Appendix for Detecting Regime Shifts in Credit Spreads

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Appendix A. The Red Noise Process

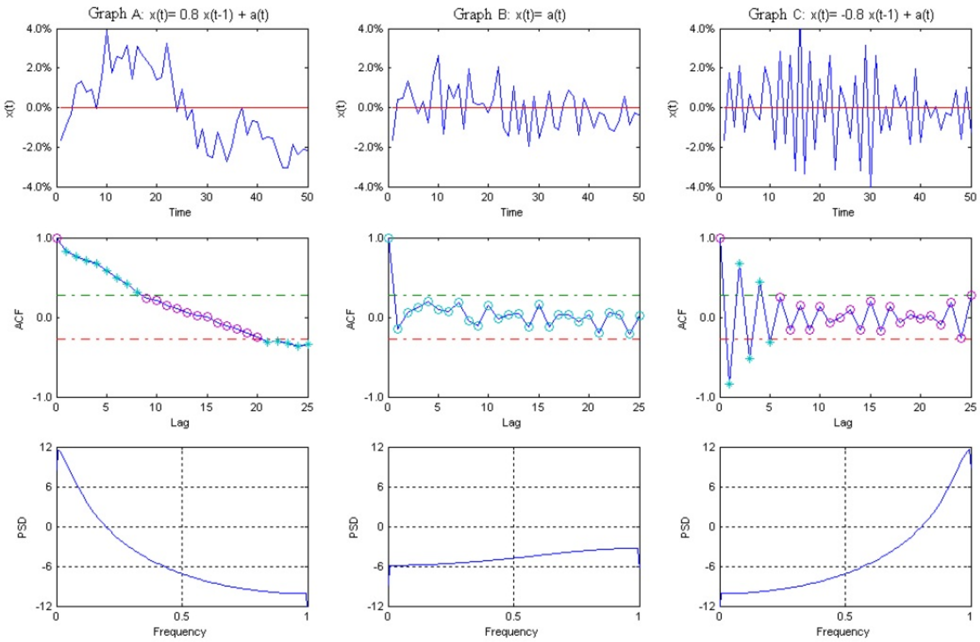
Red noise is usually modeled by an AR(1) process:

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

where $c = \mu(1-\rho)$, μ 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 σ^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 ρ. 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, μ in Equation (1), is unknown and give the formula for the expected value of the OLS estimator of ρ:

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

Because ρ 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 ρ. Solving for ρ and denoting this corrected estimate of ρ by $\widehat{\rho}^c$ yields:

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

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:

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

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

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

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:

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

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)):

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

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. β_{0t} is the limit of $R(t,T)$ as T goes to infinity and is regarded as the long-term yield. β_{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. β_{2t} and β_{3t} give the curvature of the term structure. τ_{1t} and τ_{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:

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

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.

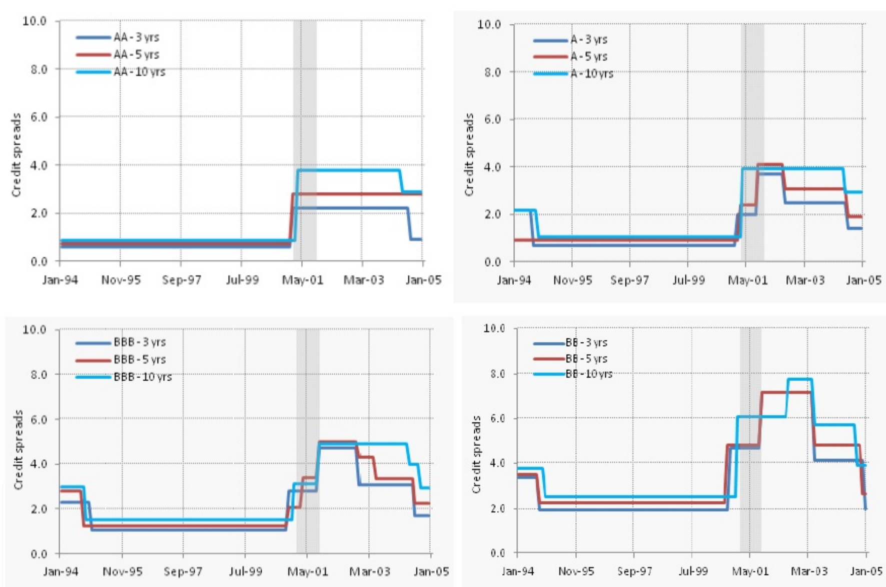
	Shift No.	Mean of Current Regime	Length of Current Regime	Date of Shift Point	Mean of New Regime	Length of New Regime	RSI Sign
Panel A : Warga Quoted Data from April 1987 to December 1996							
AA	1	0.201	36	Apr-90	0.395	11	+
	2	0.395	11	Feb-91	0.542	40	+
	3	0.542	40	Jul-94	0.333	30	-
A	1	0.222	34	Feb-90	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).[1]

