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The Impact of the FOMC's Monetary Policy Actions on the growth of Credit Risk: the Monetary Policy - Liquidity Paradox

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Abstract

Credit risk is influenced by interest rates and market liquidity. This paper examines the direct and indirect impacts of unexpected monetary policy shifts on the growth of corporate credit risk, with the aim of quantifying the size and direction of the response. The results surprisingly indicate that monetary policy and liquidity impulses move counter to each other in their effects on credit risk ("The monetary policy-liquidity paradox"). The analysis indicates that while contractionary monetary policy creates tight money which subsequently leads to a slowing in the growth of credit risk and a reduction of liquidity in credit markets, reduced liquidity indirectly affects credit risk by accelerating its growth. The net effect of these transitory opposing forces generates the final impact on credit risk. An unexpected policy shifts is captured via a combination of the forward Fed fund rate curve and the Fed's FOMC policy announcements. Following the approach of Bernanke and Kuttner (2005), Hausman and Wongswan (2006) who examined asset prices under FOMC announcements, the study found that the estimated credit risk responses to FOMC announcements vary across credit qualities. Hence the analyses indicates that a typical unanticipated 25 basis point cut in the target fed funds rate generally resulted in an acceleration in the growth of credit risk by 0.50 percent for AAA rated corporate grade debt, and by 3.5 percent for BB rated corporate debt. Moreover, the study found a direct effect of the FOMC's policy instrument on market liquidity which had a significant effect on the growth in credit risk. The results indicate that a 1 percentage point increase in liquidity for AAA and CCC rated bonds resulted in a 0.7risk respectively.

Keywords: Credit Risk, Default Risk, Credit Default Swap, Monetary Policy, Credit Markets, Financial Markets, Vector Autoregressive Model, Federal funds rate.

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ABSTRACT

Credit risk is influenced by interest rates and market liquidity. This paper examines the direct and indirect impacts of unexpected monetary policy shifts on the growth of corporate credit risk, with the aim of quantifying the size and direction of the response. The results surprisingly indicate that monetary policy and liquidity impulses move counter to each other in their effects on credit risk ("The monetary policy-liquidity paradox"). The analysis indicates that while contractionary monetary policy creates tight money which subsequently leads to a slowing in the growth of credit risk and a reduction of liquidity in credit markets, reduced liquidity indirectly affects credit risk by accelerating its growth. The net effect of these transitory opposing forces generates the final impact on credit risk.

An unexpected policy shifts is captured via a combination of the forward Fed fund rate curve and the Fed's FOMC policy announcements. Following the approach of Bernanke and Kuttner (2005), Hausman and Wongswan (2006) who examined asset prices under FOMC announcements, the study found that the estimated credit risk responses to FOMC announcements vary across credit qualities. Hence the analyses indicates that a typical unanticipated 25 basis point cut in the target fed funds rate generally resulted in an acceleration in the growth of credit risk by 0.50 percent for AAA rated corporate grade debt, and by 3.5 percent for BB rated corporate debt.

Moreover, the study found a direct effect of the FOMC's policy instrument on market liquidity which had a significant effect on the growth in credit risk. The results indicate that a 1 percentage point increase in liquidity for AAA and CCC rated bonds resulted in a 0.7% and 52.45% decrease in the rate of growth in credit risk respectively.

JEL Classification:

*Keyword*s: Credit Risk, Default Risk, Credit Default Swap, Monetary Policy, Credit Markets, Financial Markets, Vector Autoregressive Model, Federal funds rate.

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1.0 Introduction

Over the last few years a number of studies have been published that examines the impacts of unanticipated U.S. monetary policy changes on asset prices. Changes in monetary policy have either a direct or indirect effect on various macroeconomic variables. Federal Open Market Committee (FOMC) policy has direct effects on economic, and ultimately inflation, through its effect on interest rates and subsequently on the demand for goods and services by households and firms. More importantly, monetary policy can also influence economic activity through its impact on the financial markets, which in turn, will influence credit risk. Economic theory suggests that market and credit risks are intrinsically related to each other and inseparable. If the market value of a firm's assets unexpectedly changes, it generates market risk, which increases the probability of default thereby generating credit risk. Analysis of credit risk data presented in section 5 of this study shows that FOMC policy actions have direct effects on credit risk and an indirect effect on credit risk through its direct effects on liquidity.

This paper examines the effect of unanticipated FOMC policy actions on credit risk and market liquidity, particularly on shocks that push credit risks temporarily away from its long run equilibrium growth path. A number of researchers[2] have examined the reaction of financial markets to both anticipated and unanticipated monetary policy changes by the Fed. However, nothing has been done to capture the actual impacts to

[2] Kuttner (2001), Bernanke and Kuttner (2005), Hausman and Wongswan (2006),

default or credit risk given a policy shift. Like asset prices, estimating the response of credit risk to expected monetary policy changes is difficult given that credit markets are unlikely to show any meaningful reaction if the policy changes are anticipated, so the study will focus on the unanticipated policy changes so that its impacts on credit risk can be determined. Moreover, given the importance of liquidity in the pricing of credit risk[3] and the indirect impacts of Fed policy actions on credit risk through liquidity's response function, it would also be meaningful to have some quantitative measure of the impacts of monetary policy changes on market liquidity.

This work is nested in the vast monetary policy literature pertaining to financial asset pricing under unexpected FOMC announcements. The Fed monetary policy transmission methodology (FMPT) developed in this paper will provide practitioners an additional tool for quantifying monetary policy changes on credit risk. The methodology will allow credit risk managers to understand and quantitatively determine the impacts of policy changes on credit risky portfolios. Moreover, in light of the breakdown of the Value-at-Risk (VaR) approach[4] to properly quantify portfolio risks given the difficulty in pricing some newly introduced synthetic products, the FMPT approach quantifies credit risk by making use of credit default swaps (the model assumes that there are credit default swaps for the underlying portfolio). The approach's Structural Vector Autoregressive model (SVAR) analysis allows the model to explain the impacts of

[3] See Dunbar (2007), Dunbar and Edwards (2007) for a discussion on Credit Default Swap pricing under market liquidity.

[4] The Value at Risk (Var) methodology in its current form has been under pressure lately because of its inability to proactively identify potential portfolio risks. Value at risk (Var) is a measure that banks use to calculate the maximum investment portfolios can loose in a given day. One of the weaknesses in *Var* is its use of historical prices in the determination of potential losses. Most notably, during the 2007 credit market collapse the failure of some of the U.S.' biggest securities firm *Var* models resulted in cumulative sub-prime losses of approximately $130 billion.

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unexpected FOMC policy actions on a given portfolio over a period of time, thus providing a proxy *de facto* measure of the duration of credit risk.

The growing importance of the corporate debt component of the overall global debt market[5] (relative to government debt) is indicative of the growth in global credit risk, which in itself partly explains the observed exponential growth in the use of credit default swaps[6] to mitigate this growing counterparty risk. Moreover, much of this growth in counter-party risk protection stems from the ever increasing demand by banks, insurance companies, institutional investors and hedge funds seeking credit risk insurance to cover risky long bond exposures. As far back as November 2002, then Fed Chief Alan Greenspan appearing before the Foreign Relations Committee suggested that one positive outcome of this growth is the strengthening of the financial sector by spreading credit risk more broadly across the entire sector as against having it all concentrated among a few participants.

Similarly, market liquidity has become central to credit and debt markets over the last fifteen years, as evidenced by the number of innovative credit products that have been introduced to increase the depth and breadth of financial markets. This phenomenon has also contributed to the exponential growth of credit derivatives, one of the most successful financial innovative products of the past decade. The British Bankers Association estimates that the credit derivative market grew from a notional $180 billion

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[5] As of 2006, the size of the international bond market is an estimated $45 trillion, of which the outstanding U.S. bond market debt was $25.2 trillion.

[6] Credit-default swaps are financial instruments underwritten on bonds and loans that are used to speculate on a company's ability to repay its debt (counterparty credit risk). They pay the buyer face value in exchange for the underlying securities or the cash equivalent should a borrower fail to adhere to its debt agreements. A rise (decline) in the price of the CDS indicates deterioration (increase) in the perception of credit quality.

in 1997 to $5.0 trillion in 2004 and is expected to reach upwards of $17 trillion in 2006[7]. A review of the credit markets has shown that while overall quality of global credit has deteriorated the volume of corporate bonds (corporate credit risk) has risen dramatically over the past few years.

During the summer of 2007 developments in the U.S. credit markets led to a melt down in the subprime mortgage subsector[8] driven primarilarly by a combination of impacts attributable to liquidity and credit risk. The period witnessed a “flight to quality” as the fallout in the subprime market created a contraction of market liquidity for a number of risky credit instruments. The loss of liquidity and sub-prime related credit risks resulted in Billions of dollars in losses for a number of Wall Street Investment banks’. Several hedge funds and institutional investors holding credit risky products also incurred significant losses, see table 1.

As a result of the aforementioned disruptions to credit markets, several entities were forced to file for bankruptcy, see table 2 for a short list of companies impacted by the credit market fallout. These developments pose significant challenges to the steady state operations of the real economy. Moreover the expansion of structured credit products which have aided the exponential growth in credit markets have the potential for creating significant volatility shocks in the broader macro economy. Hence, idiosyncratic shocks from these credit products that the financial sector experienced during the sub-prime credit and liquidity debacle was partly to blame for the 2007 credit crisis. Investors

[7] In an August 31st 2006 Wall Street Journal article “Can Anyone Police the Swaps” the current CDS market was estimated at upwards of $17 trillion.
[8] The Mortgage Banker’s Association of America suggests that the value of U.S. subprime mortgages were estimated at $1.3 trillion as of March 2007, with over 7.5 million first-lien subprime mortgages outstanding.

