The Impact of Credit Market Sentiment Shocks – A TVAR Approach

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Investor beliefs and credit cycles

Great Financial Crisis 08 revived the interest among economists and policymakers

- about the role of financial frictions and belief formation at financial markets
- long-standing debate on the rational expectations assumption (Fama, 1970)
- how to tackle issues of financial instability from a central bank perspective (Stein, 2014)

We provide macro evidence to a current theoretical debate on credit cycles and market sentiments (Kubin et al., 2019).

Contribution

Empirical validation of the impact of credit market sentiments on the credit and business cycle

- using monthly US data between 1968 and 2014 from the FRED (McCracken and Ng, 2016)
- estimating small macroeconomic model of the US economy enriched with behavioral elements
  - disentangling 'optimistic' and 'pessimistic' credit market sentiment regimes (Balke, 2000; Kubin et al., 2019)
  - employing a psychologically grounded belief formation mechanism (Bordalo et al., 2018)
  - implementing an unexpected sentiment shock as an instrument for identification (Mertens and Ravn, 2013)

Explaining economic instability

Building on rational expectations

- early contributions show that exogenous shocks amplify and propagate business cycle movements (Bernanke and Gertler, 1989; Kiyotaki and Moore, 1997)
- Matsuyama et al. (2016) provide an endogenous explanation of credit cycles

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Using a behavioral approach:

- Barberis et al. (1998) already incorporate psychological heuristics into a model of investor sentiment
- Nofsinger (2005) highlights the importance of social mood rather than economic „fundamentals“ in investment decisions
- Bordalo et al. (2018) postulate a psychologically grounded behavioral theory of credit cycles
- Kubin et al. (2019) extends the Matsuyama et. al. model with behavioral elements

Empirical Literature

Exogenous shocks to balance-sheet measures as driver for instability

- Schularick and Taylor (2012) use credit growth as predictor of financial crisis in a long-run historical dataset over the years 1870-2008
- Mian et al. (2017) study the dynamics of household debt as predictor for GDP growth
- Baron and Xiong (2017) show that elevated credit expansion leads to a increase in bank equity crash risk

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Endogenous explanations mostly use credit sentiments as driving force

- Greenwood and Hanson (2013) stress that a decline in in issuer quality is a more reliable signal of credit market overheating than credit growth
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Moreover Bordalo et al. (2018) find predictability of analysts' forecast errors → not explainable by standard approaches

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$$p^{\theta}(\hat{\omega}_{t+1}) = p(\hat{\omega}_{t+1} \mid \omega_t = \hat{\omega}_t) \times \left[\frac{p(\hat{\omega}_{t+1} \mid \omega_t = \hat{\omega}_t)}{p(\hat{\omega}_{t+1} \mid \omega_t = \varphi \hat{\omega}_{t-1})} \right]^{\theta} \frac{1}{Z} \tag{1}$$

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- θ measures the severity of judging according to representativeness
- the state of the economy is a random variable following

$$\begin{aligned} \omega_t \mid \varphi, h_t &\sim \mathcal{N}(\varphi \omega_{t-1}, \exp(h_t)) \\ h_t \mid \mu, \phi, \sigma_h^2 &\sim \mathcal{N}(\mu + \phi(h_{t-1} - \mu), \sigma_h^2) \end{aligned} \tag{2}$$

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Taking expectations yields

$$\mathbb{E}_t^{\theta}(\hat{\omega}_{t+1}) = \mathbb{E}_t(\hat{\omega}_{t+1}) + \theta[\mathbb{E}_t(\hat{\omega}_{t+1}) - \mathbb{E}_{t-1}(\hat{\omega}_{t+1})] \tag{3}$$

Apply this approach to the difference of Baa corporate bond yield and the 10-year Treasury yield, i.e. our credit market sentiment!

