000	-0.6668	0.2062	1.0000	0.5990	0.1233
	CDS	0.7935	1.0000	0.3170	-0.6668	1.0000	0.0831	0.5990	1.0000	0.0537
	Liquidity Risk	0.3190	0.3170	1.0000	0.2062	0.0831	1.0000	0.1233	0.0537	1.0000
HSBC	Spread	1.0000	0.8110	0.2561	1.0000	-0.9182	0.2021	1.0000	0.5159	-0.0533
	CDS	0.8110	1.0000	0.2139	-0.9182	1.0000	-0.0308	0.5159	1.0000	-0.1386
	Liquidity Risk	0.2561	0.2139	1.0000	0.2021	-0.0308	1.0000	-0.0533	-0.1386	1.0000
JP Morgan	Spread	1.0000	0.8863	0.3337	1.0000	-0.6593	0.3157	1.0000	0.8251	0.1055
	CDS	0.8863	1.0000	0.3371	-0.6593	1.0000	0.1243	0.8251	1.0000	0.1201
	Liquidity Risk	0.3337	0.3371	1.0000	0.3157	0.1243	1.0000	0.1055	0.1201	1.0000
Lloyds	Spread	1.0000	0.9225	0.1863	1.0000	0.1000	-0.1073	1.0000	0.8743	-0.2190
	CDS	0.9225	1.0000	0.0887	0.1000	1.0000	0.0223	0.8743	1.0000	-0.3106
	Liquidity Risk	0.1863	0.0887	1.0000	-0.1073	0.0223	1.0000	-0.2190	-0.3106	1.0000
Rabobank	Spread	1.0000	0.6744	0.2861	1.0000	-0.4486	-0.2912	1.0000	0.3346	0.0986
	CDS	0.6744	1.0000	0.2753	-0.4486	1.0000	0.1874	0.3346	1.0000	0.0215
	Liquidity Risk	0.2861	0.2753	1.0000	-0.2912	0.1874	1.0000	0.0986	0.0215	1.0000
HBOS	Spread	1.0000	0.8636	0.1276	1.0000	-0.5977	0.3462	1.0000	0.6684	-0.2512
	CDS	0.8636	1.0000	0.1954	-0.5977	1.0000	0.0754	0.6684	1.0000	-0.1697
	Liquidity Risk	0.1276	0.1954	1.0000	0.3462	0.0754	1.0000	-0.2512	-0.1697	1.0000
RBS	Spread	1.0000	0.8237	0.1764	1.0000	-0.4142	-0.0910	1.0000	0.6592	-0.0907
	CDS	0.8237	1.0000	0.3405	-0.4142	1.0000	-0.0176	0.6592	1.0000	0.1340
	Liquidity Risk	0.1764	0.3405	1.0000	-0.0910	-0.0176	1.0000	-0.0907	0.1340	1.0000
UBS	Spread	1.0000	0.2927	0.2852	1.0000	-0.5850	0.4178	1.0000	0.0468	0.0240
	CDS	0.2927	1.0000	-0.1432	-0.5850	1.0000	0.0168	0.0468	1.0000	-0.3292
	Liquidity Risk	0.2852	-0.1432	1.0000	0.4178	0.0168	1.0000	0.0240	-0.3292	1.0000

This table includes the correlation matrices of ten USD LIBOR panel banks and the TED spread for the entire series and two equally subdivided time frames. The variables are the credit spread, CDS premium less the 5-year zero coupon rate and liquidity risk factor.

The table above shows that the dependent variables, the TED spread and USD LIBOR panel banks' credit spreads, are positively correlated with all the independent variables for the entire series. Further, the independent variables have strong positive relationships, which can lead to problems of multicollinearity within the models. An interesting fact is that the CDS factors have the strongest correlations with the credit spreads of all the USD LIBOR panel banks. In contrast, the correlation between the liquidity risk factor and the TED spread is greater than that of the CDS factor and the TED spread. This leads to the preliminary view that default risk has a stronger relationship with corporate bond spreads than liquidity risk. On the other hand, at first glance liquidity risk has a stronger relationship to the TED spread than default risk. In Addition, the correlations between the CDS factors and the ten of the eleven spreads are negative for the first half of the series. Therefore, the data point to a negative relationship between credit spreads and CDS premiums between January 1^{st} 2004 and May 17, 2007.

The following table displays the summary statistics of all the dependent variables in the analysis. It can be seen that the variables present non-normal distributions with varying characteristics that can lead to modelling difficulties.

Table 3: Summary Statistics

Spread	TED	BAC	CS	DB	HSBC	JPM	LLOY	RABO	RBS	UBS	HBOS
Mean	0.6414	1.6517	1.2362	1.6725	1.7286	1.5338	4.3242	1.1840	1.8287	2.1858	2.3768
Median	0.4300	0.9239	0.9388	0.9426	1.0371	1.0508	3.5996	0.9282	0.7498	0.9996	0.9941
Std deviation	0.5970	1.5396	0.8374	1.3609	1.3238	1.0597	2.3076	0.8534	1.6623	1.9346	2.1029
Skewness	2.4586	2.0704	2.0737	2.0498	1.0322	1.4069	0.5029	0.5110	0.9130	1.2491	1.0354
Kurtosis	11.1609	7.9980	7.2550	7.6268	3.2707	4.8081	1.8704	2.1414	2.2895	3.0938	2.7646

CDS	TED	BAC	CS	DB	HSBC	JPM	LLOY	RABO	RBS	UBS	HBOS
Mean	0.5235	68.4855	51.8367	48.8585	68.0190	53.0512	55.4867	36.4373	62.1848	58.4523	20.6908
Median	0.1543	28.6272	19.5023	16.5900	12.6884	31.9597	10.0026	5.2638	10.6822	9.9425	9.0666
Std deviation	0.5393	68.0881	52.2584	46.8752	76.6992	44.5319	67.8433	45.8601	71.3332	72.6105	29.7418
Skewness	0.8139	1.1825	1.2137	0.7843	0.8829	1.1775	0.9629	1.2634	0.7933	1.4105	1.9635
Kurtosis	2.3504	3.9653	3.8137	2.3129	3.0178	3.7754	2.5176	3.8682	2.2529	4.7246	5.3452

Liquidity	TED	BAC	CS	DB	HSBC	JPM	LLOY	RABO	RBS	UBS	HBOS
Mean	0.3692	0.3692	0.3692	0.3692	0.3692	0.3692	0.3692	0.3692	0.3692	0.3692	0.3692
Median	0.2789	0.2789	0.2789	0.2789	0.2789	0.2789	0.2789	0.2789	0.2789	0.2789	0.2789
Std deviation	0.3560	0.3560	0.3560	0.3560	0.3560	0.3560	0.3560	0.3560	0.3560	0.3560	0.3560
Skewness	1.6817	1.6817	1.6817	1.6817	1.6817	1.6817	1.6817	1.6817	1.6817	1.6817	1.6817
Kurtosis	6.9576	6.9576	6.9576	6.9576	6.9576	6.9576	6.9576	6.9576	6.9576	6.9576	6.9576

This table includes the summary statistics of the ten US LIBOR panel banks, the TED spread and the default and liquidity risk variables.

4 TED Spread Analysis

Within this section, I perform a time series analysis of the TED spread to decipher the relative importance of liquidity and default risk factors. Given that the TED spread is not a marketable security, the liquidity risk within the spread is related to the financing capabilities of the USD LIBOR panel banks. That being said, I use the previously estimated aggregate liquidity risk proxy display in Figure 3. I consider three alternative econometric models: OLS, regime-switching, and autoregressive moving average models. The OLS model is selected because it is the most commonly used in previous works. The regime-switching model allows to test if the level of liquidity risk in the market affects the relevative importance of the components of credit risk. Lastly, ARMA models are estimated because they can model the data better.

4.1 Simple Regression Analysis

The following time-series regressions are estimated to detect the risk factors within the TED spread.

$$TEDSpread_t = \alpha + \beta_1 CDS_t + \beta_2 LIQ_t + \epsilon_t \tag{7}$$

$$TEDSpread_t = \alpha + \beta_1 CDS_t + \epsilon_t \tag{8}$$

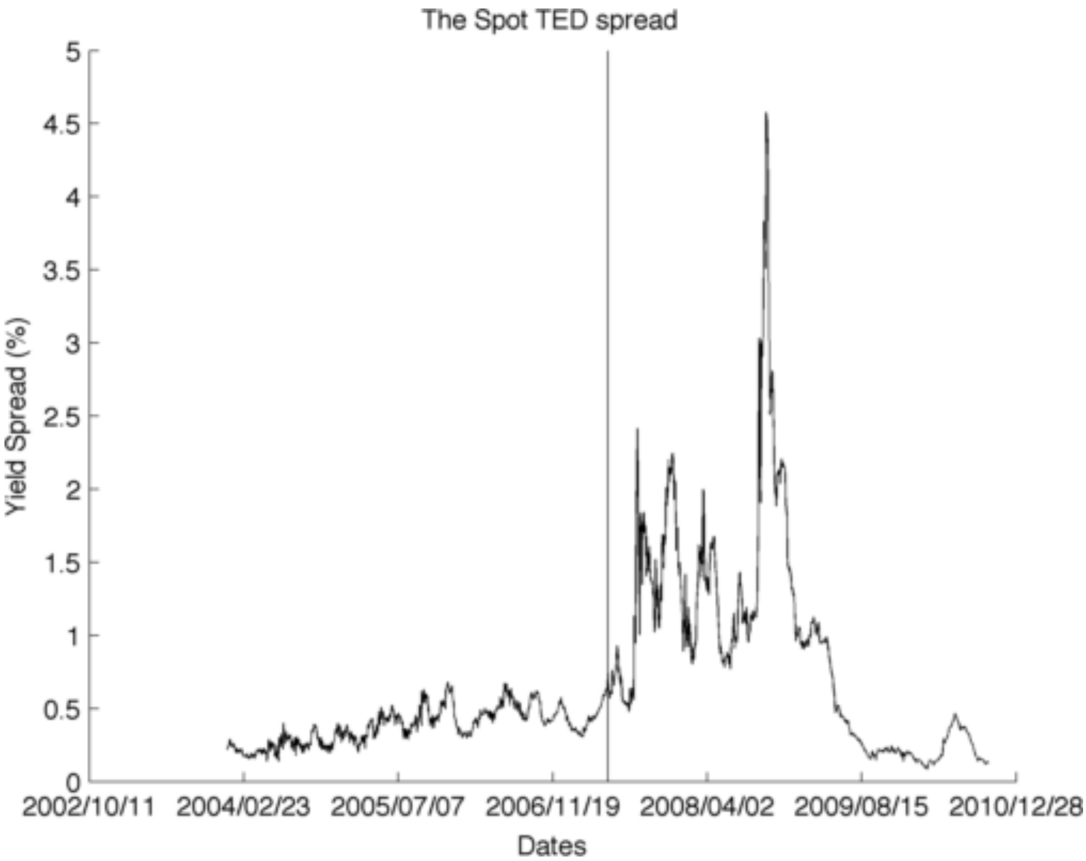
$$TEDSpread_t = \alpha + \beta_1 LIQ_t + \epsilon_t \tag{9}$$

The TED spread is the difference between the spot 3 month USD LIBOR rate and 90-day Treasury bill yield. The CDS factor is the average CDS premium of banks that make up the USD LIBOR panel, Bank of America, Credit Suisse, Deutsche Bank, HSBC, JP Morgan Chase, Lloyds, Rabobank, RBS, UBS, and HBOS, less the 5-year zero coupon treasury rate. The LIQ factor is the liquidity risk proxy calculated by taking the mean of the differences between the off-the-run 10-year note yields and the corresponding yield curve estimates.

The models are estimated with the entire sample set, which ranges from January 1, 2004 to September 30, 2010 and with two equally divided sub periods that range from January 1, 2004 to May 17, 2007 and May 18, 2007 to September 30, 2010. This procedure is implemented to verify, if the selection of time period can alter the results. The first section represents a stable period in financial markets and the second section represents a highly volatile period. Therefore, I test whether these two distinct time frames will affect the value and significance of the estimated betas. Newey-West standard errors are used to calculate the T-Statistics (Newey and West 1987), due to the heteroskedasticity of the error terms within these models.

The following figure displays the time series plot of the TED spread with a vertical line indicating the divided periods. It can be seen that on the first half of the plot, the spread fluctuates much less and than on the second half, demonstrating a large difference in market periods.

Figure 5: The TED Spread



This figure display the time series plot of the spot TED spread. The vertical line is the bisection of the series at the 17 of May 2008. I conduct a time series analysis of the entire series and also the first and second half of the series. This is due to the large differences in spreads between the two time periods.

The following table displays the regression results of the TED spread analysis. It includes the beta coefficients, T- statistics and adjusted R-squared for each estimated model.

Table 4: TED Spread Regression Outputs

This table displays the regression outputs of the TED spread analysis for the entire time series and the two equally divided time frames. The symbols ***, **, * indicate that the betas are at 0.01, 0.05, and 0.10 levels of significance, respectively, and the T-statistics calculated using Newey-West standard errors with 10 lags are within brackets.

January 1, 2004 to September 30, 2010

Model	1	2	3
Constant	0.1861***	0.4672***	0.2552***
	(3.834)	(12.603)	(5.599)
CDS Factor	0.1774**	0.3329***	
	(2.221)	(3.599)	
Liquidity Risk	0.9817***		1.0462***
	(7.581)		(7.748)
Adj-R Squared	0.4128	0.0899	0.3889

January 1, 2004 to May 17, 2007

Model	1	2	3
Constant	0.5126***	0.5539***	0.3451***
	(19.680)	(22.413)	(14.954)
CDS Factor	-1.9084***	-1.8593***	
	-(9.077)	-(7.888)	
Liquidity Risk	0.1884***		0.1531**
	(3.487)		(2.263)
Adj-R Squared	0.4399	0.3849	0.0357

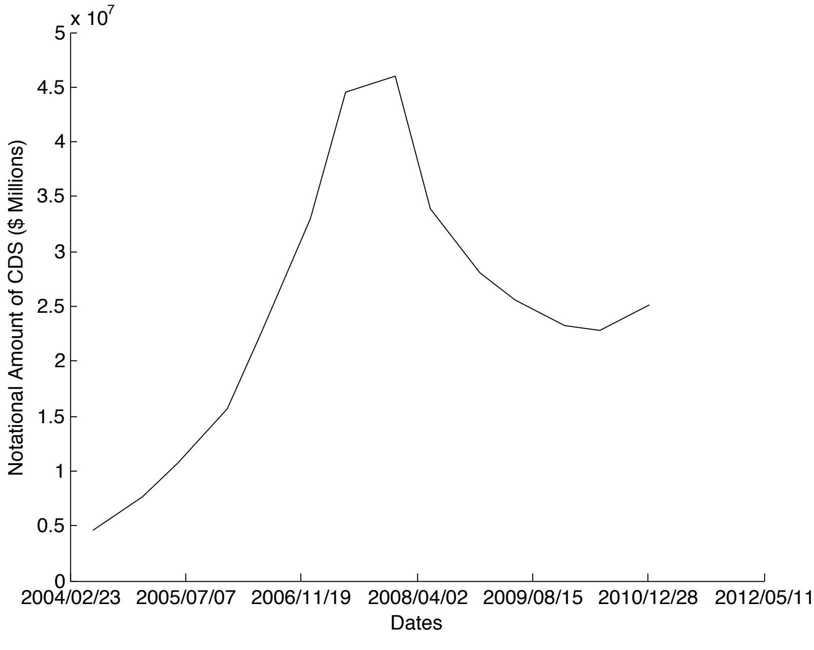
May 18, 2007 to September 30, 2010

Model	1	2	3
Constant	0.4572***	1.0232***	0.4089***
	(2.734)	(7.119)	(5.066)
CDS Factor	-0.0485	-0.1285	
	-(0.307)	-(0.827)	
Liquidity Risk	0.9892***		0.9934***
	(6.474)		(6.672)
Adj-R Squared	0.3457	0.0050	0.3456

For the linear regressions of the entire series, all the coefficients are positive and statistically significant using the Newey-West standard errors; demonstrating that an increase in default or liquidity risk results in an increase in the TED spread. It can also be seen from the regressions using only one individual risk factor, that liquidity risk plays a greater role in the modelling of the TED spread. This is demonstrated by the higher adjusted R-square. Therefore, the newly proposed liquidity risk proxy can describe the financing liquidity risk of the USD LIBOR panel banks.

As for the linear regressions of the first half of the series, January 1, 2004 to May 17, 2007, all the coefficients are statistically significant, although the CDS factor is negative. This indicates an inverse relationship between default risk and the TED spread during this time period, which is a puzzling result. One possible explanation can be that the substantial increase in volumes in the CDS market puts downward pressure on premiums. The following figure displays the large increase in the gross notational amounts of CDS contracts from 2004 to 2008. Also, in this time period, liquidity risk explains much less about the spread than the default risk factor. This can be seen from the much lower adjusted R-square of 0.0357 compared with 0.3849.

Figure 6: The Gross CDS Notational Amount



This figure presents the time series plot of the bi-annual gross notation amounts of the issue CDS contracts. It demonstrates a substantial increase in the quantity of CDS contracts issued between 2004 and 2008, which led to an oversaturation of the market and consequently lower than expected CDS premiums. Data obtained from ISDA via http://www.bis.org/statistics/otcder/dt21.csv.

