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# Detecting Regime Shifts in Credit Spreads

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**Abstract:**
Using an innovative random regime shift detection methodology, we identify and confirm two distinct regime types in the dynamics of credit spreads: a level regime and a volatility regime. The level regime is long lived and shown to be linked to Federal Reserve policy and credit market conditions, whereas the volatility regime is short lived and, apart from recessionary periods, detected during major financial crises. Our methodology provides an independent way of supporting structural equilibrium models and points toward monetary and credit supply effects to account for the persistence of credit spreads and their predictive power over the business cycle.

**Keywords:** Credit spread regimes, level regimes, volatility regimes, credit cycle, economic cycle, monetary effect, credit supply effect

**JEL Classification:** G12, E32, E42, E52

# I. Introduction

It is widely known that most existing credit risk models fail to generate the high levels of credit spreads that match empirical observations. For instance, Huang and Huang (2012) find that standard structural models, when calibrated to match historical default and recovery rates, all generate counterfactually low levels of credit spreads. The gap between observed and model-implied credit spreads is known in the literature as the credit spread puzzle.[1] While most existing studies addressing the credit spread puzzle focus on the level of credit spreads, Chen, Collin-Dufresne, and Goldstein (2009) find that standard structural models also fail to match the high volatility of credit spreads. This phenomenon, which is distinct from the credit spread level puzzle, is referred to as the credit spread volatility puzzle. By accounting for the countercyclical nature of default, the authors show that the habit formation model (Campbell and Cochrane (1999)) successfully captures the level and volatility of the BBB–AAA spread. However, this model is unable to explain either the level or the volatility of the corporate–Treasury spread, thus leaving questions about the behavior of corporate credit spreads over the risk-free rate unanswered.

The literature has often espoused the theory of countercyclical behavior in credit spread dynamics (Fama and French (1989), Stock and Watson (1989), Chen (1991)).

[1]The credit spread puzzle refers to the spread between corporate bond yields and treasuries. Standard structural models that only account for the effect of default fail to completely capture the BBB–Treasury spread. One reason is that the spread can be driven by nondefault factors such as tax differentials, liquidity, and macroeconomic factors (e.g., Collin-Dufresne, Goldstein, and Martin (2001), Elton, Gruber, Agrawal, and Mann (2001)).

However, more recent empirical studies only provide weak evidence supporting the link between economic cycles and the cyclical patterns in credit spreads (e.g., Koopman and Lucas (2005), Koopman, Kraeussl, Lucas, and Monteiro (2009)). A possible reason for this weak evidence is that the nature of the relation between credit spreads and macroeconomic factors may vary across economic regimes. A few studies have investigated the joint variation of macro factors and credit spreads by incorporating the possibility of regime shifts. For instance, David (2008) uses regime models to address the puzzling occurrence of high credit spreads for firms with low default. Hackbarth, Miao, and Morellec (2006), Bhamra, Kuehn, and Strebulaev (2010), and Chen (2010) significantly extend this literature by showing how macroeconomic factors affect firms' financing policies and yield more realistic credit spreads. However, these contributions imply that both the level and volatility of credit spreads are affected by the same macroeconomic factors.

In this article, we focus on the distinct patterns in the time series of the level and volatility of credit spreads. We shed light on the puzzling disconnect between credit spread cycles and the macroeconomy by identifying and explaining the presence of a disjoint set of level and volatility regimes in the data. To accomplish this, we introduce a novel regime detection procedure that has heretofore not been applied in a finance or economics context.[2] Our approach builds on the probabilistic-based regime

[2]Although this methodology was originally motivated by problems in detecting shifts within ecosystems, we show how it can be readily adapted for use with time series data on corporate bond transactions.

shift detection technique of Rodionov (2004), (2005), (2006). The technique has several advantages over more standard approaches: i) It detects potential breakpoints in the data in real time, ii) it is nonparametric and lets the data speak without imposing a set of priors on the number or timing of the regime shifts, and iii) the incipience of a new level or volatility regime is determined independently of one another's. In fact, a key contribution of our research is in decoupling the volatility regime from the level regime, which allows us a previously unexplored view into how the level and volatility of credit spreads interact with the macroeconomy. The new method also permits one to verify that the level and volatility of credit spreads can be driven by distinct economic factors.

Our approach adds to the literature on random regime shift detection. As Lu and Perron (2010) assert, one advantage of random regime shift models is their ability to account for abrupt changes in a time series. These models are also flexible as they do not make any restrictions on the number and the magnitude of the shifts. This feature is particularly valuable for modeling credit spread dynamics, which are subject to shocks on top of the business cycle. To the best of our knowledge, our paper is the first to apply a random regime shift model to the study of corporate credit spread dynamics.

We apply our methodology to the time series of credit spreads over the 1987–2009 period, encompassing three economic cycles, using corporate bond data from the Warga, NAIC, and TRACE databases. Our results are robust across the three different datasets. As an additional check, we construct an aggregate index of corporate bond spreads covering the same three recessionary periods using quoted prices from

Bloomberg and Warga datasets. Repeating our tests using this aggregate index yields similar patterns in the data.

We find that credit spreads have multiple regimes in their level and volatility, as opposed to two or a small number of regimes. The high levels of credit spreads always encompass yet often outlast NBER economic recessions. This result is consistent with the empirical evidence of Giesecke, Longstaff, Schaefer, and Strebulaev (2011), who find that the average duration of an NBER recession during 150 years of historical data is about half the average duration of a default cycle (1.5 versus 3.2 years). Another result is that shifts in credit spreads actually occur before the economic cycle (especially for low ratings); that is, credit spreads may have some predictive power over a forthcoming recession.[3] We also find that volatility is subject to shorter regimes, which, apart from recessionary periods, tend to coincide with periods of financial distress, such as the Asian financial crisis of 1997, the collapse of Long-Term Capital Management in 1998, and the 2007–2008 financial crisis. This suggests that level and volatility regimes might be linked to differing sets of observable economic phenomena. Motivated by these findings, we investigate possible sets of economic forces that may explain these patterns.

Since our empirical methodology does not rely on a particular economic model, another important contribution of our paper is to provide an independent assessment of different models in the literature. Chen (2010), and Bhamra, Kuehn, and Strebulaev (2010) examine the impact of macroeconomic cycles on corporate financing decisions

[3]Gilchrist and Zakrajšek (2012) also document the predictive power of credit spreads on macroeconomic fluctuations.

and credit spreads. Chen (2010) proposes a dynamic capital structure model that endogenizes firm's financing and default decisions over the business cycles. In his model, default arises endogenously through firms' responses to macroeconomic cycles. Consistent with our empirical results, the simulated results in his study indicate that default probabilities are countercyclical. The results also generate a few periods of high default rates outside recessions that can be reconciled with our volatility regimes, also detected outside recession periods. However, simulated results do not show the strong persistence that we detect after economic recessions. In Bhamra, Kuehn, and Strebulaev's (2010) model, risk-averse agents also choose their dynamic capital structure and default times. Credit spreads vary with macroeconomic conditions and reveal hysteresis. They depend on both the current macroeconomic environment and the state of the economy when the firm refinances its debt. Their spreads are countercyclical, spike up outside recessions sometimes, and show strong persistence after the recession periods, consistent with our results.

In addition to dynamic structural models, we study two other approaches that generate persistence in credit spreads. The first relates to monetary policy and emphasizes the role of inflation and the stickiness of long-term debt to obtain persistence in credit spreads (Bhamra, Fisher, and Kuehn (2011)). The second, referred to as the financial accelerator, considers frictions in the credit supply and points to the role of debt collateral constraints as a factor of persistence after a first shock to productivity (Bernanke and Gertler (1989), Kiyotaki and Moore (1997)). None of these two approaches considers the volatility of credit spreads. Finally, these works, except for the financial accelerator, do not discuss the predictive power of credit spreads toward economic cycles, which is another important result of this paper.

To see how these monetary and credit supply effects play a role in shaping the dynamics of credit spread regimes, we employ the same methodology to identify regime shifts in the time series of the Fed funds rate, along with shifts in the time series of the index of tightening loan standards. By overlaying the detected monetary policy and the credit supply regimes on our credit spread level regimes and NBER recessions, we provide exploratory evidence that monetary as well as credit supply effects contribute to the dynamics of credit spreads, their predictive power on the economic cycle, and their persistence over it.

Nevertheless, we find that macroeconomic cycles, monetary policy, and adverse credit market conditions only partially overlap with credit spread volatility regimes. The volatility of credit spreads increases when market uncertainty increases, both during and outside recessions. We test how market uncertainty links our volatility regimes to macroeconomic conditions and find a significant relation between our volatility factor and systematic forces driving both bond and equity risk premia.

The rest of this article is organized as follows. Section II describes the regime shift detection technique. Section III describes the data. Section IV presents the empirical results and Section V links our results to dynamic structural models, monetary policy, adverse credit conditions, and NBER recessions. Section VI further investigates monetary and credit supply effects on credit spread cycles. Section VII explores the link between credit spread volatility and bond and equity risk factors. Section VIII checks the robustness of our results against different data and model specifications and Section IX concludes the paper. The online-appendix provides technical developments.

## II. Regime Shift Detection

The regime shift detection procedure builds on the sequential $t$-test analysis of regime shifts developed by Rodionov (2004) for shifts in the mean. This procedure lets the data speak without imposing a set of priors on the number or timing of the regime shifts. The approach views credit spread regimes as random in the sense that, at each time $t$, one cannot predict the existence or the timing of any future breakpoint. The procedure also incorporates extensions of Rodionov (2005), (2006) in that it detects shifts in variance, overcomes problems related to the way test statistics deteriorate toward the end of time series, and accounts for hidden autocorrelation in the data that may lead to the detection of false regimes.

Alternative methods for detecting break dates in time series can be found in the econometrics literature on structural changes and include Gordon and Pollak (1994), Bai and Perron (1998), (2003), Chib (1998), Chen, Choi, and Zhou (2005), Perron and Qu (2006), Pesaran, Pettenuzzo, and Timmermann (2006), Davis, Lee, and Rodriguez-Yam (2008), Giordani and Kohn (2008), Maheu and McCurdy (2009), and Bai (2010). Our method differs from these works by offering a technique that detects breaks in the mean and the volatility of credit spreads independently of one another. The advantage is that economic shocks affecting the volatility of credit spreads will not unduly influence the detection of shifts in the levels and vice versa. Thus, our method allows level and volatility regimes to have their own patterns and to link up differently with economic phenomena. It is also a real-time method in the sense that possible breaks can be detected as new data arrive and, in contrast to parametric techniques, it is free from any assumption about the number and timing of the breaks.[4]

The regime detection test is performed in two stages. A first test identifies potential regime shifts in the data and a second test either accepts or rejects the potential shifts based on subsequent data. We first detect shifts in the mean of the level of credit spreads. After purging the level regimes from the data, we detect shifts in the variance of the residuals.

## A. The Dynamics of Credit Spreads

Consider that data on credit spreads are represented by the following time series $\{Y_t, t = 1, ..., n\}$. Suppose $Y_t$ is described by an autoregressive model:

$$Y_t - f_t = \rho(Y_{t-1} - f_{t-1}) + \varepsilon_t, \tag{1}$$

where $f_t$ captures a potentially time-varying mean, $\rho$ is the autocorrelation coefficient, and $\varepsilon_t$ is a normally distributed independent random variable with zero mean and variance $\sigma^2$. We want to test if time $t = c$ is a breakpoint for credit spreads shifting from one regime with mean value $\mu_1$ to another regime with mean value $\mu_2$. Formally,

[4]The regimes identified in the literature on credit spreads are always defined in terms of the parameters of the model of the credit spread, not formally on the volatility of the spreads. The two different regimes estimated produce different residual volatilities and are classified as either high- or low-volatility regimes.

$f_t$ is given by

$$f_t = \begin{cases} \mu_1, t = 1, 2, ..., c-1, \\ \mu_2, t = c, c+1, ..., n. \end{cases} \tag{2}$$

The regime shift detection tests the null hypothesis $H_0 : \mu_1 = \mu_2$ using a two-sample $t$-test. We present the details of the test in Section C. The detection method is real-time in that it applies the test to each arrival time of new data. This sequential detection technique is a data-driven analysis that does not require any a priori hypothesis on the existence and timing of regime shifts. In particular, at each time $t$, one cannot predict the occurrence of any future breakpoint. Therefore, the method aims at detecting random regime shifts.

The presence of a positive autocorrelation coefficient, $0 < \rho < 1$ in Equation (1), can generate patterns that resemble regimes in the data that can lead to false rejections of the null hypothesis. When the underlying data contain a stationary first-order autoregressive process with a positive autocorrelation coefficient, such a process is known as a red noise process. Thus, the removal of red noise, which involves estimating the AR(1) coefficient ($\hat{\rho}$), is an important preliminary step that facilitates the accurate detection of regime shifts in the data.

## B. The Prewhitening Procedure

A common manifestation of red noise is the presence of persistent swings in the data, whereby the observations drift above and then below their mean. The red noise process is further documented in Appendix A. These patterns are often mistaken for those generated by regimes. Given that the behavior of credit spreads within regimes is characterized by such a process,[5] standard regime shift detection techniques could lead to the false detection of regime shifts. By filtering out apparent shifts induced by red noise, we reduce the number of possible spurious breakpoints in the data. We then confirm that the detected breakpoints reflect true shifts in the data.

The difficulty with the prewhitening procedure is in obtaining an accurate estimate of the AR(1) coefficient ($\widehat{\rho}$) for short subsamples of size $n$ because the traditional techniques, such as ordinary least square, lead to biased estimates for $\rho$ in the presence of regime shifts. This makes it necessary to use subsampling and, since we have relatively short subsamples, we use the inverse proportionality with four corrections (IP4) technique to estimate the autoregressive coefficient.[6] The subsampling procedure requires that the subsample size $n$ be less than or equal to the integer part of $(m+1)/3$, where $m$ is the average length of a regime interval (Rodionov (2006)). In our case, $m$ and $n$ are expressed in months. For $m \leq 6$, the subsample size equals three months. In other words, the size of the subsamples must be chosen so that the majority of them do not contain change points. Using a subsampling procedure, the

[5]For instance, David (2008) shows strong first-order autoregressive (AR (1)) effects in credit spreads with a first-order autocorrelation coefficient of 0.86.

[6]Two alternative methods are proposed in the literature: the MPK (Marriott and Pope (1954) and Kendall (1954)) and the IP4 techniques (Orcutt and Winokur (1969); Stine and Shaman (1989)). Both methods perform better than the OLS and are similar to one another for $n \geq 10$. Estimation details using the MPK and IP4 techniques are provided in Appendix B. Rodionov (2006) shows that, based on Monte Carlo estimations, the IP4 technique substantially outperforms the MPK technique for shorter subsamples.

estimate of $\rho$ is the median among subsample estimates.[7]

After the AR(1) coefficient is accurately estimated and the red noise is removed, the filtered time series is then processed with the regime shift detection method. This filtered time series is given by

$$Z_t = Y_t - \hat{\rho} Y_{t-1}. \tag{3}$$

That is, from Equation (1),

$$Z_t = f_t - \hat{\rho} f_{t-1} + \varepsilon_t. \tag{4}$$

Note that, although the red noise is removed from $Y_t$, the filtered process $Z_t$ still has an AR(1) component in our data.[8]

## C. Shifts in the Mean

Let $Z_1, Z_2, Z_3, ..., Z_t$ be the filtered credit spread series, with new data arriving regularly.[9] When a new observation arrives, we test whether this new observation repre-

[7]As will be demonstrated, in our empirical application, the initial cut-off length $m$ is equal to six months and the subsample size $n$ is equal to three months. For the initial regime, the sample estimate of $\rho$ equals the mean of the two subsample estimates. As long as the regime length is higher than six months, the sample estimate of $\rho$ is the median among subsample estimates.

[8]Based on Durbin's $h$-test and the Breusch-Godfrey $LM$-test, we reject the null hypothesis of the absence of an AR(1) process in all our subsamples (results available upon request).