Diagnostic Expectations

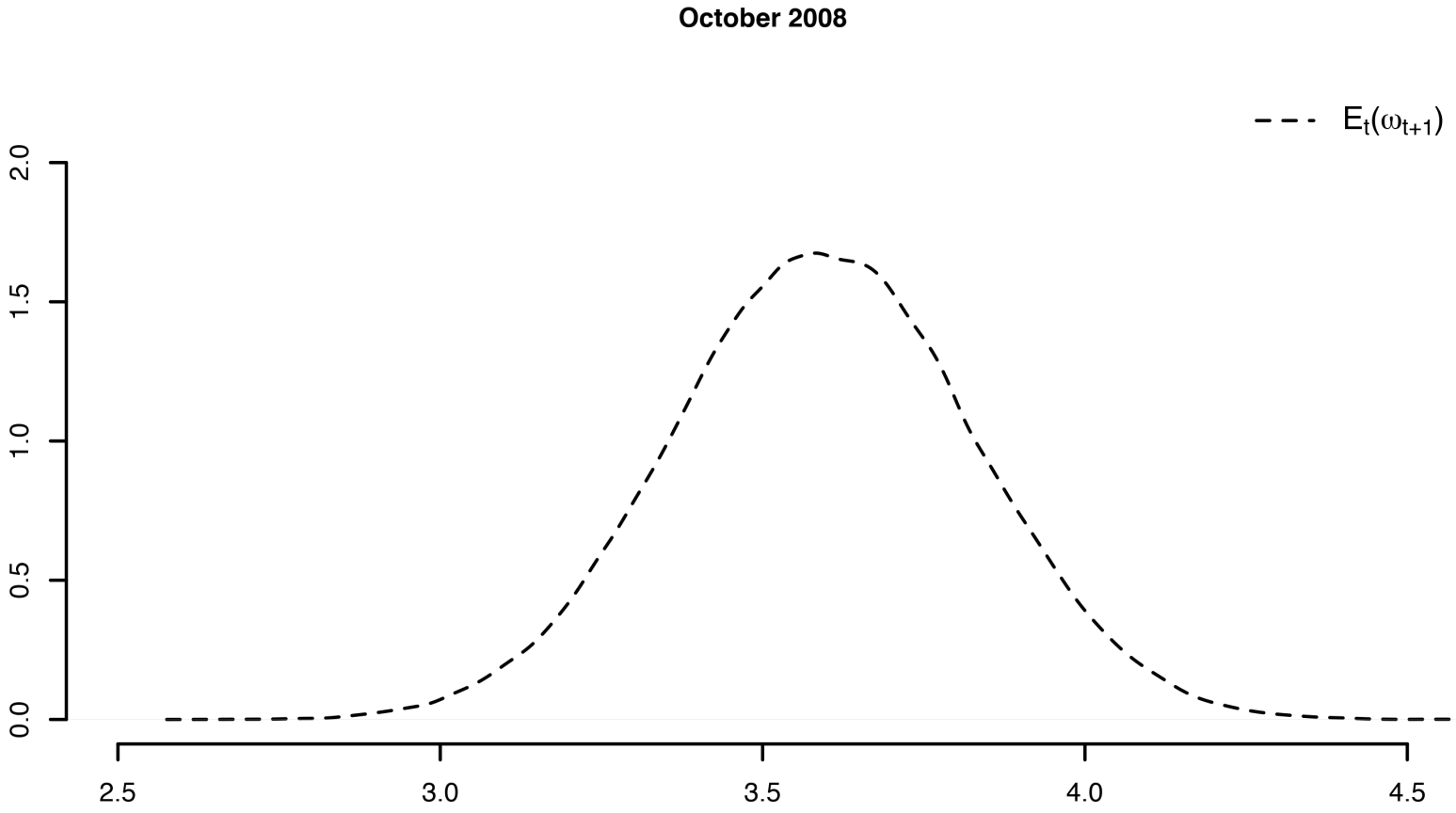
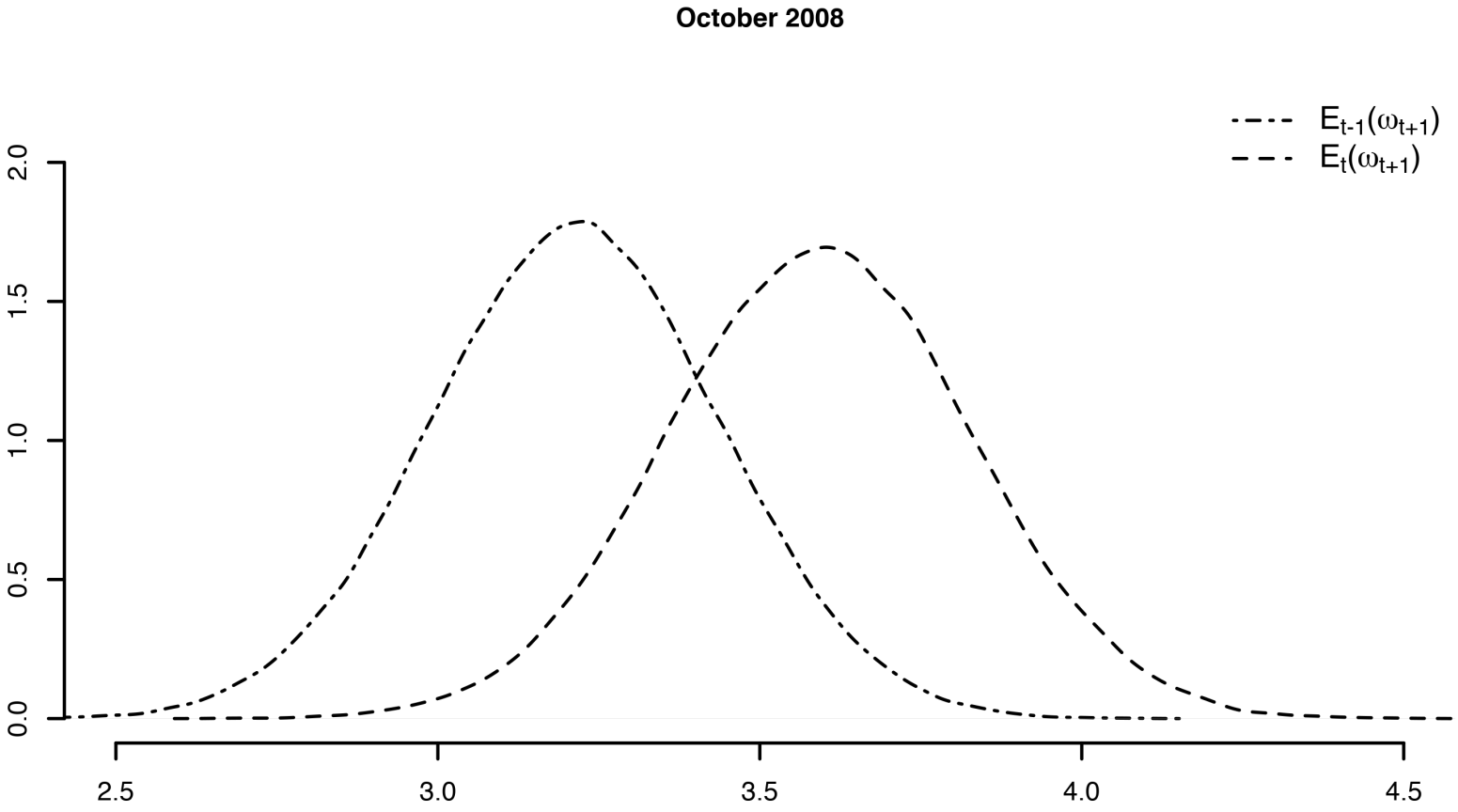


Figure 1: Diagnostic Expectations

Diagnostic Expectations



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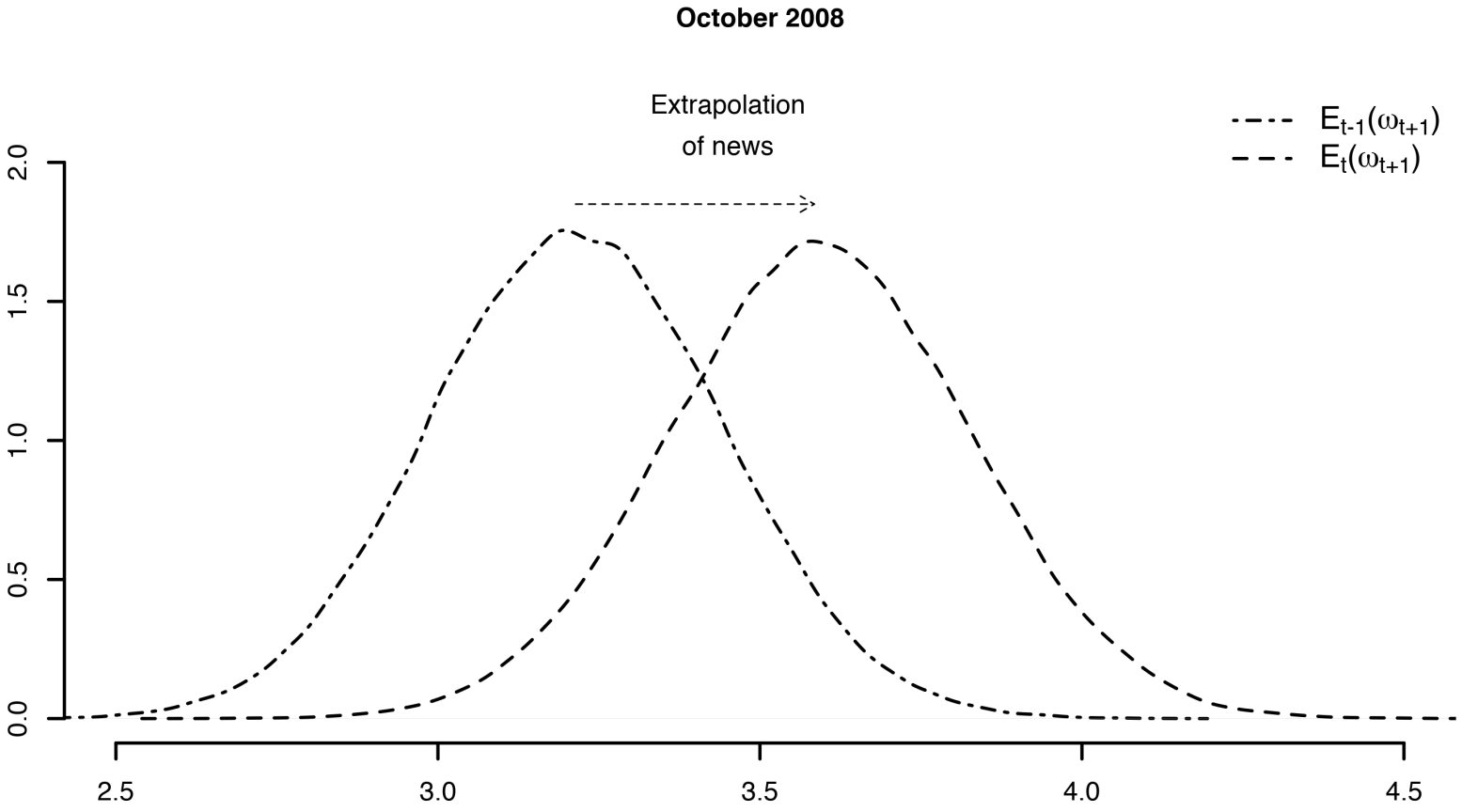