For the linear regressions of the second half of the series, May 18, 2007 to September 30, 2010, only the liquidity risk factor coefficient is significant and positive. This points to the importance of the relationship between liquidity risk and the TED spread being time varying.

Finally, this analysis displays the significant effects of the time frame selection for an analysis of the risk factors within credit spreads. If the analysis is conducted only on the first half of the time series, the result would be an inverse relationship between default risk and the TED spread. Also, liquidity risk would seem far less important in the modelling of the TED spread. However, the analysis of the TED spread over the entire time frame displays a positive relationship between both the risk factors and the TED spread. Also, the liquidity risk factor explains a majority of the TED spread fluctuations.

4.2 Regime-switching Regression

To further verify if market conditions affect the importance of default and liquidity risk within the TED spread, a regime-switching model is estimated. The regime is selected based on the level of the liquidity risk proxy. This verifies if the betas are significantly different during periods of high and low liquidity risk. This regime switching model is important to include, as many practitioners believe that liquidity risk is only prevalent during extreme market conditions like the 2008 financial crisis.

$$TEDSpread_t = \begin{cases} \alpha_1 + \beta_1 CDS_t + \beta_2 LIQ_t + \epsilon_t & \text{if } LIQ_t > C \\ \alpha_2 + \beta_3 CDS_t + \beta_4 LIQ_t + \epsilon_t & \text{if } LIQ_t < C \end{cases}$$

The critical values, C, are selected as follows. The first and last 15% of the series is removed, then the regime-switching models with the remaining values is estimated with values of C ranging from the minimum to the maximum of the LIQ factor, with an iteration of 0.01. Lastly, the value of C that minimizes the mean square error is selected. As in the standard regression, Newey-West standard errors are used to calculate the T-Statistics (Newey and West 1987).

The table below displays the regime-switching regression results of the TED spread. The switch is related to the level of liquidity risk. All of the coefficients are statistically significant at a 0.05 level except for one of the constants. An interesting outcome is that the criterion for switching, C, is much larger than the mean of the liquidity risk process. Furthermore, the coefficients are substantially different for the high and low periods. This indicates that the effects of liquidity and default risk are not static; they depend on the level of liquidity risk in the market.

Table 5: TED Spread Regime-switching Regression Outputs

This table displays the regression result of the TED spread analysis for the time series using a regime-switching model. The symbols ***, **, * indicate that the betas are at 0.01, 0.05, and 0.10 levels of significance, respectively, and the T-statistics calculated using Newey-West standard errors with 10 lags are within brackets.

	January 1, 2004 to September 30, 2010
Constant Low	0.1874***
	(3.6341)
Liquidity Risk Low	0.9499***
	(6.7985)
CDS Factor Low	0.1940**
	(2.4016)
Constant High	1.5197
	(1.1969)
Liquidity Risk High	1.2700***
	(3.3653)
CDS Factor High	-1.3761**
	-(2.1469)
C	1.2404
Mean Liquidity Risk	0.3692
Adj-R Squared	0.4322

4.3 Autoregressive Moving Average Model With Supplementary Independent Variables

The final model is an ARMA, autoregressive moving average, with supplementary independent variables. It is included to provide a more robust verification of the economic significance of the risk factors within the TED spread. The usage of the ARMA models is in response to the highly autocorrelated and non-stationary nature of the TED spread and the independent variables, and also due to the heteroskedasticity of the error terms.

A Dickey Fuller test is used to verify for unit roots (Dickey and Fuller 1979), as the presence of unit root variables can lead to spurious regressions. This test determines that all the variables, except for the proposed liquidity risk proxy, fail to reject the null hypothesis of the presence of a unit root. To resolve this issue, the first difference transformation of all the series is taken, $\Delta y_t = y_t - y_{t-1}$ to eliminate the unit root, to also improve the stationarity of the series, and decrease the high level of autocorrelation. For a detailed graphical representation of the first difference transformation, please see Appendix 9.2, where the procedure is demonstrated on the Deutsche Bank credit spread.

$$TED_t = \beta_1 CDS_t + \beta_2 LIQ_t + \phi_1 TED_{t-1} + \ldots + \phi_p TED_{t-p} + \theta_1 \epsilon_{t-1} + \ldots + \theta_{t-q}\epsilon_q + \epsilon_t \quad (10)$$

$$TED_t = \beta_1 CDS_t + \phi_1 TED_{t-1} + \ldots + \phi_p TED_{t-p} + \theta_1 \epsilon_{t-1} + \ldots + \theta_{t-q}\epsilon_q + \epsilon_t \quad (11)$$

$$TED_t = \beta_1 LIQ_t + \phi_1 TED_{t-1} + \ldots + \phi_p TED_{t-p} + \theta_1 \epsilon_{t-1} + \ldots + \theta_{t-q}\epsilon_q + \epsilon_t \quad (12)$$

All possible ARMA specifications are estimated with $p, q \leq 6$. The values p & q are selected in accordance with the Box-Jenkins methodology, which entails finding the most parsimonious model specification. For a detailed explanation of the selection of the p and q parameters, please see Appendix 9.2, where the procedure is demonstrated on the Deutsche Bank credit spread. The estimation process is also included in the appendices (see Section 9.4).

For this analysis, the ARMA model for the entire time series is not included, because white-noise residuals are not obtainable. However, models for both subdivided periods are estimated. Within the first period, January

1, 2004 to May 17, 2007, all the different models do not have significant betas for the default and liquidity risk factors. Nonetheless, for the second period, May 18, 2007 to September 30, the liquidity risk beta is positive and significant for the all factor analyses. Also, the default risk factor is positive and significant for the default risk only model. This provides further proof of a positive relationship between default and liquidity risks and the TED spread. However, the relationship might not hold during stable market conditions. In contrast to the simple regression analysis, neither default nor liquidity risk provide substantially more information the other, as shown by the similar adjusted R-squared from the ARMA models including only default and liquidity risk.

The following table shows the outputs from various ARMA models.

Table 6: ARMA TED Spread

This table displays the results of the autoregressive moving average model of theTED spread with both liquidity and default risk components, individually and together. The results include the entire time series and the two equally divided portions. The symbols ***, **, * indicate that the betas are at 0.01, 0.05, and 0.10 levels of significance, respectively, and the T-statistics are within brackets. The (p, q) specification indicates the p autoregressive components and the q moving average components.

January 1, 2004 to September 30, 2010

Model	y (t-1)	y (t-2)	y (t-3)	y (t-4)	y (t-5)	ε (t-1)	ε (t-2)	ε (t-3)	ε (t-4)	ε (t-5)	ε (t-6)	Const	CDS	LIQ	Adj- R2
N/A															
N/A															
N/A															

January 1, 2004 to May 17, 2007

Model	y (t-1)	y (t-2)	y (t-3)	y (t-4)	y (t-5)	ε (t-1)	ε (t-2)	ε (t-3)	ε (t-4)	ε (t-5)	ε (t-6)	Const	CDS	LIQ	Adj- R2
(5,6)	-0.3030	-0.3331*	-0.3051	-0.3054	0.6581***	0.0732	0.2724*	0.2125	0.2831	-0.5966***	0.1938***		-0.0021	0.1115	0.3000
	-(1.464)	-(1.880)	-(1.623)	-(1.558)	(3.907)	(0.349)	(1.718)	(1.217)	(1.604)	-(3.824)	(4.282)		-(0.119)	(0.418)	
(5,6)	-0.2427	-0.2809*	-0.2482	-0.2503	0.7089***	0.0134	0.2314	0.1650	0.2427	-0.6361***	0.1962***	0.0007		-0.0036	0.3000
	-(1.218)	-(1.648)	-(1.375)	-(1.324)	(4.391)	(0.067)	(1.486)	(0.967)	(1.405)	-(4.187)	(4.275)	(0.774)		-(0.202)	
(5,6)	-0.3514	-0.3769**	-0.3513*	-0.3512*	0.6155***	0.1207	0.3061*	0.2487	0.3161*	-0.5661***	0.1898***	0.0010	0.1191		0.3000
	-(1.621)	-(2.025)	-(1.783)	-(1.705)	(3.476)	(0.551)	(1.872)	(1.376)	(1.729)	-(3.508)	(4.201)	(1.056)	(0.446)		

May 18, 2007 to September 30, 2010

Model	y (t-1)	y (t-2)	y (t-3)	y (t-4)	y (t-5)	ε (t-1)	ε (t-2)	ε (t-3)	ε (t-4)	ε (t-5)	ε (t-6)	Const	CDS	LIQ	Adj- R2
(2,3)	0.4632***	-0.6081***				-0.2479*	0.4977***	0.0223					-0.0169	0.2257***	0.0970
	(3.170)	-(4.219)				-(1.657)	(3.554)	(0.468)					-(0.528)	(3.784)	
(2,3)	0.5947***	-0.9751***				-0.3713**	0.8612***	0.1637***				-0.0007		0.0039	0.0970
	(4.234)	-(6.964)				-(2.569)	(6.217)	(3.577)				-(0.202)		(0.124)	
(2,3)	0.4396***	-0.5936***				-0.2231	0.4881***	0.0191				-0.0008	0.2266***		0.0970
	(2.994)	-(4.116)				-(1.484)	(3.485)	(0.400)				-(0.255)	(3.805)		

5 Credit Spread Analysis

Within this section, I perform a time series analysis of the credit spreads of the USD LIBOR panel banks to decipher the relative importance of liquidity and default risk factors. The liquidity risk of the individual credit spreads is related to the marketability of the bonds i.e. the ability to trade the security at low transactional costs. I also use the aggregate liquidity risk proxy estimated in Section 3.2.2 to estimate this form of liquidity. This differs from many previous studies that focus on bond-specific liquidity measures. I consider three alternative econometric models: OLS, regime-switching, and autoregressive moving average models. The OLS model is selected because it is the most commonly used in previous works. The regime-switching model allows one to test if the level of liquidity risk in the market affects the relevative importance of the components of credit risk. Lastly, ARMA models are estimated because they can model the data better.

5.1 Simple Regression Analysis

The following time-series regressions are estimated to detect the risk factors within the credit spreads of the USD LIBOR panel banks.

$$CreditSpreadBank_{it} = \alpha + \beta_1 CDSBank_{it} + \beta_2 LIQ_t + \epsilon_t \tag{13}$$

$$CreditSpreadBank_{it} = \alpha + \beta_1 CDSBank_{it} + \epsilon_t \tag{14}$$

$$CreditSpreadBank_{it} = \alpha + \beta_1 LIQ_t + \epsilon_t \tag{15}$$

The credit spreads are calculated by taking the yield to maturity of the corporate bonds and subtracting the zero coupon risk-free rate with the same maturity. CDSBank factor is the CDS premium of the i bank less the 5-year zero coupon treasury rate. The LIQ is the same variables as used in the TED spread regression.

In accordance to the TED spread regression, the models with the complete time series are estimated. Models for the two equally divided time frames are also estimated. Again, Newey-West standard errors are used to calculate the T-Statistics (Newey and West 1987) due to the heteroskedasticity of the error terms of these models. The following figures display the time series' plots of the credit spreads of USD LIBOR panel banks with a vertical line indicating the divided periods. In comparing the two time frames, It can be seen that the first half is much less volatile than the second half, demonstrating a large difference in market periods.

Figure 7: Credit Spreads of the US LIBOR Panel Banks

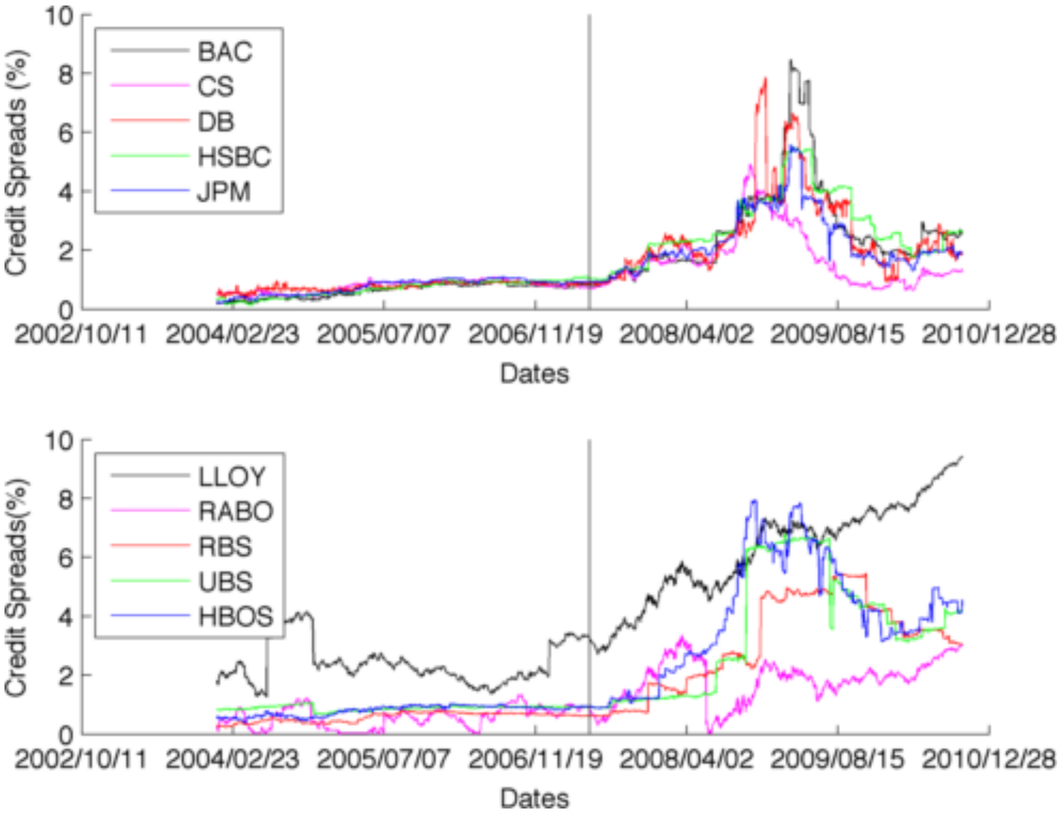


Figure 8 displays the time series plot of the credit spreads of the US LIBOR panel banks. The vertical line indicates the bisection of the series at the 17 of May 2008. I conduct a time series analysis of the entire series and also the first and second half of the series. This is due to the large differences in spreads between the two time periods.

The following tables present the regression results of US LIBOR panel banks. Table 7 reports the models using both the default and liquidity risk factors. Table 8 is the output of the default risk only model. Table 9 displays the results of the liquidity risk only models. All three of these tables include the regression of the entire time series and the two equally subdivided periods.

Lastly, the Table 10 displays the superior adjusted R-squared of the default risk only models over the liquidity risk only models.

Table 7: Banking Spread All Factors Regression Outputs

This Table displays the regression results of the credit spreads of the US LIBOR panel banks for the entire time series and the two equally divided portions. The symbols ***, **, * indicate that the betas are at 0.01, 0.05, and 0.10 levels of significance, respectively, and the T-statistics calculated using Newey-West standard errors with 10 lags are within brackets.

January 1, 2004 to September 30, 2010

Bank	BAC	CS	DB	HSBC	JPM	LLOY	RABO	RBS	UBS	HBOS
Constant	0.2477***	0.3782***	0.4749***	0.6794***	0.3884***	2.3488***	0.6508***	0.6387***	1.0768***	1.1503***
	(4.3882)	(7.6323)	(4.8238)	(9.5365)	(6.8711)	(25.2561)	(10.7624)	(8.6775)	(9.5697)	(3.5291)
CDS Factor	0.0204***	0.0101***	0.0223***	0.0137***	0.0208***	0.0311***	0.012***	0.0203***	0.0230***	0.0241***
	(15.8921)	(11.5754)	(9.6316)	(10.6872)	(16.9296)	(25.8866)	(10.9318)	(17.6201)	(12.5638)	(7.2460)
Liquidity Risk	0.0095	0.9000***	0.2867	0.3220	0.1172	0.6827***	0.2605	-0.1994	-0.6398*	1.9727***
	(0.0557)	(5.6577)	(0.8944)	(1.5600)	(0.8412)	(4.7550)	(1.4419)	-(1.1012)	-(1.6787)	(3.5898)
Adj R-Squared	0.8184	0.7223	0.6342	0.6645	0.7867	0.8618	0.4652	0.7473	0.6903	0.1940

January 1, 2004 to May 17, 2007

Bank	BAC	CS	DB	HSBC	JPM	LLOY	RABO	RBS	UBS	HBOS
Constant	0.9587***	0.886***	0.9887***	0.9877***	1.0571***	2.446***	0.8466***	0.6223***	0.9444***	0.9364***
	(32.1683)	(20.0504)	(35.0680)	(59.1095)	(24.3977)	(16.8822)	(17.0846)	(38.9671)	(130.5407)	(35.7635)
CDS Factor	-0.0267***	-0.0209***	-0.0253***	-0.0614***	-0.0223***	0.0205	-0.0641***	-0.0284***	-0.0088***	-0.024***
	-(18.4570)	-(6.7469)	-(10.9675)	-(31.7165)	-(12.9177)	(0.9336)	-(4.8260)	-(12.9719)	-(4.0523)	-(14.3877)
Liquidity Risk	0.4781***	0.5551***	0.2292***	0.2996***	0.6508***	-0.4956	-0.4871***	0.3907***	-0.0472	0.4554***
	(6.9414)	(9.4385)	(4.1964)	(5.9409)	(6.0946)	-(1.5722)	-(3.0785)	(5.9543)	-(1.4448)	(7.9639)
Adj R-Squared	0.7174	0.3891	0.5124	0.8731	0.5943	0.0198	0.2440	0.5101	0.1794	0.5241

May 18, 2007 to September 30, 2010

Bank	BAC	CS	DB	HSBC	JPM	LLOY	RABO	RBS	UBS	HBOS
Constant	0.0671	0.1255	0.4705	1.5298***	0.5606***	3.5697***	1.3385***	1.3478***	1.6403***	3.7542***
	(0.4028)	(1.2072)	(1.6038)	(6.9059)	(5.1202)	(19.7540)	(9.2226)	(4.4064)	(5.6451)	(6.8797)
CDS Factor	0.0217***	0.0119***	0.0224***	0.0093***	0.0201***	0.0240***	0.0056***	0.0165***	0.0201***	0.0031
	(13.0738)	(10.1730)	(6.0682)	(5.4537)	(13.0565)	(17.0995)	(4.3579)	(8.3750)	(8.2752)	(0.6485)
Liquidity Risk	0.0310	0.9828***	0.2961	0.0475	0.0147	0.2199	0.1525	-0.4916*	-0.8327*	0.1956
	(0.1728)	(5.8573)	(0.7991)	(0.1949)	(0.0947)	(1.3600)	(0.9576)	-(1.9559)	-(1.8626)	(0.2931)
Adj R-Squared	0.7134	0.6458	0.3657	0.2648	0.6801	0.7669	0.1183	0.4651	0.4660	0.0017

Table 8: Banking Spread Default Factors Regression Outputs

This Table displays the regression results of the credit spreads of the US LIBOR panel banks for the entire time series and the two equally divided portions. The symbols ***, **, * indicate that the betas are at 0.01, 0.05, and 0.10 levels of significance, respectively, and the T-statistics calculated using Newey-West standard errors with 10 lags are within brackets.