[9]This step follows after checking that the prewhitened data do not suffer from any statistical issues that may bias our results. We address these issues in Appendix C.

sents a statistically significant deviation from the mean value of the current regime. We define $\Delta$ as the difference between the mean values of two subsequent regimes that would be statistically significant at the level $\alpha_{mean}$ according to the Student $t$-test:

$$\Delta = t_{\alpha_{mean}}^{2m-2} \sqrt{2\overline{s}_m^2/m}, \tag{5}$$

where $m$ is the initial cut-off length of regimes similar to the cut-off point in low-pass filtering and $t_{\alpha_{mean}}^{2m-2}$ is the value of the two-tailed $t$-distribution with $(2m-2)$ degrees of freedom at the given probability level $\alpha_{mean}$. The sample variance $\overline{s}_m^2$ is assumed to be the same for both regimes and equal to the average variance over the $m$-month intervals in the time series.

The initial current regime contains the initial $m$ observed values and the initial new regime contains the subsequent $m$ observed values. The sample mean of the current regime $\overline{Z}_{cur}$ is known but the mean value of the new regime $\overline{Z}_{new}$ is unknown. At the current time $t_{cur} = t_m + 1$, the current value $Z_{cur}$ qualifies for a shift to the new regime if it is outside the critical threshold $\left]\overline{Z}_{crit}^{\downarrow}, \overline{Z}_{crit}^{\uparrow}\right[$,

$$\begin{aligned} \overline{Z}_{crit}^{\uparrow} &= \overline{Z}_{cur} + \Delta, \\ \overline{Z}_{crit}^{\downarrow} &= \overline{Z}_{cur} - \Delta, \end{aligned} \tag{6}$$

where $\overline{Z}_{crit}^{\uparrow}$ is the critical mean if the shift is upward and $\overline{Z}_{crit}^{\downarrow}$ is the critical mean if the shift is downward. If the current value $Z_{cur}$ is inside the range $\left]\overline{Z}_{crit}^{\downarrow}, \overline{Z}_{crit}^{\uparrow}\right[$, then it is assumed that the current regime has not changed and the null hypothesis $H_0$ about the existence of a shift in the mean at time $t_{cur}$ is rejected. In this case, the value $Z_{cur}$ is included in the current regime and the test continues with the next value at $t_{cur} = t_m + 2$. However, if the current value $Z_{cur}$ is greater than $\overline{Z}_{crit}^{\uparrow}$ or less than $\overline{Z}_{crit}^{\downarrow}$, the month $t_{cur}$ is marked as a potential change point and the subsequent data are used to confirm or reject this hypothesis. The test consists of calculating the regime shift index $(RSI)$ that represents a cumulative sum of normalized anomalies relative to the critical mean $\overline{Z}_{crit}$:

(7) $$RSI = \frac{1}{m\bar{s}_m} \sum_{i=t_{cur}}^{j} \left(Z_i - \overline{Z}_{crit}\right), j = t_{cur}, t_{cur}+1, ..., t_{cur}+m-1.$$

If anomalies $\left(Z_i - \overline{Z}_{crit}\right)$ are of the same sign as that at the time of a regime shift (i.e., positive if the shift is upward and negative if the shift is downward), it would increase the confidence that the shift did occur. The converse is true if anomalies have opposite signs. Therefore, if at any time during the testing period from $t_{cur}$ to $t_{cur}+m-1$ the $RSI$ turns negative when $\overline{Z}_{crit} = \overline{Z}_{crit}^{\uparrow}$ or positive when $\overline{Z}_{crit} = \overline{Z}_{crit}^{\downarrow}$, the null hypothesis for a shift at $t_{cur}$ is rejected. We include the value $Z_{cur}$ in the current regime and continue the test with the next value at $t_{cur} = t_m + 2$. Otherwise, time $t_{cur}$ is declared a change point and is significant at least at the confidence level $\alpha_{mean}$. The subsequent regime then becomes the current regime and the test continues.

## D. Shifts in the Variance

The procedure for detecting regime shifts in the variance is similar to that for the mean, except it is based on the $F$-test instead of the Student $t$-test. We now work with the residuals $\{\zeta_i\}$ left in the data after the means of the detected regimes are removed. The $F$-test (two-tailed test) consists of comparing the ratio of the sample variances for two successive regimes $\frac{s_{cur}^2}{s_{new}^2}$ with their critical value $F\left(\nu_1, \nu_2, \frac{\alpha_{var}}{2}\right)$, where $F\left(\nu_1, \nu_2, \frac{\alpha_{var}}{2}\right)$ is the value of the $F$-distribution with $\nu_1$ and $\nu_2$ degrees of freedom and significance level $\alpha_{var}$. In our application $\nu_1 = \nu_2 = m - 1$. The sample variance $s_{cur}^2$ is the sum of squares of $\zeta_i$, where $i$ spans from the previous shift point in the variance (which is the first point of the current regime) to $t_{cur} - 1$. At the current time $t_{cur}$, the variance $s_{new}^2$ is unknown. For the new regime to be statistically different from the current regime, the variance $s_{new}^2$ should be equal to or greater than the critical variance $s_{crit}^{2\uparrow}$ if the current variance is significantly increasing. However, if the current variance is significantly decreasing, the variance $s_{new}^2$ should be equal to or less than $s_{crit}^{2\downarrow}$, where

$$
\begin{aligned}
s_{crit}^{2\uparrow} &= s_{cur}^2 \times F\left(m-1, m-1, \frac{\alpha_{var}}{2}\right), \\
s_{crit}^{2\downarrow} &= s_{cur}^2 / F\left(m-1, m-1, \frac{\alpha_{var}}{2}\right).
\end{aligned} \tag{8}
$$

If at any time $t_{cur}$, the current value of $\zeta_{cur}$ satisfies the condition, $\zeta_{cur}^2 > s_{crit}^{2\uparrow}$ when the shift is up or $\zeta_{cur}^2 < s_{crit}^{2\downarrow}$ when the shift is down, then $t_{cur}$ is marked as a potential shift point and subsequent values $\zeta_{cur+1}, \zeta_{cur+2}, ...$ are used to verify this hypothesis.

The verification is based on the residual sum of squares index ($RSSI$), defined as

$$RSSI = \frac{1}{m} \sum_{i=t_{cur}}^{j} \left( \zeta_i^2 - s_{crit}^2 \right), j = t_{cur}, t_{cur}+1, ..., t_{cur}+m-1. \tag{9}$$

If at any time during the testing period from $t_{cur}$ to $t_{cur}+m-1$, the index turns negative when $s_{crit}^2 = s_{crit}^{2\uparrow}$ or positive when $s_{crit}^2 = s_{crit}^{2\downarrow}$, the null hypothesis about the existence of a shift in the variance at time $t_{cur}$ is rejected and the value $\zeta_{cur}$ is included in the current regime. Otherwise, the time $t_{cur}$ is declared a change point at time $t_{cur}+m-1$.

# III. Data

Credit spreads are obtained from the following three datasets.

*The Lehman Brothers / Warga database*: This dataset provides information on monthly prices (quote and matrix prices) of U.S. corporate bonds from January 1987 to December 1996. We consider only bonds included in the Lehman Brothers' bond indexes that have quoted rather than matrix prices.

*The NAIC database*: The NAIC database provides transaction rather than quoted price data for U.S. corporate bonds. Our sample period from the NAIC database spans January 1994 to December 2004. The database accurately reflects trading activity in the bond market from 1994 onward.

*The TRACE database*: This database only became available in July 2002. The TRACE database reports high frequency data and contains information about almost all trades in the secondary over-the-counter market for corporate bonds, accounting for 99% of the total trading volume. Our data from TRACE cover the period from October 2004 to December 2009. We employ the filter proposed by Dick-Nielsen (2009) to clean the data of duplicates and other special features.

The characteristics of the bonds are obtained from the Fixed Investment Securities Database. Our three samples (Warga, NAIC, and TRACE) are restricted to fixed-rate U.S. dollar bonds in the industrial sector with a remaining time to maturity between one year and 15 years. We exclude bonds with embedded options (callable, puttable, or convertible), overallotment options, asset-backed and credit enhancement features, and bonds associated with a pledge security. We filter out observations with missing trade details and ambiguous entries (ambiguous settlement data, negative prices, negative time to maturities, etc.). For NAIC and TRACE, we include all bonds whose average Moody's credit rating lies between AA and BB. For Warga, we only include bonds with ratings AA, A, and BBB, since this database does not contain a sufficient number of BB-rated bonds needed to extract the Nelson–Siegel–Svensson yield curve.

Hull, Predescu, and White (2004) show that Treasury bond yields, which are commonly used as risk-free rates, are contaminated by liquidity, taxation, and regulation issues. We follow their recommendation to use LIBOR-swap rates as the benchmark for risk-free rates. Swap rates are collected from Datastream and LIBOR rates from the British Bankers' Association. Because swap rates are available only from April 1987, the sample from Warga starts from this date instead of January 1987. To obtain smoothed yield curves for corporate bonds and LIBOR swaps (hereafter swap curves), we use the Nelson–Siegel–Svensson algorithm. We provide the estimation details in

Appendix D and the summary statistics in Appendix E. Overall, credit spreads are consistent with a bond rating structure. High-grade bonds have lower spread levels and volatilities. However, across the three samples, the Warga dataset reports lower levels and volatilities of credit spreads relative to those of the NAIC and TRACE datasets (on average and across ratings).

# IV. Estimation Results

Figures 1 and 2 depict the movements in the time series of credit spreads around the last three NBER recessions, starting in July 1990, March 2001, and December 2007, along with the time series of two macro variables: the Fed funds rate (Figure 1) and the index of tight credit standards (hereafter the Senior Loan Officer (SLO) survey; see Figure 2).[10] A common pattern emerges across the three graphs. The onset of higher levels of credit spreads clearly precedes the start of recessions and lasts until well after the recessions have ended. Although this pattern suggests a connection between the economic cycle and the dynamics of credit spread levels, the fact that high credit spread episodes begin before and persist until after the ends of recessions means that a countercyclical explanation alone is insufficient for linking credit spreads with the macroeconomy. Interestingly, the observed persistence is not unique to credit spread series. As the figures illustrate, both the Fed funds rate and the SLO survey exhibit patterns that are very close to those of credit spreads.

[10]The SLO Survey is published by the Federal Reserve. It summarizes results of quarterly surveys on bank lending practices, initiated by the Federal Reserve in 1964 and available since April 1990. A detailed description of the survey is given by Lown and Morgan (2006).

Thus, later on we will focus on these two macro variables to understand the economics driving the dynamics of credit spreads.

[Insert Figure 1 and 2 about here]

The plot of the raw data on credit spreads is less revealing when it comes to depicting the volatility pattern of credit spreads. Our tests involving a more formal analysis and using our regime detection approach reveal that the level and volatility of credit spreads are, in fact, subject to distinct regimes.

## A. The Level Effect

Figure 3 illustrates the results from our level regime detection procedure for 10-year maturity credit spreads. We also list the number of breakpoints, the mean and duration of the prior regime, the breakpoint date, the mean and duration of the new regime and the sign of the detected shift in Appendix F, Table F-1. All reported shifts are statistically significant at the $95\%$ confidence level ($\alpha = 5\%$). These results are obtained with an initial cut-off length $m$ set to its minimum of six months ($m = 6$) and a Huber parameter of two ($h = 2$). Other values of $m, \alpha,$ and $h$ are considered in the robustness analysis.

[Insert Figure 3 about here]

Across the three datasets, our procedure detects both positive and negative shifts in the mean. We tend to detect more shifts in the lower rating categories and fewer shifts in the higher rating categories. In all cases, positive shifts are all detected either prior to or during NBER recessions. A common pattern across the lower rating categories is the presence of two consecutive positive shifts followed by two consecutive negative shifts. With the exception of the NAIC data (Graph B , Figure 3), the pattern of two consecutive positive shifts is also found across the higher rating categories. This suggests that the transition from a low-level to a high-level regime is likely to occur as a two-step process, especially for lower-rated bonds.

The difference in means between the new and former regimes indicates that the magnitude of the shifts is generally substantial and ranges from 0.15% (AA shift of February 1991) to 3.98% (BB shift of October 2008) as shown in Appendix F, Table F-1.

Figure 3 also depicts where breakpoints are located with respect to the NBER economic cycle. The emerging pattern can be described as follows. First, we detect two consecutive upward shifts around each recession. The first positive shift is located around the official beginning date of the recession and the second one during this same recession. Interestingly, the shifting trend generally starts from the lower-grade bonds and then disseminates across all ratings.[11]

Second, spreads across all ratings do not instantly revert to their original levels at the end of an NBER recession. Instead, they exhibit persistence. It takes more than three years for credit spread levels to return to their initial levels preceding the 1990–1991 and 2001 recessions. This gradual reversion is completed after one or two downward shifts, depending on the rating category. For the 2007–2009 recession,

[11]Two exceptions are AA and A spreads in the NAIC dataset experiencing only one positive shift.

the NBER announced on September 20, 2010, that the recession ended in June 2009. Indeed, we detect the first negative shifts in June 2009 for A, BBB, and BB spreads and in July 2009 for AA spreads (Appendix F, Table F-1). As of December 2009 (the latest date in our sample), these spreads are still high and have not yet reverted to their original levels, consistent with the persistence pattern documented earlier. Again, as observed with the upward shifts, we note that the downward shifting trend originates with the lower-grade bonds.

The pattern previously identified with the 10-year credit spreads generally holds for shorter maturities (an illustration is provided in Figure F-1 in Appendix F). However, both first positive and first negative shifts are typically detected earlier for shorter maturities. This aspect is more pronounced for lower ratings. This suggests that spreads with lower ratings and shorter maturities are the first to perceive upcoming downturns.

## B. The Volatility Effect

We address the question of whether regimes of credit spread volatilities share the same patterns as regimes of credit spread levels. Our technique is precisely built to answer this question since it allows us to extract true volatility regimes that are independent from level regimes.[12]

We illustrate our results in Figure 4 and summarize them as follows. First, positive shifts in the volatility are detected around the same time as positive shifts in the

[12]Because volatility has a more straightforward economic meaning than variance, we use the term *volatility regime* to designate the variance regime.

level. Volatilities across ratings all shift up during recessions. We report details on the statistics pertaining to volatility breakpoints in Table F-2 of Appendix F. We also detect volatility breakpoints without significant changes in the levels. Outside recessionary periods, these volatility regimes highlight other adverse financial events. For example, during the period of the Asian financial crisis (officially starting in July 1997), the BBB and BB spreads are in high-volatility regimes. In addition, during the collapse of LTCM (which officially occurred in October 1998), all ratings (AA to BB) are in high-volatility regimes.

[Insert Figure 4 about here]

Our results refute a close link between the level and volatility regimes of credit spreads. We note that in most cases volatility regimes are short and not gradual, contrary to level regimes. Indeed, we detect both a level effect and a volatility effect at the beginning of NBER recessions. However, at the end of recessions, the volatility regimes show no persistence. In addition, as Figure 3 indicates, volatility regimes are not necessarily limited to recessions; rather, they result from significant shocks to the economy, including recessions.

Thus, different sets of economic phenomena drive episodes of high levels and high volatilities of credit spreads. Understanding these economic underpinnings could provide useful insights into decomposing and forecasting changes in credit spreads. Specifically, we have good reason to believe that level regimes are more closely connected with real activity, although their persistence and predictive ability remain to be explained. The pattern observed in volatility regimes also calls for specific investigation.

# V. Detected Versus Model-Implied Credit Spread Regimes

## A. Structural Equilibrium Models

Our regime detection technique is a model-free opportunity to compare the actual cyclical dynamics of credit spreads with those implied by the theoretical literature. This section relates our empirical findings to the characteristics of credit spread dynamics that arise endogenously in different strands of models.

Structural equilibrium models, initiated by Hackbarth, Miao, and Morellec (2006) and Chen, Collin-Dufresne, and Goldstein (2009), examine the impact of macroeconomic cycles on corporate financing decisions and credit spreads. The recent contributions of Chen (2010) and Bhamra, Kuehn, and Strebulaev (2010) show that time-varying macroeconomic conditions can help solve the credit spread puzzle. In these two models aggregate consumption and firms' earnings are exogenous, but their drift and volatility depend on the business cycle determined by a Markov chain. Firms decide on how much debt to hold, when to restructure the debt, and when to default based on their cash flows and macroeconomic conditions.

