Regime switches in volatility and correlation of financial institutions

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NBB Conference Endogenous Risk

October 11, 2012

Motivation and contributions

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- Forecasting volatility and correlation of financial institutions is a central concern for (i) Monitoring and managing the stability of the financial system; (ii) Internal risk management of financial institutions.
- The standard approach is to assume a single regime model and extrapolate the past to the future.
  - ✓ Challenged by a growing (especially) theoretical evidence of multiple risk regimes, with rapid transitions (e.g. due to swings in interbank confidence, liquidity);

Multiple regimes

- Question: Is there a gain in using regime-switching volatility–correlation models?
  - ✓ Relevance of the question: Single regime models are likely to fail when they are most needed, at the time of a transition between a low risk and high risk regime.

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Quid within–regime dynamics?

- Since Haas et al (2004) it has become standard to model regime switching GARCH models as:

$$\begin{cases} h_t^I = \omega^I + \alpha^I y_{t-1}^2 + \beta^I h_{t-1}^I \\ h_t^{II} = \omega^{II} + \alpha^{II} y_{t-1}^2 + \beta^{II} h_{t-1}^{II} \end{cases}$$

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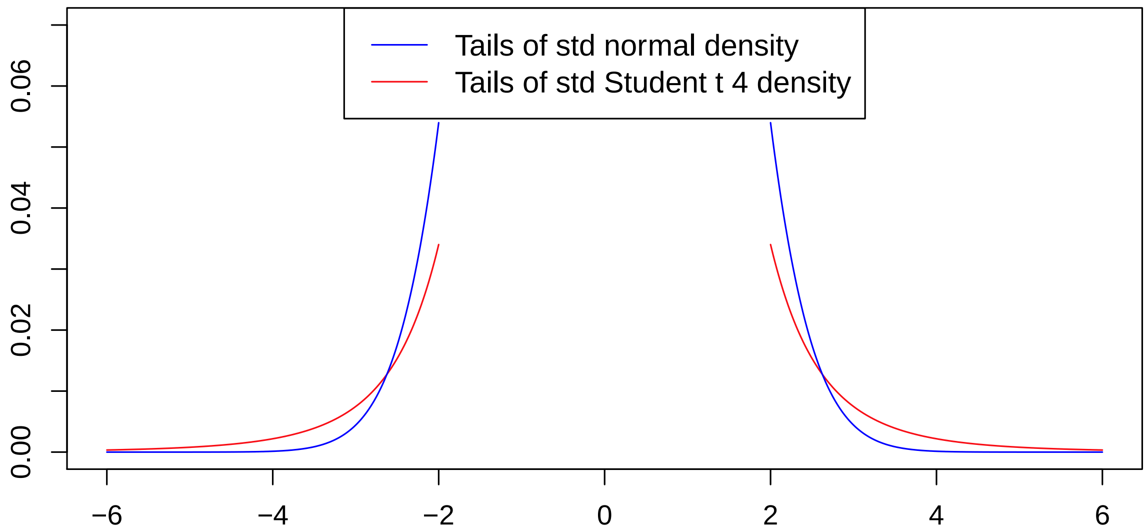
- for both Normal and Student t innovations, which is not intuitive:



Standard approach: same volatility response whatever the return distribution

- An extreme (positive/negative) return is a stronger signal of a volatility increase under the normal distribution than a fat tailed distribution $\Rightarrow$ Different volatility dynamics.
- Proposed Solution: The within–regime dynamics in volatility and correlation are driven by the score of the conditional density function
- As a result, the volatility/correlation impact of extreme returns is downweighted under a fat-tailed distribution.

- Universe of 15 largest US deposit banks over the period 1994–2011.

FDIC Federal Deposit Insurance Corporation
Each depositor insured to at least $250,000 per insured bank

Advanced Sea

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Summary of Deposits | Find Office | Deposit Market Share | Summary Tables | Charts and Graphs | Download | Institution Directory | SOD

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Deposits of all FDIC-Insured Institutions

Top 50 Bank Holding Companies by Total Domestic Deposits

Data as of June 30, 2011

Run Report

(Dollars Amounts In Thousands)

Bank Holding Company Name	BHC ID	State Headquartered	No. of Offices	Total Deposits June 30, 2012
BANK OF AMERICA CORPORATION	1073757	North Carolina	5,660	1,129,250,260
WELLS FARGO & COMPANY	1120754	California	6,316	891,436,613
JPMORGAN CHASE & CO.	1039502	New York	5,608	865,033,241
CITIGROUP INC.	1951350	New York	1,070	396,032,674
CAPITAL ONE FINANCIAL CORPORATION	2277860	Virginia	972	232,691,001
U.S. BANCORP	1119794	Minnesota	3,134	220,712,719
PNC FINANCIAL SERVICES GROUP, INC., THE	1069778	Pennsylvania	3,044	203,375,163
TORONTO-DOMINION BANK, THE	1238565	Foreign *	1,311	170,053,522
BB&T CORPORATION	1074156	North Carolina	1,775	132,489,056
SUNTRUST BANKS, INC.	1131787	Georgia	1,688	130,414,635
BANK OF NEW YORK MELLON CORPORATION, THE	3587146	New York	60	127,972,134
UK FINANCIAL INVESTMENTS LIMITED	3833526	Foreign *	1,411	101,822,343
HSBC HOLDINGS PLC	1857108	Foreign *	319	100,376,541

Top 15 largest US deposit banks	First	End
Bank of New York Mellon Corp	2008	2011
Bankamerica Corp	1994	1998
Bank One Corp	1994	2011
Barnett Banks Inc	1994	1997
Capital One Financial Corp	2006	2011
Chemical Banking Corp, Chase Manhattan Corp, JP Morgan Chase & Co	1994	2011
Citicorp	1994	1998
Citigroup	1999	2011
Fifth Third Bancorp	2001	2011
First Union Corp, Wachovia Corp	1994	2008
Fleet Financial Group Inc, Fleet Boston Corp, Fleetboston Financial Corp	1994	2003
Keycorp	1994	2011
Morgan Stanley	2009	2011
National City Corp	1996	2008
Nationsbank Corp, Bankamerica Corp, Bank of America Corp	1994	2011
Norwest Corp	1994	1998
PNC Bank Corp, PNC Financial Services GRP Inc	1994	2011
Regions Financial Corp	2005	2011
Southern National Corp NC, BB&T Corp	2000	2011
Suntrust Banks Inc	1994	2011
US Bancorp	1998	2011
Wells Fargo & Co	1994	2011

Dynamic universe

- Application: US deposit banks 1994–2011.
  - ✓ Problem: Banking universe is unstable;
  - ✓ Proposed solution: Assumption of equicorrelation across banks. Together with a copula function, it makes the proposed model computationally convenient to estimate and tractable.

