Credit Risk

Default and Liquidity Regimes in the Bond Market

Congrès de l'Association canadienne d'économique
Canadian Economic Association Meeting

May 2013, HEC Montréal

Georges Dionne, HEC Montréal

Research in collaboration with
Olfa Maalaoui Chun, Kaist Graduate School of Finance, South Korea

Motivation

Our goal is to explain the credit risk regime shifts of corporate bonds by analyzing in detail default and liquidity regime shifts.

By credit risk, we mean the difference between corporate bond yield and government bond yield. This difference is also labeled corporate yield spread or credit spread in the financial literature.

This spread is positive because corporate bond investors ask for a higher yield than do government bond investors since they are exposed to additional risks and costs.

In this paper, we focus on default risk and liquidity risk that are contained in credit risk.

The main research questions in the literature are:

1) **What portion of the corporate yield spread is explained:**
   - **by default risk?**
   - **by liquidity risk?**

2) **How corporate yield spreads shift in relation to default risk shifts and liquidity risk shifts?**

3) **How default risk shifts and liquidity risk shifts of corporate bonds are related to the last financial crisis period and the last recession?**

Tonight, I will focus on the third question.

These questions are important because:

- from an investment perspective, corporate debt is one of the largest asset classes;
- from a macroeconomic point of view, yield spreads are often linked to business and monetary cycles;
- during the recent financial crisis, liquidity risk became an important risk especially in the banking industry.

During the recent financial crisis, liquidity risk was significant for many financial assets (such as ABCP in Canada) and central banks had to use special policy measures to increase liquidity into the financial system.

Literature

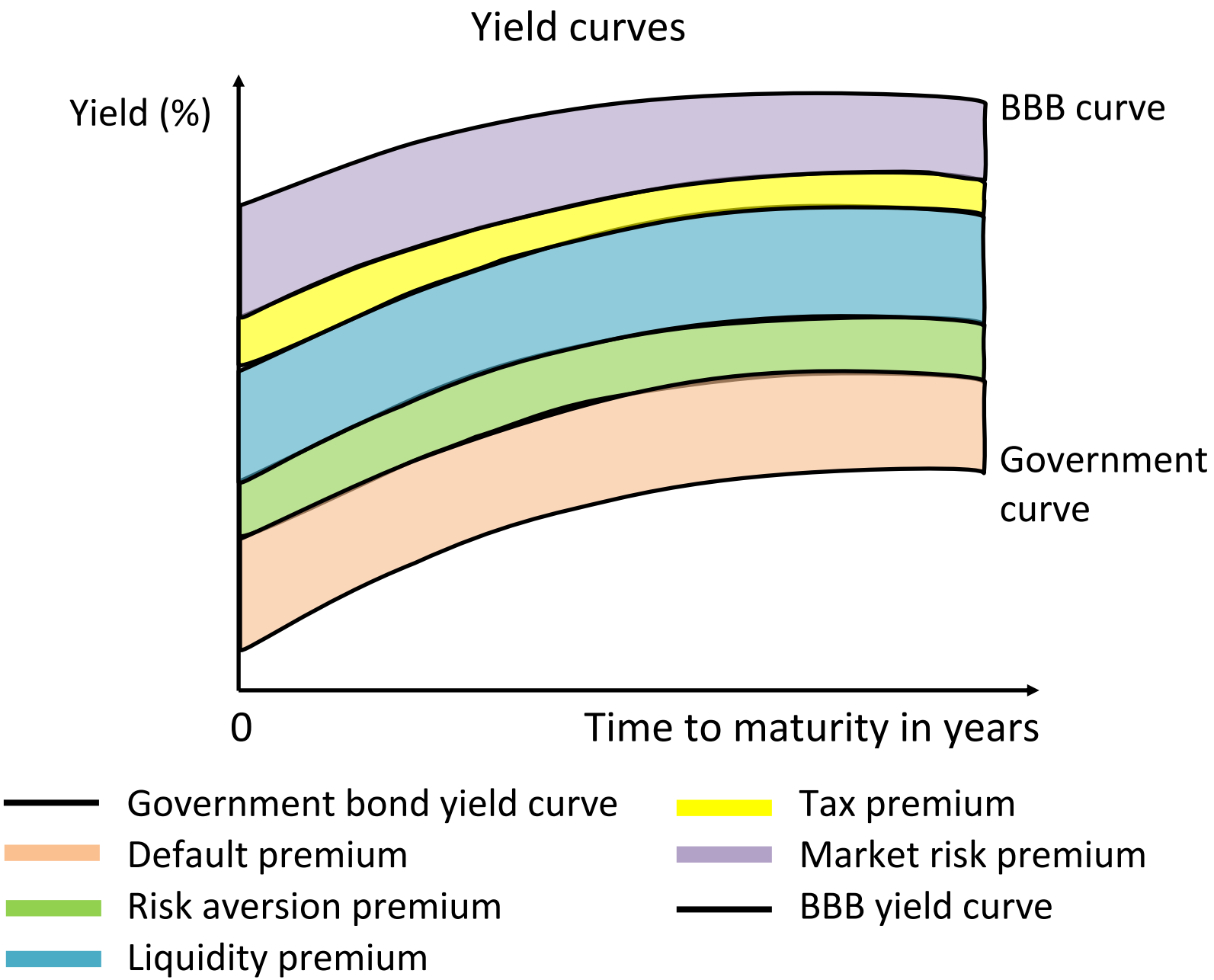
Before the 2000s, credit spread was associated to default spread.

Then many authors contributed to the Credit Risk Puzzle literature by showing that only a fraction of the credit spread is explained by the default risk. This fraction varies between 25% to 50% and is function of business cycles.

Other factors in the credit spread include:

- risk aversion;
- taxes;
- market risk;
- liquidity risk.

However, the measure of liquidity risk is not yet satisfactory, specifically because data limitation before TRACE.


Yield curves
Yield (%)
BBB curve
Government curve
0
Time to maturity in years
Government bond yield curve
Default premium
Risk aversion premium
Liquidity premium
Tax premium
Market risk premium
BBB yield curve

Another issue is related to the credit spread cycles. Credit spread cycles do not necessarily correspond to business cycles (Maalaoui Chun, Dionne, François, 2013, JFQA, forthcoming):

- high level regimes of credit spreads encompass but outlast economic recessions and show persistence after recessions;
- they occur before economic recessions so they may have some predictive power over a forthcoming recession.

These two features were recently introduced in dynamic structural models of default (Chen, *JoF*, 2010; Bhamra et al, *RFS*, 2010).

Finally, credit spread regimes are related to monetary Federal Reserve policy and SLO surveys (Senior Loan Officer surveys).