Table 1. Corporate write downs on the value of Loans, MBS and CDOs

Entity	Type	Writedown (Billion $)
Bank of america	Bank	3.3
Barclays Capital	Bank	2.7
Bearsterns	Investment Bank	1.9
CIBC	Bank	0.75
Citigroup	Bank	17.5
Credit Suisse	Bank	1.9
Deutsche Bank	Bank	3.1
Fannie Mae	Mortgage	0.896
Freddie Mac	Mortgage	3.6
Goldman Sachs	Investment Bank	1.5
HSBC	Bank	3.4
JP Morgan Chase	Investment Bank	1.6
Lehman Brothers	Investment Bank	2.1
Merrill Lynch	Investment Bank	8.4
Morgan Stanley	Investment Bank	10.3
RBC	Bank	0.36
RBS	Bank	2.6
Swiss Re	Re-Insurance	1.07
UBS AG	Investment Bank	13.7
Wachovia	Bank	1.1
WAMU	Bank	2.4
Wells Fargo	Bank	1.4

at this period turned their attention to the central bank for relief in the form of a contraction in the Fed funds rate so as to increase market liquidity[9].

These developments in U.S. financial markets highlight the perceived importance of monetary policy to market liquidity and credit risk. To this end more study needs to be done to increase the understanding of the direct and indirect effects of Fed policy shifts on these products. To explain the economic reasons for the observed credit market response to policy surprises require an assessment of the effects of policy surprises on credit risk. To do this, the study will adapt the procedure developed by Campbell (1991) and Campbell and Ammer (1993) and extended by Bernanke and Kuttner (2005), which

[9] The credit crisis created by the demise of the US sub-prime mortgage market spread uncertainty and apprehension among market participants in many countries including some emerging markets. This has prompted aggressive action by central bankers in a number of developed economies. The ECB, in an unprecedented move, injected €156 Billion in the EMU region to compensate the lack of liquidity. The US Federal Reserve injected $62 Billion into its credit markets. The Bank of Canada injected CA$ 1.64 Billion and The Bank of Japan ¥1.0 Trillion Yen

uses a vector autoregression (VAR) to determine the impacts of systemic innovations on the model's key variables.

Table 2. Entities filing for Banruptcy because of subprime exposure

Entity	Type	Bankruptcy Date
American Freedom Mortgage In	Subprime lender	Jan-07
American Home Mortgage	Mortgage	Aug-07
Ameriquest	Subprime lender	Aug-07
NetBank	Online Bank	Sep-07
New Century Financial	Subprime lender	Apr-07
SAC Capital Holdings*	Bond Insurer	n.a.
Sentinel Management Group	Investment Fund	Aug-07
Terra Securities	Investment Fund	Nov-07

* ACA Capital's debt rating was cut to Junk - CCC by Fitch in January 08. The company has been taken over by the Maryland Insurance administration.

The VAR approach appears to be a popular econometric procedure used by researchers estimating the market's reaction to Federal Reserve policy, while focusing on the unanticipated element of the actions. Using a structural Vector Autoregression (VAR) to model monetary policy, for example, Edelberg and Marshall (1996) found a large, highly significant response of bill rates to policy shocks, but only a small, marginally significant response of bond rates. Other examples of the VAR approach used in a monetary policy analysis framework include Evans and Marshall (1998) and Mehra (1996). In an effort to model the discrete nature of target rate changes, Demiralp and Jorda (1999) examined the response of interest rates using an autoregressive conditional hazard (ACH) model to forecast the timing of changes in the Fed funds target, and an ordered probit to predict the size of the change. These methods can be cumbersome and there is some debate as to the reliability of VAR-based measures of policy shocks, see Rudebusch (1998). Given this debate around the use of the VAR procedure the study will also develop a set of robustness tests to test for consistency in the main analytical model.

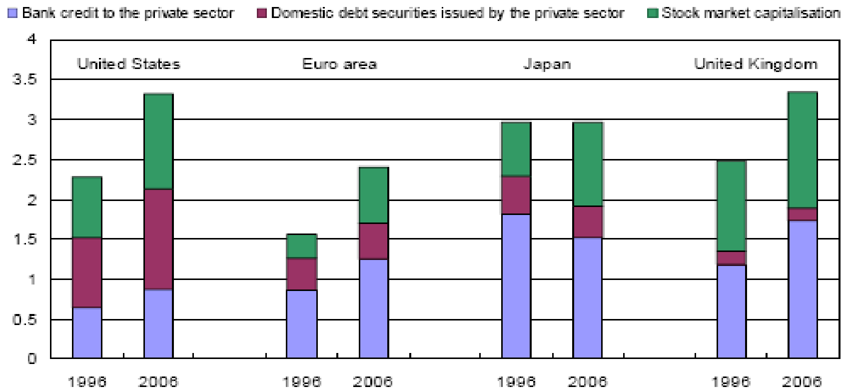
The remainder of the paper is organized into four sections. Section 2 reviews the background literature concerning the growth of financial markets and simultaneous growth in the use of credit default swaps for hedging credit risk. The section first examines the growth in U.S. financial markets through the exponential growth of innovative credit products. Section 3 introduces the theoretical foundations of the vector autoregressive model used in the study and introduces the empirical model used to capture the impacts of a expansionary or conractionary "surprise monetary policy action" change on credit risk. Section 4 gives a brief description of the study's baseline data which spans thirty five named credit default swaps (CDS), Average investment grade CDS products and an average high yield CDS credit quality, and the methodology for deriving the various explanatory variables. Section 5 presents the main empirical findings regarding the OLS and VAR models analysis. Section 6 summarizes the finding and proposes areas of future research.

2. Background Literature on Credit Risk

In the last decade gross financial assets have increased very rapidly. Between 1996 and 2006 they have risen as a ratio to GDP from 6.6 to 9.8 in the United States and 17.6 in the United Kingdom. (Figure 1).

Fig. 1 - Size of capital markets

(ratios to GDP)

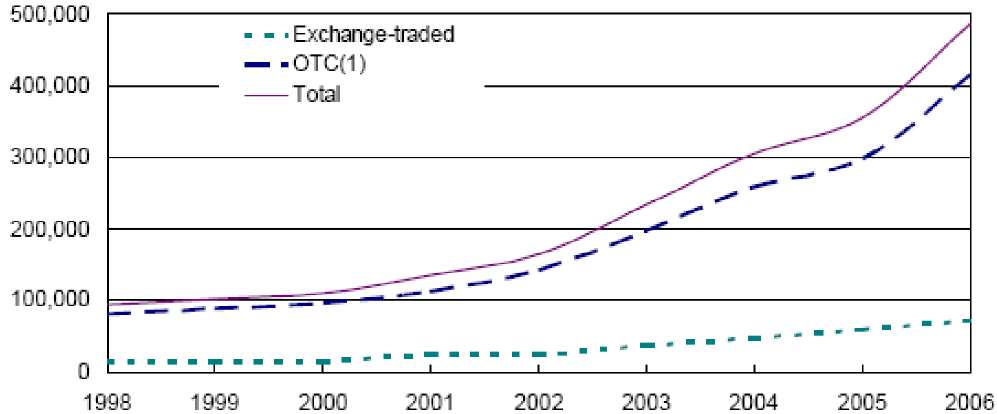


Sources: IMF International Financial Statistics, BIS, Datastream.

The use of derivatives such as futures, options, interest rate swaps and, more recently, credit default swaps together with structured products such as collateralized debt obligations and asset backed securities has dramatically changed the functioning of financial markets. They open to market participants the possibility of unbundling various risk components and allocating them among a multitude of investors; in turn, investors have more scope to hedge against future market movements or, alternatively, to increase portfolio leverage and the volume of risks assumed.

The use of derivative instruments has sharply increased in recent years: the total outstanding notional amount of over-the-counter and exchange-traded derivatives has risen from about 94 trillion U.S. dollars at the end of 1998 to around 486 trillions at the end of 2006 (Fig. 2). Credit default swaps in particular which has grown exponentially in recent years, has grown out of a need to hedge the risks in the growth of corporate risks. Credit-default swaps are contracts that protect bondholders against default in the event of a credit failure by a particular counterparty. The contract pays the buyer face value in exchange for the underlying securities or the cash equivalent should a company fail to adhere to its debt agreements.

Fig. 2 - Notional value of over-the-counter and exchange-traded derivatives
(outstanding amounts in billions of US dollars; end of year data)



Source: BIS Quarterly Review, September 2007.
(1) OTC derivatives include credit default swaps.

2.1 The effects of a FOMC policy shift on Credit Risk

As was discussed in the introduction, the study's marginal contribution focuses on the immediate impact of monetary policy on credit risk, of several credit quality classes of credit default swap products. However as noted by Benanke and Kuttner (2005), since asset markets are forward looking they tend to incorporate information about anticipated policy changes, hence it is difficult to capture the effects of this variable on credit risk.

Cook and Hahn (1989) were among a number of pioneering researchers examining market reaction to monetary policy. However the results from some of these earlier studies were mixed because they did not decompose the Feds actions into its components so that they could isolate its impacts on financial markets. Bernanke and Kuttner (2005) used an innovative policy decomposition procedure proposed by Kuttner (2001) to isolate the unexpected (surprise) policy change which might plausibly generate market and credit risk responses. This does not say that credit risk and indirectly default risk respond to monetary policy only when the Fed surprises the markets. Naturally, credit risk will also respond to expectations about future policy, which in turn may be driven by news about changing economic conditions.