Chen (2010, fig. 6) reports simulated economic cycles. Recessions correspond to negative expected consumption growth. Unfortunately, the author analyzes default rates but not credit spreads. Default rates are countercyclical in the sense that most of the high default rates (clustering of defaults) arrive in recessions. Thus, credit spreads should spike when the economy enters a bad state, which is consistent with our detected regimes. However, Chen's (2010) default rates promptly decrease every time the recession is over. The author's simulations do not reproduce the persistence in credit spreads that we detect. Finally, we note that the author's model also generates few periods of high default rates outside recessions. This model output can be reconciled with the credit spread volatility regimes that we detect outside recessions.

For Bhamra, Kuehn, and Strebulaev (2010), default rates and credit spreads are also endogenously countercyclical. Figure 3 of their article reports the time series of credit spreads and default rates in the simulated economy. As in Chen (2010), the default rates are countercyclical and some default episodes also occur outside recessions. Most importantly, credit spread levels exhibit persistence after recessions. As explained by the authors, this behavior is driven by shareholders' optimal default policy. The default boundary that they select depends not only on the current state of the economy, but also on the state prevailing at the previous refinancing time. This creates hysteresis in the distance to default, which is reflected in credit spreads being persistently high after the recession.

In sum, our findings provide some support for the structural equilibrium models. However, three important detected features in our results are not entirely captured by these models. First, the level and volatility of credit spreads exhibit distinct cycles. Chen (2010) and Bhamra, Kuehn, and Strebulaev (2010) do not explicitly examine credit spread volatility regimes. Second, the credit spread level cycle outlasts the economic recession. In Bhamra, Kuehn, and Strebulaev (2010) this effect is generated by introducing path dependence in the distance to default. Third, shifts in credit spreads actually occur before the economic cycle (especially for low ratings); that is, credit spreads may have some predictive power over the forthcoming recession. None of the previously cited structural equilibrium models captures this predictive aspect, because the credit spread cycle is tightly linked to the economic cycle and essentially the start of a recession triggers a surge in credit spreads.

## B. Models with Monetary Effects

The discrepancies between our detected credit spread regimes and those implied by the structural equilibrium models may stem from incomplete modeling of the business cycle. For instance, Bhamra, Kuehn, and Strebulaev (2010) acknowledge that their model generates insufficient comovement between credit spreads and equity returns volatility and points toward the monetary policy as a potential missing factor.

Interestingly, the model of Bhamra, Fisher, and Kuehn (2011), which takes monetary effects into account, can also generate persistence in credit spread dynamics. In this structural model, corporate default decisions depend on monetary policy through its impact on expected inflation. Since firms finance with fixed-rate nominal debt, a monetary policy shock (such as a decrease in the Fed funds rate following a tightening of credit standards) lowers expected inflation, which, in turn, makes debt refinancing more difficult and induces firms to maintain high leverage. As a consequence, credit spreads exhibit persistence. The presence of deadweight bankruptcy costs amplifies what Bhamra, Fisher, and Kuehn (2011) call a debt-deflationary spiral.

In this monetary framework, persistence in credit spreads is caused by the financing frictions that emerge directly from the nature of long-term debt. Nevertheless, as Bhamra, Fisher, and Kuehn (2011) acknowledge, other non-monetary types of financing frictions, such as shocks to the credit supply, can have a similar impact on credit spread dynamics.

## C. Models with Credit Supply Effects

The strand of literature related to the theory of *financial accelerators* (initiated in particular by Bernanke and Gertler (1989), King, (1994), Kiyotaki and Moore (1997)) considers information asymmetry and the high cost of external financing as frictions in the credit market that, in turn, amplify the effect of shocks on aggregate productivity and extend periods of high credit risk premiums.

Not only does the financial accelerator mechanism generate persistence in credit spreads, but it also entails that credit spread regimes actually precede economic cycles, two patterns that are strongly supported by our regime detection technique. Indeed, the financial accelerator literature claims that an increase in credit spreads reflects a tightening of the credit supply and causes economic activity to slow down. Consistent with this view, Gilchrist and Zakrajšek (2012) provide recent evidence that surges in credit spreads actually precede NBER recessions and show that an increase in excess bond premium causes a drop in consumption, output, and investment. Mueller (2009) provides another empirical study supporting the predictive power of credit spreads as well as their persistence, induced by the financial accelerator mechanism.

In their general equilibrium model, Gomes and Schmid (2010) examine shocks on the credit supply in the transmission channel between credit spreads and real activity. In their model, tightening credit conditions lowers the value of outstanding debt and therefore the wealth of households/investors. This, in turn, increases the cost of future debt financing and forces firms to reduce their investment and future output. Although credit supply shocks are not a necessary ingredient in their model (the predictive power of credit spreads is initially driven by endogenous fluctuations in risk aversion), the authors show that the inclusion of these shocks allows for more realistic correlations between macro and financial variables (see Gomes and Schmid (2010), Table 4).

# VI. Detecting Regimes in Monetary Policy and Credit Supply

We now look at additional empirical evidence of the link between credit spreads, monetary policy, and the credit supply.

## A. Preliminary Tests

We analyze the Fed funds rate time series as a proxy for monetary policy. Regarding the credit supply effect on credit spreads, we use the SLO Survey data as a measure of financial institutions' willingness to lend.[13] More precisely, we use the net percentage

[13] Some authors (e.g., Lown and Morgan (2006)) have used these data as a measure of subjective perception about the credit market activity (i.e., market sentiment). Other authors (Mueller (2009),

of banks tightening their lending practices, since the Federal Reserve relies on this information in formulating monetary policy actions.[14]

The Fed funds rate appears as an inverse mirror of the dynamics of credit spreads (Figure 1). Correlation coefficients are generally very high. For instance, the correlations between AA spreads and the Fed funds rate are, respectively, -0.50, -0.95, and -0.70 for Graphs A to C. Typically, the Fed anticipates a recessionary period by watching the survey (among other factors) and responds to it by lowering short rates. This economic stimulus continues until credit conditions become loose for firms and banks. The SLO Survey, plotted in Figure 2, shows how periods of high levels of credit spreads correspond to periods of adverse credit conditions (positive values in the SLO Survey data).

Granger causality tests reported in Appendix G show some evidence of feedback effects between credit spreads and the short rate. However, the Fed funds rate seems to lead investment grade spreads in most cases while BB spreads leads the Fed funds rate in all cases, indicating that low-grade spreads are more forward looking than high-grade spreads. In the case of the SLO Survey, we always obtain a unidirectional causal relation from the survey to credit spreads, supporting the idea that credit supply constraints may initiate credit cycles.

Finally, impulse responses reported in Appendix H show that credit spreads re-

Gilchrist and Zakrajšek (2012)) instead use these data as an objective measure of credit conditions (i.e., the tightness of credit standards). In this paper we adhere to the latter interpretation.

[14]The net percent of tightening equals the number of respondents reporting tightening standards less the number reporting easing divided by the total number reporting.

spond instantaneously to shocks in the survey and to shocks in the Fed funds rate. In both cases, the effect of the shocks persists for several months for all rating classes (Figure H-1). However, a shock to credit spreads has generally smaller and delayed effects on the SLO Survey and the Fed funds rate.

We extend the analysis by applying our regime detection technique on both the Fed funds rate and the SLO Survey time series. Using the same parameters and confidence level, we overlay the detected regimes on top of the credit spread regimes in Figure 3. We list the mean and duration of the prior regime, the number and dates of the breakpoints, the mean and duration of the new regime, and the sign of the detected shift in Table I-1 of Appendix I. The results are analyzed in the next two subsections.

## B. SLO Survey Regimes and Credit Spreads Regimes

Level regimes (rather than volatility regimes) are likely to drive the close connection documented in Figures 1 and 2 between credit spreads, monetary policy, and the credit supply. Across the three graphs, SLO Survey data report tightening standards several months ahead of each recession. Specifically, two tightening credit regimes precede each recessionary period, thus driving the two-step regime process observed with credit spread levels. The difference in levels between the two tightening regimes is substantial. For instance, after the 1991 recession (SLO Survey data not available before the recession), we detect a first positive SLO survey regime in October 1998 that lasts till June 2000 (Panel B of Table I-1 of Appendix I). This regime indicates that, on average, 14.91% of banks tightened their standards. Thereafter, a second positive regime shifts the level of the SLO survey to 46.43% in July 2000, several months before the 2001 recession.

Before the 2007–2009 recession, we also detect two positive regime shifts for the credit supply. The first shift occurred in July 2007 and the SLO survey data indicate that, on average, 19.63% of banks tightened their standards. This regime lasts for nine months, until a second successive positive regime in April 2008 where the average shifts to 65.20%. Again, the credit supply started tightening several months before the 2007–2009 recession.

The credit supply enters a loosening regime at least two years after the recession officially ends. For instance, during the 1990–1991 recession, the loosening regime started in July 1993 (-6.90%) while the recession officially ended in March 1991. The subsequent loosening regime started in January 2004 (-13.64%), again more than two years after the recession end, which in this case was in November 2001. As of December 2009, the credit supply was still in a tight regime (28.28%), yet the recession ended in June 2009.

## C. Fed Funds Rate Regimes and Credit Spread Regimes

In response to adverse economic conditions, the Fed intervenes by cutting short rates to ease the supply and demand for new loans and prevent the economy from entering a deep recession. In general, the Fed enters a loosening monetary policy and maintains its policy as long as the SLO Survey data continue to report tightening standards

(Figure 3). We also observe a gradual pattern in the movements of the Fed funds rate, yet monetary policy regimes do not always drive the high-level regimes of credit spreads. Again, the two-step process observed with the level regimes is likely due to the structure of the tight credit regimes.

For instance, during the 2007–2009 recession we detect two distinct easing monetary policy regimes (Panel C of Table I-1 of Appendix I ). The first regime lowers short rates from an average level of 4.99% to 2.26% and seems to respond to the regime of tight standards, which started in July 2007, following the subprime crisis. The Fed continues its stimulus by further lowering short rates until a very low level of 0.17%, on average, thus qualifying short rates to enter a new low regime starting in August 2008. Similarly, two-step loosening monetary policies were initiated in September 1990 and April 2002 in response to SLO Survey results signaling the 1990–1991 and 2001 recessions, respectively (Panel A and Panel B of Table I-1 of Appendix I ).

## VII. Information Content in the Volatility Factor

By overlaying regimes of tight credit standards on top of the volatility regimes in Figure 4, we can see that, unlike with level regimes, volatility regimes may be high even when credit standards are loose. Thus, the economic forces driving the volatility of credit spreads appear to be disjoint from those driving the level regimes.

This section investigates the economics behind the differing episodes of credit spread volatility. As a measure of uncertainty, we reconstruct the eight principal components of Ludvigson and Ng (2009), who investigate the predictability of bond risk premia, and replicate the set of macro fundamentals of Goyal and Welch (2008), who investigate the predictability of equity risk premia.

We find that our volatility factor is strongly linked to systematic forces driving both bond and equity risk premia. Across different ratings and graphs, the volatility factor is closely related to the eight factors of Ludvigson and Ng (2009), with an average adjusted R-squared value of 30% (Table 1). The relation is even stronger when we use Goyal and Welch's (2008) factors, where the average adjusted R-squared value is more than 60%. This result is meaningful because it validates results in the prior literature linking the equity premium to credit spreads (Jagannathan and Wang (1996), Chen, Collin-Dufresne, and Goldstein (2009)). It also suggests that the volatility, rather than the level, of credit spreads may be the main channel through which these two assets' risk premiums are linked. We report detailed results in Appendix J.

[Insert Table 1 about here]

# VIII. Robustness Tests

## A. Model Initial Parameters

We test whether the choice of initial parameters has a significant effect on the number and location of detected shifts. The key set of parameters is $(m, \alpha, h)$, where $m$ is the initial cut-off length, $\alpha$ is the significance level for detected shifts, and $h$ is the Huber parameter controlling for outliers. We use the 3-, and 10-year credit spreads from the NAIC datatset and repeat the analysis by allowing the initial parameter set $(m, \alpha, h)$

to take on different reasonable values and report changes in the number and location of new detected shifts. The base case applied in this study corresponds to the case where $m = 6$, $\alpha = 5\%$, and $h = 2$. We increase the initial cut-off length from 6 to 12 months and for each parameter $m$, we vary the significance level $\alpha$ between $5\%$ and $10\%$ and the Huber parameter $h$ between $1$ and $5$. We report the triplet (shifts unchanged, shifts added, shifts dropped) in Table 2, Panel A. Unchanged shifts count the number of shifts (i.e., obtained with the new parameter set $(m, \alpha, h)$) detected in the same locations or in plus or minus one month around the same locations of shifts detected in the base case. Added shifts count the number of shifts located outside shift locations of the base case and dropped shifts count the number of shifts detected in the base case but not detected in the new case. In other words, the dropped shifts count the difference between the total number of shifts detected in the base case and the number of unchanged shifts in the new case.

[Insert Table 2 about here ]

Overall, our results are robust and can be summarized as follows. First, when data values are higher than $h$ standard deviations, they are considered outliers and are then weighted inversely proportionally with their distance from the mean value of the new regime: $weight = \min(1, h\sigma/\Delta)$. When the cut-off length is $m = 6$ and the confidence level is $\alpha = 5\%$, the critical difference between the regimes is $\Delta = 1.29 \times \sigma$, which leads to $weight = 0.78$ when $h = 1$. As the initial cut-off length and/or the confidence level increase, $weight$ converges to its limit value of one and the results remain the same for different values of $h$. Panel A of Table 2 shows that the number and location of the shifts for different cut-off lengths remain unchanged with $h \geq 2$. Thus, our choice of $h = 2$ is reasonable.

Second, as the cut-off length increases, the degree of freedom increases and the value of $\Delta$ becomes smaller, which translates into higher values of anomalies $(RSI)$ when the regimes are longer than $m$. We may then detect more shifts with lower magnitudes. However, regimes shorter than the cut-off length can pass the test only if the magnitude of the shift is high. By increasing the size of the initial cut-off length, we account for more shifts in the case of three-year credit spreads, for example. However, at least four shifts out of five (detected in the base case) remain unchanged. This confirms that the shifts for the mean value of three-year A spreads are determined correctly. Furthermore, the detected regimes for the 10-year credit spread remain the same when we increase the parameter $m$ for $h \geq 2$.

Third, the lower the confidence level, the higher $\Delta$ and the lower the value of anomalies $(RSI)$, which leads to a lower number of shifts. As shown in Panel A of Table 2, for a fixed $m$, when $\alpha$ increases from $5\%$ to $10\%$, the number of shifts added increases in several cases.

The variance ratio of two successive variance regimes depends on the critical value $F(\upsilon_1, \upsilon_2, \alpha)$. When $m = 6$ and $\alpha = 5\%$, we have $F = 5.05$. This means that to detect a potential new shift in the variance, the new variance regime should be at least $5.05$ times higher (lower) than the current variance regime if the shift is up (down). As the value of the initial cut-off length increases, the degrees of freedom increase and the value of $F$ decreases for the same confidence level $\alpha$. In this case, we allow for more shifts to be detected if they pass the test. This has the same effect as an increase in the confidence level, which also decreases the value of $F$. Panel A of Table 2 shows how the number of shifts added is different from zero as $m$ and/or $\alpha$ increase.

## B. Effect of Red Noise

We apply the regime shift detection technique to the data without prewhitening and report our analysis for the sensitivity of detected shifts to model initial parameters in Panel B of Table 2.

As expected, the base case shows that the prewhitening procedure (Panel B of Table 2) reduces the magnitude and the number of shifts detected. In addition, we observe that red noise increases the number of detected shifts as we consider alternative parameterizations. These results support the conclusion of Rodionov (2006).

## C. Effect of the Benchmark Choice for the Risk-Free Curve

We test whether our results hold if the benchmark for the risk-free rates changes. Thus, we use the CMT bonds published by the Fed as an alternative measure for risk-free rates. Similar to corporate bond yield curves, we obtain the CMT yield curves using the Nelson–Siegel–Svensson algorithm. We repeat the regime shift detection analysis using the sample from the NAIC database.