Figure 2, Panel A Credit spread BBB

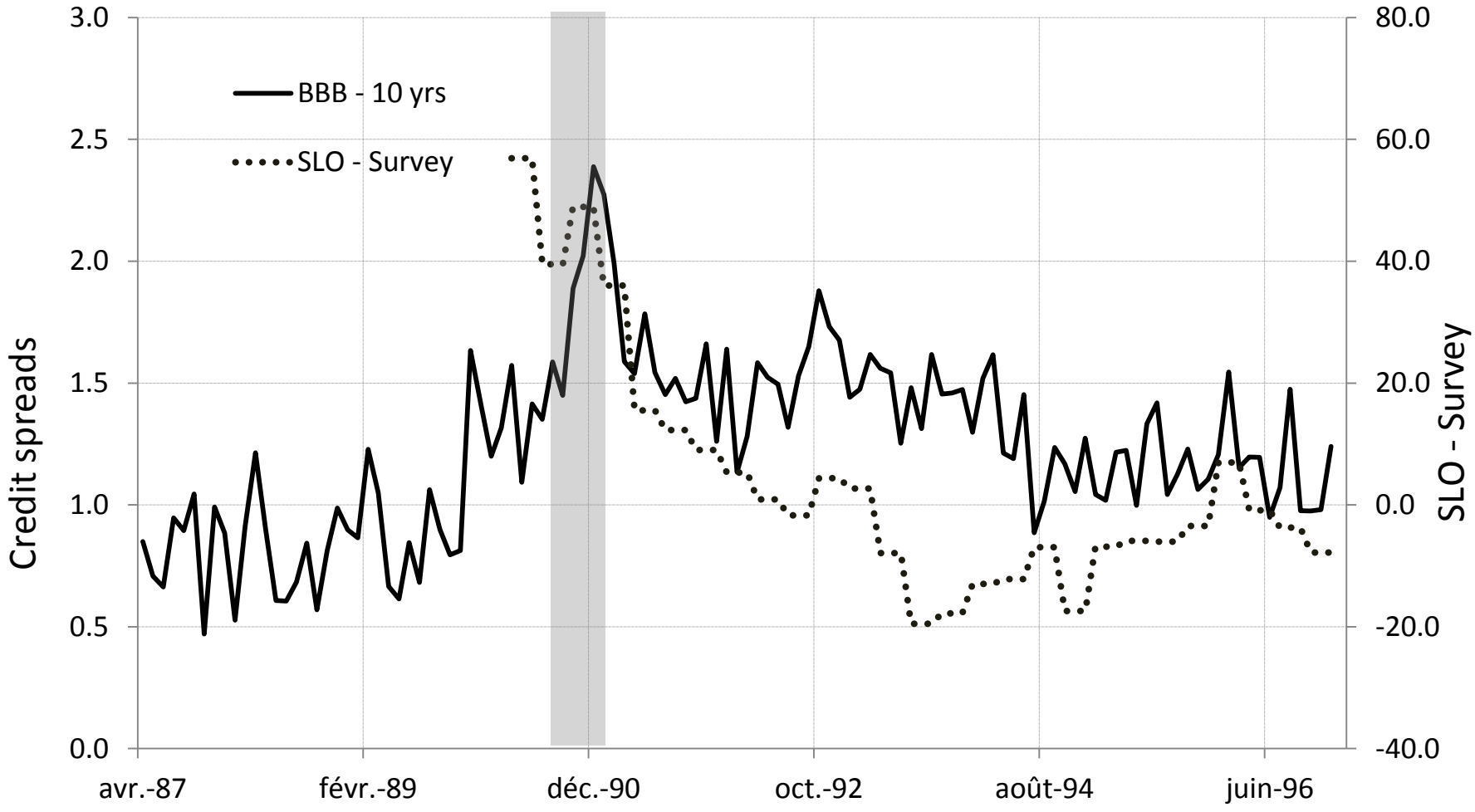


Figure 2, Panel B Credit spread BBB and BB

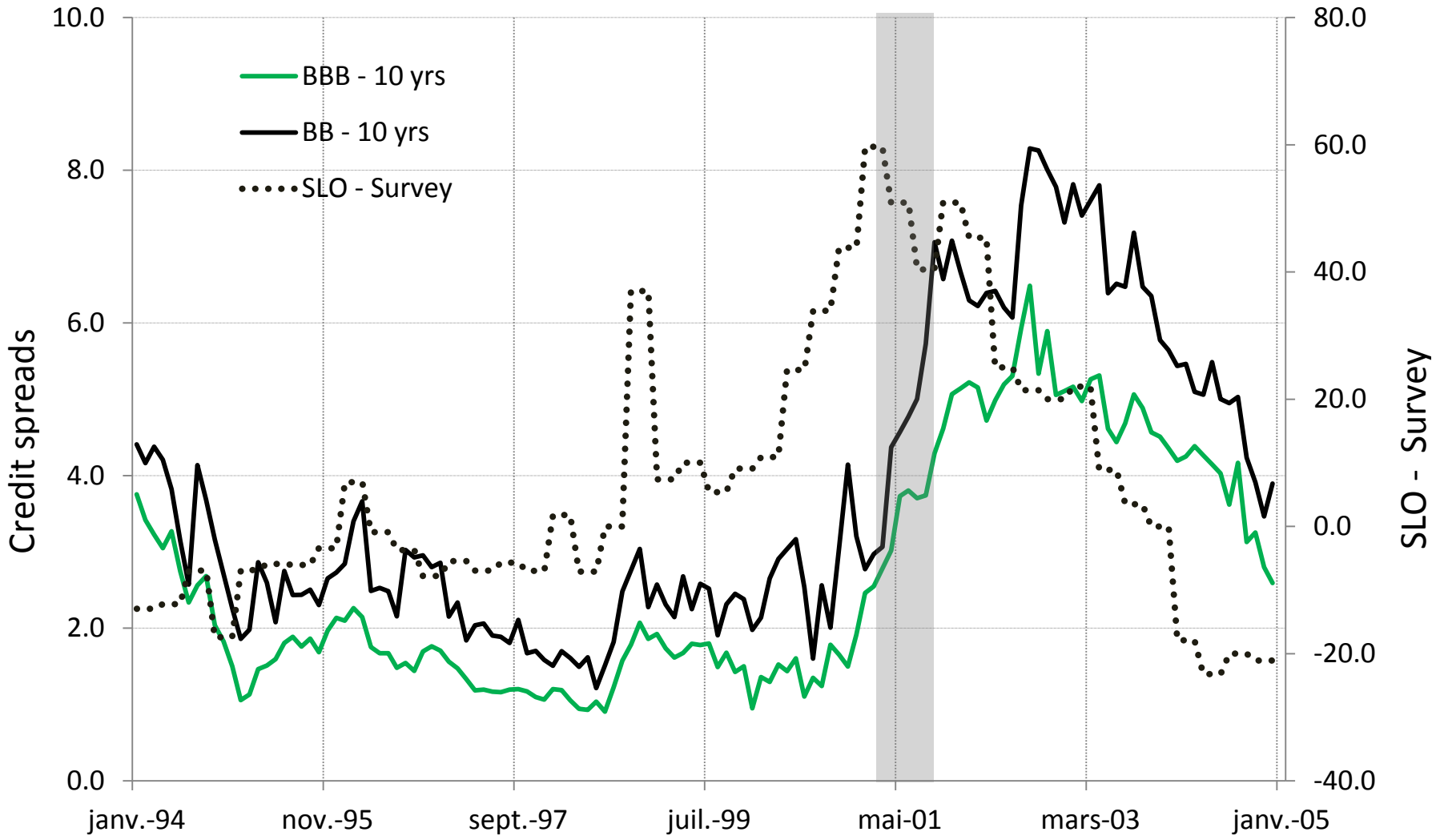
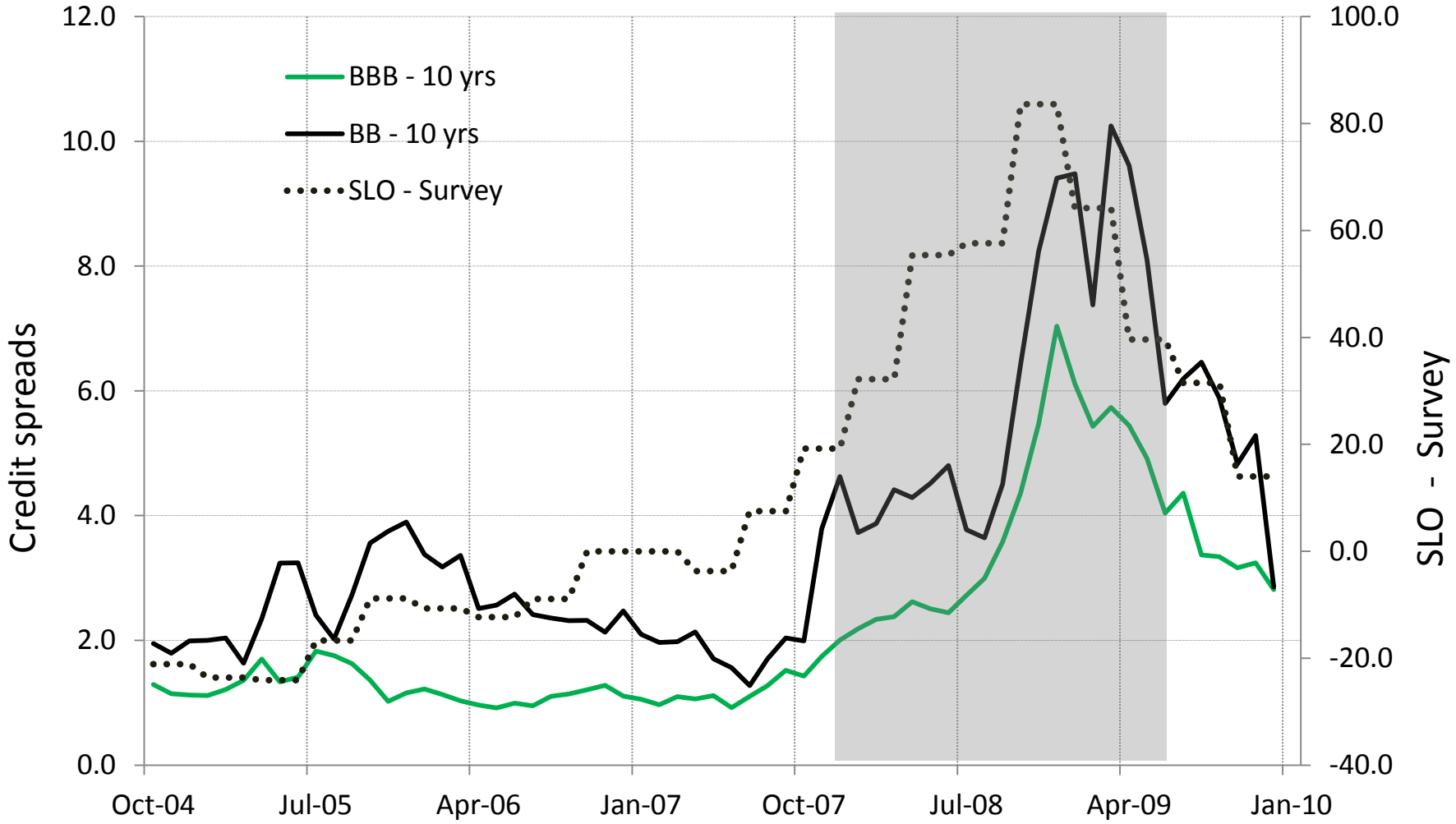


Figure 2, Panel C Credit spread BBB and BB

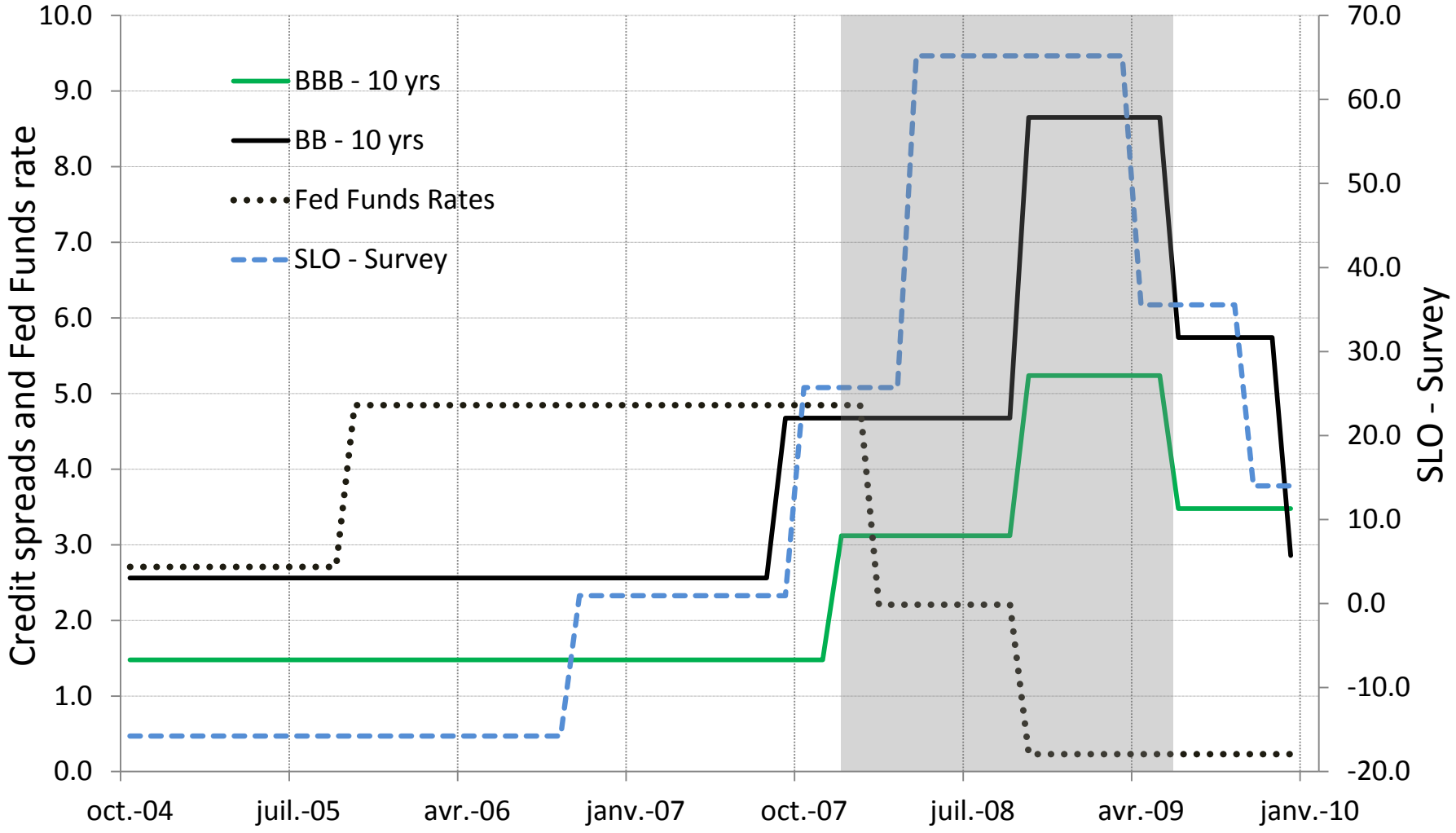


Moreover, volatility regimes can be detected outside business cycles.

This means that volatility and level regimes can be linked to differing sets of observable phenomena.

For example, we have detected a volatility regime during the Asian and LTCM crises in 1997-1998 but there was not a level regime during that period.

Figure 3, Panel C Mean regimes BBB and BB



Today, we study default risk and liquidity risk cycles.

Model

CDS premium or default spread

In a first step, we assume that the CDS (Credit Default Swap) premium measures the default spread component of the credit spread. CDS premiums can also be affected by liquidity (but contracts). The risk-neutral default intensity of the corporate bond follows a square-root diffusion (Cox-Ingersoll-Ross, CIR) process:

$$d\lambda_t^i = \beta_i\left(\alpha_i - \lambda_t^i\right)dt + \sigma_i\sqrt{\lambda_t^i}\,dZ_t^i. \qquad (1)$$

where λ_i is the intensity of the Poisson process governing the default of the reference issue *i*, Z_t^i is a standard Brownian motion, α_i, β_i, σ_i are CIR parameters estimated using the Kalman Filter.

A CDS is like an insurance contract. A bondholder or protection buyer pays a quarterly premium to a protection seller or insurer until either the default of the bond occurs or the CDS contract comes to maturity.

If default occurs, the protection seller buys the defaulted bond from the protection buyer at its face value and receives the recovery value from the bond issuer. So he loses the non-recovery value of the bond or the loss given default value.

Lets denote $(1-w)$ as the recovery rate or w the loss given default rate.