January 1, 2004 to September 30, 2010

Bank	BAC	CS	DB	HSBC	JPM	LLOY	RABO	RBS	UBS	HBOS
Constant	0.2507***	0.5952***	0.5470***	0.7765***	0.4149***	2.5832***	0.7267***	0.5772***	0.9030***	1.9486***
	(4.3522)	(17.1487)	(9.7405)	(15.2248)	(8.1951)	(33.3820)	(14.3660)	(13.5577)	(15.1569)	(9.4097)
CDS Factor	0.0205***	0.0124***	0.0230***	0.0140***	0.0211***	0.0314***	0.0126***	0.0201***	0.0219***	0.0207***
	(17.1335)	(11.6268)	(10.4995)	(11.8680)	(20.2932)	(25.8147)	(11.4583)	(16.8859)	(12.8890)	(7.2297)
Adj R-Squared	0.8184	0.5952	0.6294	0.6575	0.7854	0.8509	0.4545	0.7456	0.6782	0.0852

January 1, 2004 to May 17, 2007

Bank	BAC	CS	DB	HSBC	JPM	LLOY	RABO	RBS	UBS	HBOS
Constant	1.0629***	0.9966***	1.0359***	1.0628***	1.1840***	2.3274***	0.7447***	0.7109***	0.9327***	1.0444***
	(39.0318)	(23.7532)	(36.1836)	(71.0632)	(30.9544)	(21.1159)	(18.8055)	(46.8357)	(201.0454)	(39.2322)
CDS Factor	-0.0259***	-0.0189***	-0.0245***	-0.0617***	-0.0207***	0.0200	-0.0704***	-0.0270***	-0.0087***	-0.0237***
	-(16.0812)	-(5.2416)	-(8.1363)	-(25.9169)	-(9.7513)	(0.9271)	-(5.4217)	-(8.8031)	-(4.0168)	-(9.7076)
Adj R-Squared	0.6094	0.1961	0.4440	0.8429	0.4340	0.0089	0.2004	0.3565	0.1707	0.3414

May 18, 2007 to September 30, 2010

Bank	BAC	CS	DB	HSBC	JPM	LLOY	RABO	RBS	UBS	HBOS
Constant	0.0873	0.4771***	0.6009**	1.5593***	0.5663***	3.7303***	1.4116***	1.0307***	1.3086***	3.874***
	(0.5160)	(4.2419)	(2.6177)	(8.3908)	(5.3735)	(27.8334)	(10.0802)	(4.7406)	(5.3456)	(11.6765)
CDS Factor	0.0216***	0.0134***	0.0226***	0.0092***	0.0201***	0.0235***	0.0057***	0.0172***	0.0194***	0.0024
	(12.4299)	(9.0585)	(6.1531)	(5.3281)	(13.6795)	(16.5413)	(4.1997)	(9.1742)	(8.3212)	(0.6074)
Adj R-Squared	0.7137	0.4449	0.3581	0.2653	0.6804	0.7641	0.1109	0.4461	0.4339	0.0010

Table 9: Banking Spread Liquidity Factors Regression Outputs

This Table displays the regression results of the credit spreads of the US LIBOR panel banks for the entire time series and the two equally divided portions. The symbols ***, **, * indicate that the betas are at 0.01, 0.05, and 0.10 levels of significance, respectively, and the T-statistics calculated using Newey-West standard errors with 10 lags are within brackets.

January 1, 2004 to September 30, 2010

Bank	BAC	CS	DB	HSBC	JPM	LLOY	RABO	RBS	UBS	HBOS
Constant	1.4126***	0.7046***	1.2224***	1.377***	1.1671***	3.8784***	0.9309***	1.6086***	1.8319***	1.7548***
	(6.0620)	(7.7382)	(6.4992)	(7.8339)	(7.8735)	(14.4892)	(10.4340)	(8.0591)	(7.3153)	(6.4714)
Liquidity Risk	0.6477	1.4398***	1.2192***	0.9524***	0.9931***	1.2074***	0.6858***	0.5959*	0.9585*	1.6847***
	(1.6240)	(6.8197)	(2.9712)	(3.4012)	(3.8574)	(3.3514)	(3.8455)	(1.8327)	(1.7993)	(3.1865)
Adj R-Squared	0.0219	0.3744	0.1012	0.0651	0.1108	0.0342	0.0813	0.0157	0.0306	0.0808

January 1, 2004 to May 17, 2007

Bank	BAC	CS	DB	HSBC	JPM	LLOY	RABO	RBS	UBS	HBOS
Constant	0.5241***	0.6483***	0.7317***	0.6107***	0.6463***	2.5287***	0.7195***	0.4942***	0.9013***	0.6976***
	(11.1453)	(18.9679)	(25.8340)	(11.0080)	(12.4828)	(19.3438)	(12.4697)	(15.9229)	(58.7795)	(21.6202)
Liquidity Risk	0.4018***	0.4891***	0.1794**	0.3480**	0.5087***	-0.4853	-0.6608***	0.3437***	-0.0436	0.4448***
	(3.0749)	(5.9839)	(2.2221)	(2.2507)	(3.4905)	-(1.4985)	-(4.1791)	(3.4023)	-(0.9900)	(4.7886)
Adj R-Squared	0.0757	0.1510	0.0414	0.0397	0.0986	0.0104	0.0838	0.1189	0.0071	0.1737

May 18, 2007 to September 30, 2010

Bank	BAC	CS	DB	HSBC	JPM	LLOY	RABO	RBS	UBS	HBOS
Constant	2.9437***	1.1158***	2.3719***	2.8293***	2.1789***	6.6476***	1.7281***	3.5102***	3.6858***	3.8952***
	(8.4086)	(7.4986)	(8.4631)	(12.5545)	(10.1418)	(25.1456)	(16.6936)	(15.1692)	(11.1328)	(11.2640)
Liquidity Risk	-0.5297	1.1902***	0.3995	-0.1365	0.2393	-0.8282***	0.1644	-0.8704	-0.4141	0.1062
	-(1.1093)	(4.8397)	(0.8521)	-(0.4699)	(0.8058)	-(2.7889)	(1.0776)	-(2.6694)	-(0.6831)	(0.1785)
Adj R-Squared	0.0205	0.3020	0.0141	0.0017	0.0100	0.0469	0.0086	0.0620	0.0071	0.0000

Table 7 above shows that the default risk factor is more often statistically significant than the liquidity risk factor for all three periods, when both factors are used in the modelling of the credit spreads. For the entire series and the second half of the series, the default risk factor's betas are significant and positive. For the first half of series, the default risk factor's betas exhibit significant negative values, which is a perplexing result. As mentioned in Section 4.1, one possible explanation is the over issuance of CDS contracts, which results in a decrease in premiums (see Figure 7). These differing results demonstrate that selection of the length and time frame of the data can alter the significance and impact of the various risk factors within credit spreads.

The results in tables 7 and 8 are very similar, particularly the adjusted R-squared, signs and significance of the coefficients. This indicates that the default risk is a highly important factor in the modelling of the credit spreads.

Table 9 shows that when the default component of credit spreads is excluded from the models, the liquidity risk factors become statistically significant more often. However, when comparing the adjusted R-squared between the liquidity risk and default risk only models, the default component has a stronger relationship with the corporate bond spreads. These result are in accordance with (Longstaff, Mithal, and Neis 2005) and (Covitz and Downing 2007).

Finally, this simple regression analysis shows that the selection of the time series can significantly alter the results of the relationship between the risk factors and credit spreads. In addition, default risk plays a stronger role in the modelling of the credit spreads of the USD LIBOR panel banks in compared with liquidity risk.

Table 10: Banking Spread Regression Models Adjusted R-Squared

This Table displays the adjusted R-Squared of each of the credit spread regression models for all three time frames. The all factor model displays the model that includes both the CDS and liquidity risk variables. The default risk and liquidity risk models have only one regressor, the CDS factor for default risk and the liquidity risk proxy for liquidity risk. As shown, the default risk models have substantially higher adjusted R-Squared than the liquidity risk models.

January 1, 2004 to September 30, 2010

	BAC	CS	DB	HSBC	JPM	LLOY	RABO	RBS	UBS	HBOS
All Factors	0.8184	0.7223	0.6342	0.6645	0.7867	0.8618	0.4652	0.7473	0.6903	0.1940
Default Risk	0.8184	0.5952	0.6294	0.6575	0.7854	0.8509	0.4545	0.7456	0.6782	0.0852
Liquidity Risk	0.0219	0.3744	0.1012	0.0651	0.1108	0.0342	0.0813	0.0157	0.0306	0.0808

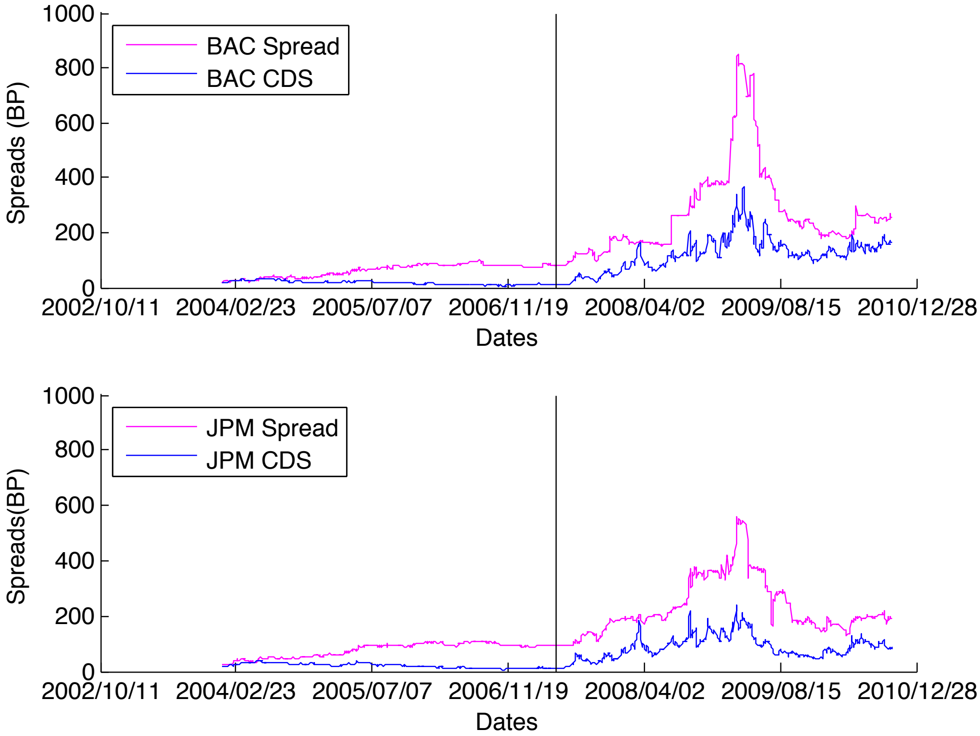
January 1, 2004 to May 17, 2007

	BAC	CS	DB	HSBC	JPM	LLOY	RABO	RBS	UBS	HBOS
All Factors	0.7174	0.3891	0.5124	0.8731	0.5943	0.0198	0.2440	0.5101	0.1794	0.5241
Default Risk	0.6094	0.1961	0.4440	0.8429	0.4340	0.0089	0.2004	0.3565	0.1707	0.3414
Liquidity Risk	0.0757	0.1510	0.0414	0.0397	0.0986	0.0104	0.0838	0.1189	0.0071	0.1737

May 18, 2007 to September 30, 2010

	BAC	CS	DB	HSBC	JPM	LLOY	RABO	RBS	UBS	HBOS
All Factors	0.7134	0.6458	0.3657	0.2648	0.6801	0.7669	0.1183	0.4651	0.4660	0.0017
Default Risk	0.7137	0.4449	0.3581	0.2653	0.6804	0.7641	0.1109	0.4461	0.4339	0.0010
Liquidity Risk	0.0205	0.3020	0.0141	0.0017	0.0100	0.0469	0.0086	0.0620	0.0071	0.0000

Figure 8: Credit and CDS Spreads of Bank of America and JP Morgan Chase



This figure displays the time series plot of the credit and CDS spreads of Bank of America and JP Morgan Chase. The vertical line indicates the bisection of the series at the 17 of May 2008. At first glance a strong positive relationship exists between the two spreads. However, during the first half of the series there is a negative relationship.

The figure above is included to demonstrate the negative correlation present between the credit spreads and CDS premiums of the USD LIBOR panel banks for the first half of the time series, January 1, 2004 to May 17, 2007. The outcome of negative betas for the default risk factor is clearly evident from the inverse relationship present in the first section of the figure. However, a strong positive relationship exists between the spreads and premiums for the remainder of the time series.

5.2 Regime-switching Regression

In addition to the analysis on the subdivided time series, regime-switching models are used. This allows better separation of the high and low credit risk periods. From observations made in this analysis, there are days with considerable credit risk, but they are assumed to be part of the less volatile market, due to their inclusion within the first half of the series. The regime-switching model does not differentiate based on the date, but rather on the level of liquidity risk. Hence, it is a better tool for the separation of time series based on a specific credit risk criterion.

$$CreditSpreadBank_{it} = \begin{cases} \alpha_1 + \beta_1 CDSBank_{it} + \beta_2 LIQ_t + \epsilon_t & \text{if } LIQ_t > C \\ \alpha_2 + \beta_3 CDSBank_{it} + \beta_4 LIQ_t + \epsilon_t & \text{if } LIQ_t < C \end{cases}$$

The criterion for the selection of the critical value, C, is the same as in the TED spread analysis. Again, as in the standard regression, Newey-West standard errors are used to calculate the T-Statistics (Newey and West 1987).

Table 11 below displays the results of the regime-switching regression on the credit spreads of the USD LIBOR panel banks. As in the case of the TED spread, the switch is related to the level of the liquidity risk proxy. Nineteen of the twenty CDS and thirteen of the twenty liquidity risk coefficients are statistically significant at a 0.05 level or better. However, nine out of ten liquidity risk factor coefficients are significant during the high liquidity risk period. The criterion for switching value, C, is much larger than the mean of the liquidity risk process for all the models except the HSBC and HBOS spreads. This indicates that liquidity risk affects credit spreads only when it has reached a substantial level, such as the credit crunch of 2008. These findings provide justification for the modelling of liquidity risk.

Table 11: Banking Spread Regime-switching Regression Outputs

This table displays the regression results of the credit spreads of the US LIBOR panel banks using a regime switching model. The symbols ***, **, * indicate that the betas are at 0.01, 0.05, and 0.10 levels of significance, respectively, and the T-statistics calculated using Newey-West standard errors with 10 lags are within brackets.

