The Impact of Credit Market Sentiment Shocks

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Macroeconomic shocks

Last financial crisis showed that financial stability is crucial for business cycles dynamics:

- How shocks affect financial stability?
- Are sentiments a source of instability?

Sentiments and the business cycle

- Sentiments are associated with lower growth (López-Salido et al., 2017).
- Points to narratives of Minsky (1977) and Kindleberger (1978).

Credit market sentiment shock

- news about the future affect decisions today,
- expectation formation on financial markets,
  - rational expectations (Fama, 1970),
  - set of heuristics (Anufriev and Hommes, 2012),
  - diagnostic expectations (Bordalo et al., 2018).

Financial markets and credit cycles

Financial markets as *amplifier* and *propagator* of shocks

- financial frictions (Bernanke and Gertler, 1989; Kiyotaki and Moore, 1997),
- balance-sheet measures as driving force (Mian et al., 2017; Schularick and Taylor, 2012).

Endogenous credit cycles

- cyclicity still hinges on financial frictions (Matsuyama et al., 2016),
- Kubin et al. (2019) introduce the lenders' perception of risk and sentiments on the credit market.

Credit market sentiments

- typically operationalized via credit spreads (López-Salido et al., 2017),
- credit quality predicts recession better than credit growth (Greenwood and Hanson, 2013),
- Bordalo et al. (2018) set up a model with a new belief formation mechanism to explain credit cycle fluctuations

This paper

Research Questions:

- How do credit market sentiments impact business cycle fluctuations?
- Does the effect depend on the general credit market perception (optimistic vs. pessimistic sentiment)?

We provide an empirical validation of theoretical models for the US economy

- by employing a threshold BVAR approach,
- with monthly data between 1968 and 2015 from the FRED (McCracken and Ng, 2016).

Identification of a credit market sentiment shock through

- implementation of an unexpected sentiment news shock,
- by utilizing a set of expectation formation mechanisms.

Credit market sentiment

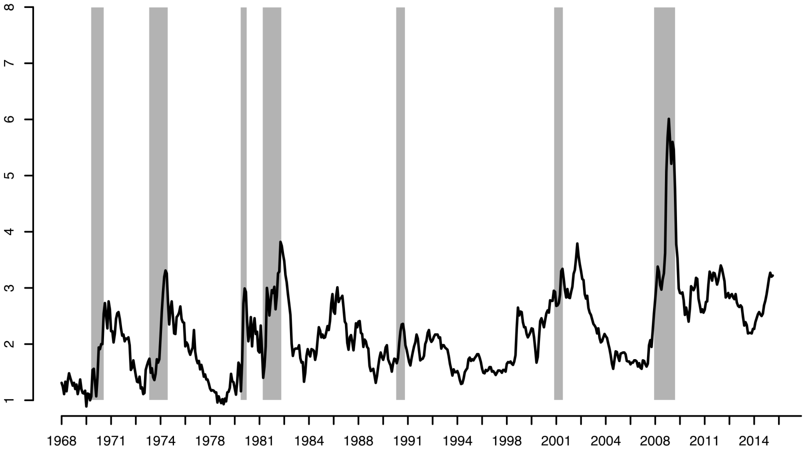


Figure 1: Baa spread 1968 – 2015.

Expectation formation

Credit market sentiment process $\{\omega_t\}_{t=1}^T$ is characterized by AR(1)

$$\omega_t = \varphi \omega_{t-1} + \varepsilon_t, \qquad \varepsilon_t \sim \mathcal{N}(0, \exp(h_t)),$$

with stochastic volatility (Kastner and Früwirth-Schnatter, 2014)

$$h_t = \mu + \phi(h_{t-1} - \mu) + \eta_t, \qquad \eta_t \sim \mathcal{N}(0, \sigma_h^2).$$

- Bordalo et al. (2018) show predictability of forecast error using rational expectations model.
- Calls for other expectation formation mechanism.

Diagnostic Expectations

Behavioral theory following Bordalo et al. (2018):

- based on the representativeness heuristic (Kahneman and Tversky, 1972)
- define distorted probability distribution $p^{\theta}(\cdot)$

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

- θ measures the severity of judging according to representativeness.