Hence, given the stream of quarterly CDS premiums, s_i, that the protection buyer makes at times $0 < t_1 < t_2 < \ldots < t_n$, we can write the present value of the **premium leg** of the CDS, $P(s_i, T)$ as follow, assuming independence between r_t and λ_t^i.

$$P(s_i, T) = \sum_{t_i=1}^{t_n} s_i D(t_i) E\left(e^{-\int_0^{t_i} \lambda_t^i ds} \right) \tag{2}$$

where $D(t_i) = e^{-\int_0^{t_i} r_t ds}$ is the discount factor, or equivalently:

$$P(s_i, T) = \sum_{t_i=1}^{t_n} s_i D(t_i) A_i(t_i) e^{B_i(t_i)\lambda_0^i}, \tag{3}$$

where $A_i(t_i)$ and $B_i(t_i)$ are expressed in terms of the CIR parameters $(\alpha_i, \beta_i, \sigma_i)$ in Equation (1).

We define in the same way the **protection leg** of the CDS contract:

$$P(w_i, T) = E\left(w_i e^{-\int_0^{\tau_i} r_s ds} 1_{\{\tau_i \le t_n\}}\right) \tag{4}$$

where w_i is the loss given default of the reference bond, or equivalently:

$$w_i \int_0^{t_n} D(t)\left(G_i(t_i) + H_i(t_i)\lambda_0^i\right) e^{B_i(t)\lambda_0^i} dt, \tag{5}$$

where $G_i(t_i)$ et $H_i(t_i)$ are expressed in terms of the CIR parameters $(\alpha_i, \beta_i, \sigma_i)$ in Equation (1). For estimation, (5) can be rewritten as:

$$w_i \sum_{t_i=1}^{t_n} D(t_i)\left(G_i(t_i) + H_i(t_i)\lambda_0^i\right) e^{B_i(t_i)\lambda_0^i} \tag{6}$$

Assuming zero profits at inception of the CDS, the actuarial CDS premium of bond *i* can be expressed as follows:

$$s_i = \frac{w_i \sum_{t_i=1}^{t_n} D(t_i)\left(G_i(t_i) + H_i(t_i)\lambda_0^i\right)e^{B_i(t_i)\lambda_0^i}}{\sum_{t_i=1}^{t_n} D(t_i)A_i(t_i)e^{B_i(t_i)\lambda_0^i}} \tag{7}$$

If λ_i is not stochastic, $s_i = \lambda^i w_i$, the expected loss on the bond. Otherwise, s_i is the present-value-weighted of $\lambda_0^i w_i$ and is lower than $\lambda^i w_i$ because there is negative correlation between λ_0^i and $e^{B_i(t_i)\lambda_0^i}$.

Liquidity premium

We use **8 liquidity measures and two indexes obtained from principal component analysis**.

1) *The Amihud illiquidity measure*

For each individual bond *i*, we compute the daily Amihud measure as follows:

$$\text{Amihud}_t^i = \frac{1}{N_t}\sum_{j=1}^{N_t}\frac{1}{Q_{j,t}^i}\frac{\left|P_{j,t}^i - P_{j-1,t}^i\right|}{P_{j-1,t}^i}, \tag{8}$$

where N_t is the number of returns in each day *t*, $P_{j,t}^i$ (in \$ per \$100 par) denotes the jth transaction price of bond *i* in day *t* and $Q_{j,t}^i$ (in \$ million) the jth trading volume of bond *i* in day *t*. This is the price impact of a trade per unit traded. It has a transaction volume component.

Two measures of bid-ask spread.

2) *The unique roundtrip cost* (also called imputed roundtrip cost)

The unique roundtrip cost (URC) is defined as:

$$\text{URC} = \frac{P_{\max} - P_{\min}}{P_{\max}} \tag{9}$$

where $P_{\max}$ and $P_{\min}$ denote the maximum and minimum trading prices during a unique roundtrip trade or size.

3) *The Roll measure of the bid-ask spread*

$$\text{Roll}_t^i = 2\sqrt{-\text{cov}\left(\Delta P_t^i, \Delta P_{t-1}^i\right)} \tag{10}$$

where ΔP denotes changes in transaction prices.

4) *First illiquidity risk measure*

The first liquidity risk measure is equal to the standard deviation of Amihud measure.

5) *Second illiquidity risk measure*

The second liquidity risk measure is equal to the standard deviation of unique roundtrip costs (URC).

6) *The turnover*

$$\text{turnover}_t = \frac{\text{total trading volume}_t}{\text{amount outstanding}} \tag{11}$$

The inverse of turnover_t can be interpreted as the average holding time of the bond.

7) *Bond zero trading days*

$$\text{bond zero}_t = \frac{\text{number of bond zero trades within the rolling window}}{\text{number of days in the rolling window}} \quad (12)$$

8) *Firm zero trading days*

$$\text{firm zero}_t = \frac{\text{number of firm zero trades within the rolling window}}{\text{number of days in the rolling window}} \quad (13)$$

Liquidity premium

The liquidity premium is a linear sum of illiquidity measures selected from a principal component analysis.

We define the daily measure of the bond specific illiquidity factor as an equally sum of the normalized illiquidity measures retained from the principal component analysis:

$$\varsigma_{it} = \sum_{j=1}^{?} \overline{I}_{it}^{\,j},$$

where $\overline{I}_{it}^{\,j}$ is the normalized measure of illiquidity *j*, $\frac{I_{it}^{j} - \mu^{j}}{\sigma^{j}}$. See Dick-Nielsen, Feldhütter and Lando (*JFE*, 2012) for more details.

Default and liquidity regime detection

We present a new regime shift detection model.

- The regime shift procedure builds on sequential t-test for shifts in the mean (level) and sequential F-test for shifts in the variance (or volatility). Non-parametric model.
- The procedure views regimes as random in the sense that, at each time *t*, one cannot predict the existence or the timing of any future breakpoint.
- The method allows level and volatility regimes to have their own patterns, in contrast to Markov switching model.
- One advantage of the method is its ability to account for abrupt changes in a time series.

- This is a real-time method, in the sense that possible breaks can be detected as new data arrive and it is free from any assumption about the number and the timing of the breaks.
- The method comes from the literature of detecting shifts within ecosystems and was applied to time series data in finance only recently (Maalaoui Chun, Dionne, François, 2013, forthcoming JFQA).

There are two stages for detecting regimes.

A first stage for detecting level regimes and a second stage for detecting volatility regimes in time series.

Consider that data is represented by the following time series $\{Y_t, t = 1,\ldots,n\}$.

Suppose Y_t is described by an autoregressive model:

$$Y_t - f_t = \rho\left(Y_{t-1} - f_{t-1}\right) + \varepsilon_t, \tag{14}$$

where f_t captures a potentially time-varying mean, ρ is the autocorrelation coefficient, and $\varepsilon_t \sim N\left(0, \sigma^2\right)$.

We define time $t = c$ as a breakpoint where the distribution of the data changes, then the mean level f_t can be expressed as:

$$f_t = \begin{cases} \mu_1, t = 1, 2, \ldots, c-1, \\ \mu_2, t = c, c+1, \ldots, n. \end{cases} \tag{15}$$

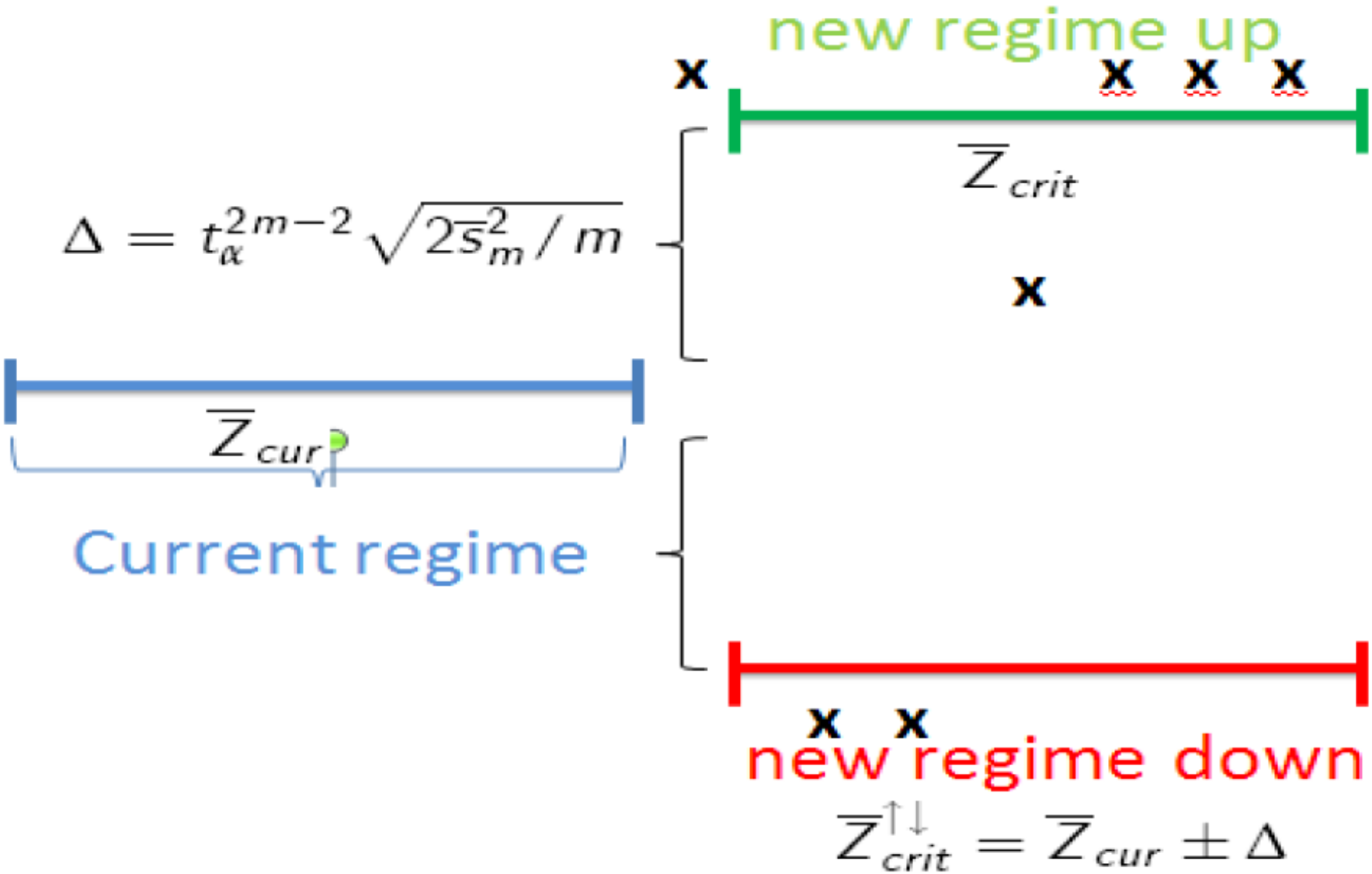
The null hypothesis $H_0 = \mu_1 = \mu_2 = \mu$ meaning that we reject a regime shift. Before testing we must estimate $\hat{\rho}$ and clean the data of any red noise and work with the filtered time series $Y_t - \hat{\rho} Y_{t-1}$.

Detection of the level regime

We start by defining the sample mean $\bar{Z}_{cur}$ of the first sequence of the data of length m. Let Δ be the difference between the mean values of two subsequent sequences:

$$\Delta = t_{\alpha_{\text{mean}}}^{2m-2} \sqrt{2\bar{s}_m^2 / m}, \tag{16}$$

where m is the initial cut-off length of regimes similar to the cut-off point in low-pass filtering, $\bar{s}_m^2$ is the sample variance, and $t_{\alpha_{\text{mean}}}^{2m-2}$ is the value of the two-tailed t-distribution with $(2m-2)$ degrees of freedom at the given probability level α_{mean}.


new regime up
$\overline{Z}_{crit}$
$\Delta = t_{\alpha}^{2m-2}\sqrt{2\overline{s}_m^2 / m}$
$\overline{Z}_{cur}$
Current regime
new regime down
$\overline{Z}_{crit}^{\uparrow\downarrow} = \overline{Z}_{cur} \pm \Delta$

The shift in the level occurs if the current value tested Z_{cur} is outside the critical threshold $\left]\bar{Z}_{\text{crit}}^{\downarrow}, \bar{Z}_{\text{crit}}^{\uparrow}\right[$,

$$\begin{aligned} \bar{Z}_{\text{crit}}^{\uparrow} &= \bar{Z}_{\text{cur}} + \Delta, \\ \bar{Z}_{\text{crit}}^{\downarrow} &= \bar{Z}_{\text{cur}} - \Delta, \end{aligned} \tag{17}$$

where $\bar{Z}_{\text{crit}}^{\uparrow}$ is the critical mean if the shift is upward and $\bar{Z}_{\text{crit}}^{\downarrow}$ is the critical mean if the shift is downward. We must then test if the shift is the starting point of a new regime or simply an accident.