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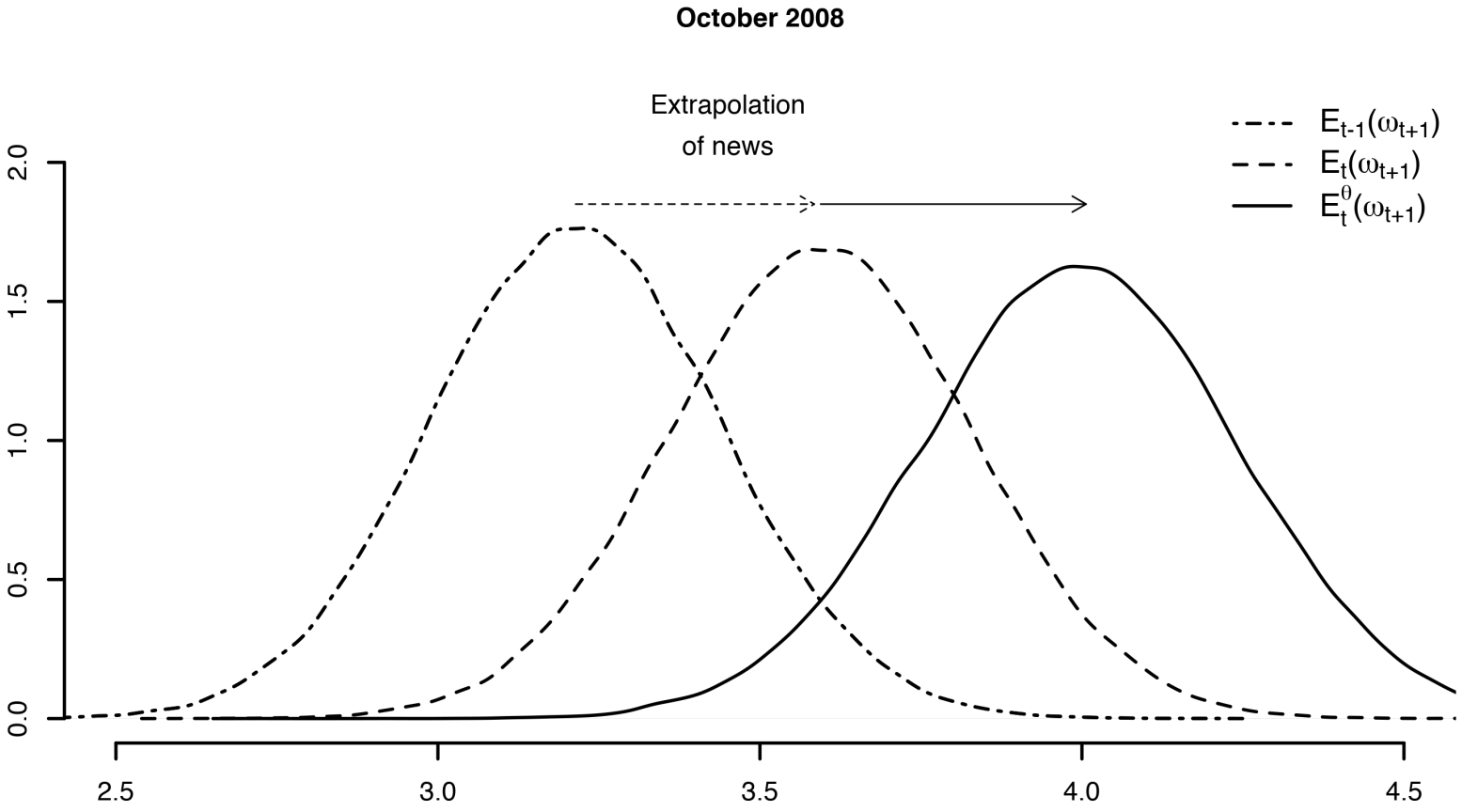