	January 1, 2004 to September 30, 2010									
Bank	BAC	CS	DB	HSBC	JPM	LLOY	RABO	RBS	UBS	HBOS
Constant low	0.3089***	0.4347***	0.6499***	0.7433***	0.3874***	2.3452***	0.6320***	0.5106***	1.1663***	2.5243***
	(3.1514)	(9.3438)	(8.2943)	(6.4872)	(4.3753)	(18.9782)	(8.7438)	(5.6398)	(10.4876)	(7.1903)
CDS Factor low	0.0210***	0.0101***	0.0216***	0.0169***	0.0220***	0.0320***	0.0131***	0.0219***	0.0246***	0.0218***
	(14.9489)	(11.8939)	(10.0375)	(12.7692)	(16.5889)	(26.7246)	(10.1535)	(19.5132)	(11.7770)	(5.7710)
Liquidity Risk low	-0.3673	0.699***	-0.2795	-1.1248*	-0.0383	0.4658	0.0683	0.1520	-1.0190***	-11.5254***
	-(1.0098)	(5.2973)	-(0.9703)	-(1.7521)	-(0.1522)	(1.2700)	(0.2640)	(0.4498)	-(2.4936)	-(7.5010)
Constant high	0.0327	4.7096***	1.0461	0.5294***	0.1567	3.1033***	2.7693***	0.1429	-2.3862***	0.2603
	(0.2792)	(4.5734)	(0.5736)	(5.7341)	(1.2047)	(11.1771)	(8.2744)	(0.3296)	-(7.0009)	(1.0970)
CDS Factor high	0.0163***	-0.0091**	0.0522***	0.0100***	0.0157***	0.0187***	0.0024	0.0109***	0.0173***	0.0264***
	(14.2422)	-(2.4500)	(3.4338)	(8.6244)	(10.5649)	(6.6721)	(0.9432)	(3.7867)	(6.2051)	(7.7960)
Liquidity Risk high	0.6839***	0.4279	-1.5836**	0.9847***	0.8135***	0.9427***	-0.7440***	1.0557**	3.0407***	3.2795***
	(4.9375)	(1.1050)	-(2.3329)	(5.5591)	(5.9749)	(3.6403)	-(3.3559)	(2.3395)	(6.4854)	(8.5878)
C	0.4504	1.4804	1.1704	0.2604	0.5004	0.6304	0.7604	0.6204	0.6304	0.1804
Adj R-Squared	0.8286	0.7491	0.6810	0.7267	0.8030	0.8728	0.5529	0.7781	0.7570	0.3910

Even though the default component seems to have a stronger relationship with corporate bond spreads, the inclusion of the liquidity risk factors helps in the modelling of credit spreads. This is true when the liquidity factor is included in a simple regression analysis or a regime-switching model. This can be explained by the higher adjusted R-squared of the regime-switching models and the simple regression models that include the liquidity risk factors.

5.3 Autoregressive Moving Average Model With Supplementary Independent Variables

The final models that are estimated on the credit spreads of the US LIBOR panel banks are ARMA with supplementary independent variables. They are included to provide a more robust verification of the economic significance of the default and liquidity risk factors.

As in the TED spread analysis, both the independent and dependant variables are highly autocorrelated and non-stationary. The error terms display heteroskedasticity. All the variables, except for the proposed liquidity risk proxy, fail to reject the null hypothesis of the presence of a unit root.

To resolve these issues, the first difference transformation of all the series is taken, $\Delta y_t = y_t - y_{t-1}$. This first difference transformation eliminates the unit root, improves stationarity of the series, and decreases the high level of autocorrelation. For a detailed graphical representation of the first difference transformation, please see Appendix 9.2 where the procedure is demonstrated on the Deutsche Bank credit spread.

The following ARMA models of the following composition with the default and liquidity risk proxies are used as independent variables on the first difference transformed series. The variables are the same as in sections 5.1 and 5.2. The variable names are shortened from $CreditSpreadBank$ to CSB. As with the standard regression model, models are estimated with the entire sample set and the two equally divided sub periods specified in the previous sections of this paper.

$$CSB_{it} = \beta_1 CDS_{it} + \beta_2 LIQ_t + \phi_1 CSB_{it-1} + \ldots + \phi_p CSB_{it-p} + \theta_1 \epsilon_{t-1} + \ldots + \theta_{t-q} \epsilon_q + \epsilon_t \quad (16)$$

$$CSB_{it} = \beta_1 CDS_{it} + \phi_1 CSB_{it-1} + \ldots + \phi_p CSB_{it-p} + \theta_1 \epsilon_{t-1} + \ldots + \theta_{t-q} \epsilon_q + \epsilon_t \quad (17)$$

$$CSB_{it} = \beta_1 LIQ_t + \phi_1 CSB_{it-1} + \ldots + \phi_p CSB_{it-p} + \theta_1 \epsilon_{t-1} + \ldots + \theta_{t-q} \epsilon_q + \epsilon_t \quad (18)$$

All possible ARMA specifications are estimated with $p, q \leq 6$. The values p & q are selected in in line the Box-Jenkins methodology, which entails finding the most parsimonious model specification. In Section 9.3, within the appendices, the selection process using the Deutsche Bank credit spread is presented. The estimation process is also included in the appendices, (see Section 9.4).

The ARMA models with liquidity and default risk factors for the credit spreads of the USD LIBOR panel banks for the entire time series are estimated, as well as the two equally subdivided periods. White noise residuals are not obtainable for the Bank of America, JP Morgan Chase, and UBS spreads for the estimated models on the entire series. Furthermore, white noise residuals are not obtainable for the Bank of America and JP Morgan Chase spreads for the estimated models on the second half of the series. Therefore, these models are excluded from the analysis. The ARMA model specifications, parameter coefficients, T-statistics and adjusted R-squared for the credit spreads of the USD LIBOR panel banks are included in Appendix 12.5.

For a simpler comparison of adjusted R-squared of the various models, see Table 12. Table 12 displays that once autoregressive and moving average components are included, neither liquidity nor default risk explains greater amounts of the fluctuations of the credit spreads.

Table 12: Banking Spread ARMA Models Adjusted R-Squared

This table displays the adjusted R-Squared of each of the credit spread ARMA models for all three time frames. The all factor model display the model that includes both the CDS and liquidity risk variables. The default risk and liquidity risk models have only one regressor, the CDS factor for default risk and the liquidity risk proxy for liquidity risk. As shown in this table, there is no discernible trend.

January 1, 2004 to September 30, 2010

	BAC	CS	DB	HSBC	JPM	LLOY	RABO	RBS	UBS	HBOS
All Factors		0.0273	0.0128	0.0138		0.0528	0.0749	0.0000		0.0044
Default Risk		**0.0246**	0.0046	0.0033		**0.0571**	**0.0716**	0.0000		0.0048
Liquidity Risk		0.0240	**0.0098**	**0.0141**		0.0257	0.0227	0.0000		0.0005

January 1, 2004 to May 17, 2007

	BAC	CS	DB	HSBC	JPM	LLOY	RABO	RBS	UBS	HBOS
All Factors	0.8700	0.1354	0.2508	0.0112	0.0870	0.0026	0.0200	0.0619	0.0780	0.1831
Default Risk	**0.0880**	0.1286	**0.2512**	0.0209	**0.0880**	0.0000	**0.0175**	**0.0494**	0.0770	**0.1839**
Liquidity Risk	0.0850	**0.1309**	0.2499	**0.0210**	0.0850	**0.0021**	0.0111	0.0489	**0.0780**	0.1806

May 18, 2007 to September 30, 2010

	BAC	CS	DB	HSBC	JPM	LLOY	RABO	RBS	UBS	HBOS
All Factors		0.0230	0.0128	0.0130		0.1231	0.1248	0.0000	0.0140	0.0023
Default Risk		0.0116	**0.0163**	0.0000		**0.0923**	**0.1269**	0.0000	0.0000	0.0028
Liquidity Risk		**0.0147**	0.0075	**0.0130**		0.0793	0.0332	0.0000	**0.0140**	**0.0064**

Table 13 displays the statistical significance of the liquidity and default risk variables at a 0.10 level of significance for all the estimated ARMA models. Looking at the comparison of the adjusted R-squared, there is no discernible trend on the importance of liquidity or default risk after inclusion of autoregressive and moving average components. However, there is a strong indication that both default and liquidity risk are components of credit spreads. This results from the observation of frequent statistically significant coefficients of the default and liquidity risk factors. Furthermore, there are more significant variables in the models estimated on the entire series and the second half of the series than the first half of the series. Consequently, there is less likelihood that a relationship exists between the risk factors and credit spreads for the first half of the time series in comparison with the second half of the time series. This result is interesting because it implies that both risk factors are more likely to influence credit spreads during volatile markets. It follows financial intuition that the importance of both risk factors increases when the overall risk in the market increases, such as during the recent financial crisis.

Table 13: Banking Spread ARMA Models Significance Of Default and Liquidity Risk Factors

This table displays the statistical significance of the default and liquidity risk coefficients at a 0.10 level for the various ARMA models. The total percentage of significant variables is displayed, where a 1 indicates statistical significance and a red value for 1 indicates a negative coefficient. As shown in this table, there is no discernible trend.

Bank	BAC	BAC	CS	CS	DB	DB	HSBC	HSBC	JPM	JPM	LLOY	LLOY	RABO	RABO	RBS	RBS	UBS	UBS	HBOS	HBOS	ToT	%
Factor	LIQ	CDS	LIQ	CDS	LIQ	CDS	LIQ	CDS	LIQ	CDS	LIQ	CDS	LIQ	CDS	LIQ	CDS	LIQ	CDS	LIQ	CDS		
January 1, 2004 to September 30, 2010																						
ALL				1	1	1		1			1	1	1						1		8	57%
LIQ model					1		1				1		1						1		5	71%
CDS model						1		1				1		1							4	57%
																					17	61%
January 1, 2004 to May 17, 2007																						
ALL		1	1	1					1			1	1	1	1						8	40%
LIQ model	1		1										1		1						4	40%
CDS model										1		1		1		1					4	40%
																					16	40%
May 18, 2007 to September 30, 2010																						
ALL					1	1		1	1		1	1	1						1		8	44%
LIQ model					1						1		1						1		4	44%
CDS model				1		1		1		1		1		1							6	67%
																					18	50%
ToT	1	1	2	3	4	4	1	4	2	2	4	6	6	4	2	1	0	0	4	0		
%	50%	50%	33%	**50%**	67%	67%	17%	**67%**	50%	50%	67%	**100%**	**100%**	67%	**33%**	17%	0%	0%	**67%**	0%		

6 GARCH

In this section I describe the GARCH estimation process on the residuals of the previously described ARMA models in sections 4.3 and 5.3.

Even though the estimated ARMA models have white noise residuals, their squared residuals might be autocorrelated. Hence, I test the residuals for ARCH, autoregressive conditional heteroskedasticity, effects using the ARCH test. If the null hypothesis of no conditional heteroskedasticity is rejected, a GARCH(p,q) with Gaussian innovations is estimated (Bollerslev 1986).

$$h_t = \alpha_0 + \sum_{t=i}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{t=i}^{p} \beta_i h_{t-i} \tag{19}$$

$$\begin{aligned} & with, \\ & p \geq 0, \quad q > 0 \qquad (20) \\ & \alpha_0 > 0, \quad \alpha_i \geq 0, \quad i = 1, \ldots, q, \\ & \beta_i \geq 0, \quad i = 1, \ldots, q, \end{aligned} \tag{21}$$

I try to find the best possible GARCH(p,q) model by seeking the specification that has the fewest parameters and a good fit. To test for fit, a Ljung-Box test on the residuals divided by the conditional variance squared is conducted. If the null hypothesis of a random series fails to be rejected at a 5% level of significance, I conclude that the model is well specified (Ljung and Box 1978). This simple selection process is used, given that the objective of the paper is to interpret the relationship between credit spreads and inherent risk factors, as opposed to modelling the conditional volatility of the credit spreads.

If the GARCH(p,q) model is well specified, this demonstrates that the movements of the squared residuals can be modelled. The previously estimated ARMA models will consequently be adequate.

Table 14 displays the credit spreads that have ARCH effects, and tables 15 to 17, present the GARCH outputs for the 15 estimated GARCH models on the 5 different credit spreads residuals. The Ljung-Box Test p-values within the tables are calculated on the residuals divided by the conditional variance squared. If the value is greater than 0.05, the process is assumed as white noise and the GARCH model is well specified. This provides further proof that the original ARMA specifications are adequate: the various ARCH effects of the residuals can be modelled with simple order GARCH processes.

Table 14: Presence Of ARCH Effects

This table displays the credit spreads where GARCH models are estimated on the residuals of the ARMA models.

	01/01/2004 to 09/30/2010	01/01/2004 to 05/17/2007	05/18/2007 to 09/30/2010
TED Spread			
Bank Of America			
Credit Suisse		GARCH	
Deutsche Bank		GARCH	
HSBC			
JP Morgan			
LLOYDS			GARCH
RABO			
RBS		GARCH	
UBS			
HBOS		GARCH	

Table 15: GARCH Output: Credit Suisse and Deustche Bank

This table includes the GARCH outputs. The symbols ***, **, * indicate that the parameters are at 0.01, 0.05, and 0.10 levels of significance, respectively. The Ljung-Box Test p-value within the table is the test performed on the residuals divided by the conditional variance squared.

Credit Suisse

January 1, 2004 to May 17, 2007

Liquidity and Default Risk Factors

GARCH(2,2)			
Parameter	Value	Std Error	T-Statistic
C	0.0001	0.0008	0.0724
K	0.0000***	0.0000	3.6338
GARCH(1)	0.0067	0.1068	0.0631
GARCH(2)	0.7732***	0.1048	7.3753
ARCH(1)	0.0649**	0.0253	2.5669
ARCH(2)	0.1054***	0.0261	4.0364
Log Likelihood Value:		1939.72	
Ljung-Box Test P-value		0.0532	

Liquidity Risk Factor

GARCH(2,2)			
Parameter	Value	Std Error	T-Statistic
C	-0.0003	0.0008	-0.4130
K	0.0000***	0.0000	3.6024
GARCH(1)	0.0041	0.1053	0.0390
GARCH(2)	0.7799***	0.1006	7.7558
ARCH(1)	0.0669**	0.0266	2.5193
ARCH(2)	0.1053***	0.0265	3.9728
Log Likelihood Value:		1933.71	
Ljung-Box Test P-value		0.0607	

Default Risk Factor

GARCH(2,2)			
Parameter	Value	Std Error	T-Statistic
C	-0.0006	0.0008	-0.7799
K	0.0000***	0.0000	3.6025
GARCH(1)	0.0041	0.1079	0.0380
GARCH(2)	0.7678***	0.0993	7.7313
ARCH(1)	0.0698***	0.0269	2.5911
ARCH(2)	0.1133***	0.0270	4.1932
Log Likelihood Value:		1943.64	
Ljung-Box Test P-value		0.0744	

Deutsche Bank

January 1, 2004 to May 17, 2007

Liquidity and Default Risk Factors

GARCH(2,1)			
Parameter	Value	Std Error	T-Statistic
C	0.0014	0.0012	1.1274
K	0.0000**	0.0000	2.4688
GARCH(1)	0.2751	0.2301	1.1956
GARCH(2)	0.6592***	0.2243	2.9395
ARCH(1)	0.0549***	0.0117	4.7021
Log Likelihood Value:		1574.13	
Ljung-Box Test P-value		0.0599	

Liquidity Risk Factor

GARCH(2,1)			
Parameter	Value	Std Error	T-Statistic
C	-0.0005	0.0012	-0.3648
K	0.0000**	0.0000	2.4379
GARCH(1)	0.2707	0.2234	1.2118
GARCH(2)	0.6634***	0.2178	3.0464
ARCH(1)	0.0553***	0.0117	4.7196
Log Likelihood Value:		1574.48	
Ljung-Box Test P-value		0.0636	

Default Risk Factor

GARCH(2,1)			
Parameter	Value	Std Error	T-Statistic
C	-0.0005	0.0013	-0.3986
K	0.0000**	0.0000	2.4181
GARCH(1)	0.2535	0.2090	1.2131
GARCH(2)	0.6827***	0.2037	3.3519
ARCH(1)	0.0535***	0.0112	4.7749
Log Likelihood Value:		1574.88	
Ljung-Box Test P-value		0.0581	

Table 16: GARCH Output: RBS and HBOS

This table includes the GARCH output. The symbols ***, **, * indicate that the parameters are at 0.01, 0.05, and 0.10 levels of significance, respectively. The Ljung-Box Test p-value within the table is the test performed on the residuals divided by the conditional variance squared.

RBS

January 1, 2004 to May 17, 2007

Liquidity and Default Risk Factors

GARCH(1,1)			
Parameter	Value	Std Error	T-Statistic
C	0.0002	0.0004	0.4176
K	0.0000	0.0000	0.9967
GARCH(1)	0.9860***	0.0022	454.2355
ARCH(1)	0.0119***	0.0019	6.1123
Log Likelihood Value:		2573.71	
Ljung-Box Test P-value		0.8545	

Liquidity Risk Factor

GARCH(1,1)			
Parameter	Value	Std Error	T-Statistic
C	-0.0003	0.0004	-0.7791
K	0.0000	0.0000	1.0222
GARCH(1)	0.9861***	0.0021	472.5365
ARCH(1)	0.0118***	0.0019	6.2653
Log Likelihood Value:		2569.63	
Ljung-Box Test P-value		0.8689	

Default Risk Factor

GARCH(1,1)			
Parameter	Value	Std Error	T-Statistic
C	-0.0003	0.0004	-0.7791
K	0.0000	0.0000	1.0222
GARCH(1)	0.9861***	0.0021	472.5365
ARCH(1)	0.0118***	0.0019	6.2653
Log Likelihood Value:		2569.20	
Ljung-Box Test P-value		0.8269	

HBOS

January 1, 2004 to May 17, 2007

Liquidity and Default Risk Factors

GARCH(1,1)			
Parameter	Value	Std Error	T-Statistic
C	0.0000	0.0008	-0.0048
K	0.0000***	0.0000	3.5980
GARCH(1)	0.9120***	0.0115	79.3853
ARCH(1)	0.0820***	0.0132	6.2124
Log Likelihood Value:		1977.56	
Ljung-Box Test P-value		0.7676	

Liquidity Risk Factor

GARCH(1,1)			
Parameter	Value	Std Error	T-Statistic
C	-0.0011	0.0008	-1.4279
K	0.0000***	0.0000	3.6805
GARCH(1)	0.9139***	0.0107	85.4009
ARCH(1)	0.0794***	0.0123	6.4290
Log Likelihood Value:		1981.87	
Ljung-Box Test P-value		0.7939	

Default Risk Factor

GARCH(1,1)			
Parameter	Value	Std Error	T-Statistic
C	-0.0012	0.0008	-1.6420
K	0.0000***	0.0000	3.6266
GARCH(1)	0.9119***	0.0107	85.0937
ARCH(1)	0.0819***	0.0123	6.6663
Log Likelihood Value:		1983.95	
Ljung-Box Test P-value		0.6515	

Table 17: GARCH Output: HBOS

This table includes the GARCH output. The symbols ***, **, * indicate that the parameters are at 0.01, 0.05, and 0.10 levels of significance, respectively. The Ljung-Box Test p-value within the table is the test performed on the residuals divided by the conditional variance squared.