Define (RSI) that represents a cumulative sum of normalized anomalies relative to the critical mean $\bar{Z}_{\text{crit}}^{\downarrow}$:

$$RSI = \frac{1}{m\bar{s}_m} \sum_{i=t_{\text{cur}}}^{j} \left(Z_i - \bar{Z}_{\text{crit}}\right), j = t_{\text{cur}}, t_{\text{cur}} + 1, \ldots, t_{\text{cur}} + m - 1. \tag{18}$$

If at any time during the testing period from t_{cur} to $t_{\text{cur}} + m - 1$ the *RSI* turns negative when $\overline{Z}_{\text{crit}} = \overline{Z}_{\text{crit}}^{\uparrow}$ or positive when $\overline{Z}_{\text{crit}} = \overline{Z}_{\text{crit}}^{\downarrow}$, the null hypothesis is not rejected.

Detection of the volatility regime

The detection of the volatility regime shifts is performed in the same way as for the level regime, except it is based on the *F*-test instead of the Student *t*-test.

At this stage, we purge our initial data of level regimes, thus obtaining the time series of the residuals.

I will not go into the details of the volatility tonight.

Data

The TRACE database

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.

Data covers the period July 2002 to December 2012. We use the Dick-Nielson filter for the duplicates and the Han and Zhou filters for the prices.

The CDS database

Data for CDS contracts are obtained from Markit. This includes all North American Financial CDS for which we can match data from TRACE. Maturities are from 6 months to 10 years. The data has a daily frequency and covers the period from 2001 to 2012.

We use the whole term structure to extract the λ-intensity of each issuer. Since we have many maturities, we use the filtering approach of Duan and Simonato (2004).

Trading days are defined by the time schedule of the NYSE.

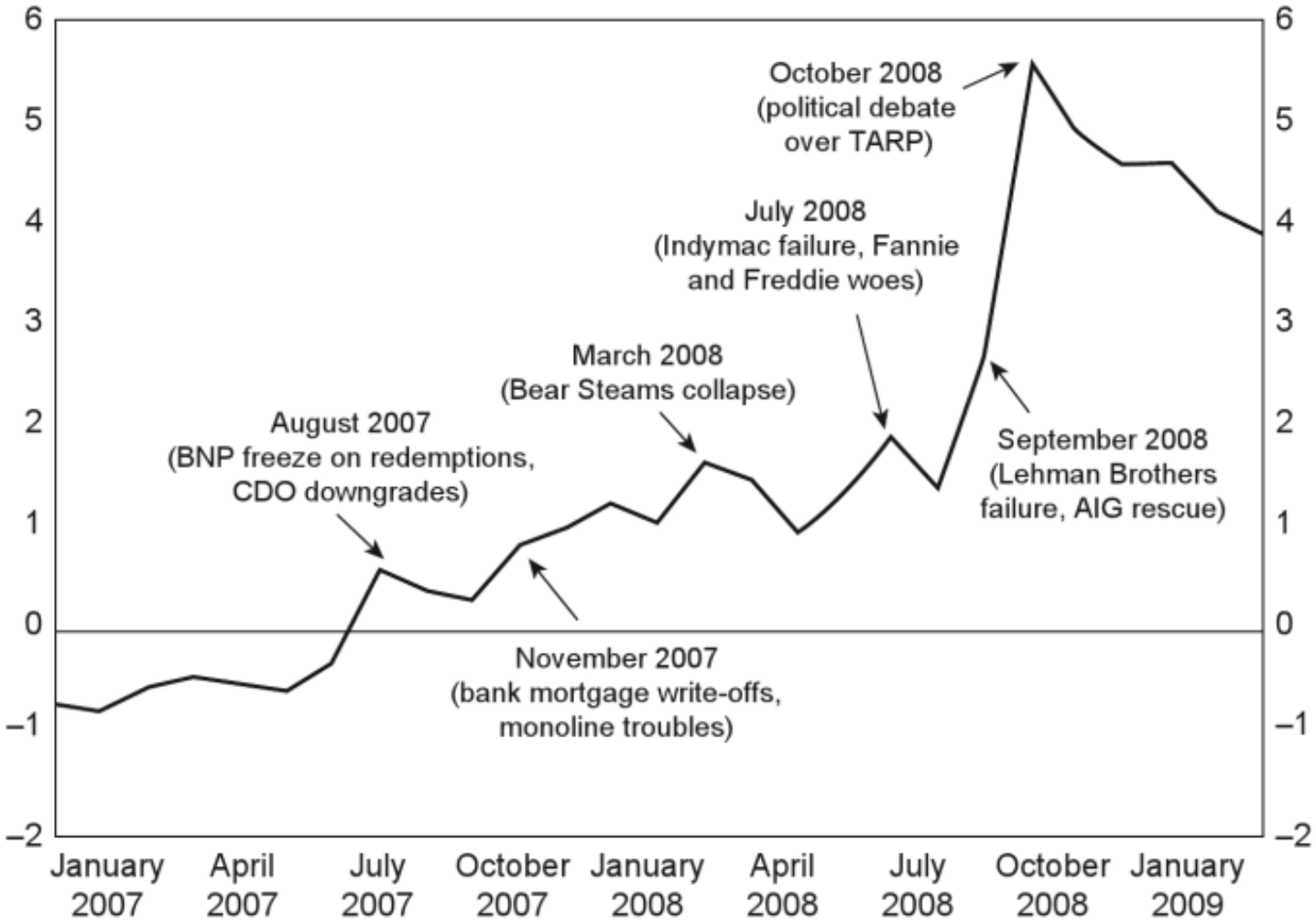


FIGURE 2.10 Kansas City Financial Stress Index 2007–2009

Note: Index is calculated using data from February 1990 to March 2009.

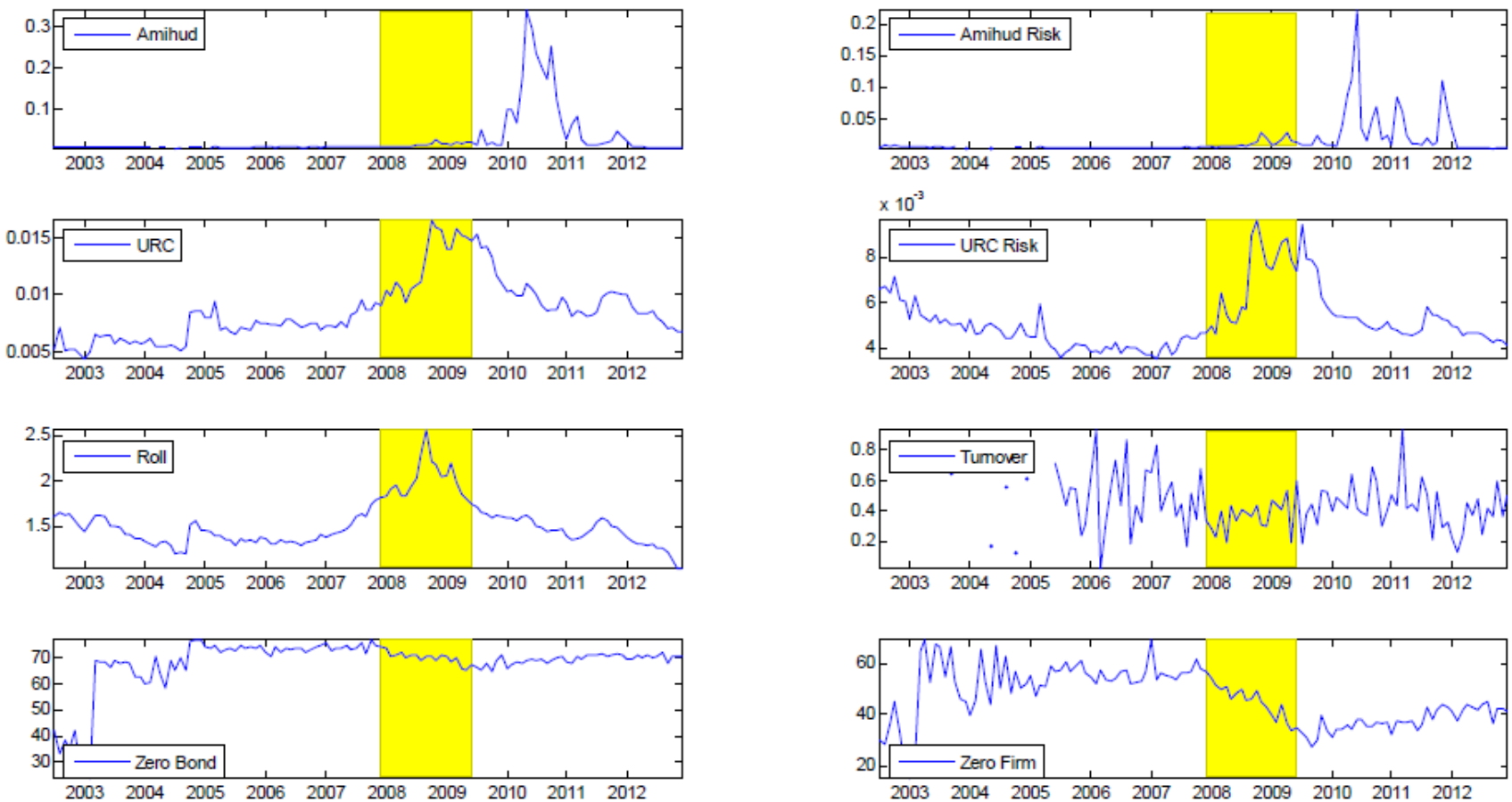
Source: C. S. Hakkio and W. R. Keeton, "Financial Stress: What Is It, How Can It Be Measured, and Why Does It Matter?" Federal Reserve Bank of Kansas City, *Economic Review*, Second Quarter 2009, Chart 3, page 26.