So as to be able to achieve the studies stated objectives, the empirical procedure in section 3 isolates and describes that set of models nested in the "surprise monetary policy asset pricing model framework", that have been developed and used by Kuttner (2001), Cook and Hahn (1989), Bernanke and Kuttner (2005), Bredin, Gavin and O'Reilly (2003). Monetary policy surprises can be measured in one of two ways, in the first, the element of surprise is treated as an event-study approach in which FOMC meeting dates are allowed to create policy surprises. The event study approach models the observed changes in the short maturity interest rate on event days that are considered an exogenous monetary shock.

In the second approach which has been used in Bernanke and Kuttner (2005), Kuttner (2001) and Poole and Rasche (2000), monetary policy surprises is derived as the change in the FED funds futures rate. Kuttner (2001) suggests that both the anticipated and unanticipated components of a FOMC decision on the FED funds target is derived from the change in the futures contract's price relative to the day prior to the policy action[10]. To be specific, for an event taking place on day *t* of month *n*, the unexpected, or "surprise" target rate change is calculated as the change in the "spot-month" (the month in which the target is changed) futures contract rate on the day of the rate change, which is then multiplied by the number of the days in the month affected by the change.

Following Bernanke and Kuttner (2005), a measure of the surprise element of any specific change in the federal funds target can be derived from the change in the futures

[10] Campbell (1991) developed a general form of a signal decomposition model which has been adapted to the Fed funds rate by Kuttner (2001).

contract's price relative to the day prior to the policy action. This measure embodies the expectations of the effective federal funds rate, averaged over the settlement month. Krueger and Kuttner (1996) found that the federal funds futures rates yielded efficient forecasts of funds rate changes.

Kuttner (2001) subsequently used these futures data to estimate the response of the term structure to monetary policy. For an event taking place on day d of month m, the unexpected, or "surprise" target funds rate change can be calculated from the change in the rate implied by the current month futures contract. But because the contract's settlement price is based on the monthly average federal funds rate, the change in the implied futures rate must be scaled up by a factor related to the number of days in the month affected by the change. The analysis in section 3.3 will employ this method to gauge the response of credit risk to unanticipated changes in the federal funds rate from 1989 through 2002.

3.0 The Econometric Model

The empirical models specified and discussed below provide a simple yet highly analytic and effective framework for quantifying the impacts of monetary policy changes under the FMPT instrument on credit and its accompanying default risk. The empirical procedure developed in section 3.1 examines the effects of changes in the FED Funds target rate on a select number of credit default swap credit qualities.

3.1 Model 1: The Baseline "Fed target Decomposition" model

(a) Calculating the surprise target fed funds rate change;

Following Berument *et al* (2007) and Bernanke and Kuttner (2005), the federal funds futures rate is defined as 100 minus the price of a futures contract. Moreover, following Kuttner (2001) and Bernanke *et al* (2005), the surprise element of any specific change in the FOMC's federal funds target rate can be derived from the change in the futures contract's price relative to the day prior to the policy action. Specifically, for an event taking place on day *d* of month *m*, the unexpected, or "surprise" target funds rate change under the Fed policy can be calculated from the change in the rate implied by the current month futures contract, which is then multiplied by the number of the days in the month affected by the change, so as to scale the implied future rate by a factor related to the number of days in the month affected by the change:

$$\Delta \tilde{ffr}_t^u = \frac{m}{m-t}\left(f_{n,t}^0 - f_{n,t-1}^0 \right) \tag{1}$$

Where;

(i) $\Delta \tilde{ffr}_t^u$ is the unanticipated target rate change;

(ii) $f_{n,t}^0$ is the current month futures rate and t is the number of days in the month;

(iii) In the case where the rate change occurs on the first day of the month, we replace In order to minimize the effect of any month-end noise in the effective funds rate, however, the un-scaled change in the one-month futures rate is used to calculate the funds rate surprise when the change falls on one of the last three days of the month. Also, when the rate change occurs on the first day of the month, $f_{n-1,t}^0$ is used instead of $f_{n,t-1}^0$

(iv) The expected portion of the rate change is defined as the actual change minus

the surprise; $$\Delta \tilde{ffr}_t^e = \Delta\tilde{ffr}_t - \Delta ffr_t^u \tag{2}$$

(b) The baseline Regression Model for the reaction of Credit Risk to the FOMC's Policy Transmission mechanism;

As discussed in the introduction, one of the contributions of this paper is the extension of Bernanke and Kuttner's analysis to credit risk analytics so as to examine the effect of FOMC target changes on credit and default risk in the US credit markets. The regression model of equation 3 returns the reaction of credit risk to the surprise component of Fed policy; the results are presented in table 3 of section 5.

$$\Delta Cr_t = \alpha_0 + \beta_1 Liq_t + \beta_2\, ffr_s + \xi_t \tag{3}$$

Where;

$C\tilde{r}_t^e$ represents the credit default swap spreads of the various risk qualities of the study. As discussed earlier the study examined the effect of changes in the FED Funds target rate on seven credit market risk classes of U.S. financial markets. These credit classes are:

i. *The S&P Investment grade and High Yield credit classes:* The S&P credit quality classes used are; Investment grade – AAA, AA, A, BBB and High yield grade – BB, B and CCC.

ii. *Liquidity Index[11]:* The liquidity index on the benchmark credit products in the secondary market. Following the popular approach of using bid-ask spreads as a measure of liquidity, the study used CDS bid-ask spreads for the CDS instruments

[11] Dunbar (2007) provides a discussion on the development of the liquidity index used in this study.

for the period under study[12]. To be able to determine liquidity levels for each credit grade, the procedure is to calculate the measure of liquidity as the "ask" minus the "bid". The size of the spread from ask to bid prices will differ mainly because of the difference in liquidity of each asset. This spread differential is then divided by the mid price to derive a unit-less bid-ask measure.

3.2 Credit risk and the Structural Vector Autoregressive Model

In this model developed for more closely analyzing the impacts of monetary policy on credit risk. The focus of the model is the determination of the shocks that impacts credit risk in an expanding or contracting macro economy. This paper uses a Structural Vector Auto Regressive[13] (SVAR) model to study whether an innovation in Fed policy and market liquidity temporarily shifts credit risk from its long run equilibrium path.

The general model assumes a pure exchange, frictionless economy with a finite horizon $[o, \tau]$ for a fixed $\tau > 0$. Trading can be discrete or continuous and traded are both defaultable and default-free zero coupon securities of all maturities. The underlying uncertainty in the economy is represented by a filtered probability space $(\Omega, \mathbf{F}, \mathbf{P})$, where Ω is a state space, $\mathbf{F}$ is the σ-algebra representing measurable events, and $\mathbf{P}$ is an empirical probability measure. Information evolves over the trading interval according to the augmented right-continuous complete filtration $\{\mathbf{F}_t : t \in [0, \tau]\}$ generated by $n \geq 1$

[12] See Tang and Yan (2006) for an elaborate discussion on using bid-ask prices as a liquidity proxy

[13] A Structural VAR is a standard VAR where the restrictions needed for identification of the underlying structural model are provided by economic theory. These can be either contemporaneous or long-run restrictions depending on whether economic theory suggests the shocks are either temporary or permanent in nature.

independent Brownian motions $\{W_1(t), W_2(t),\ldots,W_n(t): t \in [0, \tau]\}$ initialized at zero, and satisfying the usual conditions. We let $X = \{X_t : t \geq 0\}$ be a time homogeneous Markov process in S^t for some integer $t \geq 1$. The state vector X_t comprises the univariate measures of the credit market's risk assets.

The basic equation used for the SVAR framework relates expected credit risk to changes in the rational expectations of market liquidity and macroeconomic conditions. The SVAR model is suitable for the analysis of dynamic linkages among the various credit risk determinants since it can identify the main channels of interactions and simulates the responses of a given variable (credit risk) to innovations in other variables (surprise Fed funds rate and liquidity).

Consider the system of simultaneous equations represented in a first order VAR like below;

$$\Gamma Y_t = C + \Phi(L) Y_{t-1} + \xi_t \qquad (4)$$

This is a general representation where Y_t is a vector of endogenous variables, Y_{t-1} is a vector of their lagged values, and ξ_t is a white noise vector of the disturbance terms for each variable. This disturbance term captures any exogenous factors in the model. The square $n*n$ matrix Γ **,** where n is the number of variables, contains the structural parameters of the contemporaneous endogenous variables. The square $n*n$ matrix **C** contains the contemporaneous response of the variables to the disturbances or innovations. Φ ***(L)*** is a p^{th} degree matrix polynomial in the lag operator *L*, where *p* is the number of lagged periods used in the model

The SVAR approach has been extended over the last decade away from its traditional interpretation of business cycle fluctuations, to other areas in finance to help identify the effects of different innovations on economic variables. It is an extension on the traditional VAR approach developed by Sims (1980), which combines economic theory with time-series analysis to determine the dynamic response of economic variables to various disturbances[14]. The main advantage of the SVAR framework is its ability to use economic theory to produce the necessary restrictions on the estimated reduced form model, required for identification of the underlying structural model. These restrictions can be either contemporaneous or long-run in nature depending on whether the underlying disturbances are considered to be temporary or permanent in nature. Once identification is achieved it is then possible to recover the structural shocks. These shocks can then be used to generate impulse response and variance decomposition functions to assess the dynamic impacts on different economic variables.