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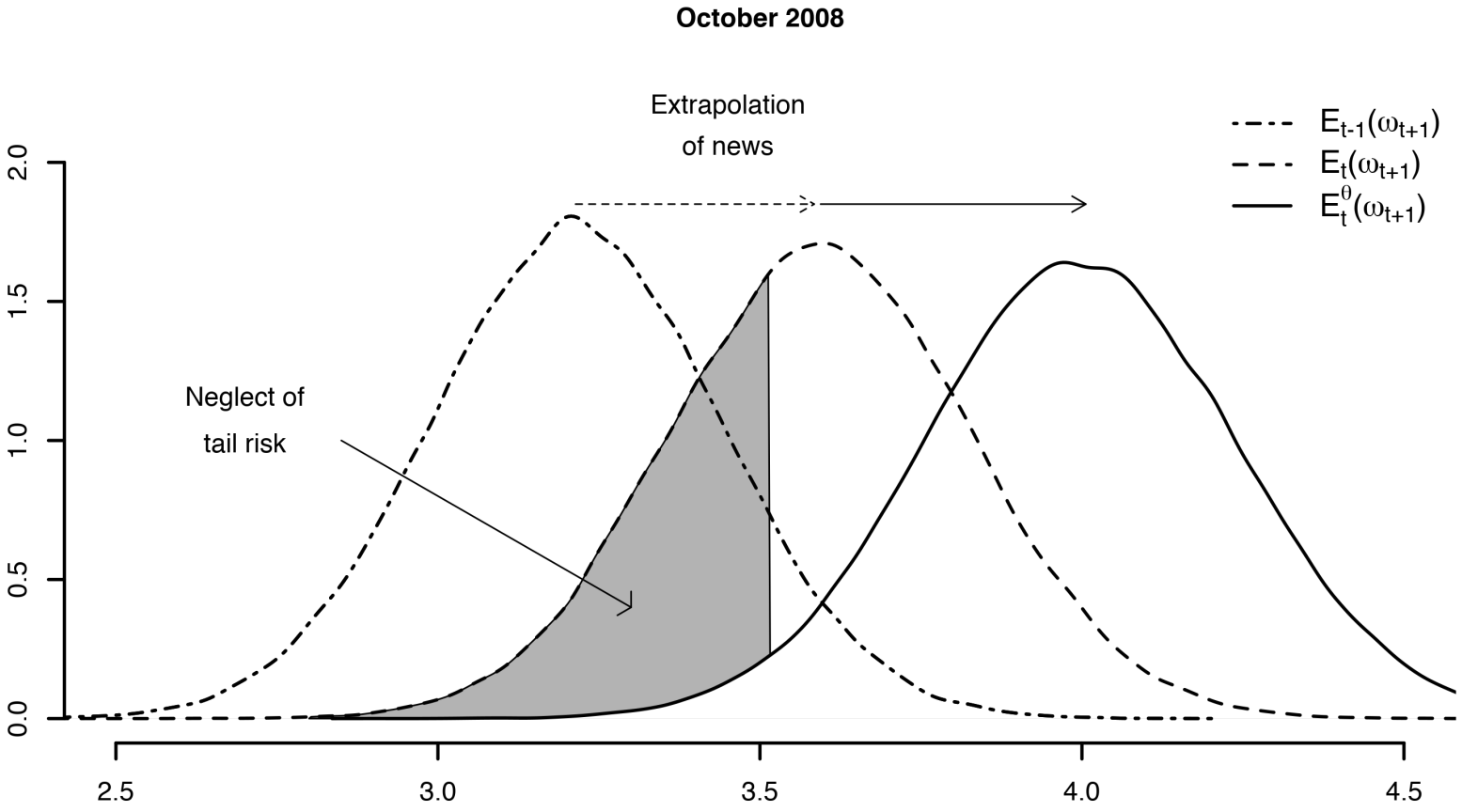

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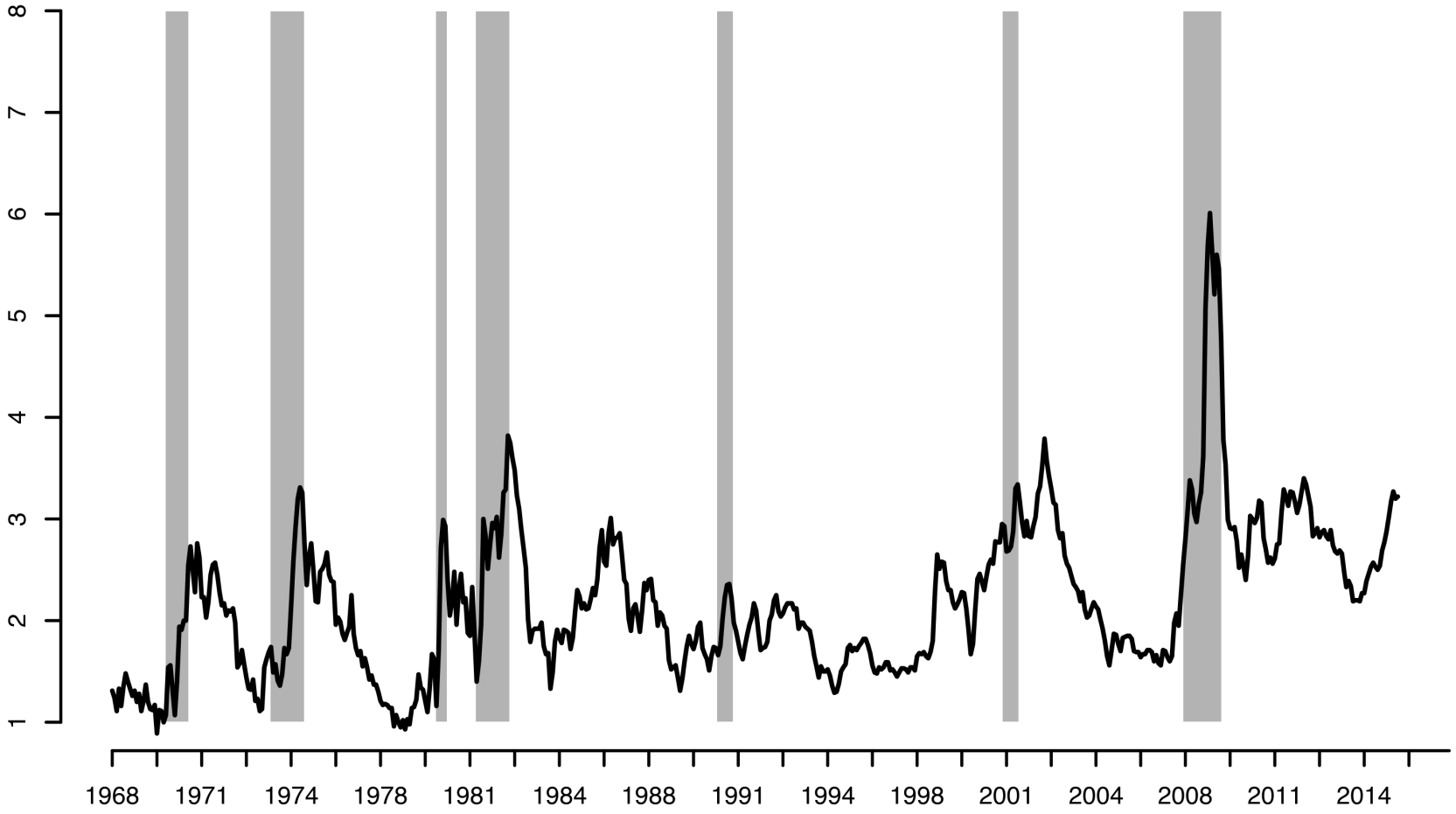

Figure 2: Baa bond - Treasury credit spread and its diagnostic expectations, ω and $\mathbb{E}_t^{\theta}(\hat{\omega}_{t+1})$