Empirical results

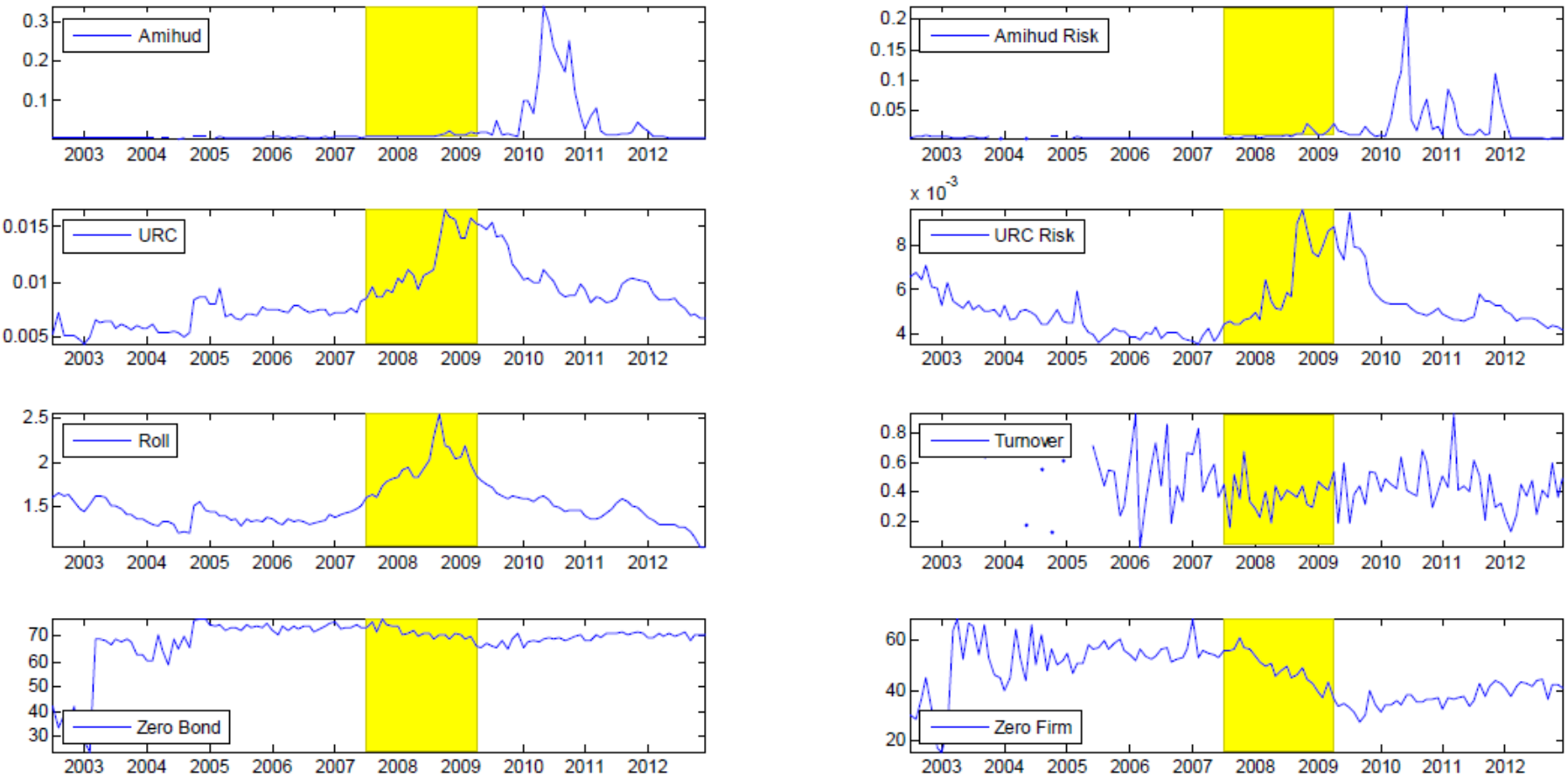
Statistics for liquidity measures

Figure 1: Dynamics of the eight liquidity variables

Panel A: Dynamics of liquidity variables during the 12-2007 to 06-2009 NBER recession

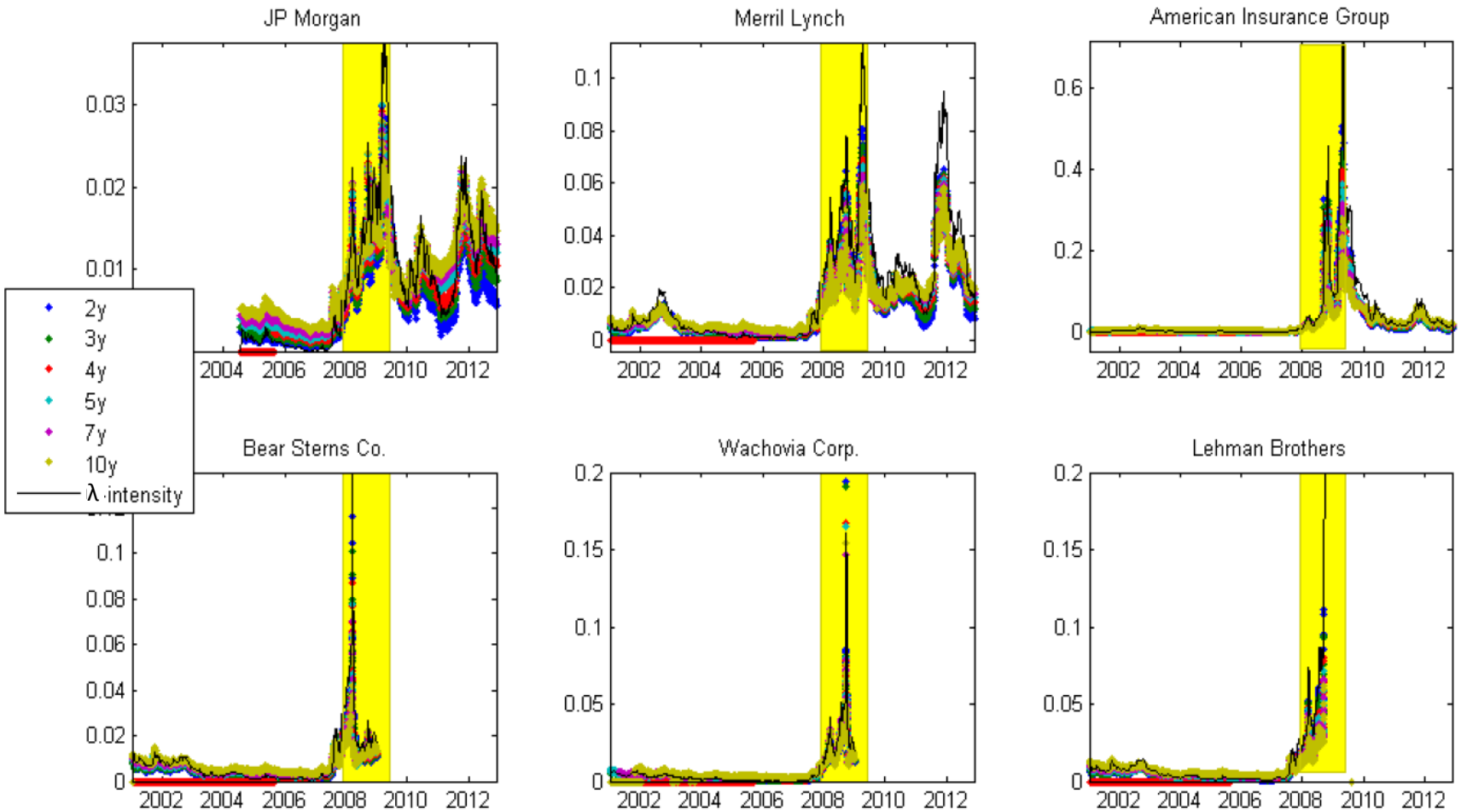


Panel B: Dynamics of liquidity variables during the 07-2007 to 03-2009 financial crisis



Statistics for default measure

The CDS and the implied intensity of default during the 12-2007 to 06-2009 NBER recession



Principal component analysis of the liquidity variables

Table 4: Principal component analysis of the liquidity variables

Panel A: Eigenvalues of the eight principal components

PCs	Eigenvalue	Difference	Proportion	Cum. % explained
1PC	3.3470	1.4709	0.4184	0.4184
2PC	1.8761	0.8845	0.2345	0.6529
3PC	0.9916	0.0602	0.1239	0.7768
4PC	0.9314	0.4887	0.1164	0.8933
5PC	0.4427	0.1855	0.0553	0.9486
6PC	0.2572	0.1421	0.0321	0.9807
7PC	0.1151	0.0762	0.0144	0.9951
8PC	0.0390	.	0.0049	1.0000

Panel B: Eigenvectors of the eight principal components

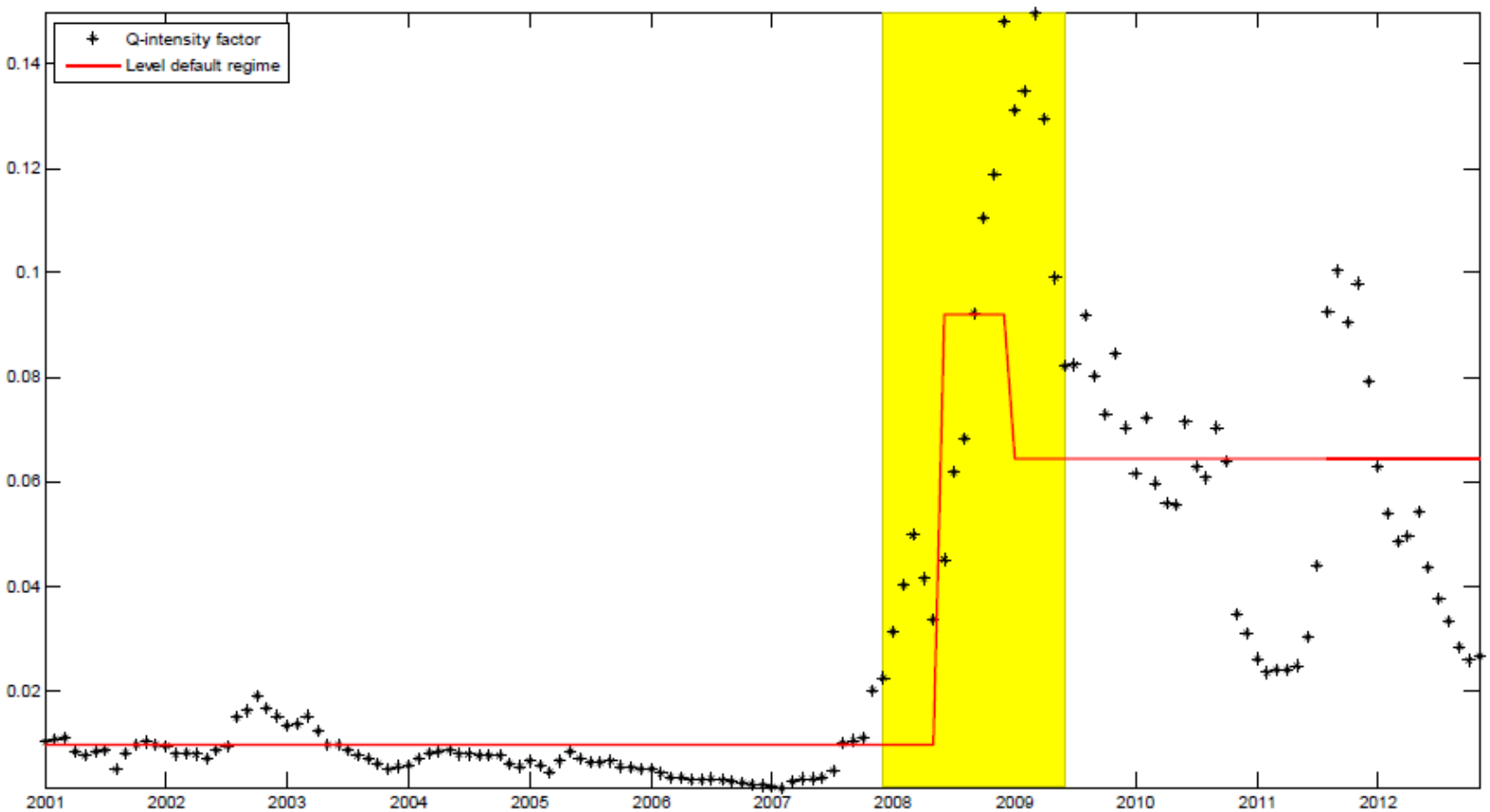
	1PC	2PC	3PC	4PC	5PC	6PC	7PC	8PC
Amihud	0.1623	0.6102	0.2803	-0.0839	-0.1056	-0.683	0.1785	0.0786
URC	0.5037	-0.1887	0.1357	0.1064	0.1837	0.0047	0.4456	-0.6698
Amihud Risk	0.1791	0.5701	0.376	-0.1321	0.1392	0.6735	-0.1054	0.002
URC Risk	0.5105	-0.201	-0.0016	0.1075	0.0513	0.1034	0.3825	0.7265
Roll	0.3725	-0.3161	0.5047	0.1502	-0.222	-0.1388	-0.6446	0.0046
Turnover	-0.1031	0.2389	-0.0557	0.9534	-0.118	0.072	0.0268	-0.0187
Zero Bond	-0.3671	-0.171	0.4806	0.1344	0.7389	-0.1437	0.0568	0.1303
Zero Firm	-0.3783	-0.2011	0.5223	-0.0544	-0.5691	0.1549	0.439	0.0064