By replacing the benchmark for the risk-free curve, we shift our credit spread curves by approximately a constant and indeed we detect similar breakpoints.

### D. Using Aggregate Data

Most studies use one of the three databases described previously (Section III). However, when studying the behavior of corporate bond spreads, it is preferable to have a sufficiently long time series covering several business cycles. In the current state of the literature, there is no such data source. Because our detection method is in real time, it should not be sensibly affected by a shorter sample. However, for robustness, we also report the results obtained with an aggregate dataset. We join the quoted prices from the Warga and Bloomberg datasets to cover the same three recessions.[15] Our results remain robust with respect to issues of stationarity and the heteroskedasticity of the residuals. The level and volatility regimes only partially coincide and their patterns are in good agreement with previous results using three subperiods from the Warga, NAIC, and TRACE datasets (see Appendix K).

## IX. Conclusion

Our research detects and analyzes both the level and volatility regimes in credit spreads separately, using a new random regime shift detection technique. The technique is an exploratory rather than a confirmatory approach and does not require

[15]The Bloomberg dataset spans from March 1992 to December 2009. The index is comprised of the most frequently traded fixed-coupon bonds represented by FINRA's TRACE. In unreported tests (available upon request), we find that the best attachment point in the overlapping period (March 1992 to December 1996) between the Bloomberg and Warga datasets is in May 1994 (for most maturities). Using the filtered aggregate data, we also reject the null of a unit root and find no significant autocorrelation of the residuals.

any prior assumptions about the number and timing of the regimes. We find both the level and volatility effects to be significantly distinct in their respective patterns and in their relation to the NBER cycle. High-level regimes coincide only partially with high-volatility regimes. Whereas our analysis demonstrates that recessions are accompanied by a long-lived level effect on credit spreads, the volatility effect is, in contrast, short lived. We also detect high-volatility regimes outside of NBER recessions, which are associated with significant financial crises, consistent with associating volatility regimes with periods of high uncertainty.

We relate the credit spread cycles that we detected to the main theoretical frameworks proposed in the literature. While structural equilibrium models generate some of the detected patterns of credit spread dynamics (i.e., the countercyclicality of credit spreads, the short default episodes outside recessions, and the persistence of credit spreads), other theoretical frameworks, such as the role of monetary policy and shocks in the credit supply, can be invoked to match specific detected features (i.e., the persistence of credit spreads, as well as their ability to predict economic downturns). We corroborate the importance of these additional factors by applying our regime detection technique to the time series of the Fed funds rate and the SLO Survey data. Our results further show evidence linking the volatility factor to important macro fundamentals that are widely accepted as predictive sources of asset risk premia.

Another potentially important determinant of credit spread dynamics, unexplored in this paper, is credit market sentiment. Buraschi, Trojani, and Vedolin (2011) develop a model in which agents disagree about firms' future cash flows and future macroeconomic conditions. The heterogeneity in beliefs increases during recessions, raising credit spreads and their volatility. As an avenue for future research, one could apply our regime detection technique on proxies for credit market sentiment, thereby gauging its empirical impact on credit spread dynamics.

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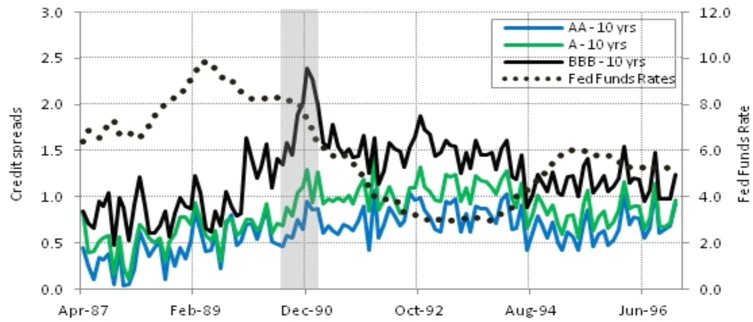
Wu, L., and F. X. Zhang. "A No-Arbitrage Analysis of Macroeconomic Determinants of the Credit Spread Term Structure." *Management Science*, 54 (2005), 1160–1175.

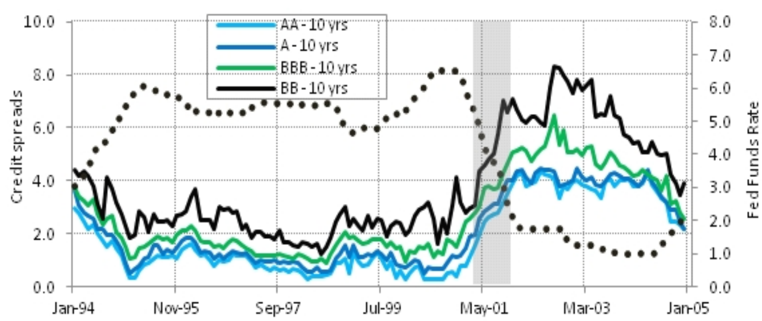
Figure 1: Times Series of Credit Spreads and the Fed Funds Rate.

We plot the time series of 10-year credit spreads (left-hand side axis) and the Fed funds rate (right-hand side axis). Time is in months, credit spreads and the Fed funds rate are in percentages. The shaded regions represent NBER recessions.

Graph A : Warga Dataset from April 1987 to December 1996




Graph B : NAIC Dataset from January 1994 to December 2004




Graph C : TRACE Dataset from October 2004 to December 2009

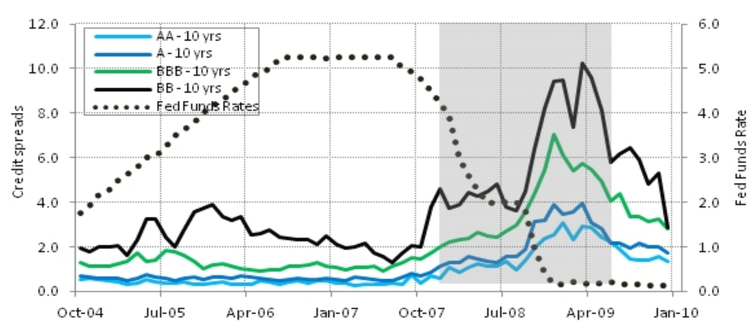
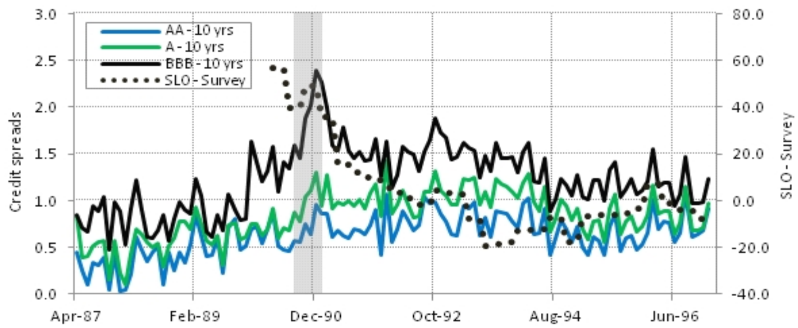


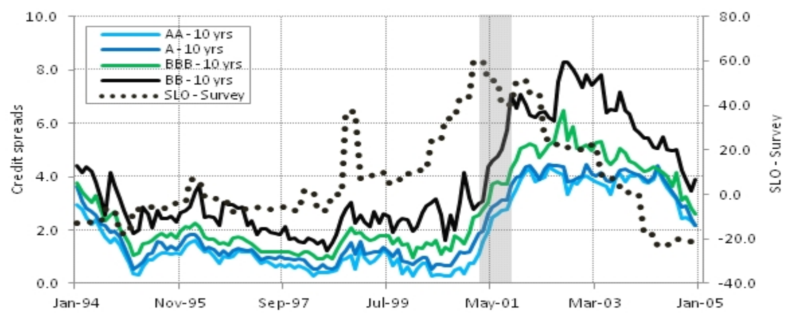
Figure 2: Time Series of Credit Spreads and the SLO Survey.

We plot the time series of 10-year credit spreads (left-hand side axis) and the SLO Survey data (right-hand side axis). Time is in months, credit spreads and the SLO Survey data are in percentages. The shaded regions represent NBER recessions.

Graph A : Warga Dataset from April 1987 to December 1996




Graph B : NAIC Dataset from January 1994 to December 2004




Graph C : TRACE Dataset from October 2004 to December 2009

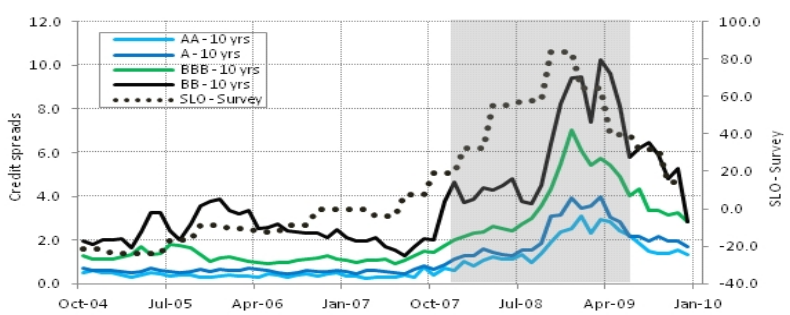
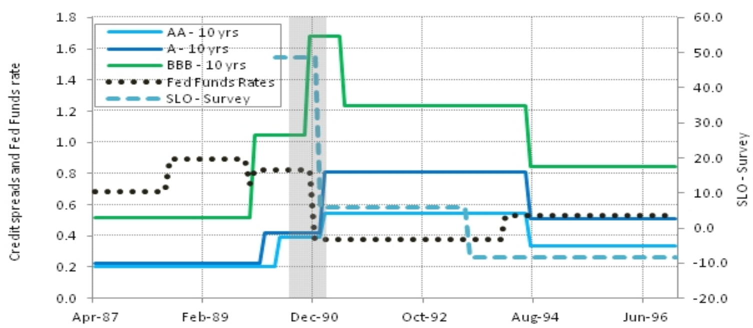
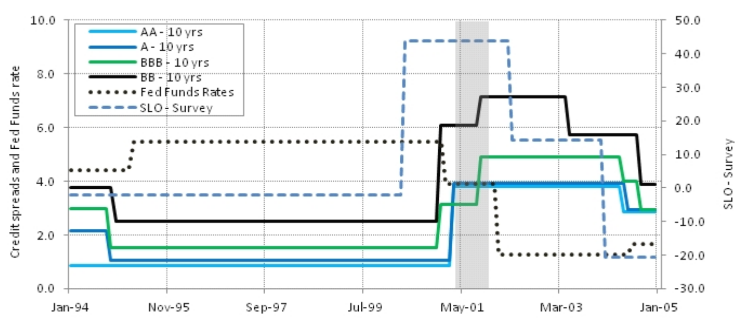


Figure 3: Regimes of Credit Spread Levels, Monetary Policy, and Credit Conditions. We plot detected mean regimes of 10-year credit spreads, the Fed funds rate (left-hand side axis) and the SLO Survey (right-hand side axis). Time is in months, credit spreads, the Fed funds rate, and the SLO Survey data are in percentages. The shaded regions represent NBER recessions. The initial cut-off length is six months and the Huber parameter is two. All detected regimes are statistically significant at the 95% confidence level or higher.

Graph A : Warga Dataset from April 1987 to December 1996




Graph B : NAIC Dataset from January 1994 to December 2004




Graph C : TRACE Dataset from October 2004 to December 2009

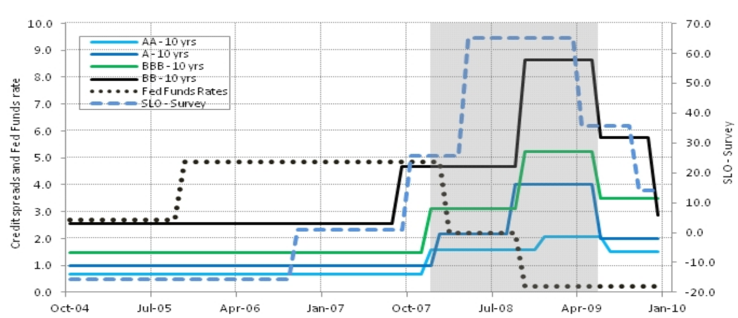


Table 1: Regression of the Volatility Factor on Uncertainty Variables.

We report the adjusted R-squared values from the regression of the volatility factor on the eight principal components of Ludvigson and Ng (2009) and a set of economic fundamentals of Goyal and Welch (2008). In Goyal and Welch's case, we omit variables causing a high variance inflation factor (i.e. $VIF > 10$) and those not available.

| | Ludvigson and Ng (2009) | | | Goyal and Welch (2008) | | |
|---|---|---|---|---|---|---|
| | Warga | NAIC | TRACE | Warga | NAIC | TRACE |
| AA | 0.171 | 0.376 | 0.428 | 0.267 | 0.682 | 0.224 |
| A | 0.284 | 0.382 | 0.197 | 0.409 | 0.622 | 0.681 |
| BBB | 0.318 | 0.303 | 0.248 | 0.324 | 0.719 | 0.752 |
| BB | | 0.15 | 0.342 | | 0.392 | 0.389 |

Table 2: Sensitivity Analysis for Model Parameters.

We report changes in the number and location of detected shifts using each of the new parameter sets ($m$,$\alpha$,$h$) through the triplet (unchanged shifts, added shifts, dropped shifts ). The base case is where $m = 6$, $\alpha = 0.05$, and $h = 2$ (second line). The parameter $m$ is the cut-off length (in months), $\alpha$ is the significance level for detected shifts, and $h$ is the Huber parameter controlling for outliers. The subsample size for serial correlation $n$ (in months) is equal to the maximum between three and the integer part of $(m+1)/3$. The dataset is the NAIC transactions data. We report results for A spreads with three and ten years to maturity.

| | | | Panel A: With Prewhitening | | | | Panel B: Without Prewhitening | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | Mean | | Variance | | Mean | | Variance | |
| $m$ | $\alpha$ | $h$ | A-3 | A-10 | A-3 | A-10 | A-3 | A-10 | A-3 | A-10 |
| 6 | 0.05 | 1 | (5,0,0) | (3,0,0) | (2,1,1) | (6,1,1) | (5,1,1) | (3,1,1) | (1,0,1) | (5,0,1) |
| 6 | 0.05 | 2 | (5,0,0) | (3,0,0) | (3,0,0) | (6,0,0) | (6,0,0) | (4,0,0) | (2,0,0) | (6,0,0) |
| 6 | 0.05 | 3 | (5,0,0) | (3,0,0) | (3,0,0) | (6,0,0) | (6,0,0) | (4,0,0) | (2,0,0) | (6,0,0) |
| 6 | 0.05 | 5 | (5,0,0) | (3,0,0) | (3,0,0) | (6,0,0) | (6,0,0) | (4,0,0) | (2,0,0) | (6,0,0) |
| 6 | 0.1 | 1 | (5,3,0) | (3,1,0) | (3,2,0) | (6,1,0) | (6,3,0) | (4,3,0) | (1,0,1) | (6,1,0) |
| 6 | 0.1 | 2 | (5,2,0) | (3,0,0) | (3,1,0) | (6,1,0) | (6,3,0) | (4,4,0) | (2,0,0) | (6,2,0) |
| 6 | 0.1 | 3 | (5,2,0) | (3,0,0) | (3,1,0) | (6,1,0) | (6,3,0) | (4,4,0) | (2,0,0) | (6,2,0) |
| 6 | 0.1 | 5 | (5,2,0) | (3,0,0) | (3,1,0) | (6,1,0) | (6,3,0) | (4,4,0) | (2,0,0) | (6,2,0) |
| 12 | 0.05 | 1 | (4,0,1) | (2,0,1) | (3,1,0) | (6,1,0) | (5,0,1) | (3,1,1) | (2,0,0) | (4,0,2) |
| 12 | 0.05 | 2 | (4,0,1) | (3,0,0) | (3,1,0) | (6,1,0) | (5,0,1) | (4,0,0) | (2,1,0) | (5,0,1) |
| 12 | 0.05 | 3 | (4,0,1) | (3,0,0) | (3,1,0) | (6,1,0) | (5,0,1) | (4,0,0) | (2,1,0) | (5,0,1) |
| 12 | 0.05 | 5 | (4,0,1) | (3,0,0) | (3,1,0) | (6,1,0) | (5,0,1) | (4,0,0) | (2,1,0) | (5,0,1) |
| 12 | 0.1 | 1 | (4,1,1) | (3,0,0) | (3,1,0) | (6,0,1) | (6,1,0) | (4,0,0) | (2,1,0) | (5,1,1) |
| 12 | 0.1 | 2 | (5,0,0) | (3,0,0) | (3,1,0) | (6,1,1) | (6,1,0) | (4,0,0) | (2,2,0) | (6,1,0) |
| 12 | 0.1 | 3 | (5,0,0) | (3,0,0) | (3,1,0) | (6,1,1) | (6,1,0) | (4,0,0) | (2,2,0) | (6,1,0) |
| 12 | 0.1 | 5 | (5,0,0) | (3,0,0) | (3,1,0) | (6,1,1) | (6,1,0) | (4,0,0) | (2,2,0) | (6,1,0) |