Outline

- Review literature on risk regimes of financial institutions;
- Model;
- Results;
- Conclusion.

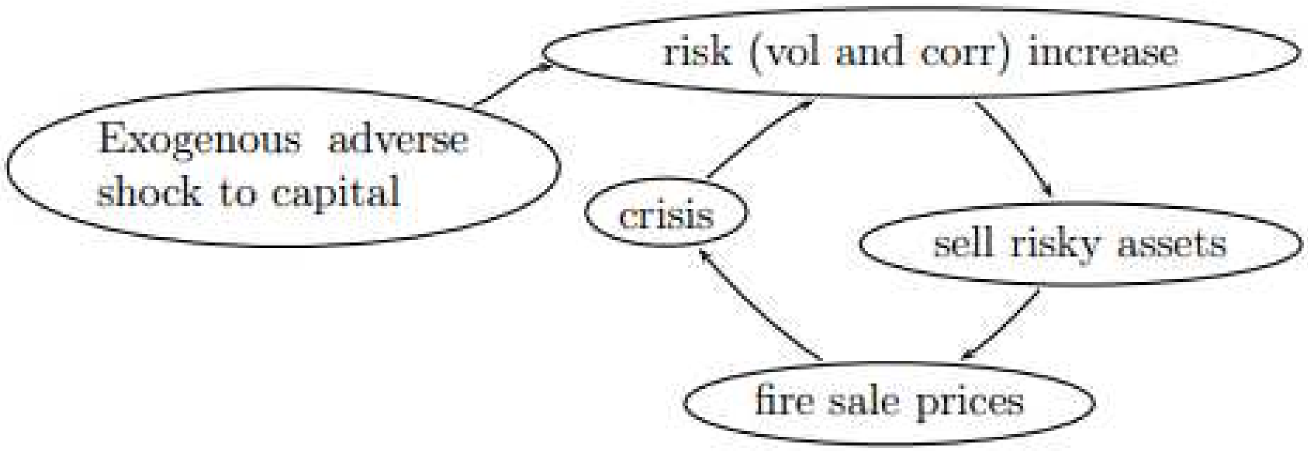
Review literature risk regimes

Exogenous and endogenous

- Danielsson and Shin (2003):
  - ✓ Exogenous risk: regimes whereby price changes are due to reasons outside the control of market participants;
  - ✓ Endogenous risk: behavior of market players creates additional risk with respect to the uncertainty of fundamental news.

Exogenous and endogenous

- Example of fire sales in Danielsson, Shin and Zigrand (2011) due a maximum risk constraint.



Exogenous and endogenous

- Example of destabilizing liquidity relation between market liquidity and equity collateralized funding liquidity in Brunnermeier and Pedersen (2009).

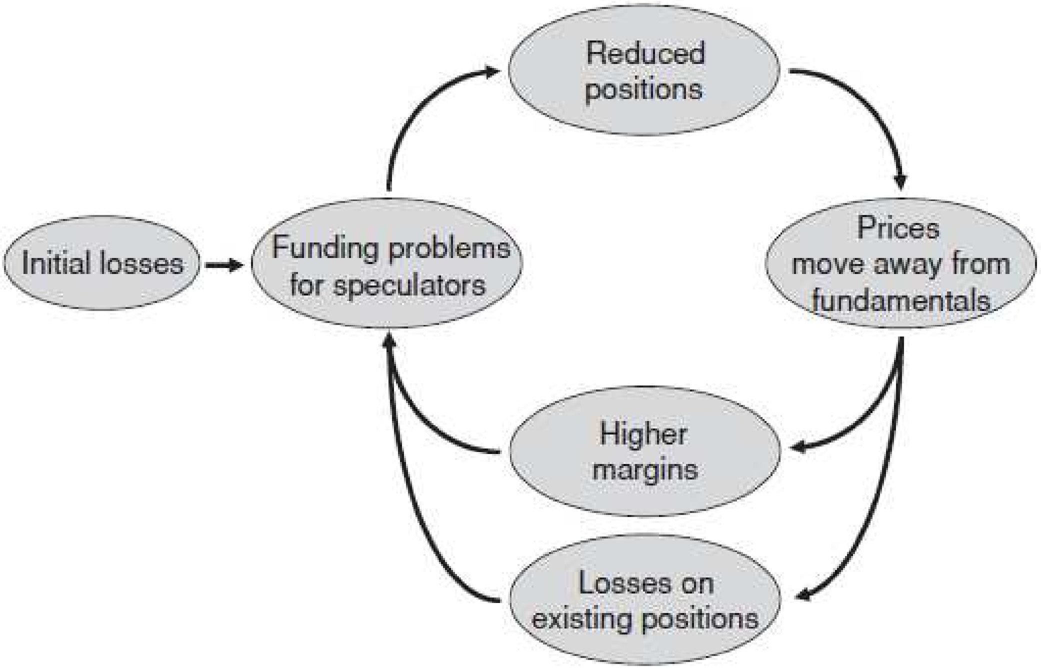


Figure 2
Liquidity spirals
The figure shows the loss spiral and the margin/haircut spiral.

Further reasons for multiple risk regimes in financial institutions

- Example of cycles between asset prices and balance sheets of financial institutions that are marked to market (Adrian and Shin, 2010):
  - ✓ When balance sheets are marked to market, increase in value assets, leads to drop in leverage $(V_A/(V_A - D))$ if banks were passive. However, historically banks seem to have a constant leverage target: during the boom, they take on more short term debt and expand their balance sheet. And vice versa during the downturn.
- Literature on endogenous risk regimes is relatively new, but existence of relation between the macroeconomy (business cycles) and financial volatility is already shown in Officer (1993), Hamilton and Lin, (1996), among others.

Model

Assumptions

- No within–regime dynamics in the mean;
- Two volatility and correlation regimes, conditional density in each regime is Student t (copula)

$$
\begin{aligned}
f_{t|t-1}(y_t;\theta) \quad &= \quad \prod_{i=1}^{N} f_{it|t-1}(y_{it};\theta_i) \\
&\quad \times c_{t|t-1}(F_{1t|t-1}(y_{1t}),\ldots,F_{Nt|t-1}(y_{Nt});\theta_*).
\end{aligned}
$$

- Across-regime dynamics: macro-financial variables;
- Within–regime dynamics: score.

The Generalized Autoregressive Score Framework to Dynamic Models

- Creal, Koopman, Lucas (2012) and Harvey and Chakravarty (2008): general framework, imposing "structure" on how dynamic models are created.