The implementation of the SVAR procedure involves the following discrete steps;

(a) A determination as to whether the variables to be included are stationary[15] or non-stationary;

(b) The outcome of the stationary test will determine whether a reduced form representation in levels or in first difference [16]is required;

[14] This is a more general but empirically realistic method for imposing restrictions, which has been put forward by Blanchard and Watson (1986), Bernanke (1986) and Sims (1986), which only places restrictions on contemporaneous structural parameters, to recover underlying structural disturbances. The procedure permits non-recursive structures and the specification of restrictions based on prior theoretical and empirical economic information.

[15] When testing for unit roots, the Augmented Dickey Fuller (ADF) test was used. The null hypothesis in this case is the presence of unit root. Failure to reject the null hypothesis leads to conducting the test on the difference of the series. Further differencing is conducted until stationarity is reached and the null hypothesis is rejected. As with the convention for annual time series, four lag lengths is used for the ADF test.

[16] It is necessary to use first differences to ensure that the series is stationary in the case of shocks that have permanent effects.

(c) Once the variables have been made stationary the next step involves estimating the reduced form VAR using OLS, ensuring that enough lags are incorporated to ensure no serial correlation from the residuals;

(d) Tests are needed to select the appropriate lag length given that VAR analysis, in trying to avoid exclusion restrictions, can quickly become over-parameterized losing important degrees of freedom for estimation purposes.

(e) When the reduced form VAR is estimated it is then essential to impose sufficient restrictions to identify the structural parameters of the model. In some cases economic theory can suggest more than the necessary restrictions, such that the model is Over-identified, but the discussion will be limited to the case of exact identification.

(f) In the case where the identified shocks in the system are assumed to have temporary effects on the variables, restrictions are imposed on the contemporaneous elements contained in Γ, C and Σ (the variance/covariance matrix of the residuals) in equation 4. Alternatively, where the shocks are assumed to have permanent effects, the restrictions are imposed on the long-run multipliers in the impulse response functions, which in effect involve restrictions on $D(L)$ in equation 5.

Equation 4 may not be fully identified so the values of the parameters in the model may not be unique. This is because the coefficients in the matrices are unknown and the variables have contemporaneous effects on each other. However, it is possible to transform equation 4 into a reduced-form model to derive the standard VAR representation, as shown in equation 5, which facilitates estimation of the model parameters. Since there are no contemporaneous effects between variables in the standard VAR representation in equation 5 and since each equation comprises a set of common regressors, this permits the use of OLS regression for estimation purposes, given

$$\Gamma Y_t = C + D(L)Y_{t-1} + \xi_t \tag{5}$$

The transformation of equation 4 into equation 5 implies that;

$$D(L) \equiv \Gamma^{-1}\Phi(L) \text{ and that } e_t \equiv \Gamma^{-1}C\xi_t \tag{6}$$

The structural disturbances are assumed to be white noise with zero covariance terms, implying that each disturbance arises from an independent source, the unique diagonal variance/covariance matrix of the structural disturbance (Ω), which results in (n^2- n)/2 restrictions being required for identification. Moreover, the matrices Γ and C are normally assumed to have main diagonal elements equal to unity. In Γ this implies normalization of a particular variable in each equation. In C this normalization is a consequence of assuming a separate shock contained in each equation. These provide further 2*n* restrictions.

In terms of orthogonality, as discussed in Bernanke-Kuttner (2005) this study also assumes that one reason for a violation of this condition would be a contemporaneous response of monetary policy to the credit market. This framework follows a straightforward method of orthogonalizing the reduced form errors by Choleski decomposition as originally applied by Sims (1980). Further, the identification approach requires the assumption that the system of equations follows a recursive structure, that is, a Wold-causal chain.

The minimum set of variables to include in the structural VAR model is governed by the aim of determining the main shocks to impact credit risk and market liquidity. The choice of variables is also influenced by insights from prior research. In other words, in line with the structural VAR models of Sims (1980), Bernanke and Blinder (1992) and Dungey and Pagan (2000), departures from trend are viewed as transient.

There are several ways of specifying the restrictions to achieve identification of the structural parameters. One procedure for determining appropriate restrictions so as to identify a structural VAR is to use the restrictions that are implied from a fully specified macroeconomic model. The structural VAR models estimated by Blanchard and Watson (1986), used theory to incorporate short run restrictions, Shapiro and Watson (1989) and Blanchard and Quah (1989), used theory to justify the inclusion of long-run restrictions, while Gali (1993), and used theory to justify both short-run and long-run restrictions. The alternative and more common approach is to choose the set of variables and identification restrictions that are broadly consistent with the preferred theory and prior empirical research. Most notably, the metric used to evaluate the appropriateness of the variables and restrictions is whether the behavior of the dynamic responses of the model is consistent with the preferred theoretical view of the expected response.

As discussed earlier in the introduction, this paper follows the same VAR approach of the Campbell (1991), Campbell-Ammer (1993), Bernanke-Kuttner (2005) framework to address the question of what explains credit risk response, an issue not addressed by prior research. As discussed in section 5 the main finding is that Fed policy's (FMPT) impact on credit risk comes predominantly through its effect on expected market liquidity. Specifically, we find that while an unanticipated rate cut in investment (high yield) grade instruments generates an immediate increase (rise) in the growth of credit risk (see table 3), the innovation is transient. Further, as noted above, the event-study results reported in section 5 rely on the assumption that the error term is orthogonal to funds rate changes.

3.3 Model 2: The Structural VAR Empirical model

This section discusses the theoretical underpinnings of the structural VAR (SVAR) model used to determine the impacts of Fed policy shocks on credit risk. As discussed in section 3.1 a major reason for developing the structural regression model in equation 3 used to evaluate the impact of changes in Fed policy actions on credit risk and liquidity is to provide a basis for eventually developing a richer model that will enable the identification and the simulation of the impact of the Feds actions and market liquidity actions on credit risk. An evaluation of the impact of Fed policy action on credit risk requires an appropriate separation of Fed policy action influences from all the endogenous variables in the model.

The selection of variables used in the structural VAR model is governed by the aim of determining the main shocks to impact corporate credit risk and liquidity in U.S. credit markets. Alternatively, the SVAR literature suggests that the choice of variables may also be determined by prior research work on credit risk impact variables. For this study the basic model includes 3 variables, each variable being explained by a structural equation that has an error term associated with it; equations 8, 9 and 10. The error term for each equation is interpreted as representing a particular innovation or shock. Appropriate specification and estimation of the system of equations capture the systematic effect of liquidity and changes in the Fed funds target in the model in the behavior of corporate credit risk. The system can also be to decompose to give an account for influences on credit by Fed fund rate changes and liquidity.

From the theory of stationary stochastic process consider the first order stationary credit risk vector autoregressive model, can be expressed as follows;

$$\Gamma Y_t = C + \Phi L Y_{t-1} + \xi_t \tag{7}$$

Where the coefficients of Γ and Φ are parameters of interest and Y_t is a $k \otimes 1$ observation vector of the random variables of interest on the t^{th} equation, ξ_t is a $k \otimes 1$ white noise vector with $\xi_t = (\xi_{1t}, ..., \xi_{kt})$ such that $E(\xi_t) = 0$, C is a $k \otimes 1$ vector of parameters, and Φ is a $k \otimes k$ matrix of first order autoregressive parameters. In the study's credit risk model, the vector Y_t is (the first difference of the Corporate Credit risk, the liquidity of the various credit qualities, and the surprise change in the Fed funds rate).

The study's SVAR structured equations can be written as;

$$lCr_t = c_1 + \phi_{11} lCr_{t-1} + \phi_{12} lCr_{t-1} + \phi_{13} lCr_{t-1} + \xi_{1t} \tag{8}$$

$$lff_t = c_2 + \phi_{21} lff_{t-1} + \phi_{22} lff_{t-1} + \phi_{23} lff_{t-1} + \xi_{2t} \tag{9}$$

$$lLiq_t = c_3 + \phi_{31} lLiq_{t-1} + \phi_{32} lLiq_{t-1} + \phi_{33} lLiq_{t-1} + \xi_{3t} \tag{10}$$

The error terms ξ_t (structured shocks) is a *n* vector of serially uncorrelated disturbances, and *var*(ξ_t)= Σ and $\Sigma_e = E(ee')$ gives the variance-covariance matrix of the structural innovations.

One key characteristic of the SVAR model is the ability of the variables or series in the system to experience a shock and ultimately returning to its equilibrium via the path called the impulse response function[17] (Hamilton (1994)). Kennedy (1998) suggests that VARs produce meaningful impulse response function so long as the structural equations are identified. In addition Kennedy (1998) further states that identification can be accomplished by using economic information in the form of recursive structures, coefficient restrictions, variance or covariance restrictions, symmetry restrictions or restrictions on long run multiplier values.

As suggested earlier, it is interesting to study the dynamic response of the vector autoregression to a unit shock in one series. Monetary policy literature in general suggests a one standard deviation innovation in the impulse variable. However the response to a particular innovation may be misleading if the historical data show a contemporaneous correlation among innovations in each series. This contemporaneous correlation can be removed by making use of a diagonalization procedure that uses an orthogonalizing transformation, ***G***, of the innovation vector such that the variance of the transformed innovation will be an identity, such that $\xi = G\xi_t$ has a variance-covariance matrix equal to the identity, ***I***. Bessler ((1984) suggests that the orthogonalizing matrix[18] should be selected based on the rule $G = H^{-1}$, where H is the Choleski decomposition of the untransformed model. From the foregoing the vector autoregression is transformed as follows;

$$G\Gamma Y_t = C + G_1\Phi Y_{t-1} + G_2\phi_2 + G\xi_t \tag{11}$$

[17] See Campbell (1991) and Kuttner (2001) for a detailed analytical discussion on Variance and policy impulse decomposition.