# Appendix for Detecting Regime Shifts in Credit Spreads

## For On-Line Publication

# Appendix A. The Red Noise Process

Red noise is usually modeled by an AR(1) process:

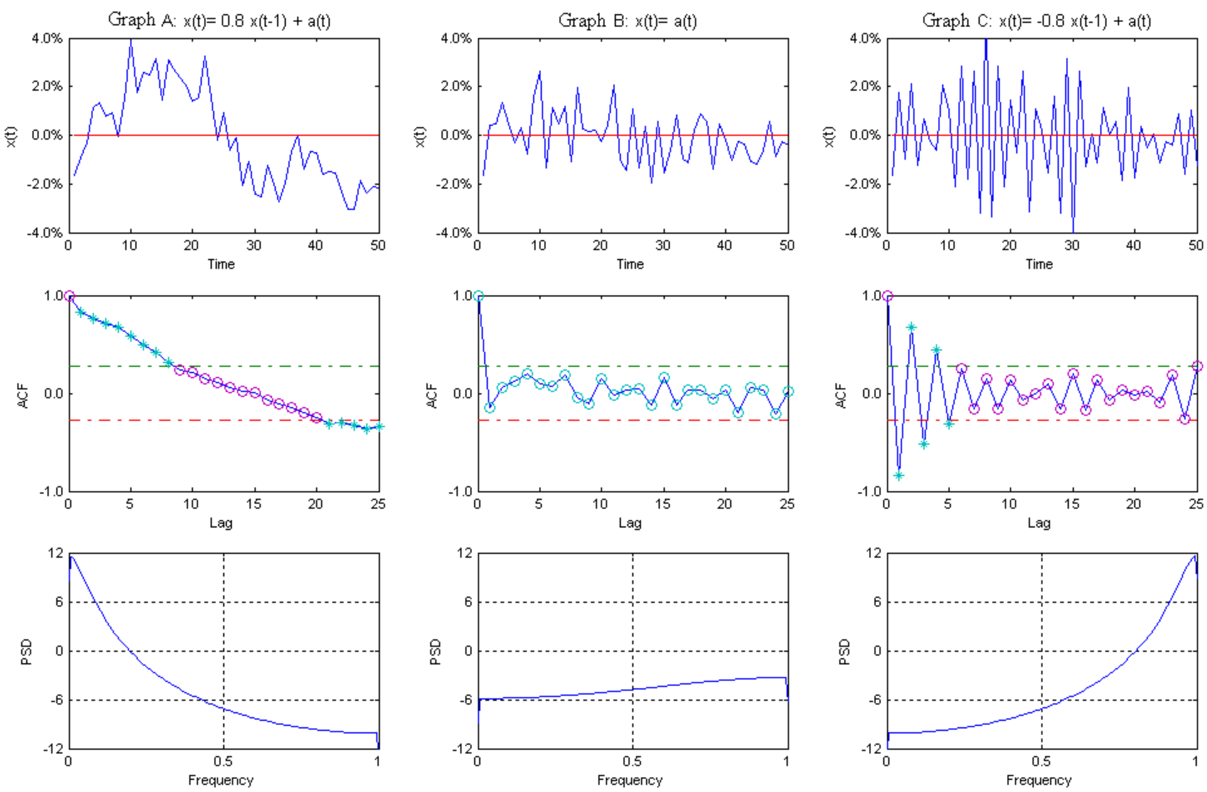
$$X_t = c + \rho X_{t-1} + a_t, \tag{A-1}$$

where $c = \mu(1- \rho)$, $\mu$ is the level about which the autoregressive variable $X_t$ fluctuates and $a_t$ is a normally distributed independent random variable with mean $0$ and variance $\sigma^2$. For the process to be stationary, the autoregressive coefficient must be inside the unit circle, i.e., $|\rho| < 1$. For $\rho > 0$, the process is red noise because its energy monotonically decreases as the frequency increases as opposed to the case of white noise for $\rho = 0$ with the same energy at all frequencies. If $\rho < 0$, the process is violet noise and its energy monotonically increases as the frequency increases. Figure A-1 plots examples of these three noise types (Graph A to Graph C). Graph A of Figure A-1 shows that positive autocorrelation of the red noise process creates long-lasting swings away from the unconditional mean, which could be misinterpreted as a regime effect. Autocorrelation functions (ACF) in the second row, for example, show that red noise is a sticky process and exhibits persistence for several lags. This pattern also appears in the power density function (PDF) in the third row. The PDF is decreasing for red noise, increasing for violet noise and almost flat for white noise (Box and Jenkins, (1970)).

Figure A-1: Representation of Noise Types

The first row plots the time series of three types of noise processes (Graph A to

Graph C). Red noise is in Graph A, white noise is in Graph B, and violet noise is in Graph C. The second row illustrates the autocorrelation function (ACF) for each of the noise processes. The third row illustrates the power spectral density of each of the processes for different normalized frequencies.




# Appendix B. Details on the MPK and IP4 Techniques

In the classical linear regression, it is well known that OLS yields unbiased estimates for $\rho$. However, in the case of autoregressive processes of the type given in Equation (A-1), the assumptions underlying the Gauss-Markov least squares theorem are violated. The lagged values of the dependent variable cannot be fixed in repeated sampling, nor can they be treated as distributed independently of the error term for all lags. Therefore, OLS estimators in the autoregressive case are biased.

Much research has been devoted to estimating the bias. Marriott and Pope (1954) and Kendall (1954) propose the MPK technique to correct for the first order term of the bias while Orcutt and Winokur (1969) and Stine and Shaman (1989) propose the IP4 technique with three additional bias corrections.

**B.1. The MPK Technique** Marriott and Pope (1954) and Kendall (1954) consider the situation where the true mean of the series, $\mu$ in Equation (1), is unknown and give the formula for the expected value of the OLS estimator of $\rho$:

$$E(\widehat{\rho}) = \rho - \frac{1+3\rho}{n-1} + O\left(\frac{1}{n^2}\right) \tag{B-1}$$

Because $\rho$ and $E(\widehat{\rho})$ are unknown, the procedure following Orcutt and Winokur (1969) is to substitute $\widehat{\rho}$, which is known, for $E(\widehat{\rho})$ and then solve Equation (B-1) for $\rho$. Solving for $\rho$ and denoting this corrected estimate of $\rho$ by $\widehat{\rho}^c$ yields:

$$\widehat{\rho}^c = \frac{(n-1)\widehat{\rho}+1}{(n-4)} \tag{B-2}$$

**B.2. The IP4 Technique** This technique is due to Orcutt and Winokur (1969) and Stine and Shaman (1989) and is based on the assumption that the first approximation of the bias is approximately inversely proportional to the subsample size $n$ and is always negative. The *first*-order bias-corrected estimate $\widehat{\rho}^{c,1}$ is then:

(B-3)
$$\widehat{\rho}^{c,1} = \widehat{\rho} + \frac{1}{n}$$

The procedure consists in substituting $\widehat{\rho}$ for $\rho$. The residual bias is also inversely proportional to $m$ and its magnitude is linear in $\rho$. Thus, additional corrections of a smaller magnitude give the $k^{th}$ order bias-corrected estimate $\widehat{\rho}^{c,k}$:

(B-4)
$$\widehat{\rho}^{c,k} = \widehat{\rho}^{c,k-1} + \left|\widehat{\rho}^{c,k-1}\right| \frac{1}{n}.$$

The IP4 technique uses three additional corrections. Both the IP4 and MPK methods are compared in a series of Monte Carlo experiments (Rodionov (2004)) and prove to be similar to each other for $n \geq 10$. However, for smaller $n$, the IP4 is shown to be less biased than the MPK and generates more stable estimates.

# Appendix C. Statistical Issues

## C.1 Stationarity

The prior literature commonly focuses on first differences rather than levels of credit spreads to circumvent claims of nonstationarity. Our regime detection technique requires a stable and well-defined mean and variance, yet stationarity issues are not a concern in our study. We test the null hypothesis for the presence of a unit root in the level of the unfiltered (raw data) and filtered credit spreads (data obtained after prewhitening). The test indicates that i) we cannot reject the null hypothesis that the unfiltered spreads have a unit root (except BBB in Panel A), and ii) the filtered spreads are stationary.

Table C-1: Augmented Dickey-Fuller (ADF) Test Statistic for Credit Spreads

The table reports values of the ADF test for unfiltered and filtered credit spread levels. Tests are specified with a constant since all series have a nonzero mean. The maximum lag considered is 12. Panel A to Panel C report results obtained using the data from Warga, NAIC and TRACE datasets, respectively. The null hypothesis states that credit spreads have a unit root. Corresponding critical values are reported separately in each Panel. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

| | ADF Test for Unfiltered Spreads | | ADF Test for Filtered Spreads | |
|---|---|---|---|---|
| | $t-$stat | $p-$value | $t-$stat | $p-$value |
| Panel A : Warga (April 1987 to December 1996) | | | | |
| AA | -2.473 | 0.125 | -6.797 | 0.000*** |
| A | -2.561 | 0.104 | -4.938 | 0.000*** |
| BBB | -2.587 | 0.099* | -6.225 | 0.000*** |
| Critical values: -3.50 (1%), -2.89 (5%), -2.58 (10%) | | | | |
| Panel B : NAIC (January 1994 to December 2004) | | | | |
| AA | -1.231 | 0.660 | -10.894 | 0.000*** |
| A | -1.226 | 0.662 | -9.550 | 0.000*** |
| BBB | -1.268 | 0.643 | -3.823 | 0.003*** |
| BB | -1.513 | 0.524 | -3.642 | 0.005*** |
| Critical values: -3.48 (1%), -2.88 (5%), -2.58 (10%) | | | | |
| Panel C : TRACE (October 2004 to December 2009) | | | | |
| AA | -1.258 | 0.644 | -3.928 | 0.003*** |
| A | -1.119 | 0.703 | -3.808 | 0.005*** |
| BBB | -1.069 | 0.723 | -6.001 | 0.000*** |
| BB | -1.662 | 0.445 | -6.742 | 0.000*** |
| Critical values: -3.54 (1%), -2.91 (5%), -2.59 (10%) | | | | |

## C.2 Analysis of the Residuals

Our test for shifts in the variance treats volatility as an independent and identically distributed process. Because many financial series show strong evidence of volatility clustering consistent with autocorrelation in the volatility process, it is straightforward to test for autocorrelation in the residuals. We use the Lagrange multiplier test to test the null hypothesis of no autoregressive conditional heteroskedasticity effects in the squared residuals and the portmanteau tests of Ljung and Box (1978) to test the null hypothesis of no autocorrelation in the residuals and squared residuals. The tests consistently indicate that i) squared residuals are homoskedastic and uncorrelated, and ii) residuals are uncorrelated. We rely on the highest confidence level for all cases except for two cases where we accept the null at the 1% confidence level.

Table C-2: Lagrange Multiplier and Portmanteau Tests for Residuals.

The table reports values of the Lagrange Multiplier ARCH test for squared residuals and the values of the Ljung-Box test for residuals and squared residuals of credit spreads. The null hypothesis in the ARCH test states that squared residuals have no ARCH effects (i.e., homoskedasticity). The null hypothesis in the Ljung-Box test states that no autocorrelation exists in the specified series of residuals. The maximum number of lags considered is 12. We only report the results for the first lag. Panel A to Panel C report the values of the tests obtained using the data from Warga, NAIC and TRACE datasets, respectively.

| | Tests with Squared Residuals | | | | Test with Residuals | |
|---|---|---|---|---|---|---|
| | | | Ljung-Box | | Ljung-Box | |
| | ARCH stat | $p-$value | $Q-$stat | $p-$value | $Q-$stat | $p-$value |
| Panel A : Warga (April 1987 to December 1996) | | | | | | |
| AA | 1.202 | 0.273 | 17.764 | 0.603 | 20.729 | 0.413 |
| A | 1.126 | 0.289 | 20.473 | 0.429 | 24.765 | 0.211 |
| BBB | 0.790 | 0.374 | 8.088 | 0.991 | 19.423 | 0.495 |
| Panel B : NAIC (January 1994 to December 2004) | | | | | | |
| AA | 0.028 | 0.867 | 8.682 | 0.986 | 11.291 | 0.938 |
| A | 0.309 | 0.578 | 29.475 | 0.079 | 19.711 | 0.476 |
| BBB | 23.667 | 0.011 | 36.142 | 0.015 | 28.913 | 0.089 |
| BB | 0.007 | 0.934 | 5.792 | 0.999 | 14.782 | 0.789 |
| Panel C : TRACE (October 2004 to December 2009) | | | | | | |
| AA | 0.000 | 0.991 | 8.196 | 0.990 | 15.642 | 0.739 |
| A | 0.838 | 0.360 | 12.496 | 0.898 | 21.783 | 0.352 |
| BBB | 0.000 | 0.998 | 14.990 | 0.777 | 19.174 | 0.511 |
| BB | 0.379 | 0.538 | 11.745 | 0.860 | 14.758 | 0.679 |

## C-3 Normality Issues

The critical values derived in Rodionov (2004) are based on an implied assumption of normality in each of the two populations to be compared. This translates, in our case, to the requirement that the filtered data in each regime be approximately normally distributed. In general, we find that the normality assumption is satisfied by our data. However, even slight deviations from normality do not represent a serious concern, since the $t$-test for the equality of the means across two regimes is fairly robust with respect to the normality assumption. This means that the power function is little modified by departure from normality, especially when the two samples have equal sizes, which is our case here (Gronow (1953)).

## C-4 Handling Outliers

Our tests are also sensitive to outliers. In particular, a large outlier can inflate the sample variance, thus decreasing the power of the test. Ideally, the weight for the data value should be chosen such that it is small if that value is considered an outlier. To reduce the effect of outliers, we use the Huber's weight function, which is calculated as:

(C-1) $$weight = \min\left(1, h/\left[\Delta/\sigma\right]\right)$$

where $h$ is the Huber parameter and $[\Delta/\sigma]$ is the deviation from the expected mean value of the new regime normalized by the standard deviation averaged for all consecutive sections of the cut-off length in the series. The weights are equal to one if $[\Delta/\sigma]$ is less than or equal to the value of $h$. Otherwise, the weights are inversely proportional to the distance from the expected mean value of the new regime. Once the timing of the regime shifts is fixed, the mean values of the regimes are assessed using the following iterative procedure. First, the arithmetic mean is calculated as the initial estimate of the mean value of the regime. Then, a weighted mean is calculated with the weights determined by the distance from that first estimate. The procedure is repeated one more time with the new estimate of the regime mean. Because we expect that most shifts occur around recessions, the choice of the Huber parameter may be critical because most significant peaks in credit spreads around this period could be considered outliers. Thus, we repeat the procedure with different values of $h$ ranging from $1$ to $5$. Our choice of a Huber parameter of $h = 2$ is such that the number of detected shifts remains stable for higher values of $h$ (see robustness analysis).