- The dynamic "Generalized Autoregressive Score" model for a parameter λ_t (e.g. variance h^k_{it}, correlation ρ^k_t) is:

$$\lambda^k_t = o^k + a^k(\lambda^k_{t-1} + S^k_{t-1}\nabla^k_{t-1}) + b^k\lambda^k_{t-1},$$

  where ∇^k_t is the score of the conditional density function:

$$\nabla^k_t = \frac{\partial \log p(y_t|m^k, H^k_t, s_t = k)}{\partial \lambda^k_t}.$$

- Scaling factor: $S^k_t = 1$ (steepest ascent), S^k_t the inverse of the conditional variance (Gauss-Newton updating) or S^k_t the inverse of the conditional standard deviation (Nelson, 1994).

Volatility model

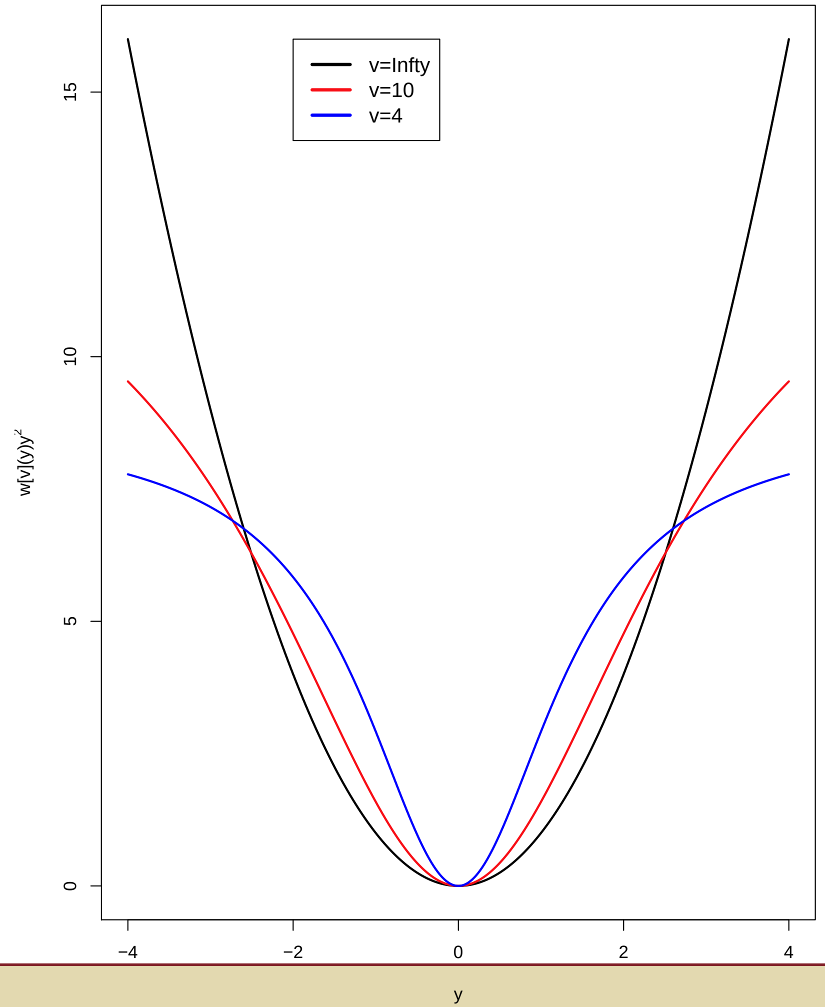
- The within-regime volatility dynamics are:

$$h_{it}^k = \omega_i^k + \alpha_i^k (1 + 3/\nu_i^k) \frac{\nu_i^k + 1}{[\nu_i^k - 2] + \frac{[y_{it-1} - \mu_i^k]^2}{h_{it-1}^k}} (y_{it-1} - \mu_i^k)^2 + \beta_i^k h_{it-1}^k .$$

- Note:
  - ✓ $\nu = \infty$: RS-GARCH model of Haas et al (JFEC, 2011, no path dependence regime specific vol)
  - ✓ The more fat-tailed the distribution is, the more extreme observations are downweighted.

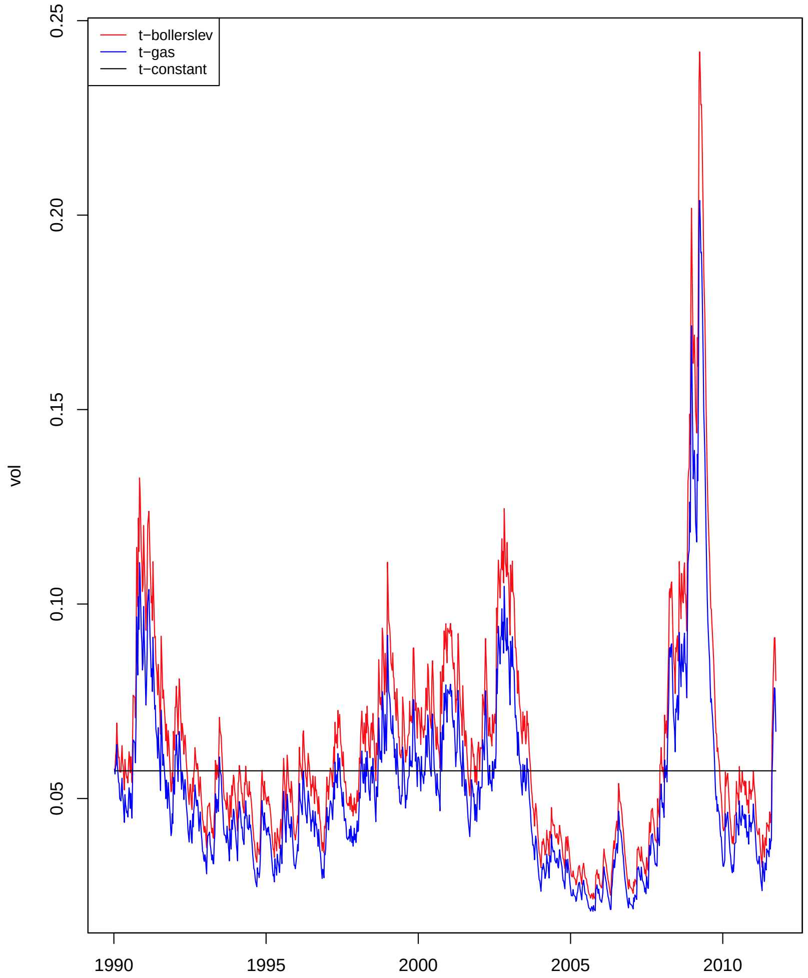
Volatility model

- News impact curve under the Student t score-based conditional variance model



Volatility model

- Conditional volatility weekly return JPM 1990-2011



Correlation model

- A single parameter, assuming equicorrelation:

$$R_t^k = \begin{pmatrix} 1 & \rho_t & \dots & \rho_t \\ \rho_t & 1 & \dots & \rho_t \\ \rho_t & \rho_t & \ddots & \rho_t \\ \rho_t & \rho_t & \dots & 1 \end{pmatrix}$$

Why?