[18] Orthogonalizing the reduced form errors is a straightforward method. This approach which was proposed by Sims (1980) orthogonalized the reduce form errors by Choleski decomposition. The approach requires the assumption that the system of equations follows a recursive structure, referred to as a Wold-casual chain. Choleski decomposition will not be appropriate in cases where there are contemporaneous interactions that are of importance to the overall model such as a model implementing the Taylor Rule; here Choleski decomposition would not allow the model's macro variable responses.

The Choleski decomposition removes the current period cross correlated error terms by setting up a Wold casual chain among current elements of the $\boldsymbol{Y_t}$ vector.

4.0 The Data

The data analyzed are the surprise in the Fed fund rate (ff_r), the mid and bid-ask credit default swap prices at daily intervals over the period November 6th 2002 to December 18th 2007. The surprise in the Fed fund rate (ff_r) is derived from a combination of the Federal funds futures rates and FOMC announcement dates. As the FED funds futures market and the credit default swap market was not operational until 1989 and 2002 respectively, the dataset covers the period November 6th 2002 to December 18th, 2007. Over this period, 22 changes have occurred in the funds rate target by the FOMC.

Thirty five individually named CDS products were obtained which were then pooled along credit qualities to derive average CDS spreads for the AAA, AA, A BBB, BB, B and CCC rated credit risk. The CDS data was based on daily observations and covered the 5 year maturity band. The data on the Federal Funds Futures Rates was obtained from Bloomberg and the *DataStream* database. The data on the target Fed funds rate was gathered from the Federal Reserve website http://www.federalreserve.gov/fomc. Data on the credit default swap spreads was obtained from JPMorgan and Bloomberg.

5.0 Discussion of the empirical results

The VARMAX[19] procedure in SAS® was used to estimate the SVAR model outlined in section 3.3. Following the Bernanke-Kuttner framework on equity price reactions to Fed policy changes discussed in section 2.1, the impact of Federal Reserve Policy on credit risk is measured by calculating credit risk's reaction function to fund rate changes. The regression model representation in equation 3 is fitted to the event-study[20] results generated by the Kuttner (2001) Fed funds rate decomposition procedure discussed in section 3.1; the results are presented in table 3.

Table 3: The response of credit risk to surprise Fed policy changes

Regressor	*Sample*						
	AAA	AA	A	BBB	BB	B	CCC
Intercept	44.93***	50.10***	122.63***	166.28**	167.44*	323.86***	161.04**
	(6.12)	(9.17)	(5.36)	(3.32)	(1.84)	(9.71)	(3.67)
Liquidity	-0.65*	-1.00***	-5.16**	-8.75	-4.00	-26.98**	-52.45***
	(2.48)	(4.61)	(3.42)	(1.49)	(0.51)	(4.72)	(4.92)
Surprise Policy Change	-1.89*	-0.95**	-3.04*	-4.36*	-14.12*	-3.77	0.31
	(2.04)	(3.46)	(2.58)	(1.90)	(2.85)	(1.01)	(0.05)
Adjusted R-Square	0.36	0.60	0.51	0.19	0.26	0.55	0.60

Note: The dependent variable is the first difference in 5 year CDS spread. Parentheses contain t-statistics calculated using heteroskedastic consistent estimates of the standard errors. The full sample consists of xx target rate changes and xx FOMC meeting dates over the sample period January xx 2001 through December xx 2007.

Like Bernanke and Kuttner (2005) the coefficient of the surprise component of a fed fund rate change is negative for all samples, while being significant in four of the seven samples. In the case of the AA rated corporate bonds the results indicate a 1 percentage point surprise rate increase by the Feds result in a corresponding -1.0 percent change in the growth of credit risk. Most noteworthy, the results suggest 0.31 percent acceleration

[19] Given a multivariate time series, the VARMAX procedure estimates the model parameters and generates the Vector Autoregressive processes with exogenous regressors.

[20] Following Bernanke and Kuttner (2005) the events are defined as the union of all days corresponding to FOMC meetings when the Fund rate target was changed.

in the growth of credit risk in response to a corresponding 1 percentage point "surprise" rate expansion by the Feds on CCC rated bonds.

Unlike the other credit classes the CCC rated corporate debt showed a positive though insignificant change to a surprise change in the FMPT instrument. Historical cumulative default rates presented in table 4 suggests that corporate debt with an S&P and Moody's rating of CCC had a 69.2% chance of defaulting. Table 3 suggests that a surprise rate cut accelerates credit risk in CCC rated products, which may probably be as a result of investors' belief that the Feds could have a far more dismal economic outlook of the economy than they have indicated publicly[21].

The results in table 3 also suggest that poorer credit bonds (BB) are several times more responsive to a surprise rate change than the higher credit quality (AAA). These credit risk results are consistent with Bernanke and Kuttner's equity price analyses, as they also found a negative relationship between equity prices and a surprise fed fund rate change.

Table 4: Cumulative Historic Default Rates

Ratings	Moody's		S&P	
	Munis	Corps	Munis	Corps
Aaa/AAA	0.00%	0.52%	0.00%	0.60%
Aa/AA	0.06%	0.52%	0.00%	1.50%
A/A	0.03%	1.29%	0.23%	2.91%
Baa/BBB	0.13%	4.64%	0.32%	10.29%
Ba/BB	2.65%	19.12%	1.74%	29.93%
B/B	11.86%	43.34%	8.48%	53.72%
Caa-C/CCC-C	16.58%	69.18%	44.81%	69.19%
Investment Grade	0.07%	2.09%	0.20%	4.14%
High Yield Grade	4.29%	31.37%	7.37%	42.35%

Source: Municipal Markets Advisors, Moody's and S&P

Other noteworthy observations from the regression analysis presented in table 3 include the Adjusted-R^2 and the reaction of the growth in credit risk to changes in market

[21] In January 2008 the U.S. Central Bank cut the Fed fund rate by 0.75 basis points on January 21st and then again nine days later on January 30th by 0.50 basis points. A few days later the Government reported that economic growth for the fourth quarter of 2007 contracted to 0.6%, one of the largest decline in several years; a troubling observation given that the U.S. economy is perceived to be entering a recession.

liquidity. The Adjusted-*R*2 ranged from 0.26 to 0.60, which implies that 26 (60) percent of the variance in the observed changes in credit risk during these events weeks is associated with monetary policy changes. Moreover in the case of liquidity conditions, all coefficients on the liquidity variable for all credit classes were negative and all coefficients except those of the BBB and BB credit were highly significant. This result highlights the importance of liquidity to credit risk. In the absence of liquidity credit risk increases, and vice versa. For the CCC credit quality the result indicates a -52.45 percent decrease in the growth of credit risk in response to a 1 percentage point increase in liquidity, whereas the AAA credit quality exhibited a -0.65 percent response to a 1 percentage point increase in liquidity.

Monetary theory suggests that a contraction in the central bank's target rate results in a reduction in interest rates and a simultaneous increase in market liquidity. This is the natural strategy of the central bank during economic downturns. Under the "*monetary policy-liquidity paradox*", highlighted by this paper, monetary policy has both a direct and an indirect effect on the credit risk response function in equation 3. Credit risk is impacted directly when the central bank cut's the target rate, as evidenced in the analysis in table 3 which indicates that credit markets experience a spontaneous increase in the growth of credit risk. Similarly, as discussed earlier a contraction of the fed funds rate results in an increase in liquidity which reduces the growth of credit risk. The net effect of both the direct and indirect effect on credit risk will ultimately determine the final effect of a monetary policy change on credit risk. In the case of the much lower quality high yield products, there is an indeterminacy of the *monetary policy-liquidity paradox*. While the indirect effect of the fed fund rate change holds for high yield products, the direct effects appear to move counter to the liquidity effect. The paper will now look to the SVAR model to gain more insights into the dynamisms of these opposing forces of monetary policy changes and market liquidity.

5.1 *Results of the VAR analysis*

The analysis will now examine more closely the effects of monetary policy innovation on the growth in credit risks. The SVAR models are constructed using the growth rates in credit risk (first differences), liquidity and the surprise change in the Feds fund rate. From section 3.2 the vector autoregressive approach facilitates a much greater investigation of dynamic interactions among the jointly endogenous variables in a given stationary multivariate system without imposing *a priori* structural restrictions. Expanding on earlier work by Bernanke and Kuttner (2005) the paper analyzes an aspect of Fed's policy adjustment processes that is of interest are; the effects of unexpected or surprise target rate change on credit risk and liquidity. The fitted SVAR models are used to evaluate the size and reason for the credit market responses. The results of the analysis shows that current credit market conditions and the associated credit risks highlight the importance of the lags of adjustment associated with monetary policy shocks.

Whereas previous studies simply assumed *level* variables without testing, unit root tests were performed for each variable credit risk model to ensure stationarity so as to alleviate what Granger (1969) referred to as spurious correlation. Moreover non-stationary variables could possibly lead to standard inferences that are incorrect. The Augmented Dickey-Fuller Unit root tests performed on the variables for all credit classes (AAA, AA, A, BBB, BB, B and CCC) concluded that all variables were stationary.