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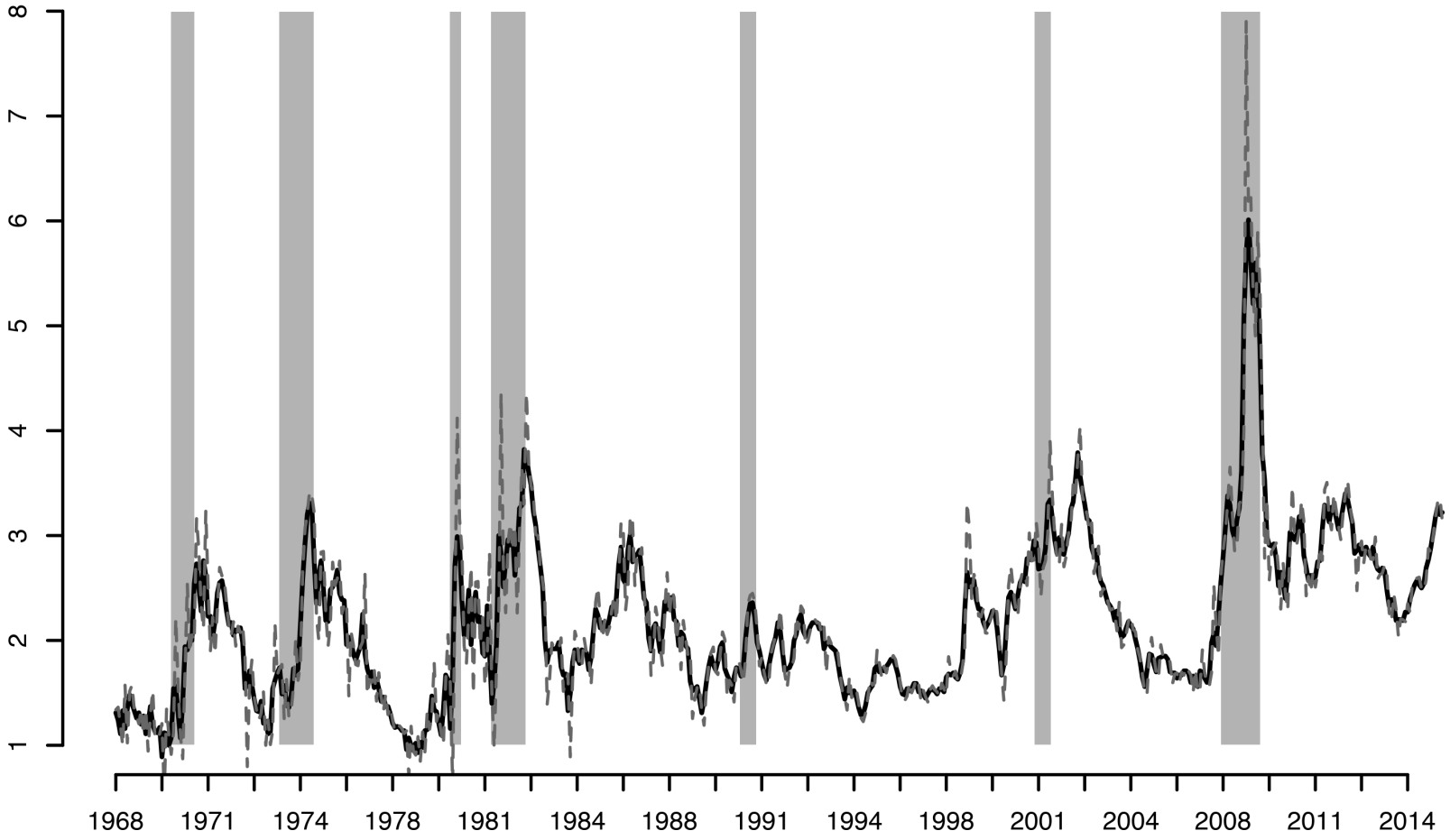

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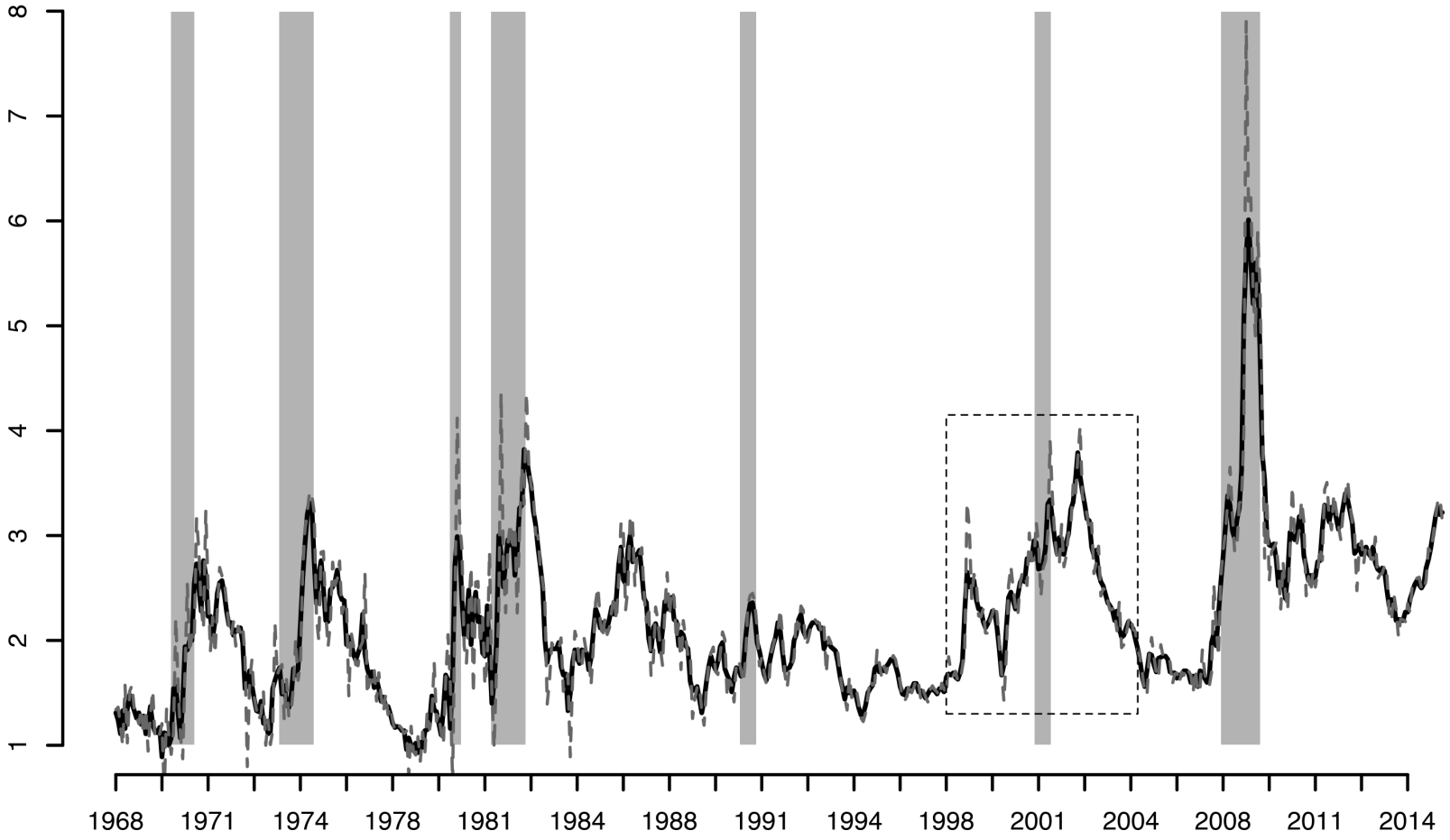