- We focuss on firms belonging to the same sector;
- Inclusion, deletions sector;
- Simplicity, both in terms of analysis, as computational convenience (no matrices calculations needed).
- See Engle and Kelly (2012, JBES) for single regime DECO.

Correlation model

- To make sure that the estimated correlations are bounded, we specify ρ_t^k as the hyperbolic tangent of an underlying process q_t^k with GAS(1,1) dynamics:

$$\rho_t^k = (\exp(2q_t^k) - 1)/(\exp(2q_t^k) + 1)).$$

$$q_t^k = \omega_*^k + \alpha_*^k(q_{t-1}^k + S_{t-1}^k \nabla_{t-1}^k) + \beta_*^k q_{t-1}^k,$$

where ∇_t^k is the score of the Student t copula density function and S_t^k is the inverse of the conditional standard deviation of the score, and $\alpha_*^k, \beta_*^k > 0$.

Correlation model

$$S_t^k \nabla_t^k = \underbrace{m_t^k}_{>0} \left[\underbrace{b_t^k}_{>0} \left(\frac{w_t^k}{(N-1)N} \sum_{i=1}^{N} \sum_{j \neq i} \tilde{y}_{it} \tilde{y}_{jt} - \rho_t^k \right) + a_t^k \left(\frac{w_t^k}{N} \sum_{i=1}^{N} \tilde{y}_{it}^2 - 1 \right) \right]$$

The score has three main components:

1. The excess value of the cross-product of weighted devolatilized returns and the conditional correlation: **enforces an increase in the conditional correlation process when the average cross-product of the devolatilized returns exceeds the conditional correlation ρ_t^k,**

Correlation model

$$S_t^k \nabla_t^k = \underbrace{m_t^k}_{>0} \Big[\underbrace{b_t^k}_{>0} \Big(\frac{w_t^k}{(N-1)N} \sum_{i=1}^{N} \sum_{j \neq i} \tilde{y}_{it} \tilde{y}_{jt} - \rho_t^k \Big) + a_t^k \Big(\frac{w_t^k}{N} \sum_{i=1}^{N} \tilde{y}_{it}^2 - 1 \Big) \Big]$$

$$a_t^k = -\rho_t^k (2 + \rho_t^k (N-2))$$

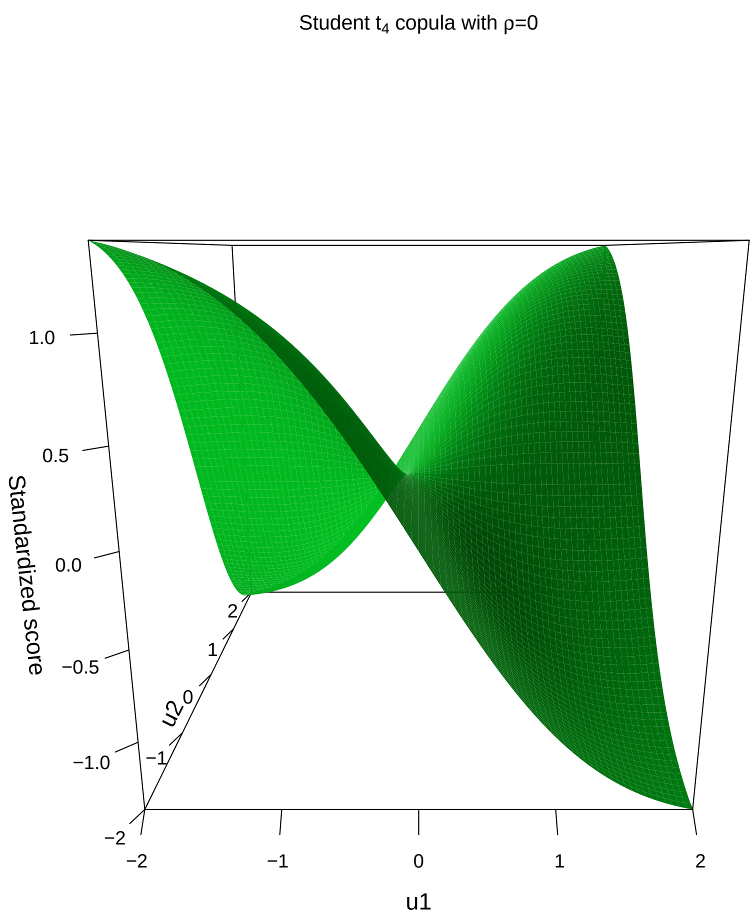
2. The excess value of the Eucledian norm of those returns and unity: **corrects for dispersion**. The higher the dispersion, the less informative high values of the cross-products are about increases in correlation. E.g. the correlation signal of $(1,1)$ is much stronger than $(1/4,4)$, even though their cross-product is the same.