Lloyds

May 18, 2007 to September 30, 2010

Liquidity and Default Risk Factors

GARCH(1,1)			
Parameter	Value	Std Error	T-Statistic
-----------	-----------	------------	-----------
C	0.0093***	0.0019	4.7761
K	0.0000	0.0000	0.9373
GARCH(1)	0.9325***	0.0122	76.4135
ARCH(1)	0.0675***	0.0129	5.2236
Log Likelihood Value:		1124.94	
Ljung-Box Test P-value		0.0932	

Liquidity Risk Factor

GARCH(1,1)			
Parameter	Value	Std Error	T-Statistic
-----------	-----------	------------	-----------
C	0.0016	0.0020	0.8304
K	0.0000	0.0000	0.7574
GARCH(1)	0.9421***	0.0110	85.2635
ARCH(1)	0.0580***	0.0117	4.9654
Log Likelihood Value:		1118.86	
Ljung-Box Test P-value		0.8992	

Default Risk Factor

GARCH(1,1)			
Parameter	Value	Std Error	T-Statistic
-----------	-----------	------------	-----------
C	0.0015	0.0022	0.7111
K	0.0000	0.0000	0.0183
GARCH(1)	0.9617***	0.0075	127.4218
ARCH(1)	0.0383***	0.0082	4.6704
Log Likelihood Value:		1071.68	
Ljung-Box Test P-value		0.9348	

7 Conclusion

During the recent turmoil in the interbank market, credit spreads exploded. The question of which risk factors were accountable for these substantial increases became a topic of discussion for many participants in financial markets. This paper analyses the risk factors that affect the interbank market credit spreads. To do so, the relative importance of the default and liquidity risk factors within the TED spread and the credit spreads of the US LIBOR panel banks were analysed using OLS, regime-switching, and autoregressive moving average models. The proxy for liquidity risk is estimated by calculating the mean spread between off-the-run notes and on-the-run par yield curves estimated from the constant maturity treasury yields. The default risk is calculated using CDS premiums.

The major findings of this paper are the following: First, both default and liquidity risk are both relevant factors affecting credit spreads. Second, the importance of the effect of liquidity risk on credit spreads increases during periods of high market volatility. Third, the relationship between the default and liquidity risk and credit spreads can be distorted due to the selection of the range and time frame of the data. Fourth, I find a negative relationship between CDS premiums and credit spreads between 2004 and 2007. Lastly, a discrepancy exists between the relative importance of the default and liquidity risk. While the credit spreads of the USD LIBOR panel banks are more strongly related to default risk, the interbank spread, i.e. the TED, is influenced to a greater extent by liquidity risk.

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References

Acharya, V. V., Y. Amihud, and S. Bharath (2010). Liquidity Risk of Corporate Bond Returns. Working Paper, New York University and University of Michigan.

Amihud, Y. (2002). Illiquidity and Stock Returns: Cross-section and Time-Series Effects. *Journal of Financial Markets 5*, 31–56.

Amihud, Y. and H. Mendelson (1986). Asset Pricing and the Bid-Ask Spread. *Journal of Financial Economics 17*, 223–249.

Amihud, Y. and H. Mendelson (1991). Liquidity, Maturity, and the Yields on U.S. Treasury Securities. *Journal of Finance 46*(4), 1411–1425.

Bao, J., J. Pan, and J. Wang (2011). The Illiquidity of Corporate Bonds. *Journal of Finance 66*, 911–946.

Bianchi, R. J., M. E. Drew, and T. R. Wijeratne (2010). Systemic Risk, the TED Spread and Hedge Fund Returns. *Working Paper*.

Blanco, R., S. Brennan, and I. Marsh (2005). An Empirical Analysis of the Dynamic between Investment-Grade Bonds and Credit Default Swaps. *Journal of Finance 60*(5), 2255–2281.

Bolder, D. and D. Streliski (1999). Yield Curve Modelling at the Bank of Canada. Technical Report 84, Bank of Canada.

Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics 31*, 307–327.

Brunnermeier, M. K. (2009). Deciphering the Liquidity and Credit Crunch. *The Journal of Economic Perspectives 23*(1), 77–100.

Chen, L., D. L. Lesmond, and J. Wei (2007). Corporate Yield Spreads and Bond Liquidity. *Journal of Finance 62*(1), 119–149.

Chen, R.-R., F. J. Fabozzi, and R. Sverdlove (2010). Corporate Credit Default Swap Liquidity and Its Implications for Corporate Bond Spreads. *Journal of Finance 20*(2), 31–57.

Collin-Dufresne, P., R. S. Goldstein, and J. S. Martin (2001). The Determinants of Credit Spread Changes. *Journal of Finance 56*(6), 2177–2207.

Covitz, D. and C. Downing (2007). Liquidity or Credit Risk? The Determinants of Very Short-Term Corporate Yield Spreads. *Journal of Finance 62*(5), 2303–2328.

Cox, J., J. Ingersoll, and S. Ross (1985). A Theory of the Term Structure of Interest Rates. *Econometrica 53*(2), 385–407.

de Jong, F. and J. Driessen (2006). Liquidity Risk Premia in Corporate Bond Markets. Working Paper, Tilburg University and University of Amsterdam.

DeSocio, A. (2009). The Interbank Market after the financial turmoil: Squeezing Liquidity in a Lemons Market or Asking Liquidity On Tap. Working Papers 819, Banca d'Italia, Eurosistema.

Dick-Nielsen, J., P. Feldhutter, and D. Lando (2012). Corporate Bond Liquidity Before and After the Onset of the Subprime Crisis. *Journal of Financial Economics 103*(1), 471–492.

Dickey, D. D. and W. A. Fuller (1979). Distribution of the Estimators for Autorgessive Time Series With a Unit Root. *Journal of the American Statistical Association 74*(366), 427–431.

Edwards, F. R. (1999). Hedge Funds and The Collapse of Long-Term Capital Managment. *Journal of Economic Perspectives 13*(2), 189–210.

Eisnschmidt, J. and J. Tapking (2009). Liquidity Risk Premia in Unsecured Interbank Money Markets. Working Paper Series 1025, European Central Bank.

Fisher, L. (1959). Determinants of Risk Premiums on Corporate Bonds. *Journal of Political Economy 67*(3), 217–237.

Friewald, N., R. Jankowitsch, and M. G. Subrahmanyam (2008). Illiquidity or Credit Deterioration: A Study of Liquidity in the US Corporate Bond Market during Financial Crises. *Journal of Financial Economics, forthcoming*.

Goldreich, D., B. Hanke, and P. Nath (2005). The Price of Future Liquidity: Time-Varying Liquidity in the U.S. Treasury Market. *Review of Finance 9*(1), 1–32.

Krishnamurthy, A. (2002). The Bond/Old-Bond Spread. *Journal of Financial Economics 66*, 463–506.

Lashgari, M. (2000). The Role of TED Spread and Confidence Index in Explaining the Behaviour of Stock Prices. *American Business Review 18*(1), 9–12.

Ljung, G. M. and G. E. Box (1978). On a Measure of Lack of Fit in Time Series Models. *Biometrika 65*(2), 297–303.

Longstaff, F. A., S. Mithal, and E. Neis (2005). Corporate Yeild Spreads: Default Risk or Liquidity? New Evidence from the Credit Default Swap Market. *Journal of Finance 60*(5), 2213–2253.

Melvin, M. and M. P. Taylor (2009). The Crisis in the Foreign Exchange Market. *Journal of International Money and Finance 28*, 1317–1330.

Merton, R. C. (1974). On the Pricing of Corporate Debt: The Risk Structure of Interest Rates. *Journal of Finance 29*, 449–470.

Newey, W. K. and K. D. West (1987). A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometerica 55*(3), 703–708.

Nobili, S. (2009). Liquidity Risk in Money Market Spreads. Working paper, Banca d'Italia, Central Banking Department.

Roll, R. (1984). A Simple Implicit Measure of the Effective Bid-ask Spread In an Efficient Market. *Journal of Finance 29*, 1127–1139.

Schwarz, K. (2010). Mind the Gap: Disentangling Credit and Liquidity in Risk Spreads. Working Paper, The Wharton School, University of Pennsylvania.

Shulman, J. (1993). Marketability and Default Influences on the Yield Premia of Speculative Grade Debt. *Financial Management 22*(3), 132.

9 Appendices

9.1 On-the-run and Off-the-run Selection Process

The 10-year treasury notes are newly issued on February, May, August, and Novemberv 15^{th} of every year. Hence, the on-the-run security note will change 4 times a year. As for the off-the-run notes, their composition will also change quarterly, with the oldest note being dropped from the group and the on-the-run security joining them. I limit the off-the-run securities to the six most recent notes to avoid the effect of stale prices and large differences in maturities. The following tables display the coupon rates, issuance dates and maturity dates of the on and off-the-run 10-year treasury notes used analysed. This provides a clearer representation of the selection process of the on and off-the-run notes.

Table 18: Coupon Rates of On-the-run and Off-the-run 10-Year Treasury Notes

PERIOD	Off the Run 6	Off the Run 5	Off the Run 4	Off the Run 4	Off the Run 3	Off the Run 2	On the Run
2004/01/01 to 2004/2/17	4.875	4.375	4	3.875	3.625	4.25	4.25
2004/2/17 to 2004/5/17	4.375	4.000	3.875	3.625	4.250	4.250	4.000
2004/5/17 to 2004/8/16	4.000	3.875	3.625	4.250	4.250	4.000	4.750
2004/8/16 to 2004/11/15	3.875	3.625	4.250	4.250	4.000	4.750	4.250
2004/11/15 to 2005/2/15	3.625	4.250	4.250	4.000	4.750	4.250	4.250
2005/2/15 to 2005/5/16	4.250	4.250	4.000	4.750	4.250	4.250	4.000
2005/5/16 to 2005/8/15	4.250	4.000	4.750	4.250	4.250	4.000	4.125
2005/8/15 to 2005/11/15	4.000	4.750	4.250	4.250	4.000	4.125	4.250
2005/11/15 to 2006/2/15	4.750	4.250	4.250	4.000	4.125	4.250	4.500
2006/2/15 to 2006/5/15	4.250	4.250	4.000	4.125	4.250	4.500	4.500
2006/5/15 to 2006/8/15	4.250	4.000	4.125	4.250	4.500	4.500	5.125
2006/8/15 to 2006/11/15	4.000	4.125	4.250	4.500	4.500	5.125	4.875
2006/11/15 to 2007/2/15	4.125	4.250	4.500	4.500	5.125	4.875	4.625
2007/2/15 to 2007/5/15	4.250	4.500	4.500	5.125	4.875	4.625	4.625
2007/5/15 to 2007/8/15	4.500	4.500	5.125	4.875	4.625	4.625	4.500
2007/8/15 to 2007/11/15	4.500	5.125	4.875	4.625	4.625	4.500	4.750
2007/11/15 to 2008/2/15	5.125	4.875	4.625	4.625	4.500	4.750	4.250
2008/2/15 to 2008/5/15	4.875	4.625	4.625	4.500	4.750	4.250	3.500
2008/5/15 to 2008/8/15	4.625	4.625	4.500	4.750	4.250	3.500	3.875
2008/8/15 to 2008/11/17	4.625	4.500	4.750	4.250	3.500	3.875	4.000
2008/11/17 to 2009/2/17	4.500	4.750	4.250	3.500	3.875	4.000	3.750
2009/2/17 to 2009/5/15	4.750	4.250	3.500	3.875	4.000	3.750	2.750
2009/5/15 to 2009/8/17	4.250	3.500	3.875	4.000	3.750	2.750	3.125
2009/8/17 to 2009/11/16	3.500	3.875	4.000	3.750	2.750	3.125	3.625
2009/11/16 to 2010/2/16	3.875	4.000	3.750	2.750	3.125	3.625	3.375
2010/2/16 to 2010/5/17	4.000	3.750	2.750	3.125	3.625	3.375	3.625
2010/5/17 to 2010/8/16	3.750	2.750	3.125	3.625	3.375	3.625	3.500
2010/8/16 to 2010/9/30	2.750	3.125	3.625	3.375	3.625	3.500	2.625

This table displays the coupon rates by period of the on and off-the-run 10-year treasury notes.

Table 19: Issuance Dates of On-the-run and Off-the-run Notes

PERIOD	Off the Run 6	Off the Run 5	Off the Run 4	Off the Run 4	Off the Run 3	Off the Run 2	On the Run
2004/01/01 to 2004/2/17	2002-02-15	2002-08-15	2002-11-15	2003-02-18	2003-05-15	2003-08-15	2003-11-17
2004/2/17 to 2004/5/17	2002-08-15	2002-11-15	2003-02-18	2003-05-15	2003-08-15	2003-11-17	2004-02-17
2004/5/17 to 2004/8/16	2002-11-15	2003-02-18	2003-05-15	2003-08-15	2003-11-17	2004-02-17	2004-05-17
2004/8/16 to 2004/11/15	2003-02-18	2003-05-15	2003-08-15	2003-11-17	2004-02-17	2004-05-17	2004-08-16
2004/11/15 to 2005/2/15	2003-05-15	2003-08-15	2003-11-17	2004-02-17	2004-05-17	2004-08-16	2004-11-15
2005/2/15 to 2005/5/16	2003-08-15	2003-11-17	2004-02-17	2004-05-17	2004-08-16	2004-11-15	2005-02-15
2005/5/16 to 2005/8/15	2003-11-17	2004-02-17	2004-05-17	2004-08-16	2004-11-15	2005-02-15	2005-05-16
2005/8/15 to 2005/11/15	2004-02-17	2004-05-17	2004-08-16	2004-11-15	2005-02-15	2005-05-16	2005-08-15
2005/11/15 to 2006/2/15	2004-05-17	2004-08-16	2004-11-15	2005-02-15	2005-05-16	2005-08-15	2005-11-15
2006/2/15 to 2006/5/15	2004-08-16	2004-11-15	2005-02-15	2005-05-16	2005-08-15	2005-11-15	2006-02-15
2006/5/15 to 2006/8/15	2004-11-15	2005-02-15	2005-05-16	2005-08-15	2005-11-15	2006-02-15	2006-05-15
2006/8/15 to 2006/11/15	2005-02-15	2005-05-16	2005-08-15	2005-11-15	2006-02-15	2006-05-15	2006-08-15
2006/11/15 to 2007/2/15	2005-05-16	2005-08-15	2005-11-15	2006-02-15	2006-05-15	2006-08-15	2006-11-15
2007/2/15 to 2007/5/15	2005-08-15	2005-11-15	2006-02-15	2006-05-15	2006-08-15	2006-11-15	2007-02-15
2007/5/15 to 2007/8/15	2005-11-15	2006-02-15	2006-05-15	2006-08-15	2006-11-15	2007-02-15	2007-05-15
2007/8/15 to 2007/11/15	2006-02-15	2006-05-15	2006-08-15	2006-11-15	2007-02-15	2007-05-15	2007-08-15
2007/11/15 to 2008/2/15	2006-05-15	2006-08-15	2006-11-15	2007-02-15	2007-05-15	2007-08-15	2007-11-15
2008/2/15 to 2008/5/15	2006-08-15	2006-11-15	2007-02-15	2007-05-15	2007-08-15	2007-11-15	2008-02-15
2008/5/15 to 2008/8/15	2006-11-15	2007-02-15	2007-05-15	2007-08-15	2007-11-15	2008-02-15	2008-05-15
2008/8/15 to 2008/11/17	2007-02-15	2007-05-15	2007-08-15	2007-11-15	2008-02-15	2008-05-15	2008-08-15
2008/11/17 to 2009/2/17	2007-05-15	2007-08-15	2007-11-15	2008-02-15	2008-05-15	2008-08-15	2008-11-17
2009/2/17 to 2009/5/15	2007-08-15	2007-11-15	2008-02-15	2008-05-15	2008-08-15	2008-11-17	2009-02-17
2009/5/15 to 2009/8/17	2007-11-15	2008-02-15	2008-05-15	2008-08-15	2008-11-17	2009-02-17	2009-05-15
2009/8/17 to 2009/11/16	2008-02-15	2008-05-15	2008-08-15	2008-11-17	2009-02-17	2009-05-15	2009-08-17
2009/11/16 to 2010/2/16	2008-05-15	2008-08-15	2008-11-17	2009-02-17	2009-05-15	2009-08-17	2009-11-16
2010/2/16 to 2010/5/17	2008-08-15	2008-11-17	2009-02-17	2009-05-15	2009-08-17	2009-11-16	2010-02-16
2010/5/17 to 2010/8/16	2008-11-17	2009-02-17	2009-05-15	2009-08-17	2009-11-16	2010-02-16	2010-05-17
2010/8/16 to 2010/9/30	2009-02-17	2009-05-15	2009-08-17	2009-11-16	2010-02-16	2010-05-17	2010-08-16

This table displays the issuance dates by period of the on and off-the-run ten year treasury notes. The purpose of including this table is to add a visual aid to show the process of selection of the on and off-the-run securities.