Hence the null hypothesis claiming unit roots in the variables series was rejected for all variables at the 5% level of significance. Prior to the unit root analysis the credit risk premia was differenced to generate the "growth in credit risk" series. The results of these tests are presented in Tables 5.

Table 5: Augmented Dickey Fuller (ADF) Statistics for the Variables growth rate of credit risk, liquidity (first difference) and surprise Feds fund rate in levels

Augmented Dickey-Fuller Test Results

	Cr	Liq	ffs
AAA	-11.63**	-27.61	-31.21**
AA	-17.12*	-23.68*	-31.21**
A	-15.92**	-23.37*	-31.21**
BBB	-18.36**	-23.42*	-31.21**
BB	-15.38***	-16.31*	-31.21**
B	-22.04**	-43.96**	-31.21**
CCC	-25.64*	-19.74**	-31.21**

Note :
*Rejecttion of null hypothesis of unit root at the 5% level of significance
**Rejection of null hypothesis of unit root at the 10% level of significance

Great care is taken in the specification of the model because the structural estimation is sensitive to the choice of the length in lags. Very different results were obtained for $p = 1$ and $p = 1+n$ so it is necessary that the suitable choice of p be determined. To determine the appropriate order of the VAR processes to be used the study relied on the partial autoregressive matrices, partial correlation matrices and the partial canonical matrices. The results indicate that the model can be obtained by an AR order p=1 since the partial auto-regression matrices were insignificant after lag 1 with respect to two standard errors. Additional support is provided for a lag length of 1 by the ARCH diagnostic tests though there remains some evidence of ARCH (1) in the residuals of equations 8 and 10 of some models of the different credit classes.

In considering the variables that are important in explaining the changes in credit risk given a change in Fed policy we look to the contemporaneous correlation (variance-covariance) matrix. The results of the contemporaneous collerlation matrix are presented in table 6. The variables are listed in the order of credit risk, liquidity and Fed fund rate. This ordering allows both credit risk and liquidity to adjust instantaneously to a shock in the feds fund rate. In general the analysis returns a negative correlation between liquidity and credit risk and the surprise in the Fed funds rate and for all periods. For the AA credit risk, the correlation between credit risk and the surprise change in the Fed fund rate was negative meaning an increase in the Fed funds rate results in a decrease in credit risk. This may be due to the flight to quality during monetary contraction cycles, wherein there is a greater level of liquidity for the higher credit quality products.

Table 6: The Contemporaneous Correlation Matrix of the Multivariate Autoregressions

Credit Rating		V_o		
		Δ *Cr*	*Liq*	*ffs*
AAA	Δ *Cr*	1.00	-0.77	-0.25
	Liq	-0.77	1.00	-0.35
	ffs	-0.25	-0.35	1.00
AA	Δ *Cr*	1.00	-0.21	-0.50
	Liq	-0.21	1.00	-0.19
	ffs	-0.50	-0.19	1.00
A	Δ *Cr*	1.00	-0.72	-0.74
	Liq	-0.72	1.00	-0.23
	ffs	-0.74	-0.23	1.00
BBB	Δ *Cr*	1.00	-0.68	-0.18
	Liq	-0.68	1.00	0.27
	ffs	-0.18	0.27	1.00
BB	Δ *Cr*	1.00	-0.12	-0.45
	Liq	-0.12	1.00	-0.11
	ffs	-0.45	-0.11	1.00
B	Δ *Cr*	1.00	-0.73	-0.22
	Liq	-0.73	1.00	-0.62
	ffs	-0.22	-0.62	1.00
CCC	Δ *Cr*	1.00	0.04	-0.75
	Liq	0.04	1.00	-0.15
	ffs	-0.75	-0.15	1.00

The Granger-Causality test statistics shows that ff_s is not influenced by credit risk and liquidity[22]. Hence, ff_s should be treated as an exogenous variable in the credit risk model. Table 7 presents the results of the Granger Causality test statistics for the *Bivariate* VAR model for credit risk impulse response.

[22] The null hypothesis of the Granger-Causality test suggests that the surprise change in the Feds fund rate (ff_s) is influenced by itself and not by liquidity and changes in credit risk. If the test fails to reject the null, then the ff_s may be considered an exogenous variable.

Table 7: The Granger-Causality Wald Test Results

Statistic	*Sample*						
	AAA	AA	A	BBB	BB	B	CCC
Test	1.00	1.00	1.00	1.00	1.00	1.00	1.00
DF	2.00	2.00	2.00	2.00	2.00	2.00	2.00
Chi-Square	5.61	16.01	5.69	4.64	4.67	6.63	7.78
Pr>ChiSq	0.061	0.000	0.058	0.093	0.097	0.036	0.020

Note :The null hypothesis (H_o) of the Granger-Causality test suggests that the surprise change in the Feds fund rate is influenced by itself and not by liquidity and changes in credit risk.

The results of model 2 are summarized and presented in table 8. Table 8 presents the coefficient estimates $\hat{\beta}_0$, the associated standard errors and likelihood ratio tests of the over-identification restrictions. The over-identification can be rejected at standard levels of significance thereby suggesting the credit risk model is consistent with corporate credit risk, Fed funds data and the regression model in equation 3. Approximate significance levels corresponding to F-tests on lagged values of each variable are also given in table 8. The table implies that there is considerable feedback between the three series; unexpected fed funds rate change, changes in credit risk and liquidity. Moreover, the empirical results presented in table 8 also imply that an unexpected Fed fund rate expansion slows the speed of growth of credit risk for investment grade products but may accelerate credit risk for some classes of high yield products. Similarly, the results also show that a Fed fund rate change has direct effects on liquidity which impacts credit risk.

The results in Table 8 which suggests that an unexpected expansion of monetary policy results in an initial reduction in the rates of growth of credit risk confirms the regression model results in table 3. Moreover, a reduction in the feds fund rate will result in an increase in liquidity in financial markets. Table 8 implies a "*granger cause*" relationship between liquidity and the surprise fed fund rate change. These results also indicate that a reduction in the fed funds rate increases (decreases) market liquidity for investment grade (high yield) products. However, significance tests like those used in the analysis presented in table 8 provide little evidence on the dynamic properties of the system. The tests only imply that a "*granger type*" casual relationship exists over the fit period or it does not exist. A more revealing analysis can be made by studying the dynamic responses of the three variables to a unit shock in the surprise Fed funds shock; the impulse response function.

Table 8: The results of the Multivariate Autoregressions

Credit Rating	*Effect*	*C*	*ffs* $_t$	*ffs* $_{t-1}$	Δ *Cr* $_{t-1}$	*Liq* $_{t-1}$	F-Value
AAA	Δ *Cr*	-1.209	-0.244	-0.250	0.145	0.078	3.34
		(2.191)	(0.277)	(0.223)	(0.079)	(0.057)	
	Liq	1.603	1.353	1.354	0.336	0.624	3.51
		(8.250)	(1.042)	(0.838)	(0.299)	(0.216)	
AA	Δ *Cr*	-1.207	-0.484	-0.147	-0.116	0.107	1.72
		(5.009)	(0.244)	(0.220)	(0.151)	(0.168)	
	Liq	15.221	-0.282	-0.012	0.273	0.438	1.6
		(8.447)	(0.411)	(0.371)	(0.255)	(0.283)	
A	Δ *Cr*	-5.721	-0.831	0.144	0.206	0.458	10.79
		(6.195)	(0.362)	(0.302)	(0.061)	(0.346)	
	Liq	6.406	0.212	-0.026	0.092	0.581	5.63
		(0.258)	(0.191)	(0.159)	(0.032)	(0.182)	
BBB	Δ *Cr*	-27.427	-0.663	0.558	0.248	3.081	2.57
		(17.896)	(1.026)	(0.863)	(0.127)	(1.887)	
	Liq	3.536	0.134	-0.067	0.021	0.568	1.49
		(2.424)	(0.139)	(0.117)	(0.017)	(0.256)	
BB	Δ *Cr*	-9.746	-2.850	3.494	0.398	0.768	14.07
		(24.066)	(1.653)	(1.477)	(0.082)	(1.867)	
	Liq	5.916	-0.075	-0.043	0.013	0.505	2.86
		(2.846)	(0.195)	(0.175)	(0.010)	0.221	
B	Δ *Cr*	7.527	3.303	-1.807	-0.034	1.868	0.52
		(27.102)	(4.206)	(5.171)	(0.424)	(8.707)	
	Liq	0.945	-0.456	-0.018	0.019	-0.094	3.8
		(1.077)	(0.167)	(0.205)	(0.017)	(0.350)	
CCC	Δ *Cr*	42.811	0.298	-4.019	0.011	0.014	0.08
		(53.32)	(8.83)	(9.73)	(0.24)	(15.38)	
	Liq	0.059	-0.191	0.069	0.009	0.191	7.41
		(0.65)	(0.11)	0.12	0.00	0.19	

Note :Cr = First difference of credit risk, Liq is the market liquidity, ffs is the surprise change in the Feds fund rate Standard errors are in parenthesis and the F-Value is from the test of joint significance

Table 9 presents the orthogonalized impulse responses that describe how the system reacts to shocks to the underlying structural system. The orthogonal impulse responses of credit risk and liquidity to a shock in the Fed funds rate - ff_s represents the responses of a one standard deviation shock or innovation to each variable over an 8 week period. The shock and the subsequent responses are normalized by the historical standard error of the innovations in each series. A notable observation is the small standard errors on the coefficients in the $\hat{\beta}_0$ matrix; large standard errors are not uncommon in these models.