Regimes detected with respect to the financial crisis period and last recession

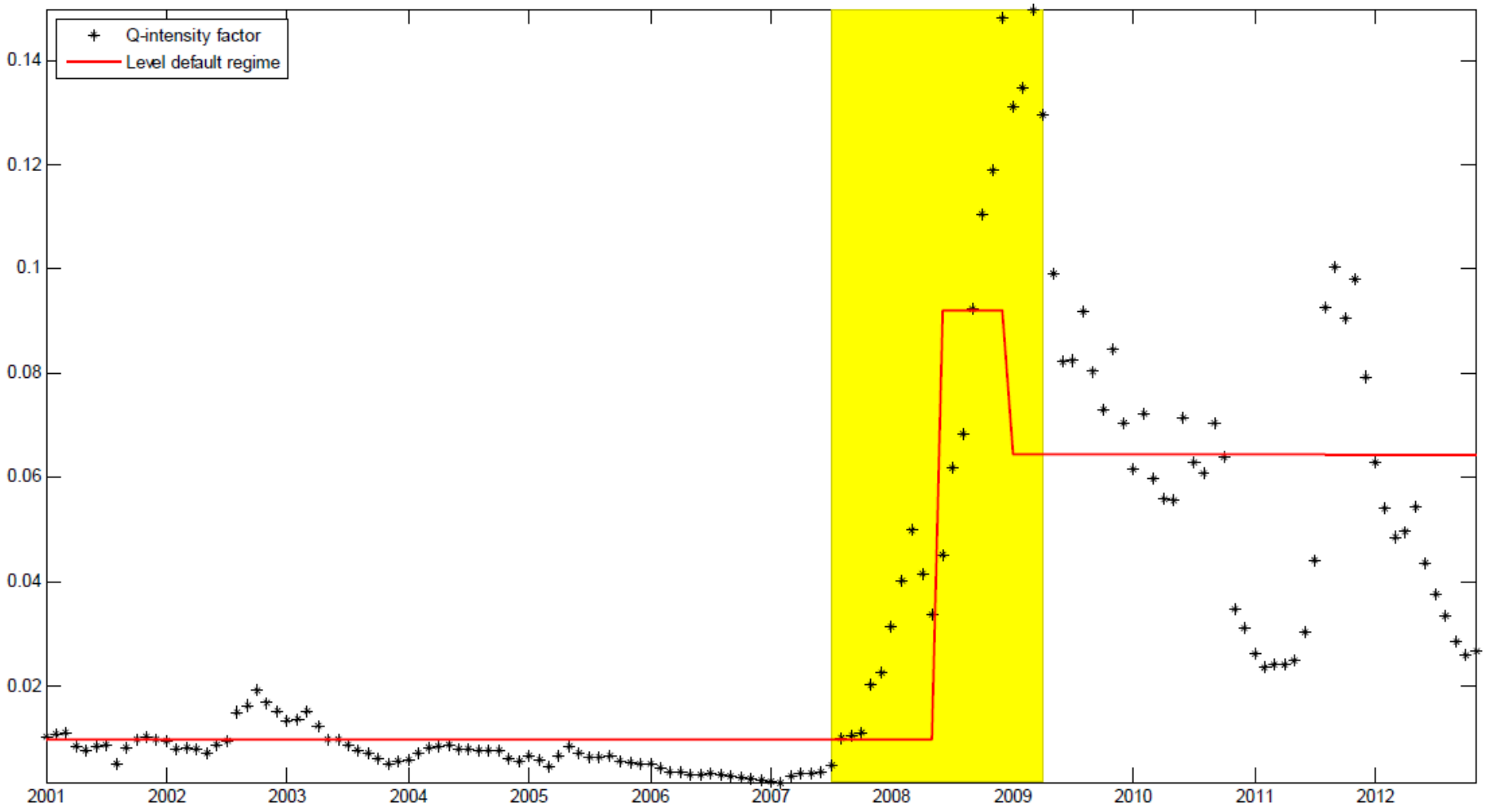
Default regimes

Figure 2: Dynamics of the default factor

Panel A: Default factor during the 12-2007 to 06-2009 NBER recession



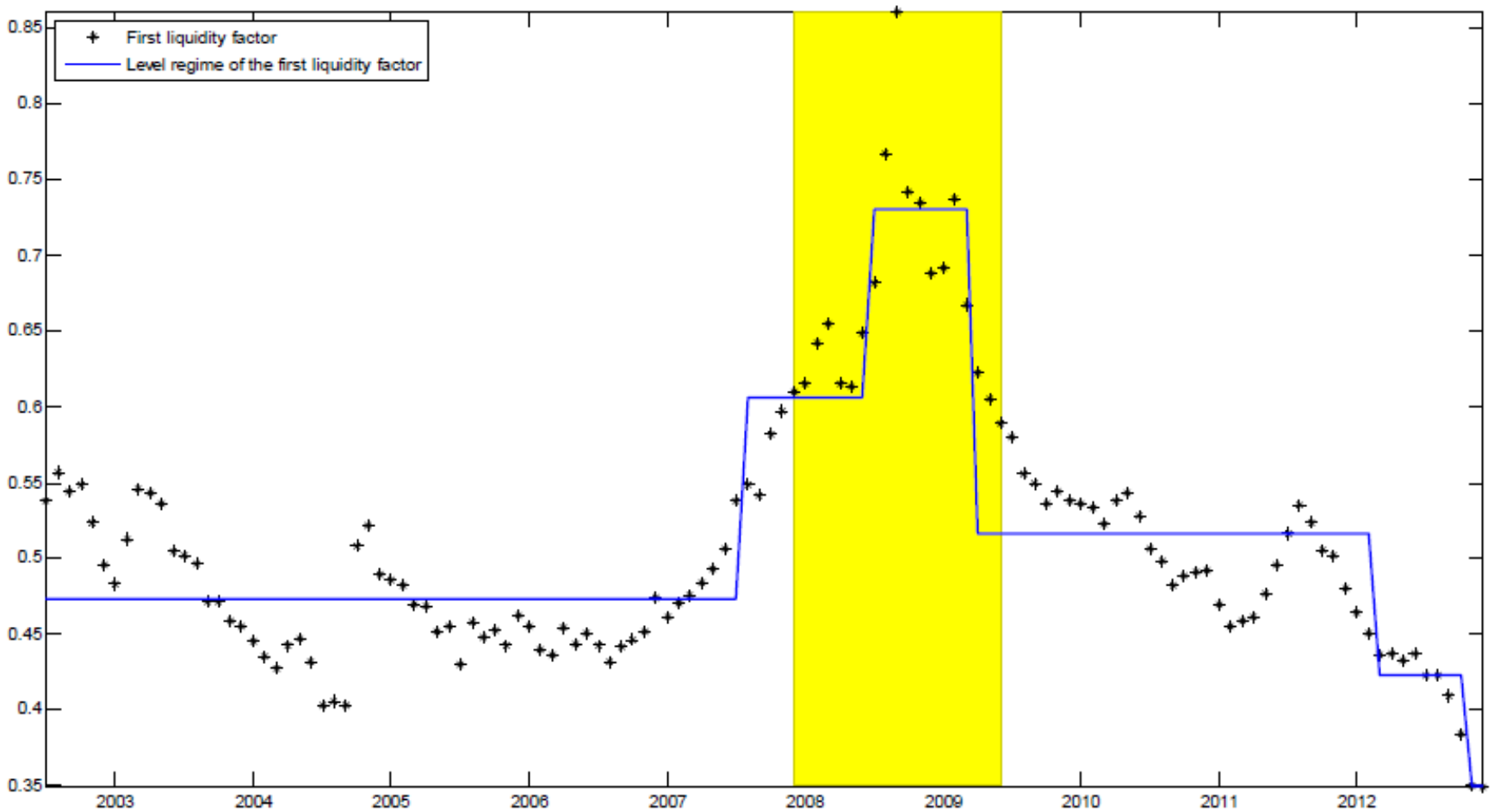
Panel B: Default factor during the 07-2007 to 03-2009 financial crisis