Table 20: Maturity Dates of On-the-run and Off-the-run 10-Year Treasury Notes

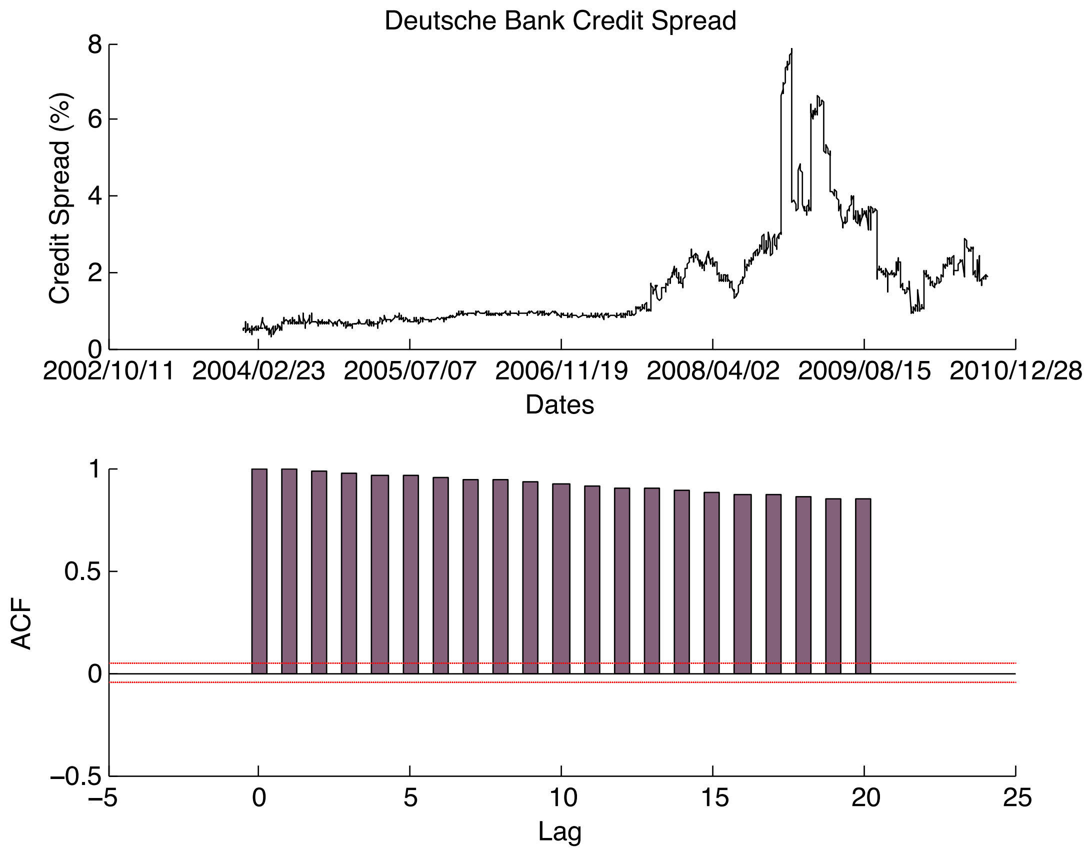
PERIOD	Off the Run 6	Off the Run 5	Off the Run 4	Off the Run 4	Off the Run 3	Off the Run 2	On the Run
2004/01/01 to 2004/2/17	2012-02-15	2012-08-15	2012-11-15	2013-02-15	2013-05-15	2013-08-15	2013-11-15
2004/2/17 to 2004/5/17	2012-08-15	2012-11-15	2013-02-15	2013-05-15	2013-08-15	2013-11-15	2014-02-15
2004/5/17 to 2004/8/16	2012-11-15	2013-02-15	2013-05-15	2013-08-15	2013-11-15	2014-02-15	2014-05-15
2004/8/16 to 2004/11/15	2013-02-15	2013-05-15	2013-08-15	2013-11-15	2014-02-15	2014-05-15	2014-08-15
2004/11/15 to 2005/2/15	2013-05-15	2013-08-15	2013-11-15	2014-02-15	2014-05-15	2014-08-15	2014-11-15
2005/2/15 to 2005/5/16	2013-08-15	2013-11-15	2014-02-15	2014-05-15	2014-08-15	2014-11-15	2015-02-15
2005/5/16 to 2005/8/15	2013-11-15	2014-02-15	2014-05-15	2014-08-15	2014-11-15	2015-02-15	2015-05-15
2005/8/15 to 2005/11/15	2014-02-15	2014-05-15	2014-08-15	2014-11-15	2015-02-15	2015-05-15	2015-08-15
2005/11/15 to 2006/2/15	2014-05-15	2014-08-15	2014-11-15	2015-02-15	2015-05-15	2015-08-15	2015-11-15
2006/2/15 to 2006/5/15	2014-08-15	2014-11-15	2015-02-15	2015-05-15	2015-08-15	2015-11-15	2016-02-15
2006/5/15 to 2006/8/15	2014-11-15	2015-02-15	2015-05-15	2015-08-15	2015-11-15	2016-02-15	2016-05-15
2006/8/15 to 2006/11/15	2015-02-15	2015-05-15	2015-08-15	2015-11-15	2016-02-15	2016-05-15	2016-08-15
2006/11/15 to 2007/2/15	2015-05-15	2015-08-15	2015-11-15	2016-02-15	2016-05-15	2016-08-15	2016-11-15
2007/2/15 to 2007/5/15	2015-08-15	2015-11-15	2016-02-15	2016-05-15	2016-08-15	2016-11-15	2017-02-15
2007/5/15 to 2007/8/15	2015-11-15	2016-02-15	2016-05-15	2016-08-15	2016-11-15	2017-02-15	2017-05-15
2007/8/15 to 2007/11/15	2016-02-15	2016-05-15	2016-08-15	2016-11-15	2017-02-15	2017-05-15	2017-08-15
2007/11/15 to 2008/2/15	2016-05-15	2016-08-15	2016-11-15	2017-02-15	2017-05-15	2017-08-15	2017-11-15
2008/2/15 to 2008/5/15	2016-08-15	2016-11-15	2017-02-15	2017-05-15	2017-08-15	2017-11-15	2018-02-15
2008/5/15 to 2008/8/15	2016-11-15	2017-02-15	2017-05-15	2017-08-15	2017-11-15	2018-02-15	2018-05-15
2008/8/15 to 2008/11/17	2017-02-15	2017-05-15	2017-08-15	2017-11-15	2018-02-15	2018-05-15	2018-08-15
2008/11/17 to 2009/2/17	2017-05-15	2017-08-15	2017-11-15	2018-02-15	2018-05-15	2018-08-15	2018-11-15
2009/2/17 to 2009/5/15	2017-08-15	2017-11-15	2018-02-15	2018-05-15	2018-08-15	2018-11-15	2019-02-15
2009/5/15 to 2009/8/17	2017-11-15	2018-02-15	2018-05-15	2018-08-15	2018-11-15	2019-02-15	2019-05-15
2009/8/17 to 2009/11/16	2018-02-15	2018-05-15	2018-08-15	2018-11-15	2019-02-15	2019-05-15	2019-08-15
2009/11/16 to 2010/2/16	2018-05-15	2018-08-15	2018-11-15	2019-02-15	2019-05-15	2019-08-15	2019-11-15
2010/2/16 to 2010/5/17	2018-08-15	2018-11-15	2019-02-15	2019-05-15	2019-08-15	2019-11-15	2020-02-15
2010/5/17 to 2010/8/16	2018-11-15	2019-02-15	2019-05-15	2019-08-15	2019-11-15	2020-02-15	2020-05-15
2010/8/16 to 2010/9/30	2019-02-15	2019-05-15	2019-08-15	2019-11-15	2020-02-15	2020-05-15	2020-08-15

This table displays the issuance dates by period of the on and off-the-run ten year treasury notes. The purpose of including this table is to add a visual aid to show the process of selection of the on and off-the-run securities.

9.2 First Difference Transformation: Deutsche Bank Case

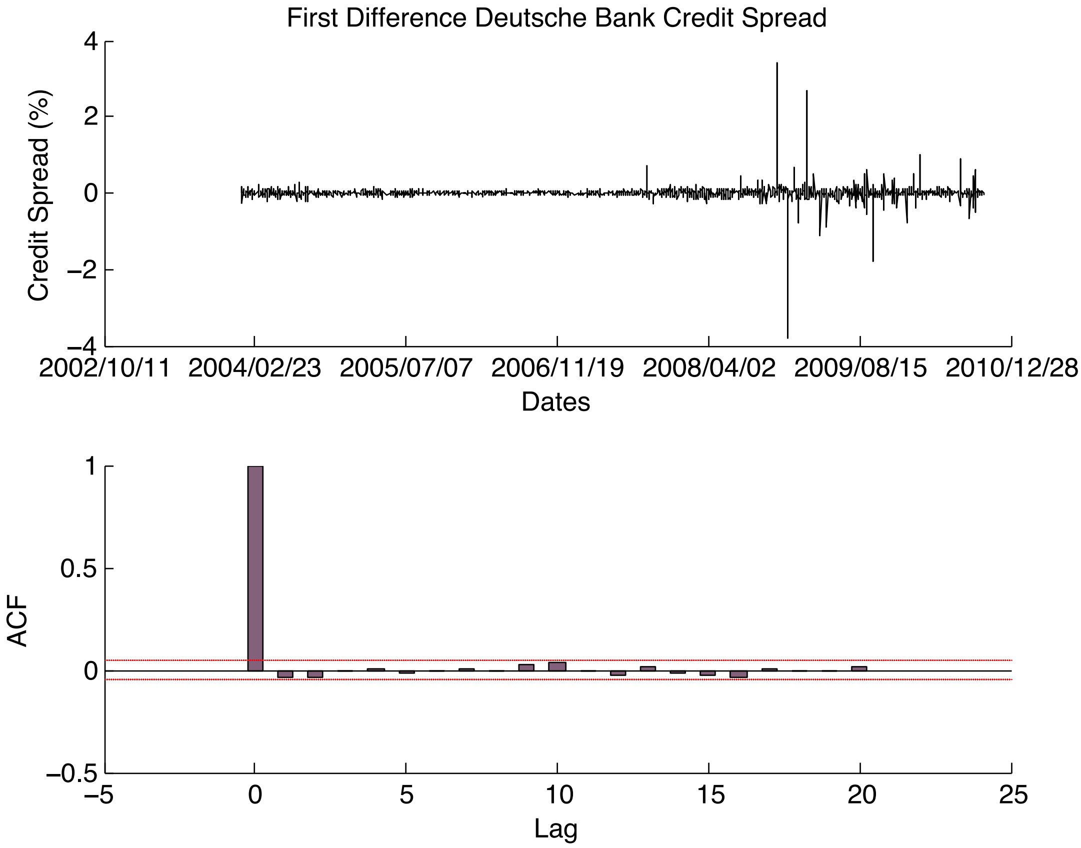
The following two figures display the time series' plots and autocorrelation functions of the Deutsche Bank credit spread before and after the first difference transformation. As shown, the transformed series does not exhibit a persistent autocorrelation function and seems to be weakly stationary. Furthermore, the Dickey-Fuller test on all the first difference transformed series rejects the null hypothesis of the presence of a unit root.

Figure 9: Credit Spread and Autocorrelation Function of Deutsche Bank Bond



This figure displays the time series' plot of the credit spread of the Deutsche Bank Bond and the corresponding autocorrelation function. Within the bottom graph, the bars display the autocorrelation at 0 to 20 lags and the horizontal lines indicate the 95% confidence interval for the significance of the autocorrelation values. As shown, the credit spread is not stationary and is persistent, which can be an indication of a unit root process.

Figure 10: First Difference Credit Spread and Autocorrelation Function of Deutsche Bank Bond



This figure displays the time series' plot of the credit spread of the Deutsche Bank Bond after a first difference transformation and the corresponding autocorrelation function. In the bottom graph, the bars display the autocorrelation at 0 to 20 lags, and the horizontal lines indicate the 95% confidence interval for the significance of the autocorrelation values. The first difference transformation allows the series to be weakly stationary, excluding a few outliers.

9.3 ARMA(p,q) Selection: Deutsche Bank Case

This Appendix displays the selection process of the ARMA specification of the Deustche Bank credit spread using the entire time series. It is included to serve as an example of the process I use for all the ARMA model specifications, beacause the inclusion of all the p and q selection criteria would increase the overall length of the paper without increasing supplementary benefits.

To begin I estimate all possible ARMA specifications with $p, q \leq 6$, where I select the value of 6 due to the higher likelihood of parameter estimation error by extending the limit. I then conduct a Ljung-Box test on the residuals for each of these models, where the null hypothesis is that the process is random (Ljung and Box 1978). Hence, a failure to reject the null hypothesis would indicate that the residuals are a white noise process and that the model is well specified. Furthermore, I calculate the Akaike information criteria (AIC) and Bayesian information criteria (BIC) values. The AIC and BIC suggest a particular specification. I examine whether the T-statistics of models near the proposed AIC and BIC selection with white noise residuals are statistically significant. Lastly, I conduct an ARCH test on the residuals to test whether there is conditional heteroskedasticity of the errors.

In the Deutsche Bank case, I first verify if the models have white-noise residuals. All the p-values of the Ljung-Box tests are greater than 0.05, which signifies that all the models have white noise residuals and are well specified. This is displayed in the top figure of Table 21. In many cases, the models do not have white-noise residuals, so I exclude them from the selection pool due to their misspecification.

My next step is to analyse the AIC and BIC values. In this case, both AIC and BIC suggest a ARMA(1,0). This can be seen in the middle and bottom figures of Table 21 by the bolded values indicating the smallest AIC and BIC values. In the case where the models do not have white noise residuals, I ignore the AIC and BIC values that correspond to these misspecified models.

I verify the significance of the parameters of models near the suggested

ARMA(1,0). The top figure of Table 29 displays the T-statistics. It can be seen that ARMA(1,0) and ARMA(0,1) are the only models that have every autoregressive and moving average parameter that are statistically significant. Hence, I do not select a model that has supplementary non-statistically significant parameters. So I must select either the ARMA(1,0) or ARMA(0,1). I decide to select the ARMA(1,0) which is preferred by the AIC and BIC criterion.

As a final step, I verify if the ARMA(p,q) that I selected has any ARCH effects. If so, I estimate a GARCH(p,q) on the residuals. In this case, we see the value of 0 for all models in the bottom figure of Table 22. This indicates a failure to reject the null hypothesis of no conditional heteroskedasticity. As a result, there is no justification to estimate a GARCH model.

Table 21: ARMA(p,q) Selection Criteria 1

This table presents the Akaike and Bayesian information criteria and the Ljung Box Test p-values. The bolded figures within the criteria are the smallest values that are the 'P' and 'Q' values for the models.

Ljung-Box Test

	P=0	P=1	P=2	P=3	P=4	P=5	P=6
Q=0	NaN	0.9023	0.9505	0.9284	0.8931	0.8560	0.8193
Q=1	0.9051	0.8720	0.9337	0.9052	0.8623	0.8155	0.7934
Q=2	0.9437	0.9308	0.8640	0.8792	0.7392	0.5925	0.5014
Q=3	0.9198	0.9012	0.9041	0.4229	0.5235	0.5228	0.6500
Q=4	0.8872	0.8628	0.7612	0.1752	0.4643	0.4133	0.6474
Q=5	0.8479	0.8140	0.6902	0.4995	0.3911	0.3919	0.5933
Q=6	0.8055	0.7915	0.5121	0.4088	0.3307	0.6049	0.2818

Akaike Information Criteria

	P=0	P=1	P=2	P=3	P=4	P=5	P=6
Q=0	NaN	**1487.17**	1492.94	1492.10	1491.58	1492.45	1496.15
Q=1	1490.13	1487.37	1493.13	1490.29	1488.80	1489.32	1491.89
Q=2	1497.92	1494.57	1492.20	1502.21	1496.32	1509.69	1509.36
Q=3	1499.99	1495.57	1502.45	1523.30	1529.26	1577.81	1626.09
Q=4	1502.00	1496.59	1500.93	1546.30	1531.85	1527.78	1557.05
Q=5	1504.02	1500.00	1501.93	1534.35	1526.60	1630.74	1562.97
Q=6	1507.69	1505.54	1516.57	1538.16	1534.26	1613.77	1631.22

Bayesian Information Criteria

	P=0	P=1	P=2	P=3	P=4	P=5	P=6
Q=0	NaN	**1492.64**	1509.36	1513.99	1518.93	1525.27	1534.44
Q=1	1495.60	1492.84	1509.54	1512.17	1516.15	1522.14	1530.18
Q=2	1514.34	1510.98	1514.09	1529.57	1529.14	1547.98	1553.12
Q=3	1521.87	1517.46	1529.81	1556.13	1567.55	1621.56	1675.32
Q=4	1529.35	1523.94	1533.75	1584.59	1575.61	1577.01	1611.74
Q=5	1536.84	1532.82	1540.22	1578.10	1575.83	1685.43	1623.13
Q=6	1545.97	1543.83	1560.32	1587.38	1588.96	1673.93	1696.85

Table 22: ARMA(p,q) Selection Criteria 2

This table displays the T-statistics of the models suggested by the Akaike and Bayesian information criterion. It also includes the T-statistics of the models that are near the suggested models. i.e ARMA(0,2), ARMA(2,0) and ARMA(1,1). The ARCH test results are also shown. The value '0' indicates a failure to reject the null hypothesis of no conditional heteroskedasticity and the value '1' displays a rejection of the null hypothesis for the alternative, conditional heteroskedasticity of the series.