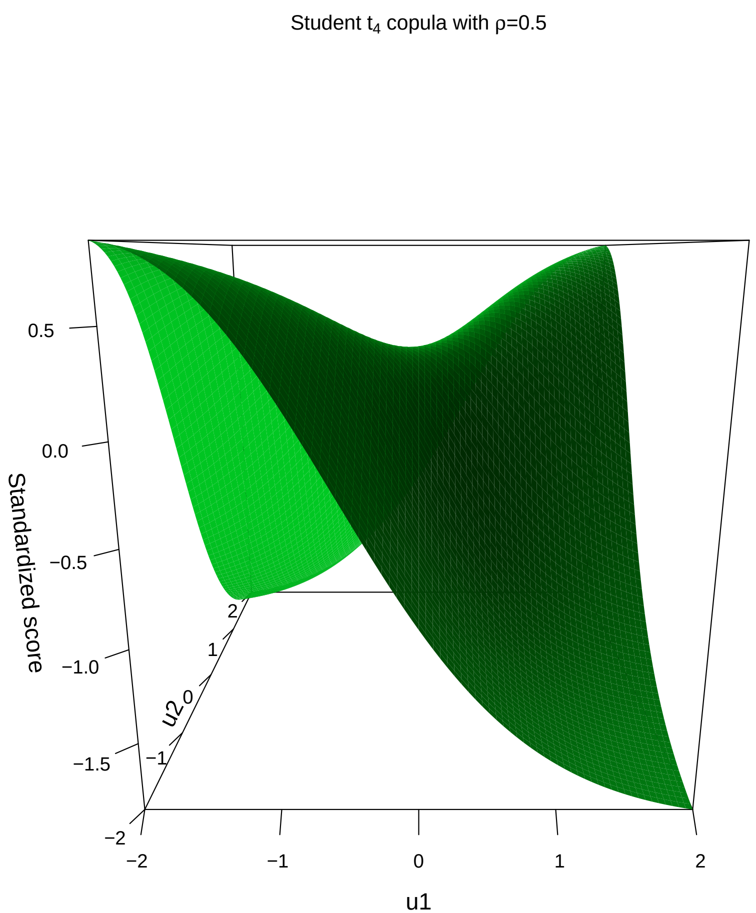
Correlation model

$$S_t^k \nabla_t^k = m_t^k \left[b_t^k \left(\frac{w_t^k}{(N-1)N} \sum_{i=1}^{N} \sum_{j \neq i} \tilde{y}_{it} \tilde{y}_{jt} - \rho_t^k \right) + a_t^k \left(\frac{w_t^k}{N} \sum_{i=1}^{N} \tilde{y}_{it}^2 - 1 \right) \right]$$

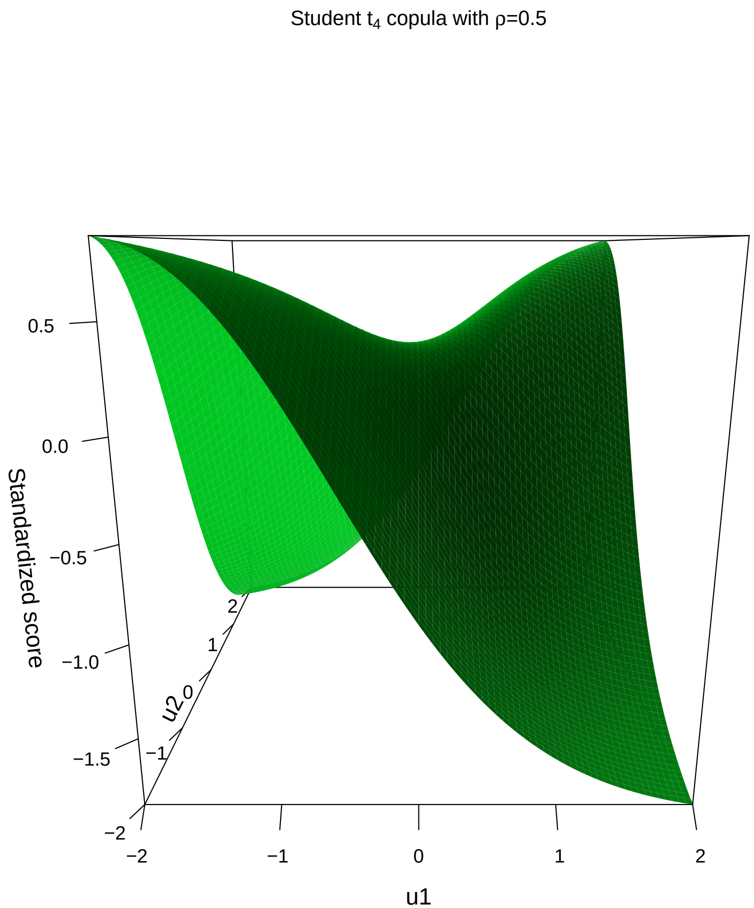
3. The weights applied to the devolatilized returns.

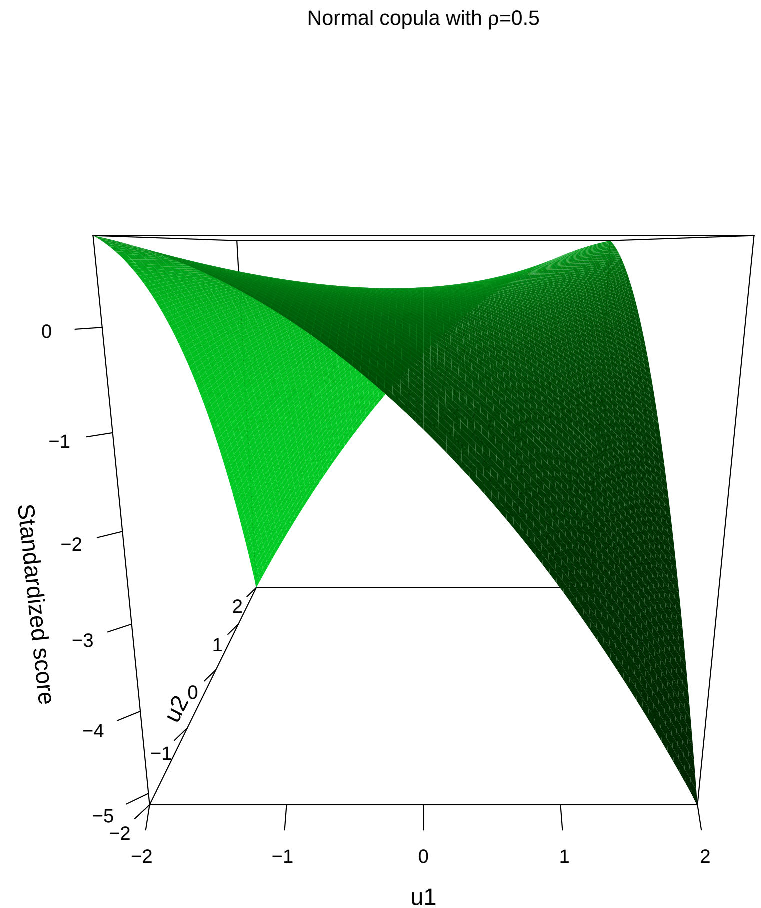
$$w_t^k = \frac{N + {\nu_*}^k}{{\nu_*}^k - 2 + (\tilde{y}_t^k)'(R_t^k)^{-1}(\tilde{y}_t^k)}$$





- Downweighting in function of squared Mahalanobis distance. Correlation coefficient impacts the curvature and which values are considered as extreme.





- The thicker the tails, the more likely it is that abnormally large values of the realized covariance are due to the heavy-tailed feature of the distribution rather than changes in correlation, and therefore the smaller the impact relatively to the Gaussian case.