Figures 3 and 4 present the estimated impulse response functions of the credit risk variables to innovations in the Fed funds rate. The graphs show point estimates at the 95 percent confidence intervals of the responses of the exogenous variables (of credit risk) over an 8 week period to a one standard deviation innovation in the unexpected change in the Fed fund rate. From figures 3 and 4 an expansion in monetary policy has the following effects. With the exception of AAA and CCC rated corporate credit risk, the level of liquidity initially falls by as much as 0.15% to 0.70% between 1 and 8 weeks, however after approximately 2 weeks the decline in liquidity improves. Growth in credit risk also falls initially with an expansion in monetary policy. For B and CCC rated debt credit risk first increases then declines. In all cases these effects are not permanent but transitory in nature with rates eventually oscillating around zero.

Inspection of the results in tables 3, 9 and graphs 3 and 4 indicates that this model is a satisfactory description of the effects of monetary policy on credit risk. Most notably, in response to an increase in the fed funds rate, there is an observable decline in market liquidity for all classes of credit risk. Similarly, the growth in credit risk decays with a contraction in monetary policy. On this basis model 2 is accepted as having accurately identified the impacts of policy on credit risks. Table 9 also presents empirical evidence that suggests, whereas a Fed fund rate shock in period zero affects credit risk and liquidity in a positive but decaying manner, the effects of a shock will be felt several weeks later.

Table 9: The Orthogonalized Impulse Responses of Credit Risk, Liquidity and Unexpected Fed funds rate change to a One-Time only shock in Unexpected feds fund rate.

Period	***AAA***		***AA***		***A***		***BBB***		***BB***		***B***		***CCC***	
	Liq	C_r	Liq	C_r	Liq	C_r	Liq	C_r	Liq	C_r	Liq	C_r	Liq	C_r
0	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
1	0.31157	-0.25622	-0.75680	-0.75255	-0.26193	-0.19235	-0.42793	-0.41519	-0.28290	-0.36037	-0.16946	0.60934	0.21200	0.73375
2	-0.12193	0.01125	-0.44296	0.06276	-0.14549	-0.03316	-0.36655	-0.05269	-0.08422	-0.06356	-0.10687	-0.06938	0.01379	-0.13030
3	-0.03716	-0.02141	-0.26365	-0.18940	-0.11119	-0.04768	-0.24193	-0.09018	-0.06893	-0.06255	0.06040	0.00686	-0.00998	-0.03223
4	-0.05213	0.00280	-0.17304	-0.02883	-0.06962	-0.02306	-0.16834	-0.04691	-0.03237	-0.02351	-0.02404	-0.00383	0.00070	0.01062
5	-0.02779	-0.00132	-0.06715	-0.05262	-0.04741	-0.01788	-0.11435	-0.03595	-0.01962	-0.01504	0.00978	0.00199	0.00053	0.00061
6	-0.01988	0.00071	-0.06715	-0.01974	-0.03097	-0.01101	-0.07838	-0.02355	-0.01037	-0.00739	-0.00410	-0.00085	-0.00010	-0.00068
7	-0.01178	0.00012	-0.04158	-0.01742	-0.02063	-0.00755	-0.05354	-0.01637	-0.00586	-0.00423	0.00173	0.00035	-0.00002	0.00004
8	-0.00752	0.00022	-0.02624	-0.00898	-0.01361	-0.00491	-0.03662	-0.01112	-0.00319	-0.00225	-0.00073	-0.00015	0.00001	0.00003

Table 10 reports the variance decomposition credit risk model. The variance decomposition of credit risk suggests that innovations in the growth of credit risk generally explain a significant proportion of the changes seen in credit risk. Secondly, following credit risk, innovations in liquidity play a major role in explaining the variability seen in credit risk after a shock. With the exception of BB rated credit risk liquidity was more significant to credit risk than changes brought on by a surprise change in the Feds fund rate.

Table 10: Variance Decomposition - Proportion of prediction per variable

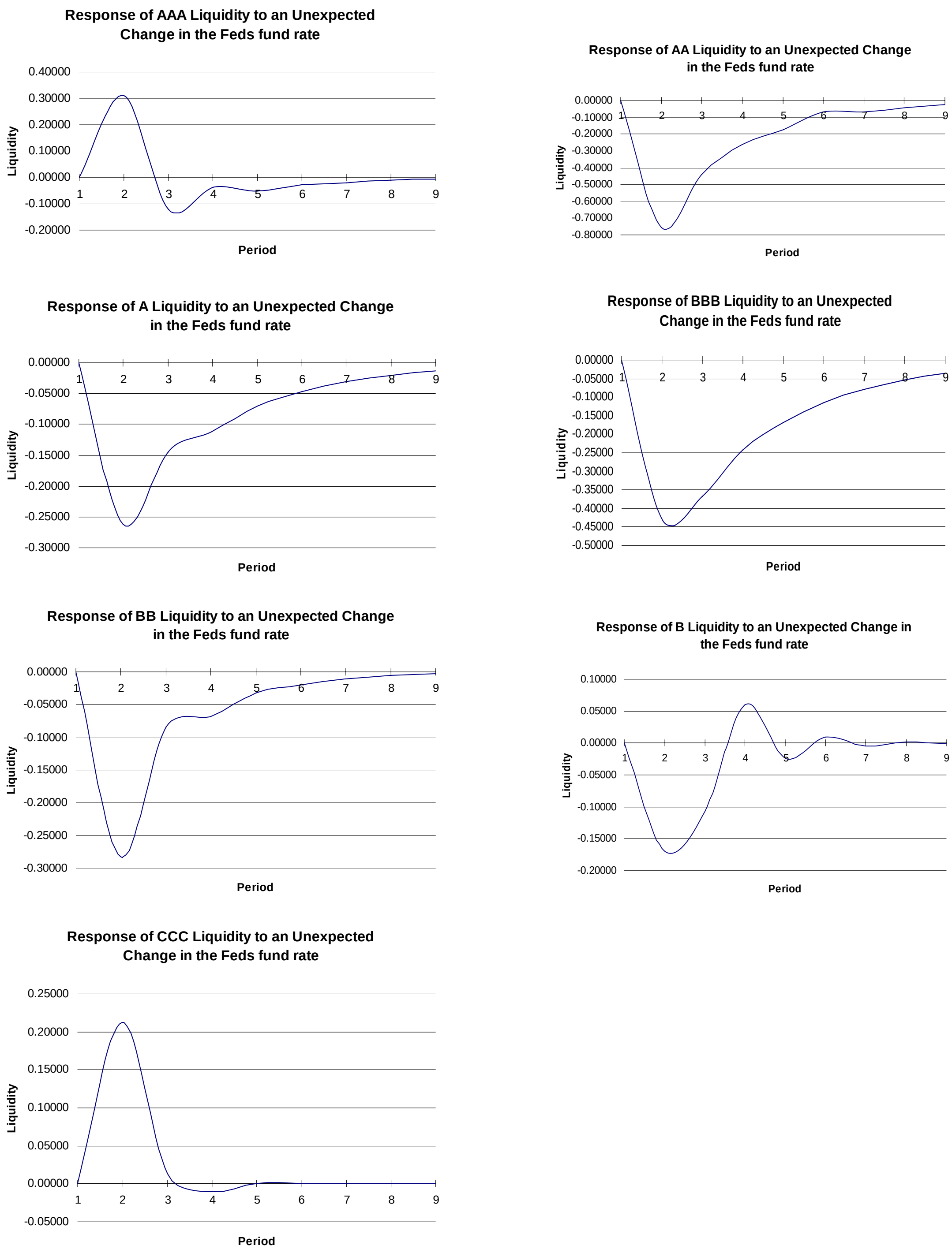
Credit Rating	C_r	ffs_t	Liq_t
AAA	0.401	0.061	0.538
AA	0.586	0.221	0.193
A	0.368	0.304	0.329
BBB	0.542	0.034	0.424
BB	0.772	0.199	0.029
B	0.385	0.049	0.566
CCC	*0.620*	*0.025*	*0.355*

Robustness Check

In this section we examine the robustness of the results discussed in section 5.1 above. First the cumulative sum of recursive residuals (CUSUM) tests proposed by Brown et al (1975) is employed to assess constancy of the parameters across time. If the plots of CUSUM lie outside the area between the two critical lines, then the parameters and variance are said to be unstable. The upper and lower control limits[23] are estimated at the 95% level of confidence. Each of the SVAR equations indicates that the parameters are stable or almost stable. See Figure 5.