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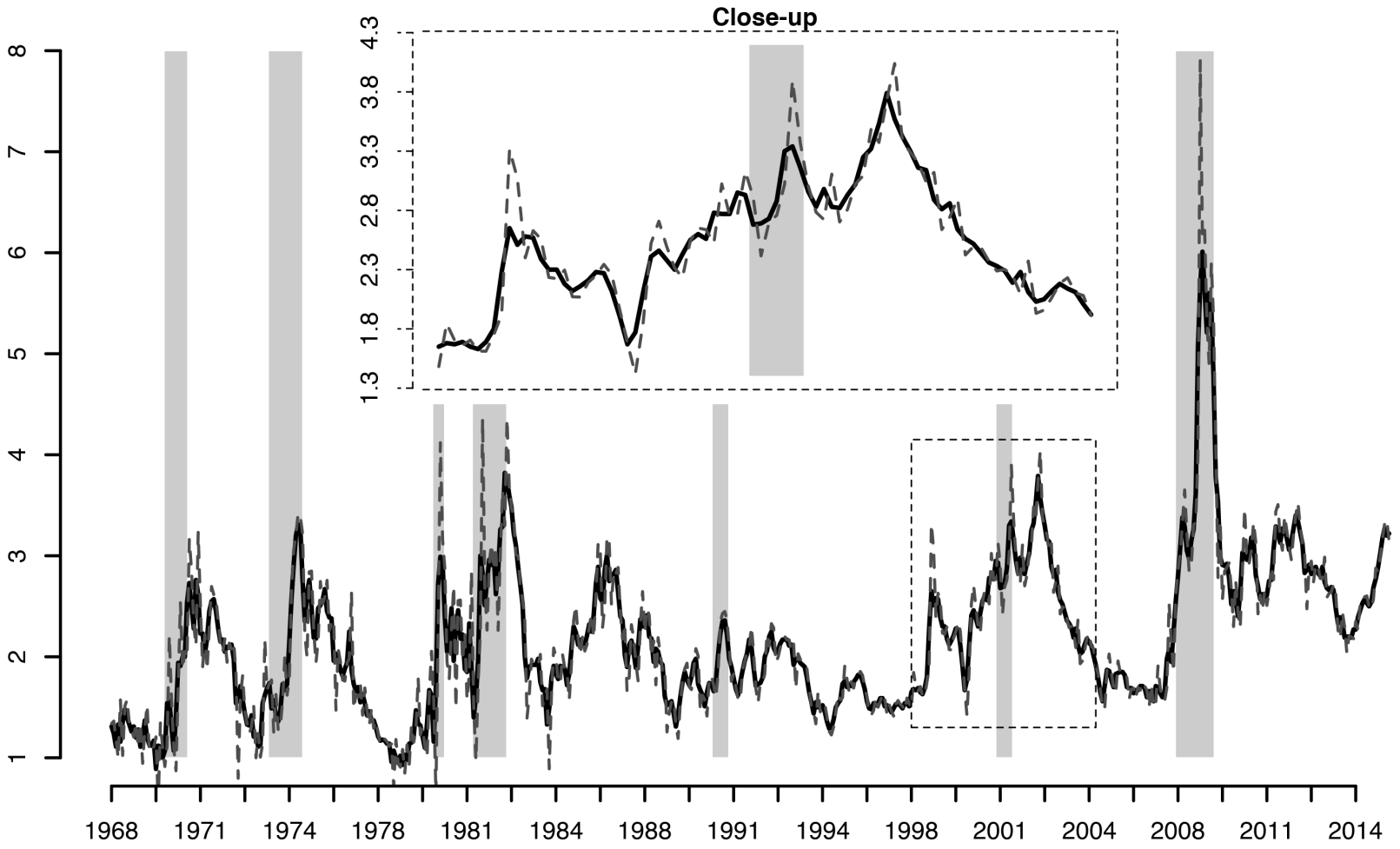

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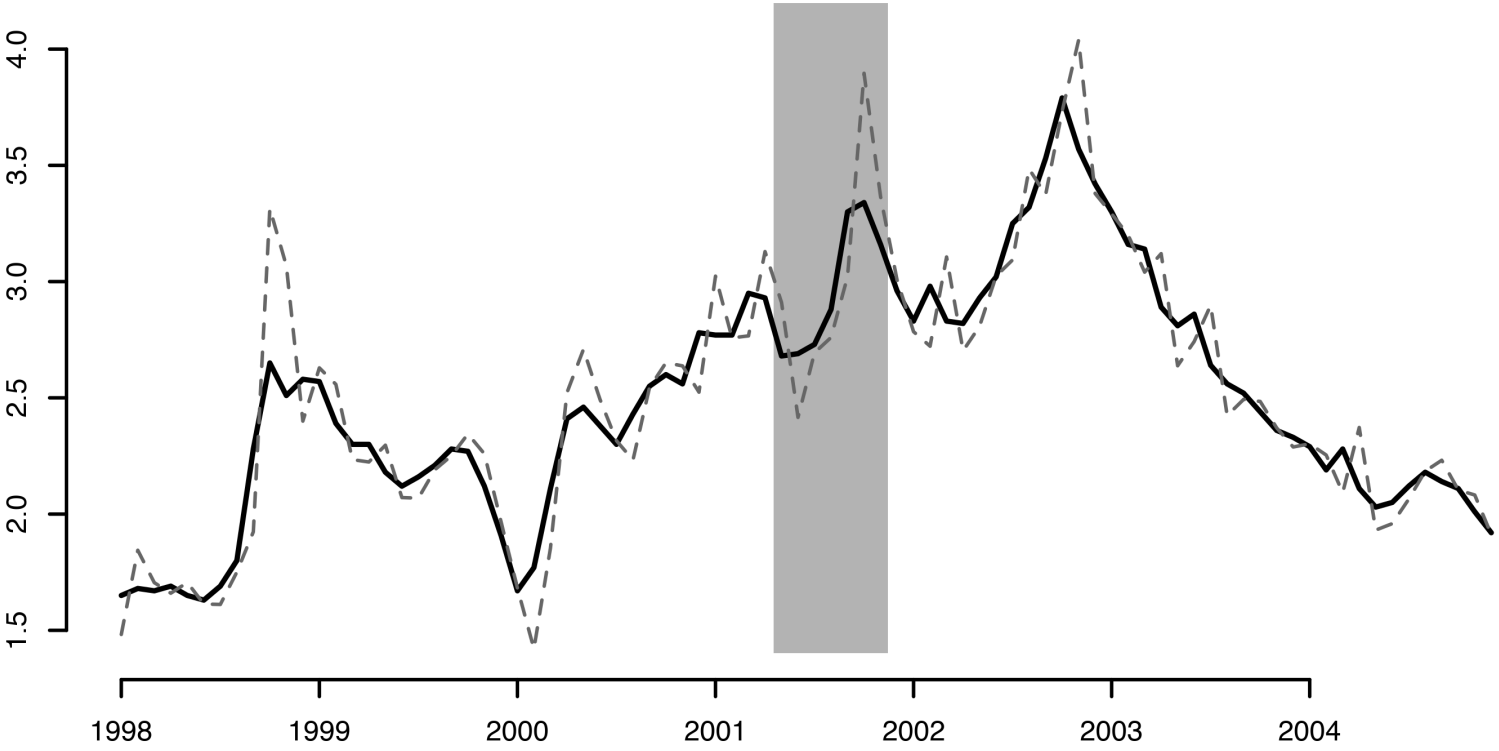