Taking expectations yields

$$\mathbb{E}_t^{\theta}(\hat{\omega}_{t+1}) = \mathbb{E}_t(\hat{\omega}_{t+1}) + \theta[\mathbb{E}_t(\hat{\omega}_{t+1}) - \mathbb{E}_{t-1}(\hat{\omega}_{t+1})]. \quad (2)$$

Diagnostic Expectations

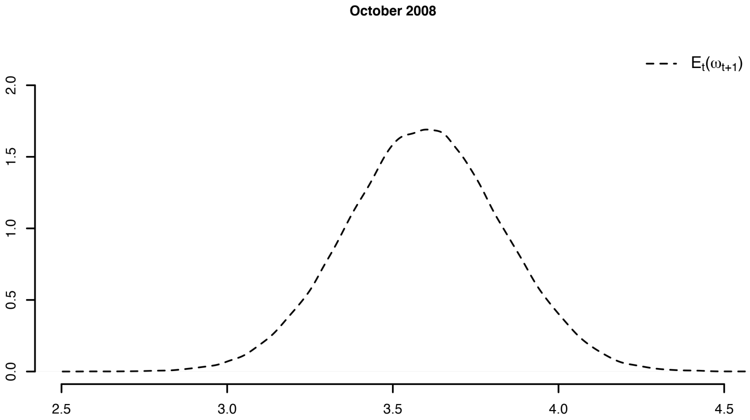


Figure 1: Rational Expectations in t.

Diagnostic Expectations

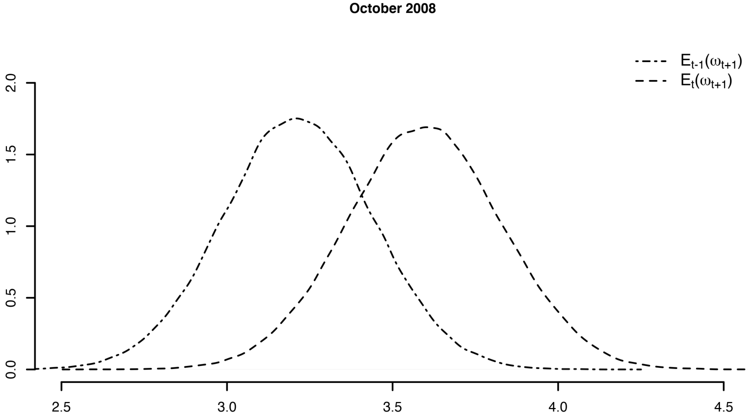
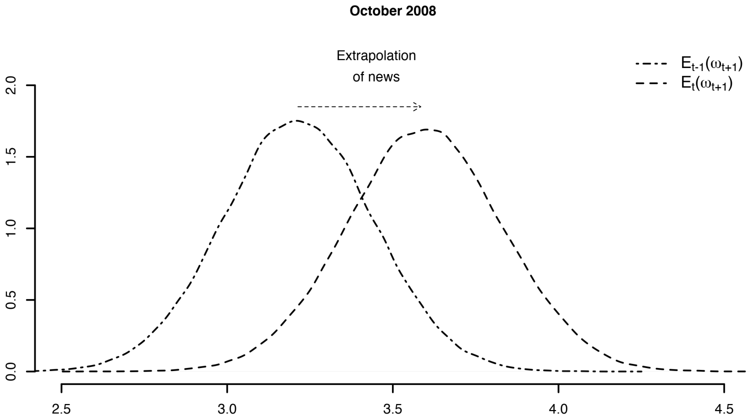


Figure 1: Rational Expectations in t and $t-1$.

Diagnostic Expectations



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Diagnostic Expectations

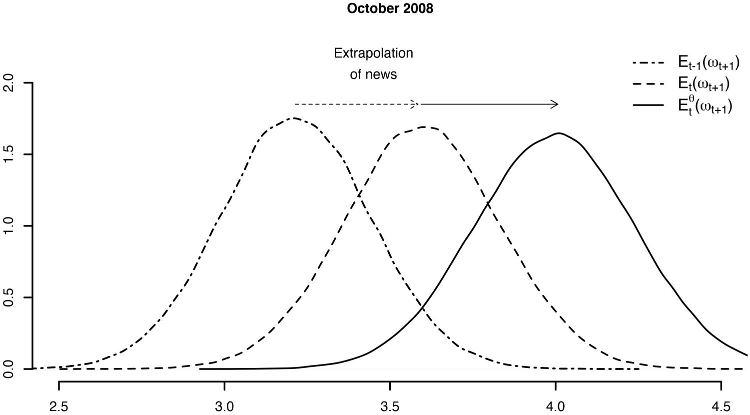


Figure 1: Rational and Diagnostic Expectations.