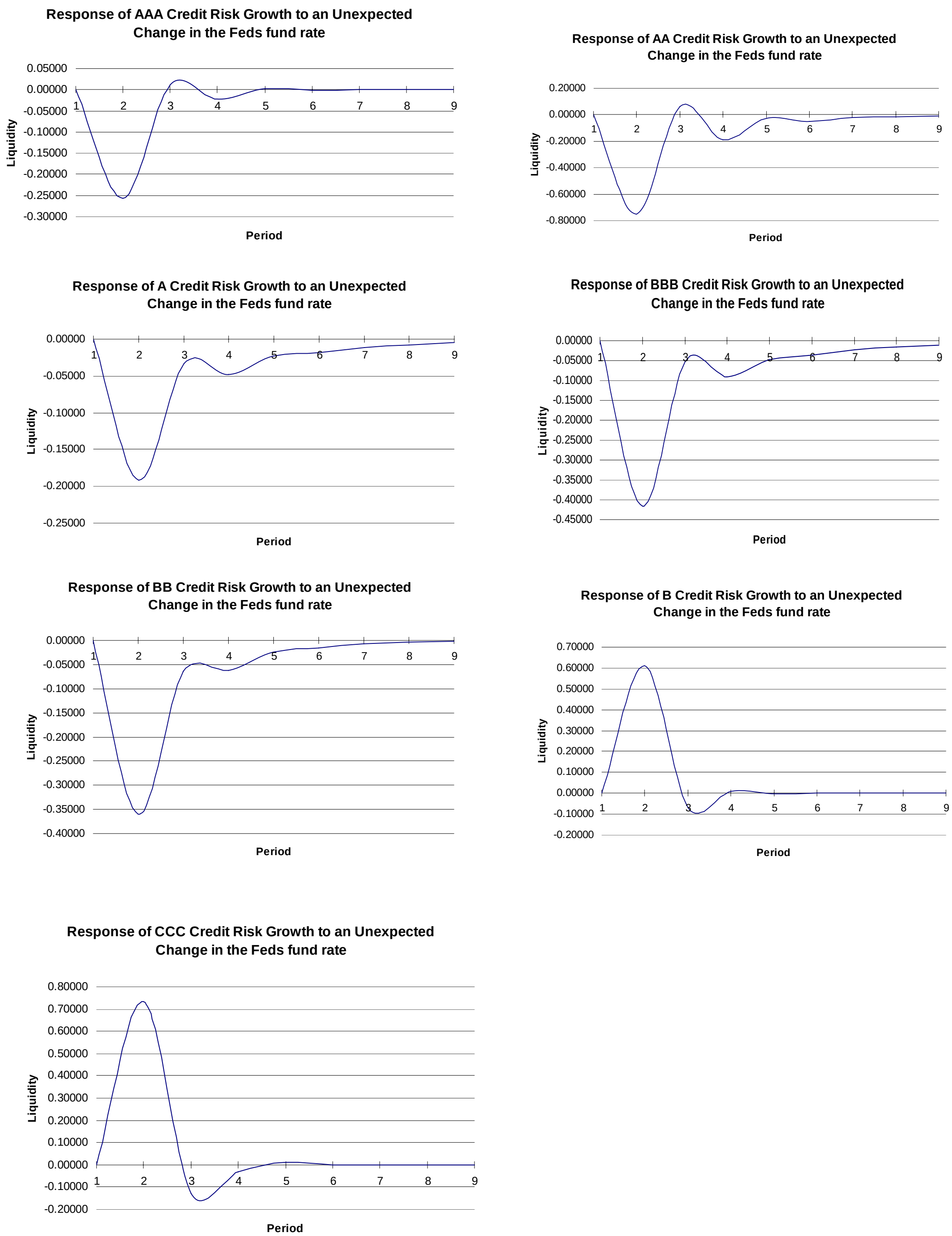
[23] The control limit is given by $CL = \pm\left\{\alpha\sqrt{T-k} + 2\alpha\left(t-k\right)/\left(T-k\right)^{1/2}\right\}$, where α =0.948 for a significance level of 5% and 0.850 for 10%.

Figure 3: Response of Liquidity to a one standard deviation Innovation in the Unexpected Fed Funds rate[24]



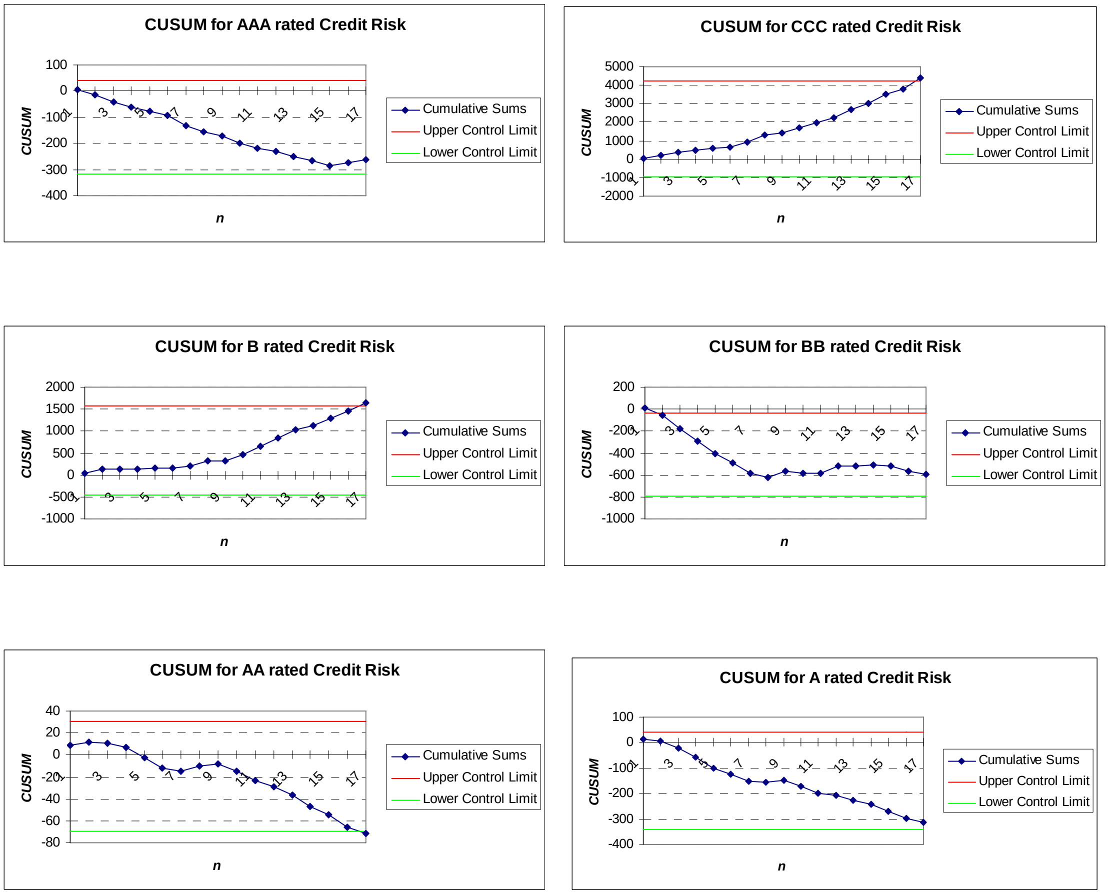
[24] The graphs show the point estimates at the 95 percent confidence intervals of credit risk over an 8 week period. Following a one standard deviation innovation, the unexpected Federal funds rate responds endogenously to the system.

Figure 4: Response of Growth in Credit Risk to a one standard deviation Innovation in the Unexpected Fed Funds rate[25]



[25] The graphs show the point estimates at the 95 percent confidence intervals of credit risk over an 8 week period. Following a one standard deviation innovation, the unexpected Federal funds rate responds endogenously to the system.

Figure 5: Robustness tests of the parameter estimates under the CUSUM framework



6.0 Summary and Conclusion

This study examines and documents strong evidence of the Feds monetary policy on corporate credit risk in U.S. financial markets. This is partly explained by the monetary policy's share of the overall variability in the growth of credit risk. The paper provide direct evidence that U.S. monetary policy affects the growth of credit risk directly and affects credit risk indirectly through its effects on liquidity. The study used a Fed fund decomposition procedure developed by Kuttner (2001) to derive the unexpected component of a Fed fund rate change from Fed fund futures data. Initial impact analysis using regression analyses found that the different credit qualities responded differently to monetary policy surprises.

Naturally the growth in investment grade corporate risk generally slows with an unexpected fed fund rate expansion. Whereas the lower levels of the high yield credit class appears to experience acceleration in the growth of credit risk in the event of a surprise fund rate increase. For AAA rate credit risk a 25 basis point rate cut leads to an increase in the growth of credit risk by approximately 0.5 percent. Whereas BB rated credit debt grows by about 3.5 percent on news of a 25 basis point fund rate cut. The study also found that a 1 percent decrease in market liquidity for AAA rated debt results in a 0.7% increase in the growth in credit risk, whilst a 1 percentage point decrease in market liquidity for CCC rated debt accelerates the growth in credit risk to the order of 52 percent.

The results highlight the effects of the opposing forces of monetary policy and liquidity on credit risk. The analysis indicates that while contractionary monetary policy creates tight money and subsequently reduced liquidity in credit markets, reduced liquidity indirectly affects credit risk by accelerating the growth of credit risk. Hence the contractionary effect of any monetary policy needs to be strong enough so as to dampen the opposing effects of market liquidity.

These findings have implications for policy given the growing size of the global corporate component of the international bond market. The U.S. central bank's robust linkage to corporate debt market allows the bank to play a major role in reducing credit risk particularly during periods of market instability such as during the sub-prime market meltdown of 2007. Given the importance of the linkages between monetary policy and credit markets, equity markets (Benanke and Kuttner (2005)), global asset prices (Hausman and Wongswan (2006)) and contrary to the views of a number of central bank watchers it is important for the central bank to intervene during periods of financial market instability to restore markets and investor confidence.

Further, these findings indicates that the creation of "tight money" through monetary policy contraction could reduce the willingness of investors to bear risk because of the "*monetary policy-liquidity paradox*", hence the reduction in the perceived growth in risk as in Bernanke and Kuttner (2005).

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