# Appendix D. Estimation of Credit Spread Curves

To obtain credit spread curves for different ratings and maturities, we use the extended Nelson-Siegel-Svensson specification (Svensson (1995)):

$$R(t,T) = \beta_{0t} + \beta_{1t}\lambda_1 + \beta_{2t}\left(\lambda_1 - \exp(-\frac{T}{\tau_{1t}})\right) + \beta_{3t}\left(\lambda_2 - \exp(-\frac{T}{\tau_{2t}})\right) + \varepsilon_{t,j}, \tag{D-1}$$

with $\lambda_i \equiv \frac{1-\exp(-\frac{T}{\tau_{it}})}{\frac{T}{\tau_{it}}}$, $i = 1,2$, and $\varepsilon_{t,j} \sim N(0,\sigma^2)$. $R(t,T)$ is the continuously compounded yield at time $t$ with time to maturity $T$. $\beta_{0t}$ is the limit of $R(t,T)$ as $T$ goes to infinity and is regarded as the long-term yield. $\beta_{1t}$ is the limit of the spread $R(t,T)-\beta_{0t}$ as $T$ goes to infinity and is regarded as the long- to short-term spread. $\beta_{2t}$ and $\beta_{3t}$ give the curvature of the term structure. $\tau_{1t}$ and $\tau_{2t}$ measure the yield at which the short-term and medium-term components decay to zero. Each month $t$ we estimate the parameters vector $\Omega_t = (\beta_{0t},\beta_{1t},\beta_{2t},\beta_{3t},\tau_{1t},\tau_{2t})'$ by minimizing the sum of squared bond price errors over these parameters. We weigh each pricing error by the inverse of the bond's duration because long-maturity bond prices are more sensitive to interest rates:

$$\widehat{\Omega}_t = \arg\min_{\Omega_t} \sum_{i=1}^{N_t} w_i^2 \left(P_{it}^{NS} - P_{it}\right)^2, \qquad w_i = \frac{1/D_i}{\sum_{i=1}^{N} 1/D_i}, \tag{D-2}$$

where $P_{it}$ is the observed price of the bond $i$ at month $t$, $P_{it}^{NS}$ the estimated price of the bond $i$ at month $t$, $N_t$ is the number of bonds traded at month $t$, $N$ is the total number of bonds in the sample, $w_i$ the bond's $i$ weight, and $D_i$ the modified Macaulay duration. The specification of the weights is important because it consists in overweighting or underweighting some bonds in the minimization program to account for the heteroskedasticity of the residuals. A small change in the short-term rate does not really affect the prices of the bond. The variance of the residuals should be small for a short maturity. Conversely, a small change in the long-term zero coupon rate will have a larger impact on prices, suggesting a higher volatility of the residuals.

# Appendix E. Summary Statistics

Table E-1: Summary Statistics on Credit Spreads

This table reports summary statistics on 10-year credit spreads for straight fixed-coupon corporate bonds in the industrial sector. A summary of different rating classes is reported when the data are available. Panel A reports Warga quoted data from January 1987 to December 1996, Panel B reports NAIC transaction data from January 1994 to December 2004, and Panel C reports TRACE high-frequency transaction data from October 2004 to December 2009. The benchmark for risk-free rates is the swap curve fitted to all maturities using the Nelson–Siegel–Svensson algorithm. The spreads are given as annualized yields in percentages.

| | All | AA | A | BBB | BB |
|---|---|---|---|---|---|
| Panel A : Warga Quoted Data from April 1987 to December 1996 | | | | | |
| Mean | 0.902 | 0.632 | 0.835 | 1.241 | - |
| Median | 0.865 | 0.638 | 0.839 | 1.229 | - |
| St. Dev. | 0.386 | 0.229 | 0.260 | 0.366 | - |
| 5% Quantile | 0.358 | 0.216 | 0.400 | 0.632 | - |
| 95% Quantile | 1.587 | 0.987 | 1.241 | 1.846 | - |
| Panel B : NAIC Transaction Data from January 1994 to December 2004 | | | | | |
| Mean | 2.603 | 1.852 | 2.120 | 2.676 | 3.766 |
| Median | 2.149 | 1.188 | 1.462 | 1.900 | 2.941 |
| St. Dev. | 1.716 | 1.369 | 1.342 | 1.506 | 1.932 |
| 5% Quantile | 0.580 | 0.309 | 0.634 | 1.059 | 1.608 |
| 95% Quantile | 6.083 | 4.091 | 4.378 | 5.258 | 7.598 |
| Panel C : TRACE Transaction Data from October 2004 to December 2009 | | | | | |
| Mean | 2.057 | 0.920 | 1.241 | 2.244 | 3.825 |
| Median | 1.419 | 0.494 | 0.658 | 1.427 | 3.240 |
| St. Dev. | 1.873 | 0.776 | 0.973 | 1.551 | 2.248 |
| 5% Quantile | 0.345 | 0.300 | 0.483 | 0.958 | 1.678 |
| 95% Quantile | 5.875 | 2.644 | 3.472 | 5.566 | 9.433 |

# Appendix F. Further Details on the Detected Regimes

## F.1 Changing Points in Level Regimes

Table F-1 and Table F-2 summarize the results from our regime detection procedure for 10-year maturity credit spreads. Specifically, we list the breakpoint number, the mean and duration of the prior regime, the breakpoint date, the mean and duration of the new regime and the sign of the detected shift. All reported shifts are statistically significant at the $95\%$ confidence level ($\alpha = 5\%$). These results are obtained with an initial cut-off length $m$ set to its minimum of six months ($m = 6$) and a Huber parameter of $2$ ($h = 2$).

Table F-1: Summary Statistics for Changing Points in Level Regimes.

We report the results of the regime shift detection technique applied to the level of credit spreads with 10 remaining years to maturity. Panel A to Panel C refer to the data from Warga, NAIC and TRACE datasets, respectively. The initial cut-off length is 6 months, the Huber parameter is 2, and all detected regimes are statistically significant at the 95% confidence level or higher. The sign of the Regime Shift Index (RSI sign) provides the direction of detected shifts. Regime means are expressed in percentages and regime lengths in months.

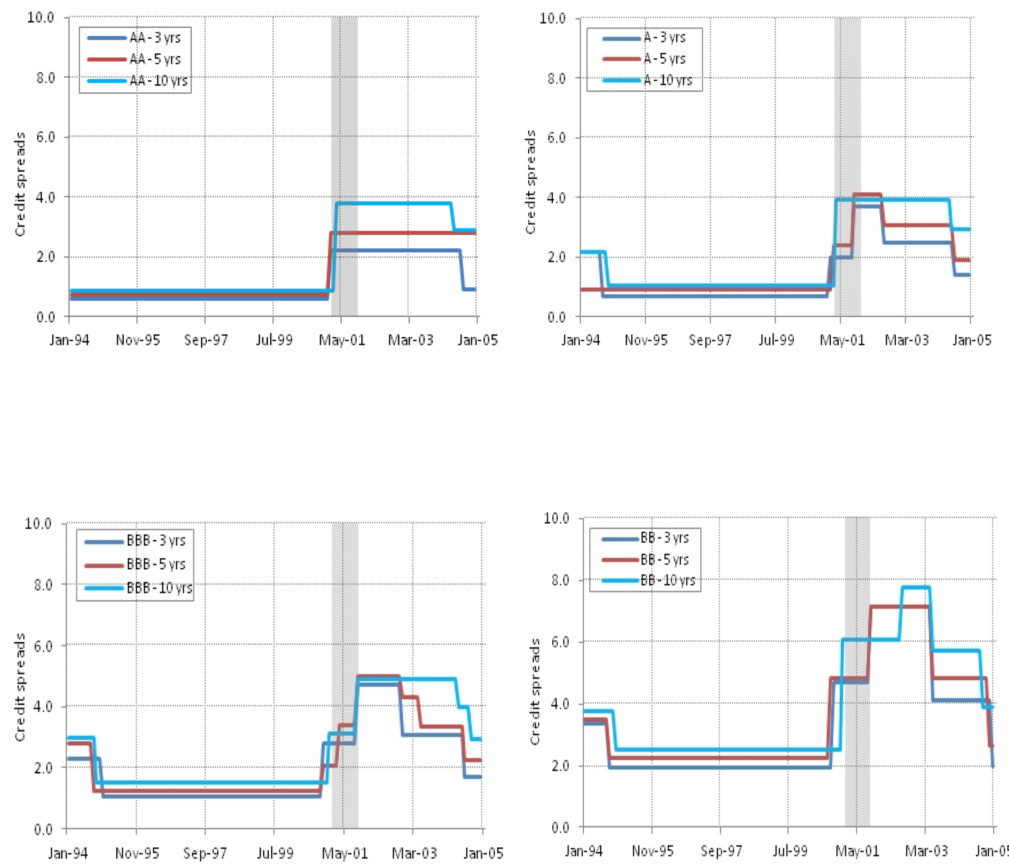
| | Shift No. | Mean of Current Regime | Length of Current Regime | Date of Shift Point | Mean of New Regime | Length of New Regime | RSI Sign |
|---|---|---|---|---|---|---|---|
| Panel A : Warga Quoted Data from April 1987 to December 1996 | | | | | | | |
| AA | 1 | 0.201 | 36 | Apr-90 | 0.395 | 11 | + |
| | 2 | 0.395 | 11 | Feb-91 | 0.542 | 40 | + |
| | 3 | 0.542 | 40 | Jul-94 | 0.333 | 30 | - |
| A | 1 | 0.222 | 34 | Feb-90 | 0.422 | 12 | + |
| | 2 | 0.422 | 12 | Feb-91 | 0.807 | 41 | + |
| | 3 | 0.807 | 41 | Jul-94 | 0.511 | 30 | - |
| BBB | 1 | 0.528 | 32 | Dec-89 | 1.045 | 11 | + |
| | 2 | 1.045 | 11 | Nov-90 | 1.683 | 7 | + |
| | 3 | 1.683 | 8 | Jun-91 | 1.235 | 37 | - |
| | 4 | 1.235 | 37 | Jul-94 | 0.847 | 30 | - |
| Panel B : NAIC Transaction Data from January 1994 to December 2004 | | | | | | | |
| AA | 1 | 0.874 | 86 | Mar-01 | 3.795 | 38 | + |
| | 2 | 3.795 | 38 | May-04 | 2.867 | 8 | - |
| A | 1 | 2.162 | 10 | Oct-94 | 1.058 | 76 | - |
| | 2 | 1.058 | 76 | Mar-01 | 3.935 | 39 | + |
| | 3 | 3.935 | 39 | Jun-04 | 2.935 | 7 | - |
| BBB | 1 | 2.993 | 9 | Oct-94 | 1.513 | 74 | - |
| | 2 | 1.513 | 74 | Dec-00 | 3.119 | 9 | + |
| | 3 | 3.119 | 9 | Sep-01 | 4.905 | 32 | + |
| | 4 | 4.905 | 32 | May-04 | 3.989 | 4 | - |
| | 5 | 3.989 | 4 | Sep-04 | 2.943 | 4 | - |
| BB | 1 | 3.747 | 10 | Nov-94 | 2.491 | 73 | - |
| | 2 | 2.491 | 73 | Dec-00 | 6.065 | 9 | + |
| | 3 | 6.065 | 9 | Sep-01 | 7.140 | 20 | + |
| | 4 | 7.140 | 20 | May-03 | 5.738 | 16 | - |
| | 5 | 5.738 | 16 | Sep-04 | 3.875 | 4 | - |

Table F-1 (Continued).

| | Shift No. | Mean of Current Regime | Length of Current Regime | Date of Shift Point | Mean of New Regime | Length of New Regime | RSI Sign |
|---|---|---|---|---|---|---|---|
| Panel C : TRACE Transaction Data from October 2004 to December 2009 | | | | | | | |
| AA | 1 | 0.676 | 38 | Dec-07 | 1.575 | 12 | + |
| | 2 | 1.575 | 12 | Dec-08 | 2.063 | 7 | + |
| | 3 | 2.063 | 7 | Jul-09 | 1.504 | 6 | - |
| A | 1 | 0.976 | 39 | Jan-08 | 2.187 | 8 | + |
| | 2 | 2.187 | 8 | Sep-08 | 4.009 | 9 | + |
| | 3 | 4.009 | 9 | Jun-09 | 2.010 | 7 | - |
| BBB | 1 | 1.479 | 38 | Dec-07 | 3.120 | 10 | + |
| | 2 | 3.120 | 10 | Oct-08 | 5.235 | 8 | + |
| | 3 | 5.235 | 8 | Jun-09 | 3.477 | 7 | - |
| BB | 1 | 2.562 | 35 | Sep-07 | 4.674 | 13 | + |
| | 2 | 4.674 | 13 | Oct-08 | 8.652 | 8 | + |
| | 3 | 8.652 | 8 | Jun-09 | 5.741 | 6 | - |
| | 4 | 5.741 | 6 | Dec-09 | 2.857 | 1 | - |

Figure F-1: Maturity Effects on Credit Spread Regimes.

We plot mean regimes of credit spreads with remaining maturities of 3, 5, and 10 years. The data are from NAIC dataset and cover the period from January 1994 to December 2004. The X-axis expresses the time in months and the Y-axis expresses the mean of the regime in percentages. The shaded region represents the 2001 NBER recession. The initial cut-off length is 6 months and the Huber parameter is 2. All detected shifts are statistically significant at the 95% confidence level or higher.



## F.2 Changing Points in Volatility Regimes

Table F-2: Summary Statistics for Changing Points in Volatility Regimes.

We report the results of the regime shift detection technique applied to credit spread residuals with 10 years remaining to maturity. Panel A to Panel C refer to the data from Warga, NAIC and TRACE datasets, respectively. The initial cut-off length is 6 months, the Huber parameter is 2, and all detected regimes are statistically significant at the 95% confidence level or higher. The sign of the Residual Sum of Squares Index (RSSI sign) provides the direction of detected shifts. Regime variances are expressed in percentages and regime lengths in months.

| | Shift No. | Variance of Current Regime | Length of Current Regime | Date of Shift Point | Variance of New Regime | Length of New Regime | RSSI Sign |
|---|---|---|---|---|---|---|---|
| Panel A : Warga Quoted Data from April 1987 to December 1996 | | | | | | | |
| AA | 1 | 0.019 | 113 | Sep-96 | 0.006 | 4 | - |
| A | 1 | 0.020 | 116 | Dec-96 | 0.009 | 1 | - |
| BBB | 1 | 0.053 | 13 | May-88 | 0.028 | 33 | - |
| | 2 | 0.028 | 33 | Feb-91 | 0.215 | 8 | + |
| | 3 | 0.215 | 8 | Aug-91 | 0.023 | 63 | - |
| Panel B : NAIC Transaction Data from January 1994 to December 2004 | | | | | | | |
| AA | 1 | 0.042 | 14 | Mar-95 | 0.022 | 36 | - |
| | 2 | 0.022 | 36 | Mar-98 | 0.077 | 11 | + |
| | 3 | 0.077 | 11 | Feb-99 | 0.034 | 24 | - |
| | 4 | 0.034 | 24 | Feb-01 | 0.108 | 7 | + |
| | 5 | 0.108 | 7 | Sep-01 | 0.049 | 24 | - |
| | 6 | 0.049 | 24 | Sep-03 | 0.021 | 16 | - |
| A | 1 | 0.038 | 29 | Jun-96 | 0.024 | 20 | - |
| | 2 | 0.024 | 20 | Feb-98 | 0.073 | 12 | + |
| | 3 | 0.073 | 12 | Feb-99 | 0.041 | 23 | - |
| | 4 | 0.041 | 23 | Jan-01 | 0.114 | 8 | + |
| | 5 | 0.114 | 8 | Sep-01 | 0.069 | 13 | - |
| | 6 | 0.069 | 13 | Oct-02 | 0.029 | 27 | - |
| BBB | 1 | 0.051 | 28 | May-96 | 0.039 | 11 | - |
| | 2 | 0.039 | 11 | Apr-97 | 0.113 | 22 | + |
| | 3 | 0.113 | 22 | Feb-99 | 0.053 | 22 | - |
| | 4 | 0.053 | 22 | Dec-00 | 0.145 | 11 | + |
| | 5 | 0.145 | 11 | Nov-01 | 0.073 | 18 | - |
| | 6 | 0.073 | 18 | May-03 | 0.048 | 20 | - |

Table F-2 (Continued).

| | Shift No. | Variance of Current Regime | Length of Current Regime | Date of Shift Point | Variance of New Regime | Length of New Regime | RSSI Sign |
|---|---|---|---|---|---|---|---|
| BB | 1 | 0.151 | 9 | Oct-94 | 0.092 | 27 | - |
| | 2 | 0.092 | 27 | Jan-97 | 0.176 | 26 | + |
| | 3 | 0.176 | 27 | Mar-99 | 0.093 | 20 | - |
| | 4 | 0.093 | 20 | Nov-00 | 0.271 | 14 | + |
| | 5 | 0.271 | 14 | Jan-02 | 0.116 | 16 | - |
| | 6 | 0.116 | 16 | May-03 | 0.176 | 12 | + |
| | 7 | 0.176 | 12 | May-04 | 0.101 | 8 | - |
| Panel C : TRACE Transaction Data from October 2004 to December 2009 | | | | | | | |
| AA | 1 | 0.017 | 34 | Aug-07 | 0.056 | 17 | + |
| | 2 | 0.056 | 17 | Jan-09 | 0.022 | 12 | - |
| A | 1 | 0.021 | 37 | Nov-07 | 0.124 | 13 | + |
| | 2 | 0.124 | 13 | Dec-08 | 0.040 | 13 | - |
| BBB | 1 | 0.042 | 35 | Sep-07 | 0.189 | 16 | + |
| | 2 | 0.189 | 16 | Jan-09 | 0.039 | 12 | - |
| BB | 1 | 0.112 | 23 | Sep-06 | 0.172 | 13 | + |
| | 2 | 0.172 | 13 | Oct-07 | 0.342 | 15 | + |
| | 3 | 0.342 | 15 | Jan-09 | 0.103 | 12 | - |

# Appendix G. Causality Tests

We use the Granger causality test to investigate the causal pairwise relationship between credit spreads, Fed funds rates, and survey data. As this test is critically dependent on the lag length specification of the VAR, we first identify the appropriate lag length for each pairwise relation based on Bayesian Information Criteria (BIC).[16]

Table G-1: Pair-wise VAR Lag Length Selection.