T-Statistics

	y (t-1)	**y (t-2)**	**ε (t-1)**	**ε (t-2)**	**CDS**	**LIQ**
ARMA(0,1)			**-2.155**		2.3391	3.9002
ARMA(0,2)			**-2.0658**	-1.3651	2.3181	3.8705
ARMA(1,0)	**-2.0463**				2.5201	3.8312
ARMA(2,0)	**-2.0978**	-1.5113			2.5362	3.8158
ARMA(1,1)	1.3966		**-3.599**		2.2065	3.8944

ARCH test

	P=0	P=1	P=2	P=3	P=4	P=5	P=6
Q=0	NaN	0	0	0	0	0	0
Q=1	0	0	0	0	0	0	0
Q=2	0	0	0	0	0	0	0
Q=3	0	0	0	0	0	0	0
Q=4	0	0	0	0	0	0	0
Q=5	0	0	0	0	0	0	0
Q=6	0	0	0	0	0	0	0

9.4 ARMA Estimation

I estimate the ARMA models through maximum likelihood estimation of the conditional log likelihood function. The initial values of ϵ is set to 0.

$$\epsilon_0 = \epsilon_{-1} = \ldots = \epsilon_{-q+1} \tag{22}$$

Then I calculate each value of ϵ_t with the following equation.

$$\epsilon_t = y_t - \phi_1 y_{t-1} - \ldots - \phi_p y_{t-p} - \theta_1 \epsilon_{t-1} - \ldots - \theta_q \epsilon_{t-q} - \beta_1 CDS_t - \beta_2 LIQ_t \tag{23}$$

Lastly, I estimate the parameters of the models, Θ, by maximizing with the conditional log likelihood function below.

$$\begin{aligned} L(\Theta) &= \log f_{Y_t, Y_{t-1}, \ldots, Y_1 | Y0, \epsilon_0}(y_T, y_{T-1}, \ldots, y_1 \mid y_0, \epsilon_0; \Theta) \\ &= \frac{-T}{2}\log(2\pi) - \frac{-T}{2}\log(\sigma^2) - \sum_{t=1}^{T} \frac{\epsilon_t^2}{2\sigma^2} \\ with\ \Theta &= (\phi_1, \ldots, \phi_p, \theta_1, \ldots, \theta_q, \beta_1, \beta_2, \sigma^2) \end{aligned} \tag{24}$$

9.5 ARMA US LIBOR Panel Bank Credit Spread Outputs

The following ten tables display the regression outputs for the ARMA models with default and liquidity factors estimated on the US LIBOR panel credit spreads. Some of the credit spreads are excluded from the analysis and represented by N/A, due to the inability to correctly model them.

Table 23: ARMA: Bank Of America

This table displays the results of the autoregressive moving average model of the Bank Of America credit spread with both liquidity and default risk components, individually and together. The results include the entire time series and the two equally divided portions. The symbols ***, **, * indicate that the betas are at 0.01, 0.05, and 0.10 levels of significance, respectively, and the T-statistics are within brackets. The (p, q) specification indicates the p autoregressive components and the q moving average components.

January 1, 2004 to September 30, 2010

Model	y (t-1)	y (t-2)	y (t-3)	y (t-4)	y (t-5)	y (t-6)	ε (t-1)	ε (t-2)	ε (t-3)	ε (t-4)	ε (t-5)	Const	CDS	LIQ	Adj- R2
N/A															
N/A															
N/A															

January 1, 2004 to May 17, 2007

Model	y (t-1)	y (t-2)	y (t-3)	y (t-4)	y (t-5)	y (t-6)	ε (t-1)	ε (t-2)	ε (t-3)	ε (t-4)	ε (t-5)	Const	CDS	LIQ	Adj- R2
(2,1)	-0.2364***	-0.1228***					-0.065*						0.0304*	-0.0008	0.0870
	-(7.070)	-(3.679)					-(1.921)						(1.951)	-(0.950)	
(2,1)	-0.3161***	-0.1457***					0.0141					0.0011		0.0319**	0.0880
	-(9.454)	-(4.366)					(0.416)					(1.440)		(2.048)	
(2,1)	-0.0745**	-0.0756**					-0.2304***					0.0008	-0.0010		0.0850
	-(2.223)	-(2.262)					-(6.809)					(1.113)	-(1.220)		

May 18, 2007 to September 30, 2010

Model	y (t-1)	y (t-2)	y (t-3)	y (t-4)	y (t-5)	y (t-6)	ε (t-1)	ε (t-2)	ε (t-3)	ε (t-4)	ε (t-5)	Const	CDS	LIQ	Adj- R2
N/A															
N/A															
N/A															

Table 24: ARMA: Credit Suisse

This table displays the results of the autoregressive moving average model of the Credit Suisse credit spread with both liquidity and default risk components, individually and together. The results include the entire time series and the two equally divided portions. The symbols ***, **, * indicate that the betas are at 0.01, 0.05, and 0.10 levels of significance, respectively, and the T-statistics are within brackets. The (p, q) specification indicates the p autoregressive components and the q moving average components.

January 1, 2004 to September 30, 2010

Model	y (t-1)	y (t-2)	y (t-3)	y (t-4)	y (t-5)	y (t-6)	ε (t-1)	ε (t-2)	ε (t-3)	ε (t-4)	ε (t-5)	Const	CDS	LIQ	Adj- R2
(1,4)	0.9232***						-0.9812***	-0.0005	0.0348	0.0447*			0.0005*	0.0166	0.0273
	(6.056)						-(6.357)	-(0.020)	(1.388)	(1.858)			(1.669)	(1.029)	
(2,5)	-0.0091	0.8688***					-0.0295	-0.926***	0.0324	0.0581**	0.0745***	0.0000		0.0146	0.0246
	-(0.062)	(5.978)					-(0.199)	-(6.264)	(1.264)	(2.289)	(3.096)	(0.033)		(0.910)	
(1,4)	0.9297***						-0.985***	0.0047	0.0370	0.0405*		0.0000	0.0005		0.0240
	(5.664)						-(5.937)	(0.186)	(1.476)	(1.691)		(0.006)	(1.618)		

January 1, 2004 to May 17, 2007

Model	y (t-1)	y (t-2)	y (t-3)	y (t-4)	y (t-5)	y (t-6)	ε (t-1)	ε (t-2)	ε (t-3)	ε (t-4)	ε (t-5)	Const	CDS	LIQ	Adj- R2
(1,4)	0.4565*						-0.8142***	0.1017	0.1097***	-0.1361***			0.0025*	0.0352*	0.1354
	(1.903)						-(3.363)	(1.111)	(3.008)	-(3.460)			(1.651)	(1.706)	
(2,0)	-0.3508***	-0.18***										0.0004		0.0789***	0.1286
	-(10.593)	-(5.440)										(0.368)		(3.867)	
(1,4)	0.643**						-0.9917***	0.1671	0.1215***	-0.1379***		0.0001	0.0021		0.1309
	(2.295)						-(3.514)	(1.615)	(3.226)	-(3.350)		(0.107)	(1.444)		

May 18, 2007 to September 30, 2010

Model	y (t-1)	y (t-2)	y (t-3)	y (t-4)	y (t-5)	y (t-6)	ε (t-1)	ε (t-2)	ε (t-3)	ε (t-4)	ε (t-5)	Const	CDS	LIQ	Adj- R2
(1,3)	0.9292***						-0.9471***	-0.0345	0.0749**				0.0005	0.0170	0.0230
	(4.563)						-(4.588)	-(1.010)	(2.129)				(1.278)	(0.740)	
(6,3)	0.2630	-0.4049	0.815***	0.0542	0.0407	0.0521	-0.2646	0.3758	-0.8278***			0.0001		0.0386	0.0116
	(0.802)	-(1.188)	(2.963)	(1.551)	(0.951)	(1.227)	-(0.803)	(1.098)	-(2.981)			(0.034)		(1.600)	
(2,3)	0.8858***	-0.4399					-0.8904***	0.4060	0.0338			0.0002	0.001***		0.0147
	(2.961)	-(1.510)					-(2.959)	(1.387)	(0.952)			(0.094)	(2.706)		

Table 25: ARMA: Deutsche Bank

This table displays the results of the autoregressive moving average model of the Deutsche Bank credit spread with both liquidity and default risk components, individually and together. The results include the entire time series and the two equally divided portions. The symbols ***, **, * indicate that the betas are at 0.01, 0.05, and 0.10 levels of significance, respectively, and the T-statistics are within brackets. The (p, q) specification indicates the p autoregressive components and the q moving average components.

January 1, 2004 to September 30, 2010

Model	y (t-1)	y (t-2)	y (t-3)	y (t-4)	y (t-5)	ε (t-1)	ε (t-2)	ε (t-3)	ε (t-4)	ε (t-5)	Const	CDS	LIQ	Adj- R2
(1,0)	-0.0514**											0.0036***	0.1221**	0.0128
	-(2.046)											(3.831)	(2.520)	
(1,0)	-0.0392										0.0008		0.1474***	0.0046
	-(1.644)										(0.184)		(2.815)	
(0,1)						-0.0525**					0.0006	0.0038***		0.0098
						-(2.198)					(0.141)	(4.112)		

January 1, 2004 to May 17, 2007

Model	y (t-1)	y (t-2)	y (t-3)	y (t-4)	y (t-5)	ε (t-1)	ε (t-2)	ε (t-3)	ε (t-4)	ε (t-5)	Const	CDS	LIQ	Adj- R2
(2,1)	0.2991***	-0.0715**				-0.8313***						0.0014	-0.0149	0.2508
	(9.744)	-(2.332)				-(24.457)						(0.704)	-(0.457)	
(2,1)	0.2989***	-0.0716**				-0.833***					0.0003		-0.0142	0.2512
	(9.756)	-(2.337)				-(24.514)					(0.195)		-(0.436)	
(1,1)	0.3163***					-0.8652***					0.0003	0.0016		0.2499
	(5.424)					-(12.835)					(0.186)	(0.818)		

May 18, 2007 to September 30, 2010

Model	y (t-1)	y (t-2)	y (t-3)	y (t-4)	y (t-5)	ε (t-1)	ε (t-2)	ε (t-3)	ε (t-4)	ε (t-5)	Const	CDS	LIQ	Adj- R2
(1,1)	-0.2099***					0.1799***						0.0031**	0.2184***	0.0128
	-(6.202)					(5.317)						(2.439)	(2.749)	
(2,2)	-0.5788**	-0.9017***				0.5665**	0.8789***				0.0030		0.2634***	0.0163
	-(2.369)	-(3.778)				(2.300)	(3.652)				(0.365)		(3.064)	
(1,0)	-0.0342										0.0008	0.0037***		0.0075
	-(1.008)										(0.095)	(2.851)		

Table 26: ARMA: HSBC

This table displays the results of the autoregressive moving average model of the HSBC credit spread with both liquidity and default risk components, individually and together. The results include the entire time series and the two equally divided portions. The symbols ***, **, * indicate that the betas are at 0.01, 0.05, and 0.10 levels of significance, respectively, and the T-statistics are within brackets. The (p, q) specification indicates the p autoregressive components and the q moving average components.

January 1, 2004 to September 30, 2010

Model	y (t-1)	y (t-2)	y (t-3)	y (t-4)	y (t-5)	ε (t-1)	ε (t-2)	ε (t-3)	ε (t-4)	ε (t-5)	Const	CDS	LIQ	Adj- R2
(1,1)	0.8884***					-0.8767***						0.0004***	-0.0001	0.0138
	(37.492)					-(36.665)						(2.596)	-(0.003)	
(2,2)	-0.921**	-0.6448*					0.937***	0.6866*			0.0034**		0.0398**	0.0033
	-(2.621)	-(1.830)					(2.660)	(1.928)			(2.038)		(2.148)	
(1,1)	0.8861***					-0.8747***					0.0001	0.0004**		0.0141
	(4.700)					-(4.602)					(0.076)	(2.600)		

January 1, 2004 to May 17, 2007

Model	y (t-1)	y (t-2)	y (t-3)	y (t-4)	y (t-5)	ε (t-1)	ε (t-2)	ε (t-3)	ε (t-4)	ε (t-5)	Const	CDS	LIQ	Adj- R2
(1,2)	-0.9069***					0.7393***	-0.1543***					-0.0004	0.0075	0.0112
	-(3.223)					(2.635)	-(2.763)					-(0.314)	(0.615)	
(1,0)	-0.152***										0.0009		0.0000	0.0209
	-(4.566)										(1.623)		(0.001)	
(1,0)	-0.1525***										0.0009	-0.0002		0.0210
	-(4.574)										(1.619)	-(0.211)		

May 18, 2007 to September 30, 2010

Model	y (t-1)	y (t-2)	y (t-3)	y (t-4)	y (t-5)	ε (t-1)	ε (t-2)	ε (t-3)	ε (t-4)	ε (t-5)	Const	CDS	LIQ	Adj- R2
(1,1)	0.8862***					-0.8724***						0.0004*	0.0001	0.0130
	(26.407)					-(25.753)						(1.884)	(0.002)	
(1,0)	0.0114										0.0018		0.0274	0.0000
	(0.336)										(0.640)		(1.020)	
(1,1)	0.8844***					-0.8709***					0.0001	0.0004*		0.0130
	(3.395)					-(3.314)					(0.045)	(1.880)		

Table 27: ARMA: JP Morgan Chase

This table displays the results of the autoregressive moving average model of the JP Morgan Chase credit spread with both liquidity and default risk components, individually and together. The results include the entire time series and the two equally divided portions. The symbols ***, **, * indicate that the betas are at 0.01, 0.05, and 0.10 levels of significance, respectively, and the T-statistics are within brackets. The (p, q) specification indicates the p autoregressive components and the q moving average components.

January 1, 2004 to September 30, 2010

Model	y (t-1)	y (t-2)	y (t-3)	y (t-4)	y (t-5)	ε (t-1)	ε (t-2)	ε (t-3)	ε (t-4)	ε (t-5)	Const	CDS	LIQ	Adj- R2
N/A														
N/A														
N/A														

January 1, 2004 to May 17, 2007

Model	y (t-1)	y (t-2)	y (t-3)	y (t-4)	y (t-5)	ε (t-1)	ε (t-2)	ε (t-3)	ε (t-4)	ε (t-5)	Const	CDS	LIQ	Adj- R2
(3,1)	0.5797***	0.095***	0.104***			-0.8558***						0.0025	0.0019***	0.0840
	(17.181)	(2.758)	(3.112)			-(25.125)						(0.187)	(2.789)	
(3,1)	-0.9996***	-0.3182***	-0.0840			0.749**					0.0019**		0.0202	0.0780
	-(3.022)	-(3.457)	-(1.571)			(2.249)					(2.547)		(1.485)	
(3,1)	0.5851***	0.0952**	0.1003**			-0.8668***					0.0002	0.0019***		0.0890
	(3.584)	(1.757)	(2.569)			-(5.244)					(0.271)	(2.829)		

May 18, 2007 to September 30, 2010

Model	y (t-1)	y (t-2)	y (t-3)	y (t-4)	y (t-5)	ε (t-1)	ε (t-2)	ε (t-3)	ε (t-4)	ε (t-5)	Const	CDS	LIQ	Adj- R2
(0,4)	0.4724***					-0.421***	-0.0579	-0.0842**				0.03	0.0033***	0.0810
	(4.128)					-(3.517)	-(1.687)	-(2.446)				(0.892)	(6.482)	
(0,4)	0.0423					0.0443	-0.0614	-0.1206***			0.0011		0.0535	0.0220
	(0.170)					(0.177)	-(1.527)	-(3.290)			(0.289)		(1.532)	
(2,1)	0.4834***					-0.4308***	-0.059**	-0.0851**			0.0003	0.0032***		0.0800
	(4.184)					-(3.567)	-(1.721)	-(2.473)			(0.086)	(6.411)		

Table 28: ARMA: Lloyds

This table displays the results of the autoregressive moving average model of the Lloyds credit spread with both liquidity and default risk components, individually and together. The results include the entire time series and the two equally divided portions. The symbols ***, **, * indicate that the betas are at 0.01, 0.05, and 0.10 levels of significance, respectively, and the T-statistics are within brackets. The (p, q) specification indicates the p autoregressive components and the q moving average components.