Figure 3: Baa bond - Treasury credit spread and its diagnostic expectations, ω and $\mathbb{E}_t^{\theta}(\hat{\omega}_{t+1})$

Threshold Bayesian Vectorautoregressive Model

Non-linear M-dimensional VAR:

$$Y_t = \begin{cases} c_1 + \sum_{j=1}^{p} A_{1j} Y_{t-j} + \Lambda_1 e_t, & \text{if } S_t = 1, \\ c_2 + \sum_{j=1}^{p} A_{2j} Y_{t-j} + \Lambda_2 e_t, & \text{if } S_t = 2, \end{cases} \tag{4}$$

- multivariate M-dimensional time series process $\{Y_t\}_{t=1}^{T}$
- c_i is a $M \times 1$ intercept vector for regime i,
- A_{ij} is a $M \times M$ coefficient matrix of lag j for regime i,
- Λ_i is the lower triangular Cholesky factor of regime i,
- $\Sigma_i = \Lambda_i \Lambda_i^T$ holds,
- $e_t \sim \mathcal{N}_M(0, I_M)$,
- $\{S_t\}_{t=1}^{T}$ is a latent indicator vector

Data & Threshold Variable

Our time series process consists of: $Y_t = \{\omega_t, y_t, L_t, \pi_t, i_t\}$

- ω_t: difference of Baa corporate bond yield and the 10-year Treasury yield (Greenwood and Hanson, 2013)
- y_t: industrial production growth rate
- L_t: business loans growth rate
- π_t: inflation
- i_t: Federal funds rate extended with shadow rate (Wu and Xia, 2016)

We use the credit sentiment variable, ω_t, as threshold variable:

$$\begin{aligned} S_t = 1 &\Longleftrightarrow \omega_{t-d} \leq \gamma, \\ S_t = 2 &\Longleftrightarrow \omega_{t-d} > \gamma, \end{aligned} \tag{5}$$

- latent threshold parameter γ
- delay parameter $d = 1$ for our specification

Identification based on External Instruments

Approach by Mertens and Ravn (2013) and Gertler and Karadi (2015):

$$\epsilon_{S_t} = \Lambda_i e_{S_t}, \qquad \text{if } S_t = i, \tag{6}$$

with the following assumptions

$$\begin{aligned} \mathbb{E}(Z_t e_t^{\omega T}) &= \Phi, \\ \mathbb{E}(Z_t e_t^{-\omega T}) &= 0. \end{aligned} \tag{7}$$

Z_t is the difference between the one-step ahead forecast using diagnostic expectations and the realized value of the credit market sentiment

Robustness: Cholesky identification with ω_t ordered first

Prior setup & Posterior simulation

Adaptive shrinkage priors following Huber and Feldkircher (2019) illustrated as follows

$$\begin{aligned} \beta_{ij} \mid \psi_{ij}, \lambda_j^2 &\sim N(0, \frac{2}{\lambda_j^2}\psi_{ij}), \\ \psi_{ij} &\sim G(\omega, \omega), \quad \omega \sim Exp(1), \\ \lambda_j^2 &= \prod_{k=1}^{j} \zeta_k, \quad \zeta_k \sim G(0.01, 0.01). \end{aligned} \tag{8}$$

We employ a MCMC algorithm to draw from the conditional posterior densities, iterating over the following steps

(i) draw the VAR coefficients regime-wise using the triangular algorithm (Carriero et al., 2015)

(ii) draw the threshold parameter γ using an adaptive RW-MH step (Chen and Lee, 1995; Haario et al., 2001)

Impulse Response Analysis

(unexpected 100 basis point BAAT10 increase → news shock)