[16]We also apply the Akaike Final Prediction Error criteria (FPE) and sometimes identify longer lags. However, when we use the identified lag structure based on BIC or on FPE, we obtain similar results. Thus, we only report the BIC lag structure.

We use the Bayesian Information Criteria (BIC) to identify the appropriate lag structure for the pairwise VAR relationship between credit spreads, Fed funds rates, and survey data. The lag length remains the same for a different variable ordering. Credit spreads are from Warga, NAIC and TRACE datasets, respectively.

| | Warga | NAIC | TRACE |
|---|---|---|---|
| AA - Fed funds rate | 3 | 2 | 2 |
| A - Fed funds rate | 2 | 2 | 3 |
| BBB - Fed funds rate | 2 | 2 | 2 |
| BB - Fed funds rate | - | 1 | 1 |
| AA - Survey | 1 | 2 | 1 |
| A - Survey | 1 | 1 | 1 |
| BBB - Survey | 1 | 1 | 1 |
| BB - Survey | - | 1 | 1 |

Using the lag structure reported in Table G-1, we perform pairwise causality tests (Table G-2). The results show that at the specified number of lags, there is some evidence of feedback effects between the Fed funds rate and credit spreads. However, the causal relation from the Fed funds rate to credit spreads is stronger for AA, A, and BBB spreads while the causal relation from credit spreads to the Fed funds rate is stronger for BB spreads. For instance, at the 1% confidence level, Fed funds rate always Granger-cause AA, A, and BBB spreads. In three cases out of nine, AA, A, and BBB also Granger-cause the Fed funds rate. For BB spreads, the causal relation is always unidirectional from BB spreads to the Fed funds rate.

In the case of the survey, the causal relation appears to be almost always in one direction from the survey to credit spreads, under the 1% confidence level (except for AA spreads in the NAIC dataset).

Table G-2: Pair-wise Granger Causality Tests.

We test the null hypothesis for the absence of pairwise Granger causality between i) Fed funds rates and credit spreads, and ii) survey and credit spreads. The lags used in the VAR are identified based on Bayesian Information Criteria. * indicates rejection of the null at the 1% confidence level. Credit spreads with 10 remaining years to maturity are from Warga, NAIC and TRACE datasets, respectively.

| | Warga | NAIC | TRACE |
|---|---|---|---|
| Null Hypothesis: | $F$-stat ($p$-value) | $F$-stat ($p$-value) | $F$-stat ($p$-value) |
| FFO does not Granger-cause AA | 8.211 (0.00)* | 17.629 (0.00)* | 12.903 (0.00)* |
| AA does not Granger-cause FFO | 3.701 (0.01) | 7.747 (0.00)* | 1.903 (0.16) |
| FFO does not Granger-cause A | 5.287 (0.01)* | 11.205 (0.00)* | 12.673 (0.00)* |
| A does not Granger-cause FFO | 1.969 (0.14) | 8.575 (0.00)* | 1.977 (0.09) |
| FFO does not Granger-cause BBB | 19.928 (0.00)* | 13.006 (0.00)* | 13.441 (0.00)* |
| BBB does not Granger-cause FFO | 2.169 (0.14) | 10.326 (0.00)* | 0.282 (0.75) |
| FFO does not Granger-cause BB | | 0.242 (0.62) | 0.926 (0.52) |
| BB does not Granger-cause FFO | | 27.141 (0.00)* | 4.170 (0.00)* |
| Survey does not Granger-cause AA | 22.636 (0.00)* | 11.182 (0.00)* | 24.730 (0.00)* |
| AA does not Granger-cause Survey | 0.149 (0.70) | 5.953 (0.00)* | 6.599 (0.01) |
| Survey does not Granger-cause A | 8.994 (0.00)* | 28.435 (0.00)* | 14.663 (0.00)* |
| A does not Granger-cause Survey | 0.036 (0.00) | 4.257 (0.04) | 0.311 (0.58) |
| Survey does not Granger-cause BBB | 14.134 (0.00)* | 16.797 (0.00)* | 9.255 (0.00)* |
| BBB does not Granger-cause Survey | 0.165 (0.68) | 3.817 (0.05) | 0.222 (0.64) |
| Survey does not Granger-cause BB | | 8.746 (0.00)* | 12.588 (0.00)* |
| BB does not Granger-cause Survey | | 2.412 (0.12) | 0.347 (0.56) |

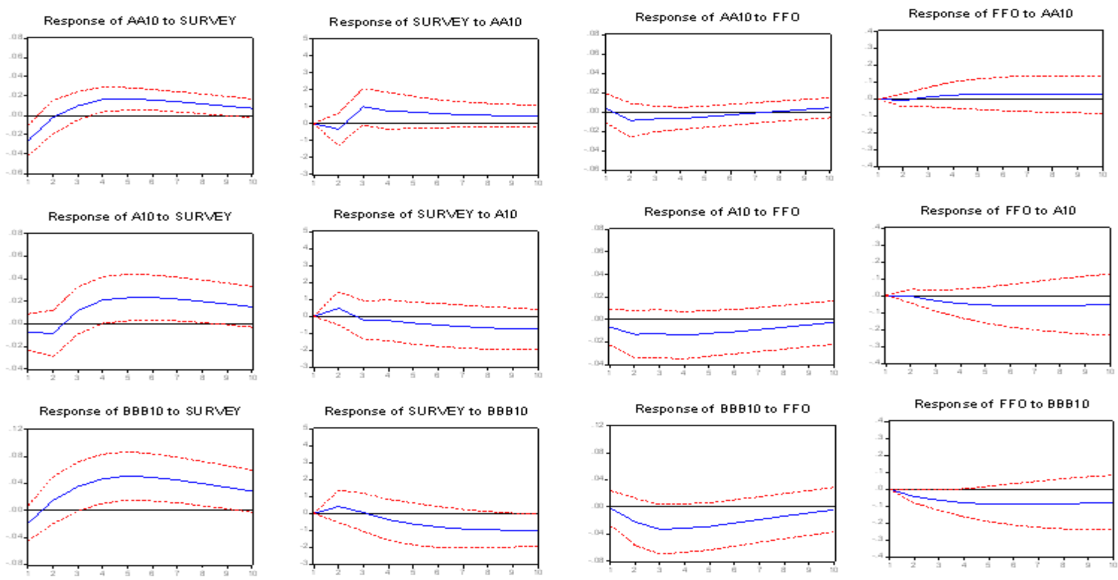
# Appendix H. Impulse-Response Functions

The impulse responses indicate that an increase by one standard deviation in the survey instantaneously increases the level factor of credit spreads of all ratings whereas a decrease by one standard deviation of the Fed funds rate instantaneously decreases the level factor of credit spreads. These effects last for several months before fading. On the other hand, a one standard deviation increase in the level factor of credit spreads does not have an immediate effect on the survey and the Fed funds rate. During subsequent months, the effect on the survey is weak and lasts only for one to two months. In the case of the Fed funds rate, the effect lasts for more months for some ratings.

Figure H-1: Impulse Responses.

The plots show the impulse-response paths for i) the survey to 1% innovation in the level factor of credit spreads (column 1), ii) the level factor of credit spreads to 1% innovation in the survey (column 2), iii) the Fed funds rate to 1% innovation in the level factor of credit spreads (column 3), and iv) the level factor of credit spreads to 1% innovation in the Fed funds rate (column 4). Impulse-response functions are based on estimating VARs with Cholesky decomposition. The ordering of the variables (Survey, Fed funds rate, credit spreads) is based on results of the Granger causality and is robust to changes in the ordering. The critical number of lags in the VAR is based on the Likelihood Ratio test statistic and in most cases is confirmed by the information criteria. Graph A to Graph C refer to Warga, NAIC and TRACE datasets, respectively.

Graph A : Warga Dataset from April 1987 to December 1996




Graph B : NAIC Dataset from January 1994 to December 2004

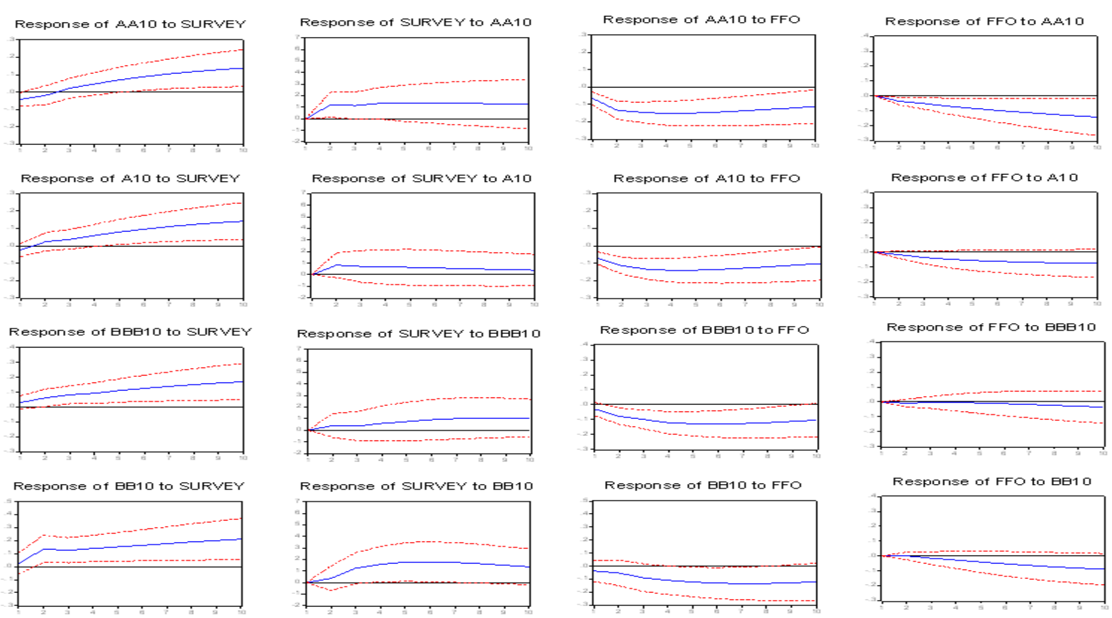
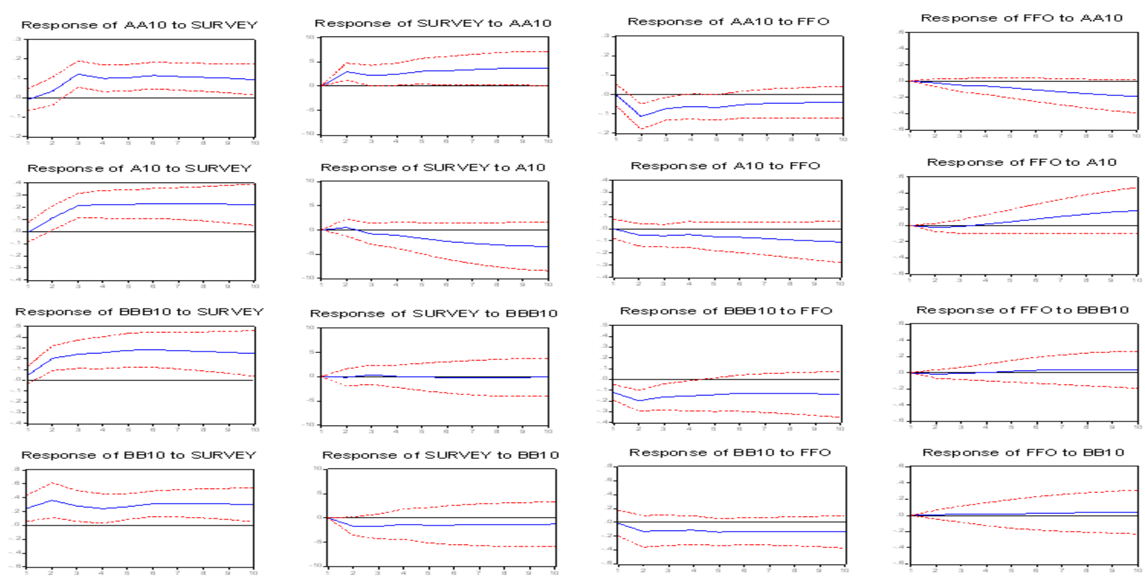



Figure H-1 (Continued)

Graph C : TRACE Dataset from October 2004 to December 2009




# Appendix I. Summary Statistics for Changing Points in SLO Survey and Fed Funds Rate Regimes

Table I-1 : Changing Points in SLO Survey and Fed Funds Rate Regimes.