[1]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

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

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

FPE, we obtain similar results. Thus, we only report the BIC lag structure.

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)

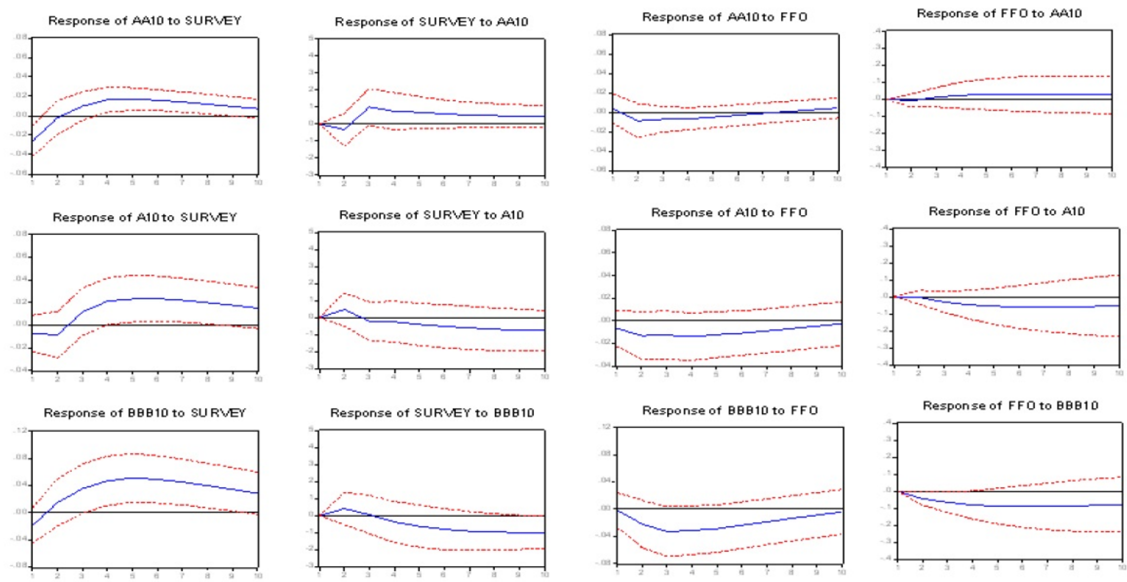
Appendix H. Impulse-Response Functions

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

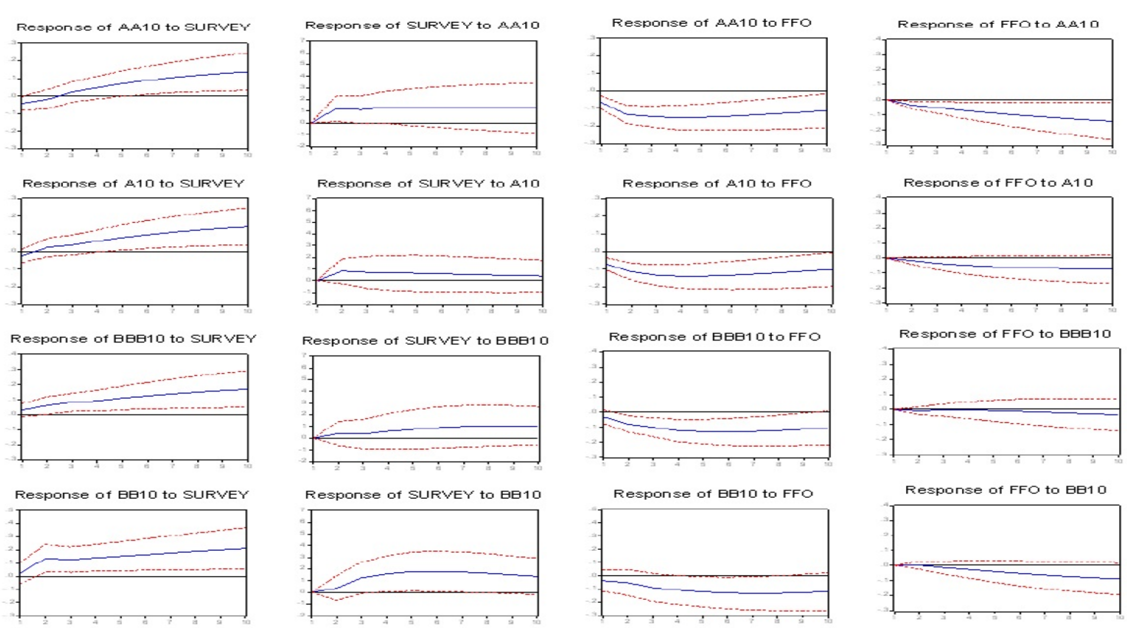
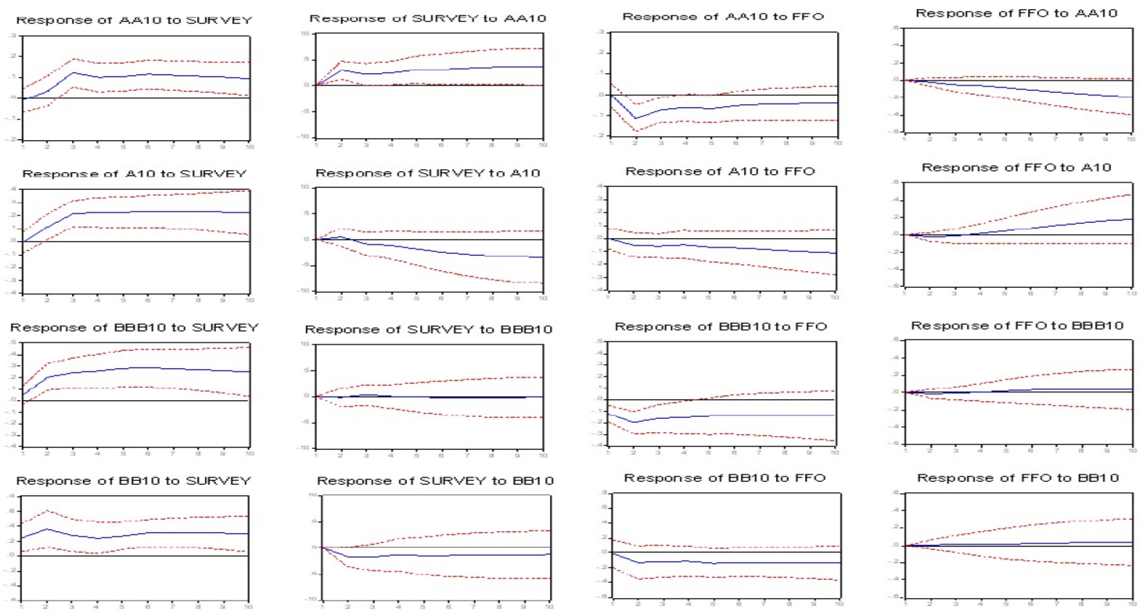


Figure H-1 (Continued)

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.