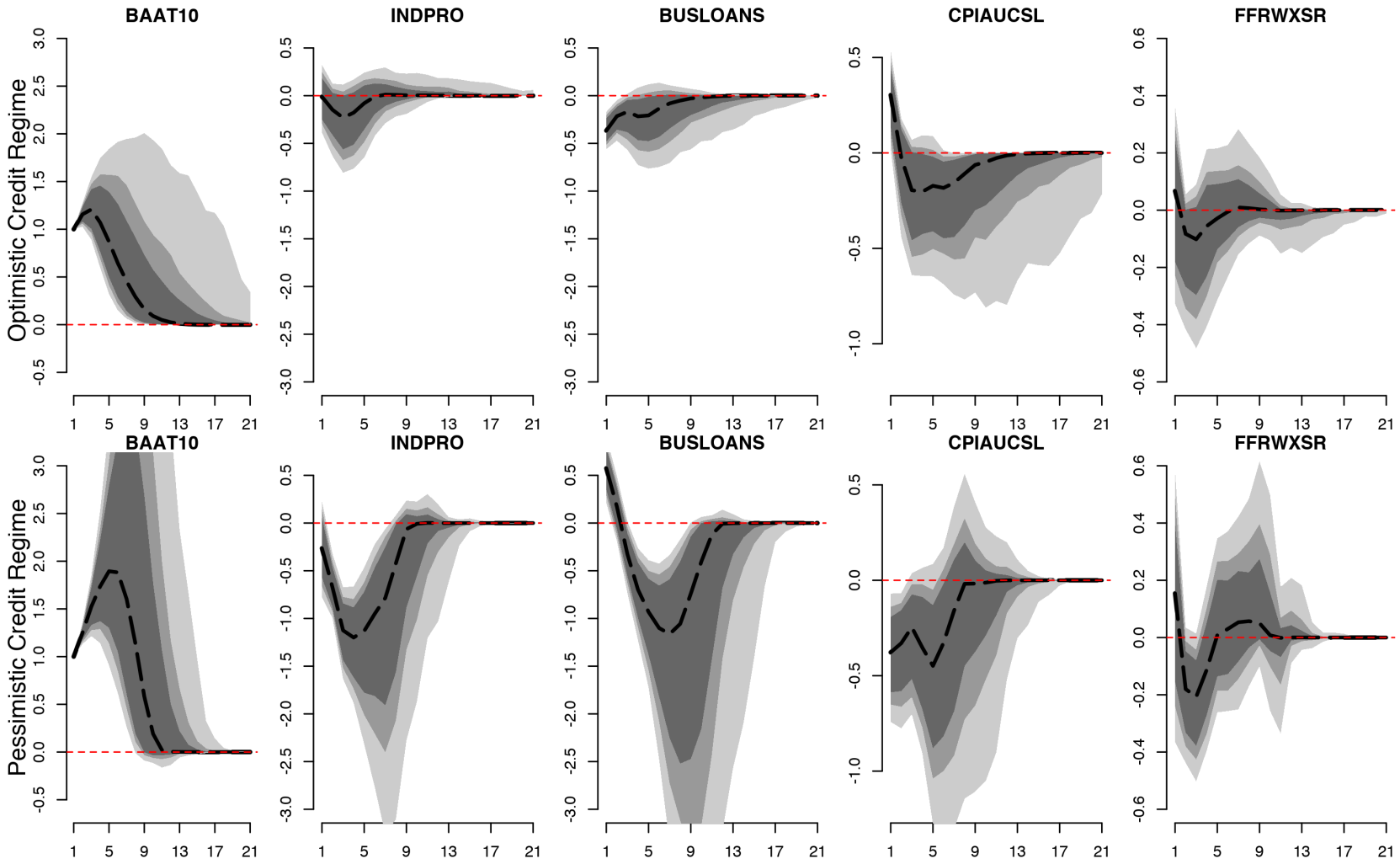

Figure 4: Identification based on the external instrument

Robustness

(unexpected 100 basis point BAAT10 increase → news shock)

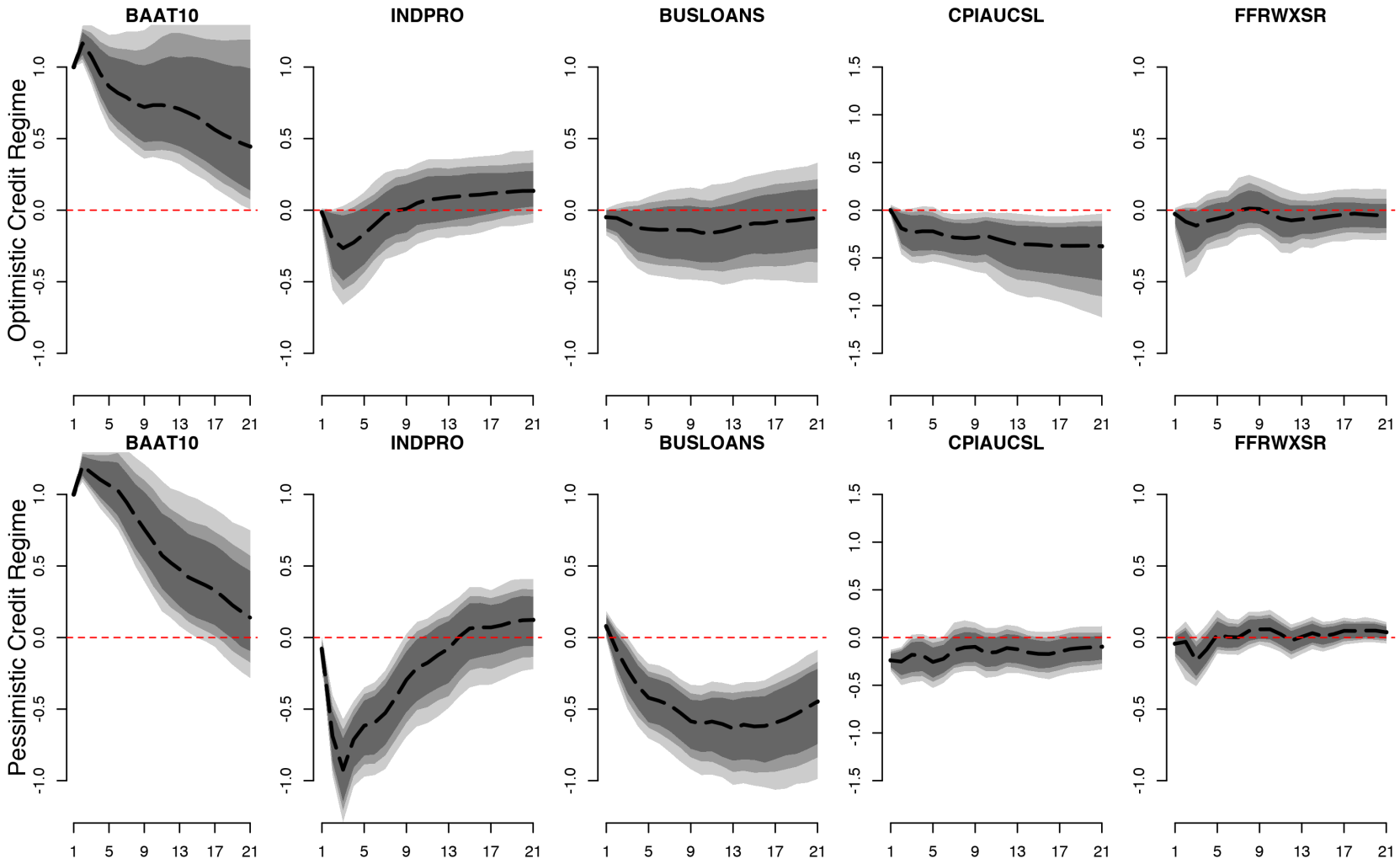

Figure 5: Identification based on recursive ordering (Cholesky)

Conluding remarks

Our results suggest:

- macrofundamentals are affected by sentiment shocks
- strong asymmetries across 'optimistic' and 'pessimistic' credit market sentiment regimes
- only moderate to rather muted effects in the 'optimistic' regime
- strong impact on the business and credit cycle in the 'pessimistic' regime

Diagnostic expectations and market sentiments in a nonlinear framework provide a valuable behavioral framework for macroeconometric analysis!

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Diagnostic Expectations

First and second moment:

$$\begin{aligned}\mu_\theta &= \mu_0 + \frac{\theta\sigma_0^2}{\sigma_{-1}^2 + \theta(\sigma_{-1}^2 - \sigma_0^2)}(\mu_0 - \mu_{-1}),\\ \sigma_\theta^2 &= \sigma_0^2 \frac{\sigma_{-1}^2}{\sigma_{-1}^2 + \theta(\sigma_{-1}^2 - \sigma_0^2)},\end{aligned} \tag{9}$$

with

$$\mathbb{E}_t^\theta(\omega_{t+1}) = \mathbb{E}_t(\omega_{t+1}) + \theta[\mathbb{E}_t(\omega_{t+1}) - \mathbb{E}_{t-1}(\omega_{t+1})], \tag{10}$$

where

$$\begin{aligned}\mu_0 &= \mathbb{E}_t(\omega_{t+1}) = \rho\hat{X}_t,\\ \sigma_0^2 &= \sigma_t^2,\end{aligned} \tag{11}$$

and

$$\begin{aligned}\mu_{-1} &= \mathbb{E}_{t-1}(\omega_{t+1}) = \rho^2\omega_{t-1},\\ \sigma_{-1}^2 &= \sigma_{t-1}^2.\end{aligned} \tag{12}$$