We report results of the regime shift detection technique applied to the time series of the Senior Officer Opinion Survey (SLO survey) data and the Fed funds rate. Panel A to Panel C report shifts detected over time horizons of Warga, NAIC and TRACE datasets, respectively. The initial cut-off length is 6 months, the Huber parameter is 2, and all detected regimes are statistically significant at least at the 95% confidence level. The sign of the Regime Shift Index (RSI sign) provides the direction of detected shifts. Regime means are expressed in percentages and regime lengths in months. In Panel A, SLO Survey data are only available from April 1990.

| | Shift No. | Mean of Current Regime | Length of Current Regime | Date of Shift Point | Mean of New Regime | Length of New Regime | RSI Sign |
|---|---|---|---|---|---|---|---|
| Panel A : Data from April 1987 to December 1996 | | | | | | | |
| SLO survey | 1 | 45.325 | 12 | Apr-91 | 4.500 | 27 | - |
| | 2 | 4.500 | 27 | Jul-93 | -6.900 | 42 | - |
| Fed funds rate | 1 | 6.902 | 13 | May-88 | 8.646 | 28 | + |
| | 2 | 8.646 | 28 | Sep-90 | 6.029 | 11 | - |
| | 3 | 6.029 | 11 | Aug-91 | 3.439 | 33 | - |
| | 4 | 3.439 | 33 | May-94 | 5.483 | 32 | + |
| Panel B : Data from January 1994 to December 2004 | | | | | | | |
| SLO survey | 1 | -6.900 | 57 | Oct-98 | 14.914 | 21 | + |
| | 2 | 14.914 | 21 | Jul-00 | 46.428 | 21 | + |
| | 3 | 46.428 | 21 | Apr-02 | 14.400 | 21 | - |
| | 4 | 14.400 | 21 | Jan-04 | -13.642 | 12 | - |
| Fed funds rate | 1 | 3.439 | 4 | May-94 | 5.483 | 81 | + |
| | 2 | 5.483 | 81 | Feb-01 | 2.349 | 18 | - |
| | 3 | 2.349 | 18 | Aug-02 | 1.242 | 26 | - |
| | 4 | 1.242 | 26 | Oct-04 | 3.213 | 3 | + |
| Panel C : Data from October 2004 to December 2009 | | | | | | | |
| SLO survey | 1 | -13.642 | 33 | Jul-07 | 19.633 | 9 | + |
| | 2 | 19.633 | 9 | Apr-08 | 65.200 | 12 | + |
| | 3 | 65.200 | 12 | Apr-09 | 28.366 | 9 | - |
| Fed funds rate | 1 | 3.213 | 12 | Oct-05 | 4.991 | 24 | + |
| | 2 | 4.991 | 24 | Oct-07 | 2.256 | 10 | - |
| | 3 | 2.256 | 10 | Aug-08 | 0.175 | 17 | - |

# Appendix J. The Link Between the Volatility Factor and Uncertainty

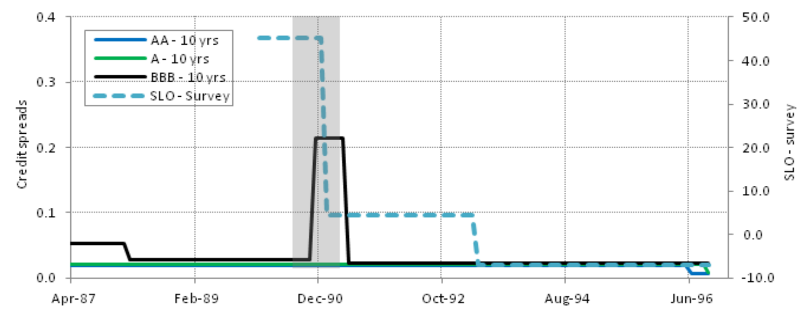
Table J-1 : Regression of the Volatility Factor on Goyal and Welch (2008) Economic Variables.

We regress the volatility factor on a set of economic fundamentals from Goyal and Welch (2008). The variable selection is dictated by the Variance Inflation Factor ($VIF < 10$) and the availability of the data. The sample period ranges from April 1987 to December 2008. The Warga dataset ranges from April 1987 to December 1996. The NAIC dataset ranges from January 1994 to December 2004. The TRACE dataset ranges from October 2004 to December 2008. The $p-$values are in parenthesis.

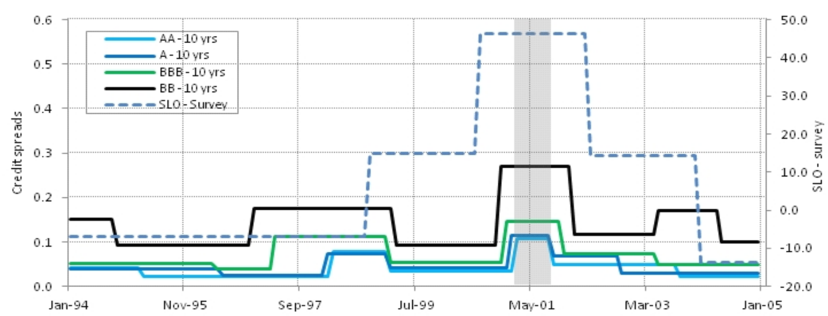
Figure 4: Regimes of Credit Spread Volatilities and Credit Conditions.

We plot detected variance regimes of 10-year credit spreads residuals (left-hand side axis), and mean regimes of the SLO Survey (right-hand side axis). Time is in months, credit spreads, and the SLO Survey data are in percentages. The shaded regions represent NBER recessions. The initial cut-off length is six months and the Huber parameter is two. All detected regimes are statistically significant at the 95% confidence level or higher.

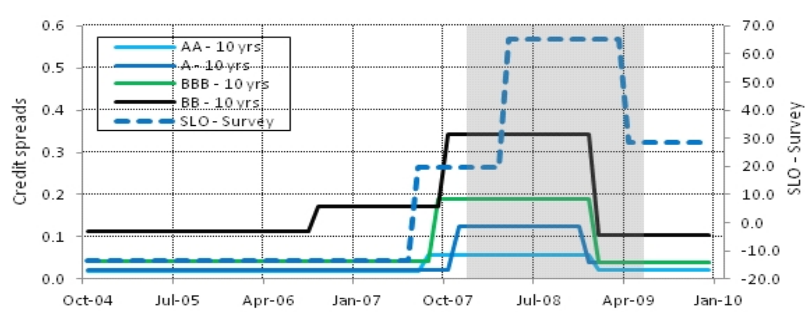
Graph A : Warga Dataset from April 1987 to December 1996




Graph B : NAIC Dataset from January 1994 to December 2004




Graph C : TRACE Dataset from October 2004 to December 2009



| | Warga | | | NAIC | | | | TRACE | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Variable | AA | A | BBB | AA | A | BBB | BB | AA | A | BBB | BB |
| Dividend price ratio | 0.18 | 0.19 | -0.05 | -0.17 | -0.05 | -0.64 | 1.55 | | | | |
| | (0.39) | (0.33) | (0.85) | (0.64) | (0.90) | (0.09) | (0.00) | | | | |
| Dividend payout ratio | -0.01 | -0.01 | 0.09 | 1.39 | 1.63 | 1.01 | -3.53 | 0.20 | 0.24 | 0.81 | -0.34 |
| | (0.93) | (0.91) | (0.79) | (0.05) | (0.03) | (0.19) | (0.00) | (0.22) | (0.11) | (0.00) | (0.55) |
| Book to market | 0.75 | 0.99 | 0.85 | 4.89 | 3.54 | 7.72 | 1.05 | 0.09 | -1.14 | -1.16 | -2.59 |
| | (0.10) | (0.02) | (0.18) | (0.00) | (0.03) | (0.00) | (0.63) | (0.92) | (0.19) | (0.30) | (0.43) |
| Treasury-bill rate | 3.32 | 3.30 | -0.77 | 4.36 | 5.59 | -20.19 | -55.12 | -1.82 | 5.64 | 7.78 | -2.43 |
| | (0.23) | (0.20) | (0.84) | (0.68) | (0.62) | (0.08) | (0.00) | (0.52) | (0.03) | (0.02) | (0.80) |
| Long-term yield | -9.26 | -7.64 | -2.53 | -26.37 | -22.26 | -20.76 | -21.52 | 4.43 | -23.80 | -18.83 | -42.76 |
| | (0.00) | (0.00) | (0.52) | (0.01) | (0.03) | (0.04) | (0.13) | (0.67) | (0.02) | (0.13) | (0.25) |
| Net equity expansion | -0.77 | 0.79 | -3.86 | 25.51 | 23.02 | 23.89 | 21.55 | -2.02 | 2.56 | 4.04 | 4.56 |
| | (0.69) | (0.66) | (0.16) | (0.00) | (0.00) | (0.00) | (0.00) | (0.26) | (0.12) | (0.06) | (0.46) |
| Inflation | -10.09 | -4.75 | -20.08 | -31.96 | 1.63 | 2.91 | 51.02 | -16.49 | 2.67 | 3.75 | -0.18 |
| | (0.11) | (0.41) | (0.02) | (0.08) | (0.93) | (0.88) | (0.06) | (0.00) | (0.57) | (0.54) | (0.99) |
| Long-term return | -3.36 | -4.25 | -4.72 | -2.64 | -3.01 | -1.77 | -3.15 | -1.89 | -2.61 | 0.66 | 2.81 |
| | (0.00) | (0.00) | (0.00) | (0.09) | (0.07) | (0.29) | (0.17) | (0.05) | (0.00) | (0.56) | (0.40) |
| Stock variance | 1.72 | 3.23 | -2.16 | -32.28 | -25.17 | 2.61 | 38.25 | -11.73 | 20.20 | 12.85 | 47.09 |
| | (0.34) | (0.05) | (0.39) | (0.07) | (0.19) | (0.89) | (0.15) | (0.00) | (0.00) | (0.01) | (0.00) |
| Cross sectional premium | 50.31 | 70.06 | 62.72 | 339.47 | 300.26 | 464.21 | 228.91 | | | | |
| | (0.09) | (0.01) | (0.12) | (0.00) | (0.00) | (0.00) | (0.03) | | | | |
| Adj. R2 | 0.27 | 0.41 | 0.32 | 0.68 | 0.62 | 0.72 | 0.39 | 0.22 | 0.68 | 0.75 | 0.39 |

Table J-2 : Regression of the Volatility Factor on Ludvigson and Ng (2009) Macro Factors.

We regress the volatility factor on the eight principal components of Ludvigson and Ng (2009). The sample period ranges from April 1987 to December 2009. The Warga dataset ranges from April 1987 to December 1996. The NAIC dataset ranges from January 1994 to December 2004. The TRACE dataset ranges from October 2004 to December 2009. The $p-$values are in parenthesis.

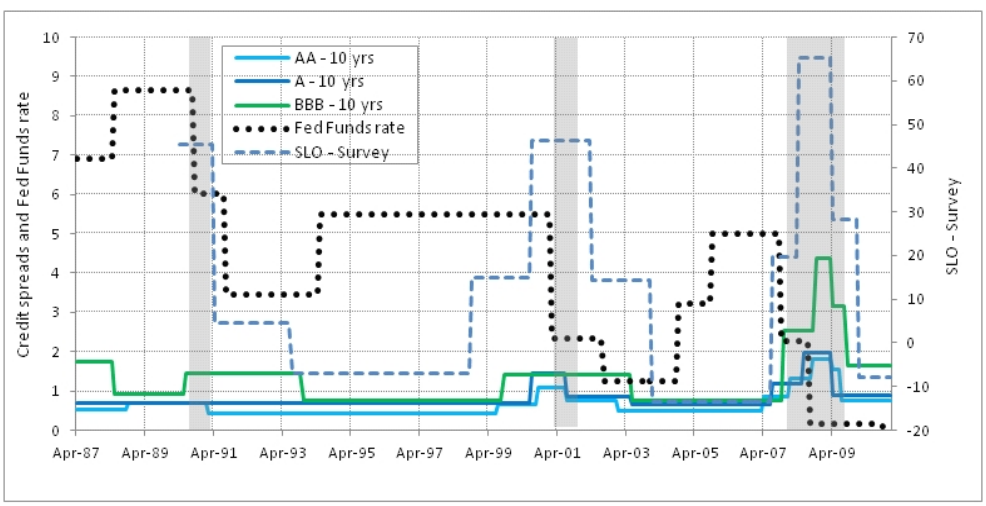
|  | Warga |  |  | NAIC |  |  |  | TRACE |  |  |  |
|---|---|---|---|---|---|---|---|---|---|---|---|
|  | AA | A | BBB | AA | A | BBB | BB | AA | A | BBB | BB |
| Fhat1 | 0.03 | 0.00 | 0.00 | -0.33 | -0.27 | -0.15 | 0.09 | -0.01 | 0.03 | 0.06 | 0.26 |
|  | (0.11) | (0.81) | (0.83) | (0.00) | (0.00) | (0.14) | (0.45) | (0.87) | (0.52) | (0.50) | (0.35) |
| Fhat2 | -0.03 | -0.03 | -0.09 | 0.38 | 0.44 | 0.58 | 0.35 | 0.09 | 0.04 | 0.16 | 0.29 |
|  | (0.34) | (0.17) | (0.01) | (0.00) | (0.00) | (0.00) | (0.00) | (0.14) | (0.33) | (0.10) | (0.08) |
| Fhat3 | -0.00 | -0.01 | 0.03 | 0.05 | 0.08 | 0.07 | 0.06 | 0.03 | -0.01 | 0.05 | 0.05 |
|  | (0.86) | (0.55) | (0.21) | (0.27) | (0.05) | (0.19) | (0.32) | (0.04) | (0.34) | (0.01) | (0.30) |
| Fhat4 | -0.04 | -0.08 | -0.14 | -0.09 | -0.12 | -0.22 | -0.10 | 0.12 | 0.05 | -0.02 | 0.51 |
|  | (0.01) | (0.00) | (0.00) | (0.18) | (0.06) | (0.01) | (0.29) | (0.01) | (0.15) | (0.81) | (0.00) |
| Fhat5 | -0.04 | -0.08 | -0.02 | -0.11 | -0.09 | -0.13 | -0.14 | 0.11 | 0.07 | -0.01 | 0.30 |
|  | (0.11) | (0.00) | (0.49) | (0.04) | (0.10) | (0.05) | (0.06) | (0.00) | (0.01) | (0.83) | (0.01) |
| Fhat6 | 0.01 | 0.01 | -0.02 | -0.31 | -0.31 | -0.38 | -0.37 | 0.07 | 0.03 | -0.09 | 0.01 |
|  | (0.76) | (0.77) | (0.45) | (0.00) | (0.00) | (0.00) | (0.00) | (0.22) | (0.53) | (0.34) | (0.95) |
| Fhat7 | 0.06 | 0.02 | 0.06 | -0.16 | -0.17 | -0.18 | -0.11 | -0.10 | -0.05 | -0.12 | -0.07 |
|  | (0.00) | (0.19) | (0.03) | (0.00) | (0.00) | (0.00) | (0.07) | (0.00) | (0.09) | (0.02) | (0.55) |
| Fhat8 | -0.01 | 0.00 | 0.01 | -0.02 | -0.04 | -0.03 | -0.04 | 0.03 | 0.04 | -0.03 | 0.29 |
|  | (0.46) | (0.94) | (0.57) | (0.63) | (0.36) | (0.63) | (0.56) | (0.24) | (0.13) | (0.43) | (0.02) |
| Adj. R2 | 0.17 | 0.28 | 0.32 | 0.38 | 0.38 | 0.30 | 0.15 | 0.43 | 0.20 | 0.25 | 0.34 |

# Appendix K. Credit Spreads Regimes Using Aggregate Data

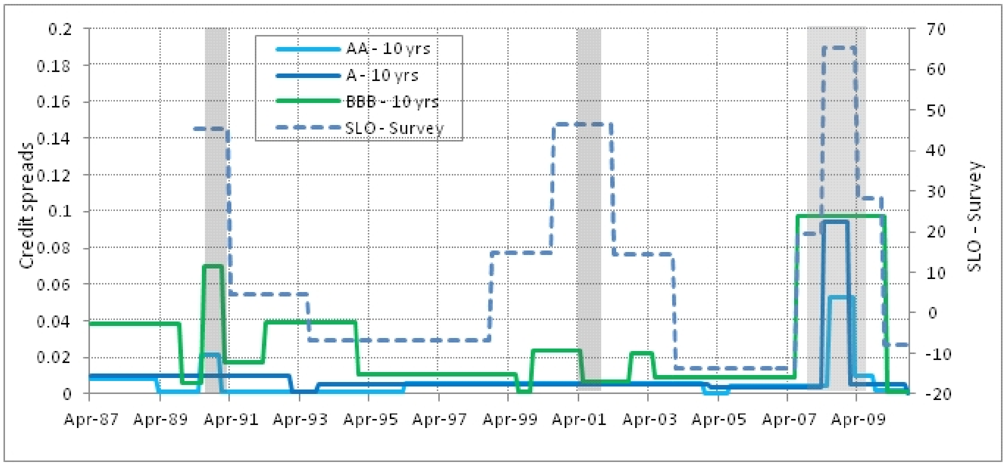
Figure K-1 : Credit Spreads Regimes Using Aggregate Data.

Graph A and Graph B show, respectively, the mean and variance regimes of credit spreads with 10 years to maturity. The sample period ranges from April 1987 to December 2009. Data are constructed by combining Warga and Bloomberg datasets. The X-axis expresses the time in months, the Y-axis (left-hand side) expresses the mean regime of credit spreads and Fed funds rate in percentages, and the Z-axis (right-hand side) expresses the mean regime of the survey in percentages. Shaded regions represent NBER recessions. The initial cut-off length is 6 months and the Huber parameter is 2. Detected regimes are statistically significant at the 95% confidence level or higher.

Graph A: Mean Regimes for the Aggregate Data




Graph B: Volatility Regimes for the Aggregate Data

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