Model for transition probabilities

- We assume the states follow a Markov process with the 2×2 dynamic transition matrix $P_{i|t}$. The diagonal elements of this matrix are parameterized using the logit transformation of the time-varying quantities π_{it}^{I} and π_{it}^{II}:

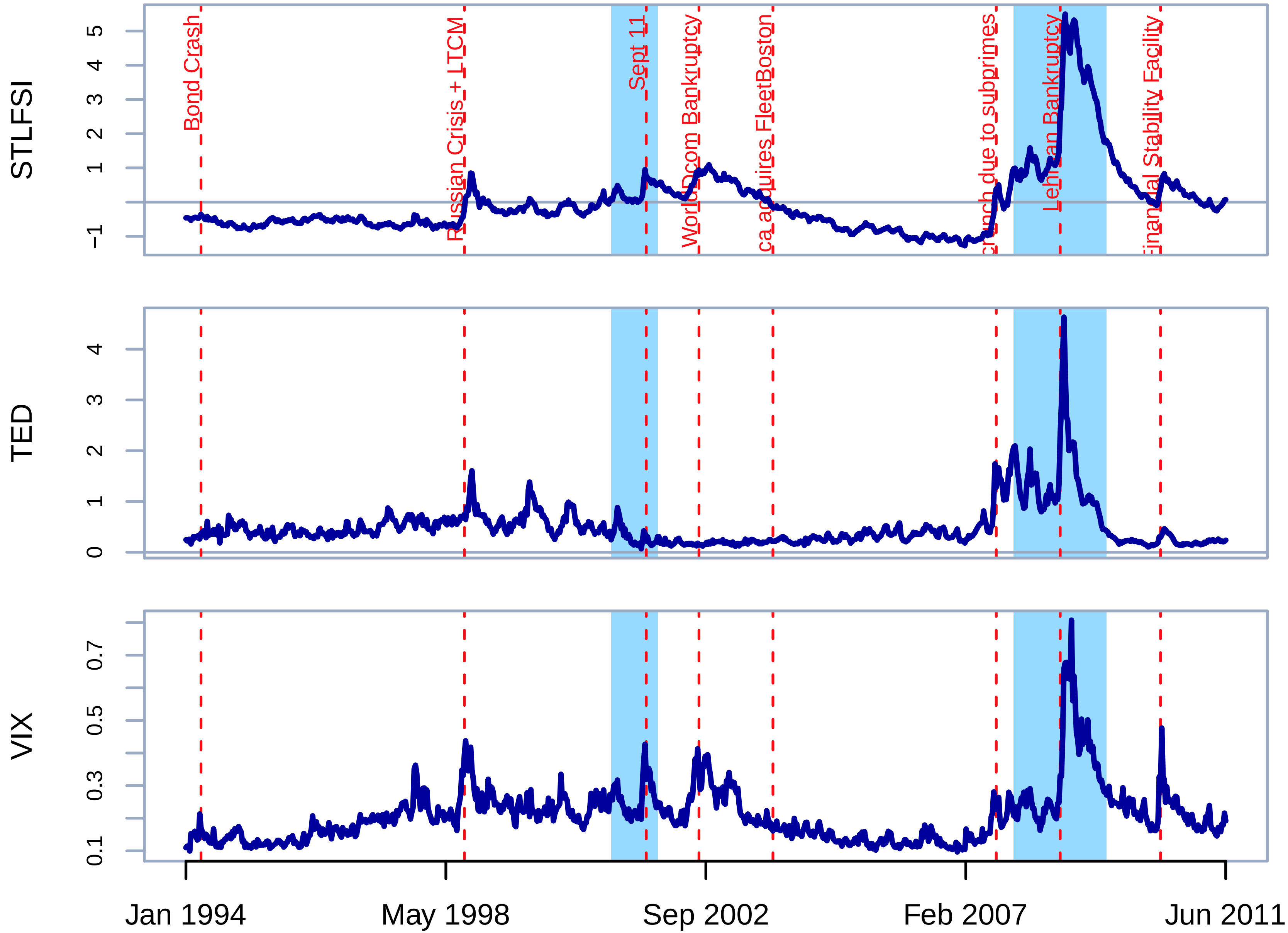
$$
\begin{aligned}
P_{(11)it} &= \exp(\pi_{it}^{I})/[1+\exp(\pi_{it}^{I})]; \\
P_{(22)it} &= \exp(\pi_{it}^{II})/[1+\exp(\pi_{it}^{II})]. \\
\pi_{it}^{I} &= c_i^{I} + d_i^{I} x_{t-1} \\
\pi_{it}^{II} &= c_i^{II} + d_i^{II} x_{t-1},
\end{aligned}
$$

with x_{t-1} the time $t-1$ value of the exogenous variable (VIX, TED spread, Saint Louis Financial Stability Index).

State variables

- Used as drivers for changes in the transition probabilities between risk regimes;
  - ✓ Implied Volatility: VIX
  - ✓ Credit risk: TED spread (3-month LIBOR - T-bill)
  - ✓ Saint Louis Financial Stability Index (STLFSI) is defined as the first principal component of eighteen major financial time series capturing some aspect of financial stress (7 interest rates, 6 yield spreads, VIX, Merrill Lynch Bond Market Volatility Index,...).

- Time series of weekly values of the Saint-Louis Financial Stability Index, the TED spread and the VIX.