	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.

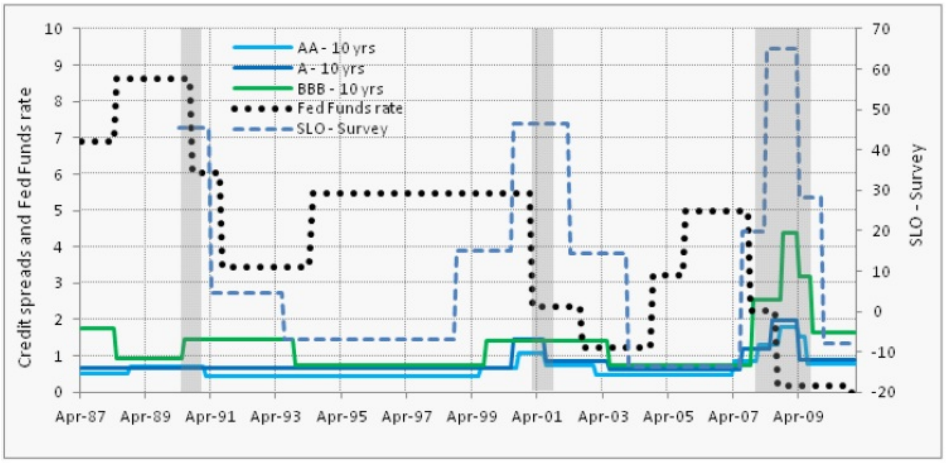
	Warga			NAIC				TRACE			
	AA	A	BBB	AA	A	BBB	BB	AA	A	BBB	BB
Fhat1	0.03	0.00	0.00	-0.33	-0.27	-0.15	0.09	-0.01	0.03	0.06	0.26
	(0.11)	(0.81)	(0.83)	(0.00)	(0.00)	(0.14)	(0.45)	(0.87)	(0.52)	(0.50)	(0.35)
Fhat2	-0.03	-0.03	-0.09	0.38	0.44	0.58	0.35	0.09	0.04	0.16	0.29
	(0.34)	(0.17)	(0.01)	(0.00)	(0.00)	(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

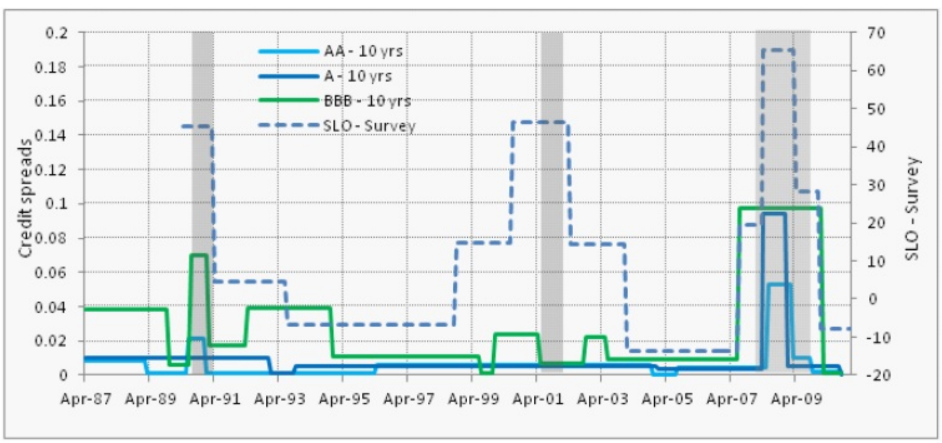
Figure K-1 : Credit Spreads Regimes Using Aggregate Data.

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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