Liquidity regimes

Figure 3: Dynamics of the first liquidity factor

Panel A: First liquidity factor during the 12-2007 to 06-2009 NBER recession



Panel B: First liquidity factor during the 07-2007 to 03-2009 financial crisis

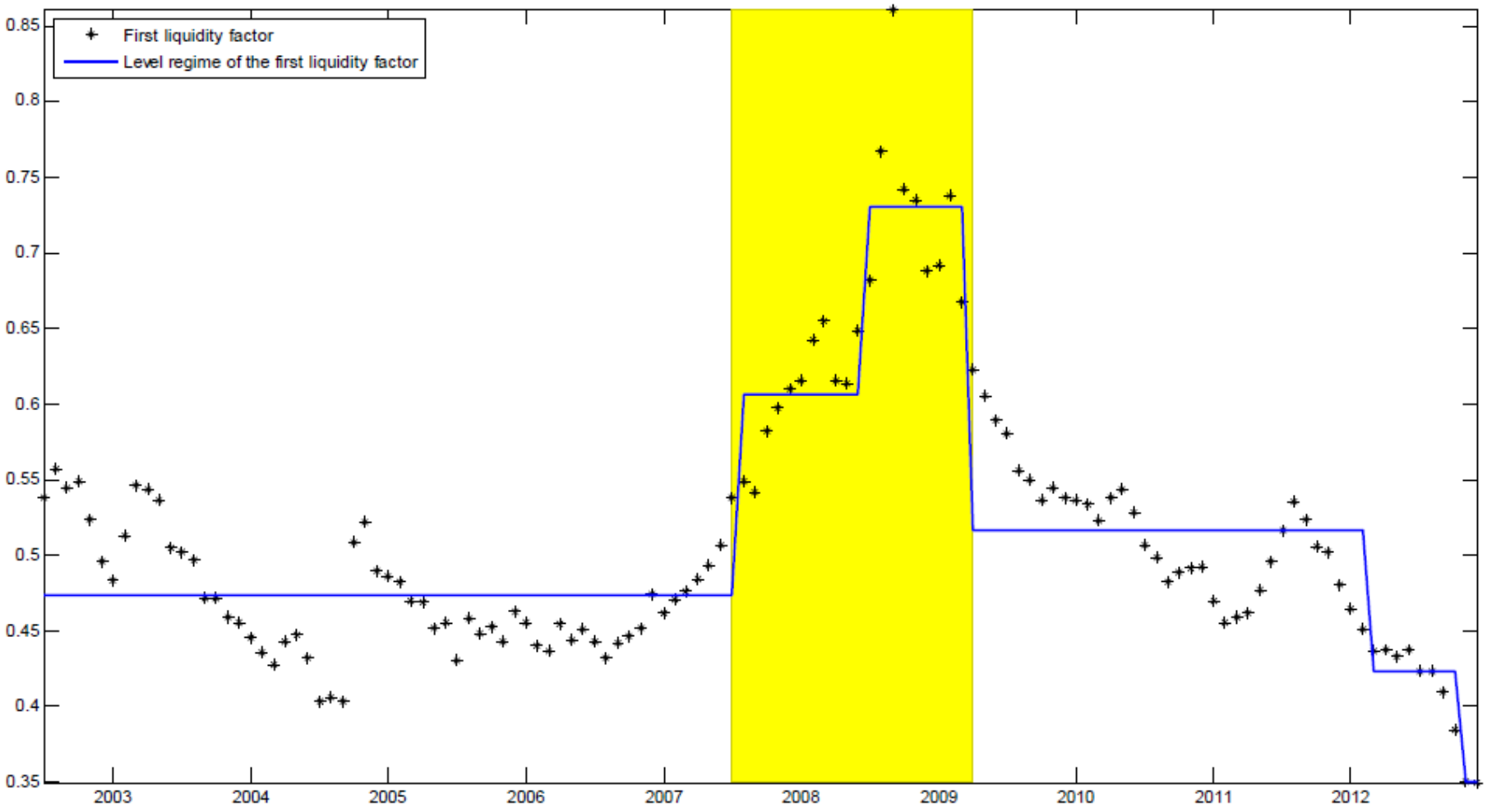
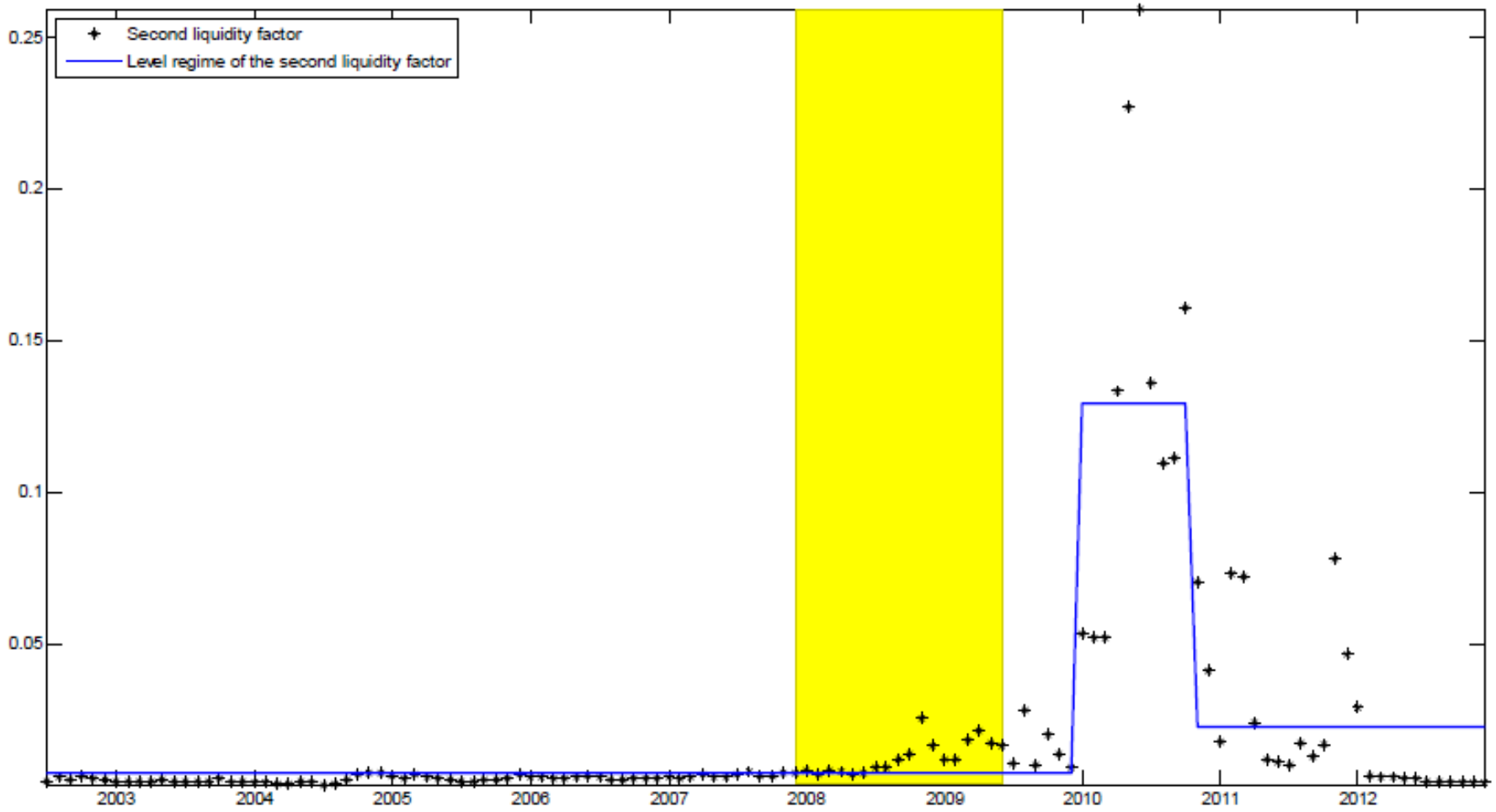
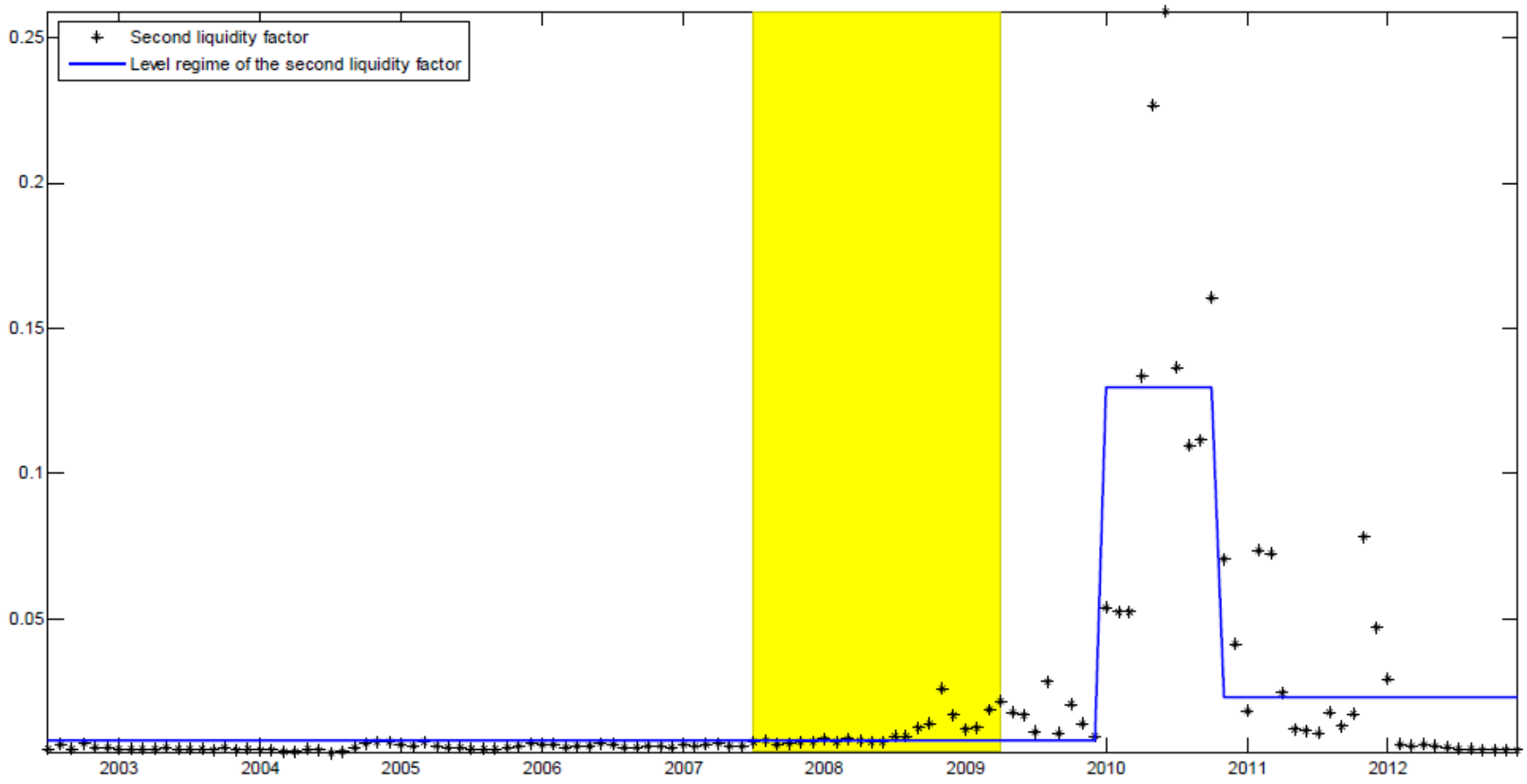


Figure 4: Dynamics of the second liquidity factor

Panel A: Second liquidity factor during the 12-2007 to 06-2009 NBER recession



Panel B: Second liquidity factor during the 07-2007 to 03-2009 financial crisis



Conclusion

The preliminary results are very encouraging.

They indicate that the rating and the pricing of bonds must introduce a liquidity factor in their analysis, not only a default factor.

They indicate that the new regime detection methodology adequately captures the shifts in default and liquidity risks.

It seems that during the two crises, the bid-ask spread measures of liquidity risk were the most important ones.

The illiquid measure of Amihud seems being more important after the two crises for measuring the low volume of trading. We still try to find an interpretation but it is well known that the trading activity in financial markets was very low after the financial crisis.

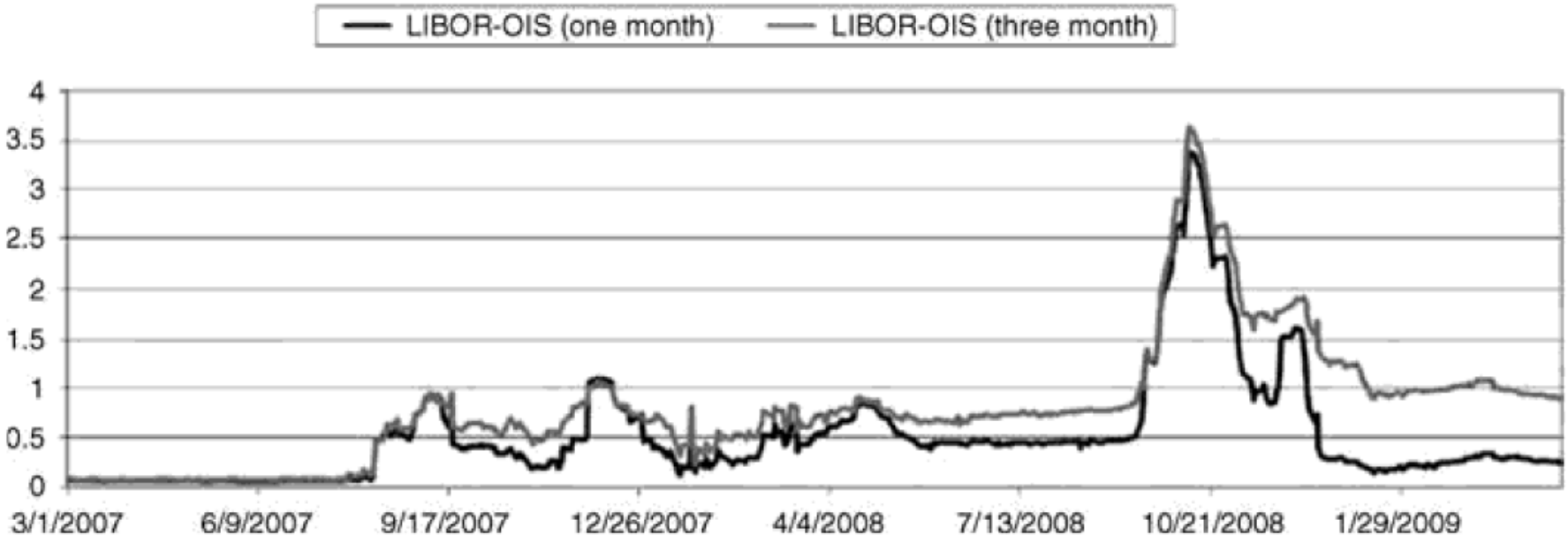


FIGURE 2.6 The Increasing Cost of Short-Term Liquidity: Difference between the LIBOR and the Overnight Index Swap Rate
Source: "Domestic Open Market Operations During 2008," Federal Reserve Bank of New York, Markets Group report, January 2009, Chart 1.