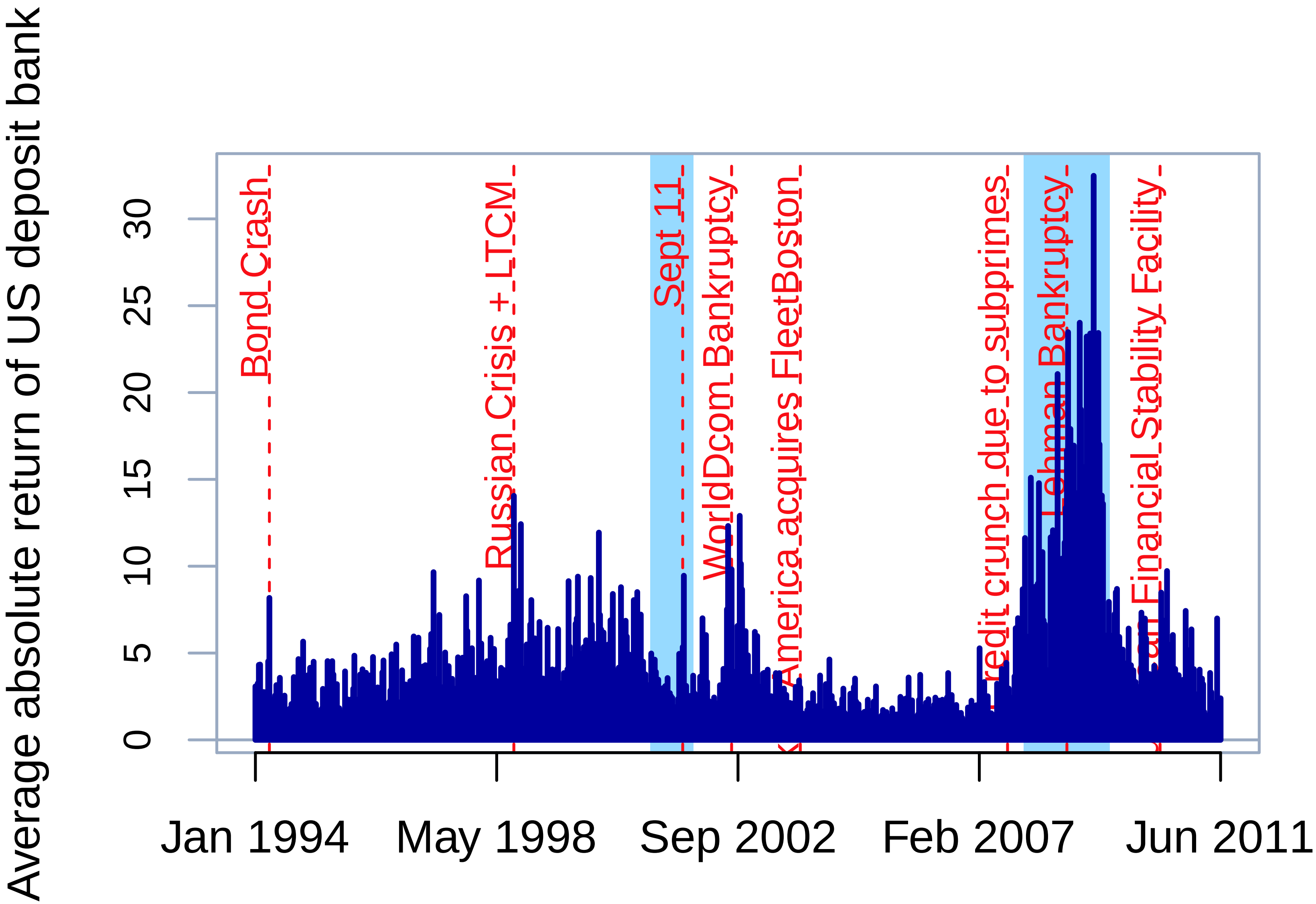


Estimation

- Inference on regime probabilities through the standard Hamilton filter;
- Two–step maximum likelihood (copula assumption);
  - ✓ marginal and copula LLH are tractable (efficient implementation in c++);
  - ✓ still complex, because of multiple local optima (differential evolution to obtain good starting values).

Results

- Time series of 1994–2011 weekly values of the mean absolute returns across US deposit bank holding companies.



Q1: How to model volatility of US deposit banks

- Of all models considered, the lowest BIC is always achieved by a double regime volatility model, with time-varying transition probabilities.
- The STLFSI, TED spread and VIX are selected 6, 6, and 10 times respectively.
- For shorter return series, at least one of the regimes tends to be characterized by constant volatility.
- The t-garch model is selected for 8 banks, the t-gas model for 10 banks.

- Average standardized BIC of volatility models for US deposit banks.

R1	R2	BIC	BIC-STLFSI	BIC-TED	BIC-VIX
t-constant		0.965			
g-GAS		0.933			
t-gas		**0.923**			
t-GARCH		0.931			
t-constant	t-constant	0.947	0.893	0.887	<u>0.832</u>
t-gas	t-constant	0.941	0.859	0.83	<u>0.8</u>
t-garch	t-constant	0.94	0.855	0.83	<u>0.818</u>
g-gas	g-gas	0.935	0.885	0.868	<u>0.854</u>
t-gas	t-gas	0.935	**0.852**	**0.825**	<u>0.789</u>
t-garch	t-garch	0.945	0.855	0.828	<u>**0.788**</u>