January 1, 2004 to September 30, 2010

Model	y (t-1)	y (t-2)	y (t-3)	y (t-4)	y (t-5)	ε (t-1)	ε (t-2)	ε (t-3)	ε (t-4)	ε (t-5)	Const	CDS	LIQ	Adj- R2
(2,2)	-0.5283***	-0.5323***				0.492***	0.4696***					0.0023***	0.2213***	0.0528
	-(5.024)	-(5.260)				(4.569)	(4.551)					(5.097)	(7.520)	
(2,2)	-0.9989***	-0.9939***				0.9998***	0.9942***				0.0137***		0.3121***	0.0571
	-(8.820)	-(7.999)				(8.619)	(7.856)				(5.677)		(9.299)	
(2,0)	-0.0559**	-0.0512**									0.0045**	0.0029***		0.0257
	-(2.355)	-(2.172)									(2.018)	(6.332)		

January 1, 2004 to May 17, 2007

Model	y (t-1)	y (t-2)	y (t-3)	y (t-4)	y (t-5)	ε (t-1)	ε (t-2)	ε (t-3)	ε (t-4)	ε (t-5)	Const	CDS	LIQ	Adj- R2
(1,1)	0.4622***					-0.486***						0.0157**	-0.0431	0.0026
	(13.703)					-(14.368)						(2.328)	-(0.559)	
(1,0)	-0.0196										0.0018		-0.0377	0.0000
	-(0.580)										(0.499)		-(0.488)	
(1,0)	-0.0206										0.0019	0.0124*		0.0021
	-(0.609)										(0.519)	(1.842)		

May 18, 2007 to September 30, 2010

Model	y (t-1)	y (t-2)	y (t-3)	y (t-4)	y (t-5)	ε (t-1)	ε (t-2)	ε (t-3)	ε (t-4)	ε (t-5)	Const	CDS	LIQ	Adj- R2
(0,4)						-0.0665*	-0.1316***	0.0861**	-0.0323			0.0024***	0.1906***	0.1231
						-(1.936)	-(3.835)	(2.508)	-(0.955)			(6.268)	(7.632)	
(0,4)						-0.0546	-0.1637***	0.0786**	-0.0355		0.0072***		0.2078***	0.0923
						-(1.613)	-(4.789)	(2.286)	-(1.048)		(2.768)		(8.219)	
(2,1)	-0.2541**	-0.12***				0.1387					0.0093***	0.003***		0.0793
	-(2.192)	-(3.597)				(1.152)					(3.345)	(7.828)		

Table 29: ARMA: Rabobank

This table displays the results of the autoregressive moving average model of the Rabobank credit spread with both liquidity and default risk components, individually and together. The results include the entire time series and the two equally divided portions. The symbols ***, **, * indicate that the betas are at 0.01, 0.05, and 0.10 levels of significance, respectively, and the T-statistics are within brackets. The (p, q) specification indicates the p autoregressive components and the q moving average components.

January 1, 2004 to September 30, 2010

Model	y (t-1)	y (t-2)	y (t-3)	y (t-4)	y (t-5)	ε (t-1)	ε (t-2)	ε (t-3)	ε (t-4)	ε (t-5)	Const	CDS	LIQ	Adj- R2
(2,2)	-0.959***	-0.9747***				0.9635***	0.9793***					0.0004	0.3263***	0.0749
	-(9.934)	-(9.347)				(9.648)	(9.199)					(0.627)	(10.680)	
(2,2)	-0.9818***	-0.9802***				0.9821***	0.9824***				0.0054***		0.3293***	0.0716
	-(9.783)	-(8.923)				(9.492)	(8.786)				(2.614)		(10.592)	
(1,0)	-0.0488**										0.0016	0.0045***		0.0227
	-(2.054)										(0.748)	(6.415)		

January 1, 2004 to May 17, 2007

Model	y (t-1)	y (t-2)	y (t-3)	y (t-4)	y (t-5)	ε (t-1)	ε (t-2)	ε (t-3)	ε (t-4)	ε (t-5)	Const	CDS	LIQ	Adj- R2
(2,1)	0.6411***	-0.0695**				-0.6004***						0.0078*	-0.0952**	0.0200
	(19.117)	-(2.070)				-(17.735)						(1.732)	-(2.140)	
(2,1)	0.6091***	-0.0711**				-0.5635**					0.0003		-0.0988**	0.0175
	(2.555)	-(1.964)				-(2.342)					(0.126)		-(2.209)	
(2,1)	0.7066**	-0.0763**				-0.66**					0.0002	0.0081*		0.0111
	(2.505)	-(2.064)				-(2.322)					(0.100)	(1.757)		

May 18, 2007 to September 30, 2010

Model	y (t-1)	y (t-2)	y (t-3)	y (t-4)	y (t-5)	ε (t-1)	ε (t-2)	ε (t-3)	ε (t-4)	ε (t-5)	Const	CDS	LIQ	Adj- R2
(2,2)	-0.9758***	-0.9789***				0.9799***	0.9852***					0.0003	0.3998***	0.1248
	-(9.261)	-(8.435)				(8.714)	(8.202)					(0.380)	(9.903)	
(2,2)	-0.9862***	-0.9889***				0.9917***	0.9997***				0.0027		0.3989***	0.1269
	-(9.526)	-(8.697)				(8.992)	(8.478)				(0.772)		(9.997)	
(1,0)	-0.0836**										0.0024	0.0046***		0.0332
	-(2.490)										(0.676)	(5.370)		

Table 30: ARMA: RBS

This table displays the results of the autoregressive moving average model of the RBS credit spread with both liquidity and default risk components, individually and together. The results include the entire time series and the two equally divided portions. The symbols ***, **, * indicate that the betas are at 0.01, 0.05, and 0.10 levels of significance, respectively, and the T-statistics are within brackets. The (p, q) specification indicates the p autoregressive components and the q moving average components.

January 1, 2004 to September 30, 2010

Model	y (t-1)	y (t-2)	y (t-3)	y (t-4)	y (t-5)	ε (t-1)	ε (t-2)	ε (t-3)	ε (t-4)	ε (t-5)	Const	CDS	LIQ	Adj- R2
(1,1)	-0.3567***					0.3428***						0.0000	-0.0246	0.0000
	-(14.940)					(14.355)						-(0.068)	-(1.201)	
(1,0)	-0.0122										0.0016		-0.0224	0.0000
	-(0.511)										(0.974)		-(1.093)	
(1,0)	-0.0116										0.0016	0.0000		0.0000
	-(0.486)										(0.969)	(0.127)		

January 1, 2004 to May 17, 2007

Model	y (t-1)	y (t-2)	y (t-3)	y (t-4)	y (t-5)	ε (t-1)	ε (t-2)	ε (t-3)	ε (t-4)	ε (t-5)	Const	CDS	LIQ	Adj- R2
(2,1)	0.3657***	0.0976***				-0.5934***						0.0021***	-0.0247**	0.0619
	(10.920)	(2.922)				-(17.522)						(2.663)	-(2.551)	
(1,0)	-0.2142***										0.0005		-0.0179*	0.0494
	-(6.514)										(1.073)		-(1.832)	
(1,0)	-0.2101***										0.0005	0.0013*		0.0489
	-(6.376)										(1.080)	(1.687)		

May 18, 2007 to September 30, 2010

Model	y (t-1)	y (t-2)	y (t-3)	y (t-4)	y (t-5)	ε (t-1)	ε (t-2)	ε (t-3)	ε (t-4)	ε (t-5)	Const	CDS	LIQ	Adj- R2
(1,1)	-0.3529***					0.3422***						0.0000	-0.0270	0.0000
	-(10.431)					(10.115)						-(0.063)	-(0.856)	
(1,0)	-0.0085										0.0028		-0.0232	0.0000
	-(0.250)										(0.848)		-(0.739)	
(1,0)	-0.0078										0.0028	0.0000		0.0000
	-(0.231)										(0.845)	(0.061)		

Table 31: ARMA: UBS

This table displays the results of the autoregressive moving average model of the UBS credit spread with both liquidity and default risk components, individually and together. The results include the entire time series and the two equally divided portions. The symbols ***, **, * indicate that the betas are at 0.01, 0.05, and 0.10 levels of significance, respectively, and the T-statistics are within brackets. The (p, q) specification indicates the p autoregressive components and the q moving average components.

January 1, 2004 to September 30, 2010

Model	y (t-1)	y (t-2)	y (t-3)	y (t-4)	y (t-5)	ε (t-1)	ε (t-2)	ε (t-3)	ε (t-4)	ε (t-5)	Const	CDS	LIQ	Adj- R2
N/A														
N/A														
N/A														

January 1, 2004 to May 17, 2007

Model	y (t-1)	y (t-2)	y (t-3)	y (t-4)	y (t-5)	ε (t-1)	ε (t-2)	ε (t-3)	ε (t-4)	ε (t-5)	Const	CDS	LIQ	Adj- R2
(2,1)	-0.5065***	-0.1758***				0.2242***						0.0117	-0.0010	0.0780
	-(15.059)	-(5.246)				(6.624)						(0.866)	-(1.012)	
(2,1)	-0.4492*	-0.1616**				0.1646					0.0001		0.0131	0.0770
	-(1.711)	-(2.173)				(0.622)					(0.219)		(0.966)	
(2,1)	-0.5743**	-0.1903**				0.2966					0.0001	-0.0010		0.0780
	-(2.199)	-(2.576)				(1.126)					(0.233)	-(1.020)		

May 18, 2007 to September 30, 2010

Model	y (t-1)	y (t-2)	y (t-3)	y (t-4)	y (t-5)	ε (t-1)	ε (t-2)	ε (t-3)	ε (t-4)	ε (t-5)	Const	CDS	LIQ	Adj- R2
(1,1)	-0.9428***					0.9626***						0.0105	0.0011	0.0140
	-(28.106)					(28.448)						(0.181)	(1.562)	
(1,1)	-0.9294					0.9357					0.0072		0.0176	0.0000
	-(0.896)					(0.902)					(0.984)		(0.300)	
(1,1)	-0.9462***					0.9651***					0.0070	0.0010		0.0140
	-(3.695)					(3.737)					(1.127)	(1.513)		

Table 32: ARMA: HBOS

This table displays the results of the autoregressive moving average model of the HBOS credit spread with both liquidity and default risk components, individually and together. The results include the entire time series and the two equally divided portions. The symbols ***, **, * indicate that the betas are at 0.01, 0.05, and 0.10 levels of significance, respectively, and the T-statistics are within brackets. The (p, q) specification indicates the p autoregressive components and the q moving average components.

January 1, 2004 to September 30, 2010

Model	y (t-1)	y (t-2)	y (t-3)	y (t-4)	y (t-5)	ε (t-1)	ε (t-2)	ε (t-3)	ε (t-4)	ε (t-5)	Const	CDS	LIQ	Adj- R2
(1,1)	0.2076***					-0.2463***						0.0005	0.0926***	0.0044
	(8.674)					-(10.316)						(0.472)	(2.735)	
(1,0)	-0.0411*										0.0023		0.096***	0.0048
	-(1.718)										(0.842)		(2.841)	
(1,5)	-0.9115***					0.8768**	-0.0276	0.0162	-0.0061	-0.0391	0.0042	0.0002		0.0005
	-(2.645)					(2.542)	-(1.035)	(0.675)	-(0.248)	-(1.574)	(1.458)	(0.159)		

January 1, 2004 to May 17, 2007

Model	y (t-1)	y (t-2)	y (t-3)	y (t-4)	y (t-5)	ε (t-1)	ε (t-2)	ε (t-3)	ε (t-4)	ε (t-5)	Const	CDS	LIQ	Adj- R2
(1,4)	0.3137					-0.7727***	0.1268	0.1011***	-0.1691***			0.0009	0.0279	0.1831
	(1.469)					-(3.591)	(1.230)	(2.963)	-(4.286)			(0.704)	(1.381)	
(1,4)	0.3004					-0.7596***	0.1182	0.1002***	-0.1695***		0.0003		0.0284	0.1839
	(1.405)					-(3.524)	(1.143)	(2.934)	-(4.318)		(0.317)		(1.410)	
(1,4)	0.3753*					-0.8313***	0.1531	0.1016***	-0.1685***		0.0003	0.0012		0.1806
	(1.674)					-(3.684)	(1.427)	(2.974)	-(4.211)		(0.307)	(0.937)		

May 18, 2007 to September 30, 2010

Model	y (t-1)	y (t-2)	y (t-3)	y (t-4)	y (t-5)	ε (t-1)	ε (t-2)	ε (t-3)	ε (t-4)	ε (t-5)	Const	CDS	LIQ	Adj- R2
(1,1)	0.2753					-0.3018***						0.0005	0.1016**	0.0023
	8.1145***					-(8.921)						(0.351)	(1.967)	
(1,1)	0.2682					-0.2957					0.0030		0.1036**	0.0028
	(0.614)					-(0.675)					(0.528)		(1.970)	
(2,2)	0.9759***	-0.9513***				-0.9996***	0.9845***				0.0040	0.0008		0.0064
	(3.273)	-(3.240)				-(3.337)	(3.303)				(0.722)	(0.519)		

9.6 Glossary

Risk Factors of Credit Spreads

Fixed income yield premiums have several risk factors. The two most commonly considered are default and liquidity risk. Default risk is the probability that a firm is unable to meet its financial obligations. Liquidity has two forms. The first form is related to the market depth and volume of trading in a financial security. For instance, a security that is heavily traded will have a lower bid-ask spread and a lower transaction cost compared to a less actively traded instrument. The second form is firm liquidity risk, the lack of cash and short term investments to service debt. Hence, investors will demand a premium for holding a security that is illiquid and/or has a higher likelihood of default. Consequently, this premium is measured by the credit spread of the security.

To quantify liquidity risk, a measure using the yield spread between off-the-run and on-the-run treasury securities is constructed. The on-the-run treasury note is the most recently auctioned note and the off-the-run securities are all the previously issued notes with the same maturity at issuance. The works of Krishnamurthy (2002), Goldreich, Hanke, and Nath (2005), and Collin-Dufresne, Goldstein, and Martin (2001) show that on-the-run securities are more liquid. In consequence, the on-the-run securities demand a lower yield at higher price compared with off-the-run securities.

As for default risk, credit default swap premiums are used. The credit default swap premiums are assumed to be correctly priced and to adequately represent default risk within fixed income securities. The usage of credit default premiums stems from the work of Longstaff, Mithal, and Neis (2005).

LIBOR

LIBOR, an acronym for London InterBank Offered Rate, represents the cost of borrowing for a given term and currency in the London interbank market. It serves as a benchmark for various financial products including loan agreements, swaps, futures, and options. LIBOR is constructed by selecting the lowest response from a panel of banks, which are selected on the basis of activity and size in the currency market, where the question "At what rate could you borrow funds, were you to do so by asking for and then accepting inter-bank offers in a reasonable market size just prior to 11 am?" is asked. For instance in 2005, the panel of banks that provided quotes for USD LIBOR was composed of Bank of America, Barclays Bank, Citibank, Credit Suisse First Boston, Deutsche Bank, HBOS, HSBC, JP Morgan Chase, Lloyds, Rabobank, Royal Bank of Canada, The Bank of Tokyo-Mitsubishi, The Norinchukin Bank, The Royal Bank of Scotland, UBS, and Westdeutsche Landesbank. Note that the composition of USD LIBOR panel changes on a yearly basis. For this reason, in this paper, only banks that are part of the panel throughout 2004 to 2010 are analysed.

The TED Spread

The TED spread is the difference between the spot 3-month USD LIBOR and 90-day Treasury bill yield. The name generates from its original specification as the difference between the implied rates on the 3-month T-bill futures and Eurodollar futures contracts, where T stands for T-bill and ED stands for Eurodollar.

In times of low credit risk, the TED spread is narrow due to the willingness of banks to lend to each other at near US treasury rates. However, during periods of excessive credit risk, such as the 2008 financial crisis, the TED spread widens substantially, which has been exhibited by Brunnermeier (2009). This results from an increase in counterparty risk between the various banks. Moreover, in such periods, a flight to quality takes place. This is when investors prefer highly credit worthy and liquid investments. This results in a transfer of demand from various higher risk instruments to lower risk products. For example, a transfer from interbank funding to US treasury bills.

In addition, a wide TED spread is indicative of a crisis in the interbank market, where banks are unwilling to lend to each other. In consequence, credit markets may freeze and a financial crisis may occur unless appropriate measures are undertaken to alleviate the strain in the system. Therefore, understanding the dynamics of the TED spread can help prevent and/or remedy a financial crisis.

USD LIBOR Panel Corporate Bond Spreads

In addition to the TED spread, the corporate bond spreads of various USD LIBOR panel banks are also analysed. To do so, the difference between the individual corporate bond yields and the corresponding zero coupon yield estimated from the US treasury market is calculated. For each USD LIBOR panel bank, a bond with the following criteria is selected: fixed rate, non-callable, maturity greater than 10 years at issuance and active between 2004 and 2011. This allows the analysis of the components of credit risk within the corporate bond spreads of the global banking industry and provides a case study for future bond spread research.

Credit Default Swaps

Credit default swaps are financial products that allow a transfer of default risk between two counterparties, a buyer and a seller of protection. The buyer pays the seller a premium on a quarterly basis. In the case of a default, the seller must pay the buyer notational amount to the buyer in exchange for the defaulted bond. For example, a CDS premium of 150 with a notational amount of $100m$ would entail the buyer paying quarterly payments of $0.015/4 * 100m$ and receiving $100m$ in exchange for the underlying bond in the case of default.