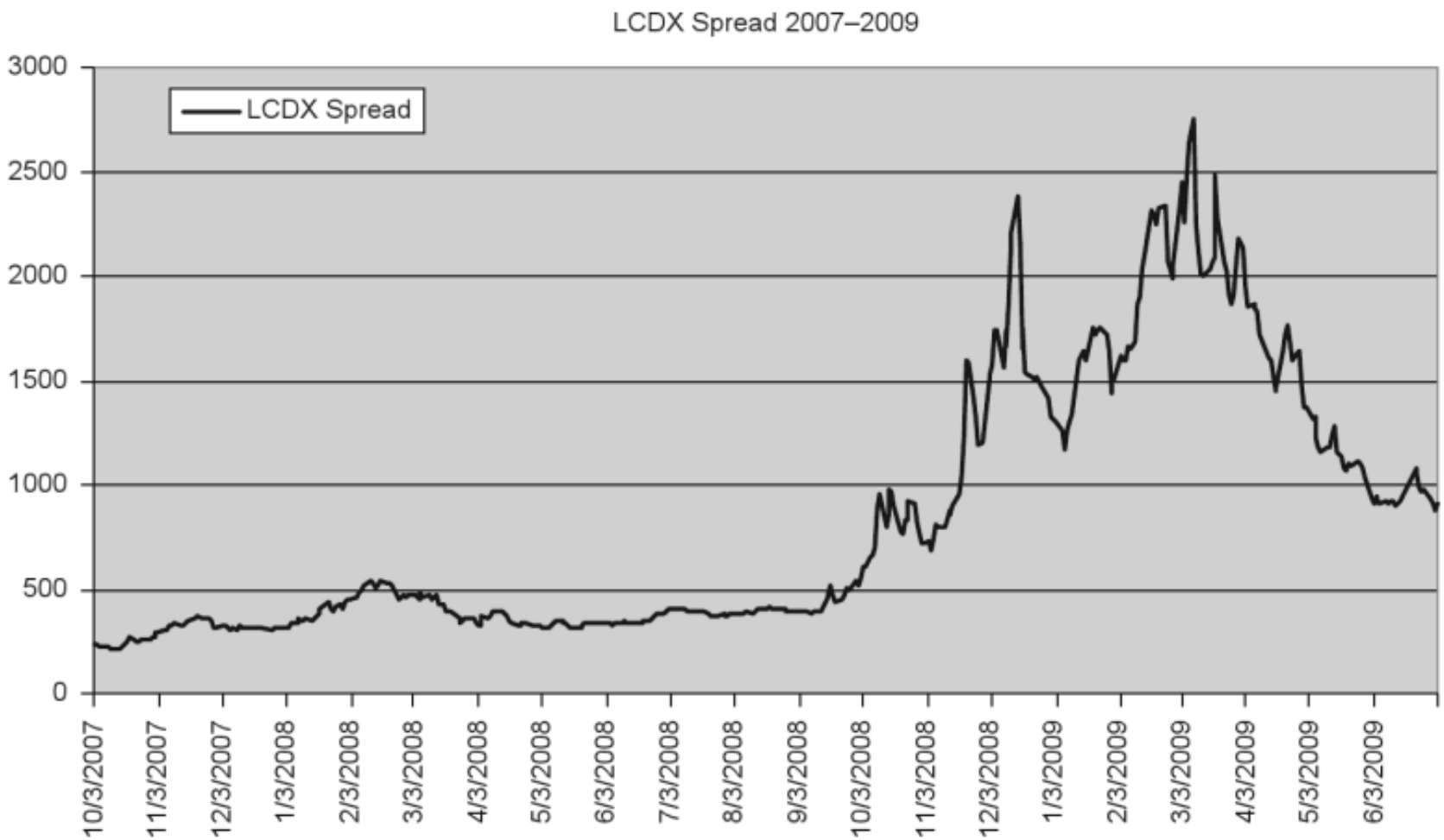


FIGURE 2.7 The Cost of Credit Risk and Loan Index Swap Spreads
The LCDX is a composite of three different indices that were offered consecutively over the time period.
Source: Reuters Loan Pricing Corporation web site, www.loanpricing.com/.

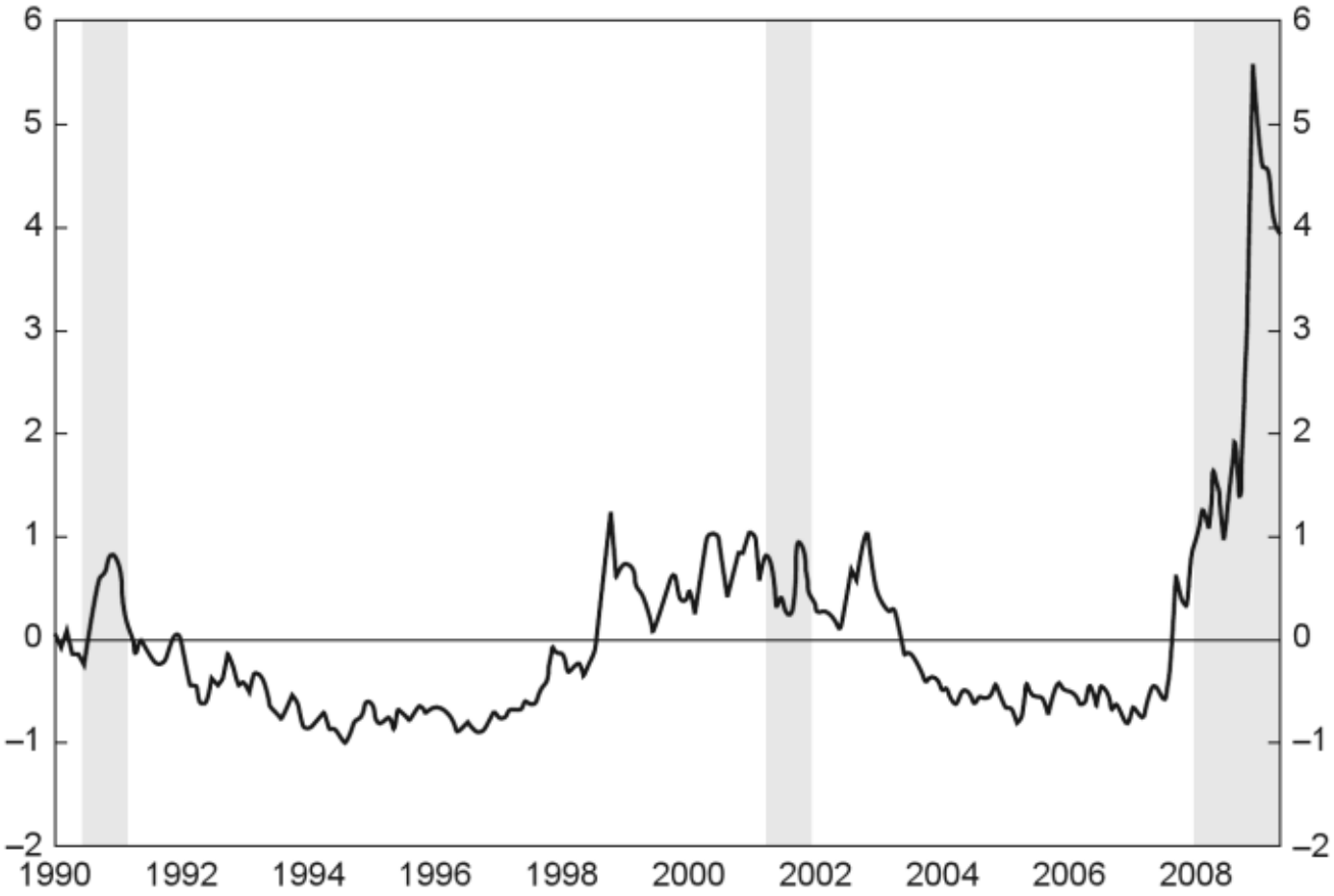


FIGURE 2.9 Kansas City Financial Stress Index (KCFSI)
Note: Index is calculated using data from February 1990 to March 2009. Shaded areas are recessions.
Source: C. S. Hakkio and W. R. Keeton, "Financial Stress: What Is It, How Can It Be Measured, and Why Does It Matter?" Federal Reserve Bank of Kansas City, *Economic Review*, Second Quarter 2009, Chart 1, page 21.

Figure 3, Panel A Mean regimes BBB

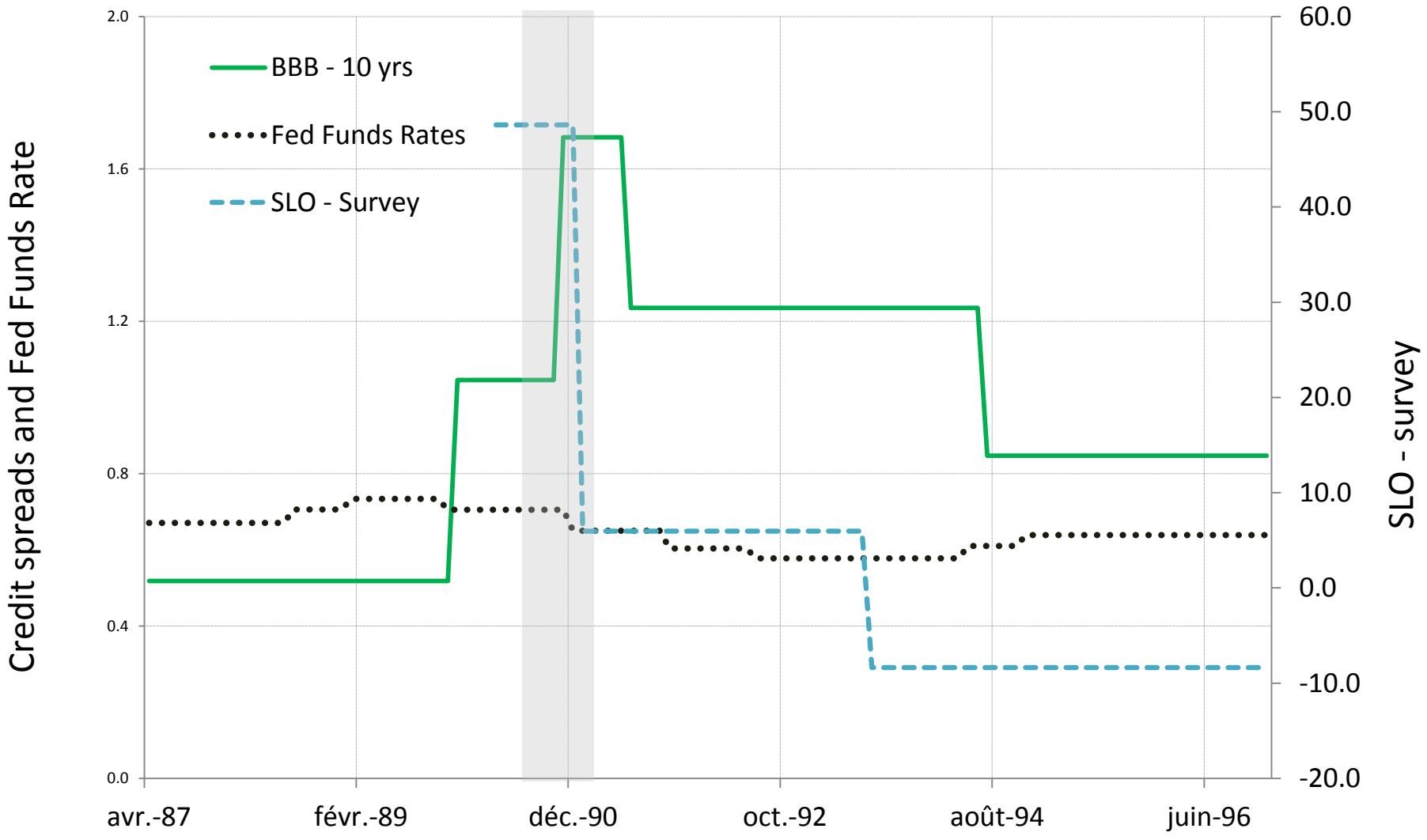


Figure 3, Panel B Mean regimes BBB and BB