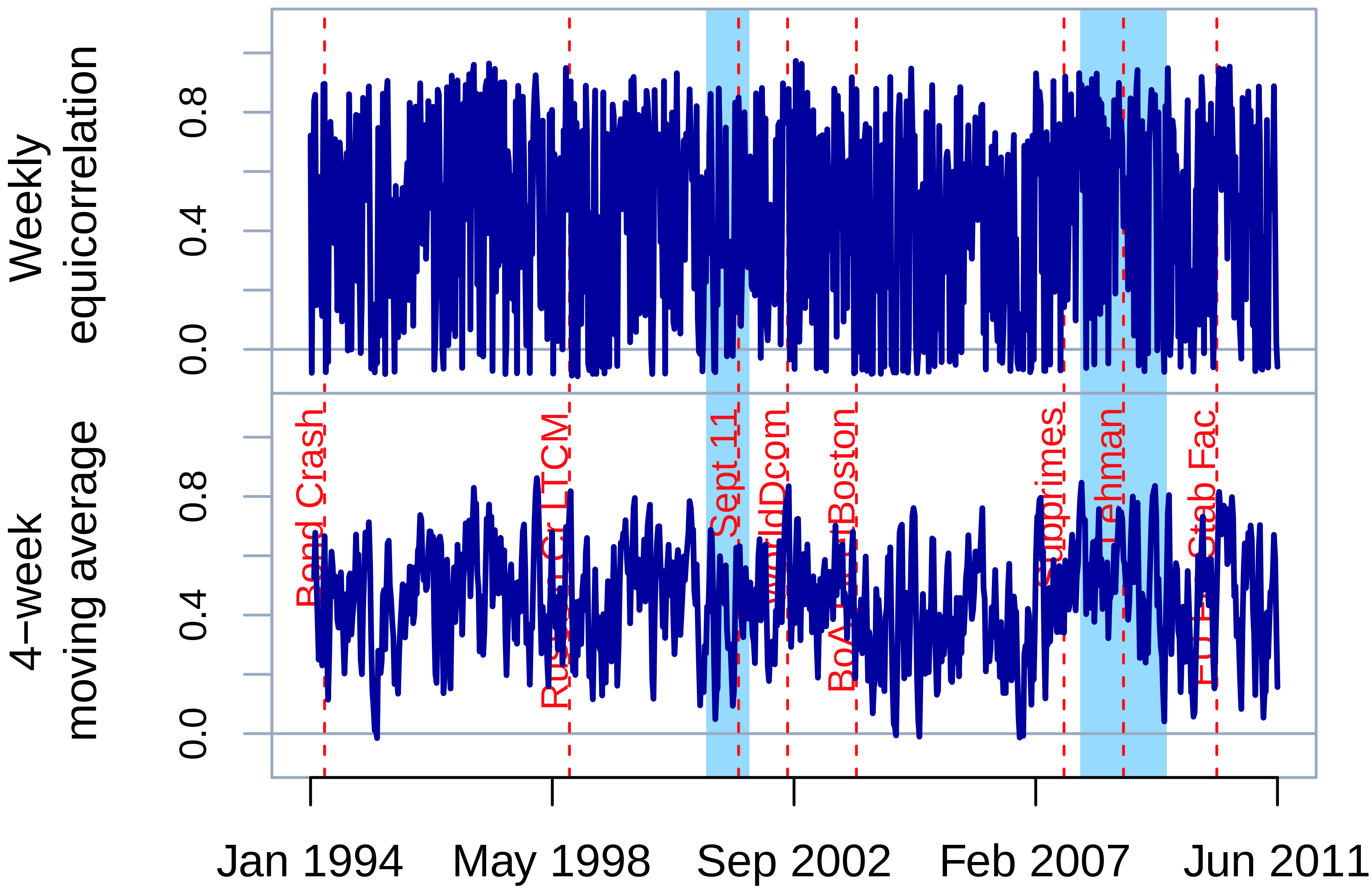
Equicorrelations

- The ratio between the cross-sectional covariance between the returns in the universe and the variance of these returns can be seen as a proxy for the equicorrelation:

$$r_t = [\frac{1}{\sum_{i=1}^{N-1}\sum_{j=i+1}^{N} I_{it}I_{jt}} \sum_{i=1}^{N-1}\sum_{j=i+1}^{N} y_{it}y_{jt}I_{it}I_{jt}]/[\frac{1}{\sum_{i=1}^{N} I_{it}} \sum_{i=1}^{N} y_{it}^2 I_{it}],$$

with I_{it} the dummy variable indicating that bank i belongs to the top 15 of US deposit bank holding firms in year t.

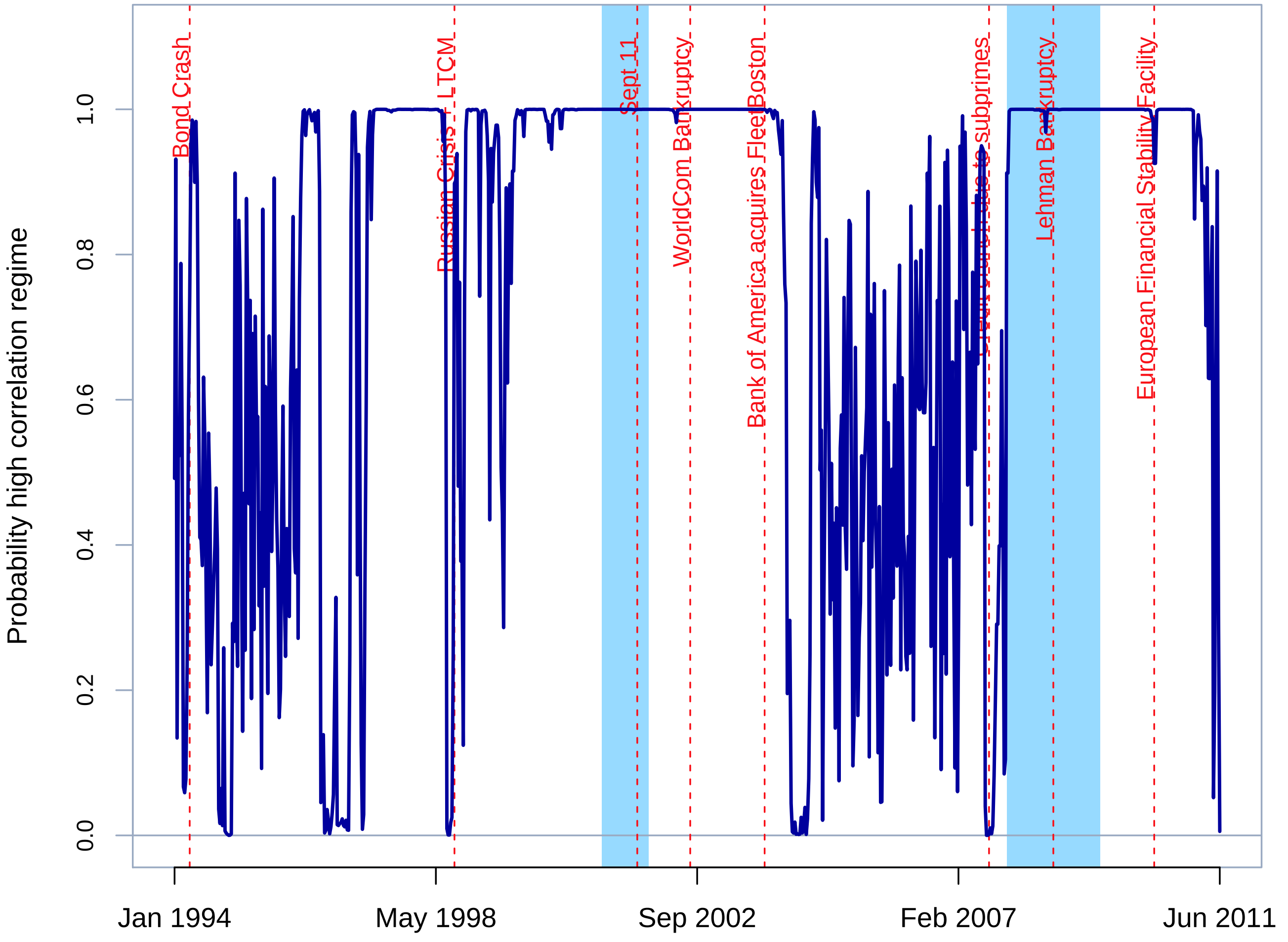
- Time series of realized equicorrelations across US deposit bank holding companies, its rolling 4-week average value and the sample average.



Q2: Dynamics in the t-copula?

- (challenging, not finished)
- There does not seem to be much to gain from modeling the within–regime dynamics, which is in support of the regime switching constant correlation model of Pelletier (2006), but with time-varying transition probabilities;
- Best model is a 2-regime model with correlations around 0.42 and 0.75, with time-variation driven by the VIX.

- Time series of predicted probabilities to be in the high correlation regime.



Conclusion

Conclusion

- Recent literature on exogenous and endogenous risk regimes implies *potential* usefulness of regime switching models;
- We study this question for the volatility and correlation regimes in weekly returns of financial institutions;
- For this, a regime switching volatility–correlation model is proposed;
- Key feature: within–regime dynamics are driven by the score; across–regime dynamics by macroeconomic financial time series;
- Main finding: Strong evidence of regime switches in volatility and correlation, when using time-varying trainsition probabilities (especially VIX).

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