Credit Market Sentiment

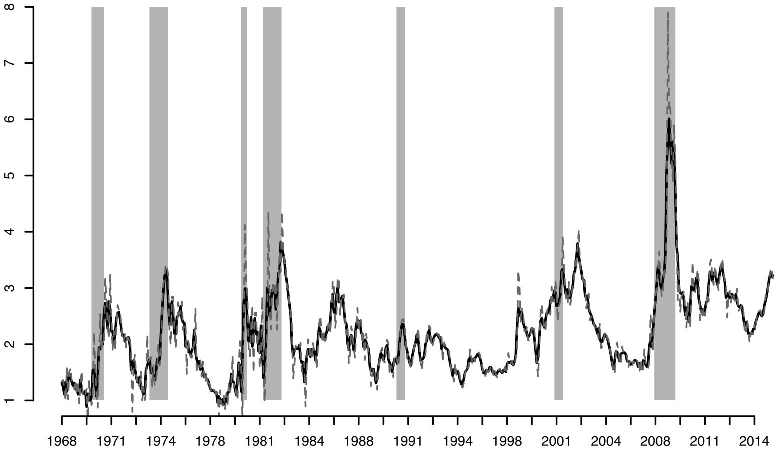
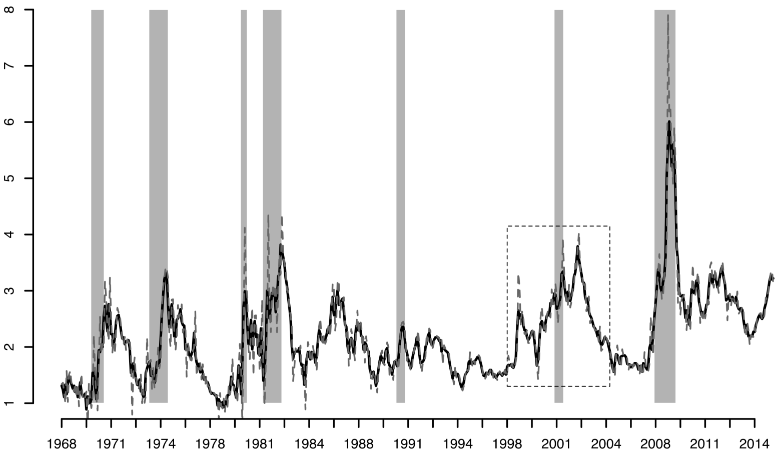


Figure 1: Baa spread 1968 – 2015 and its diagnostic expectations.

Credit Market Sentiment



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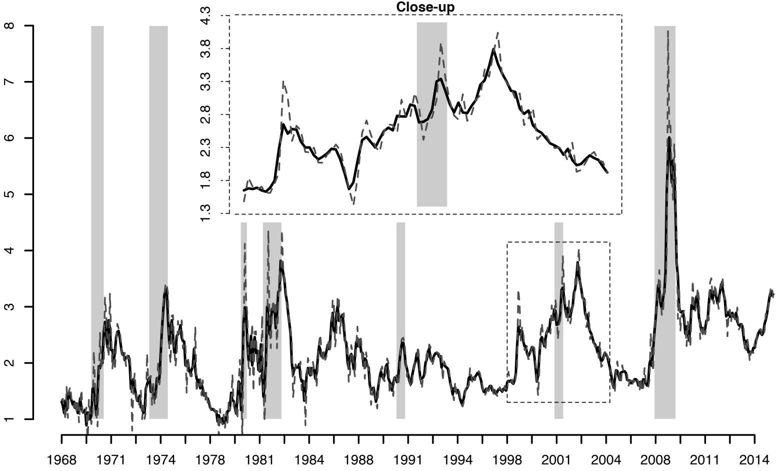

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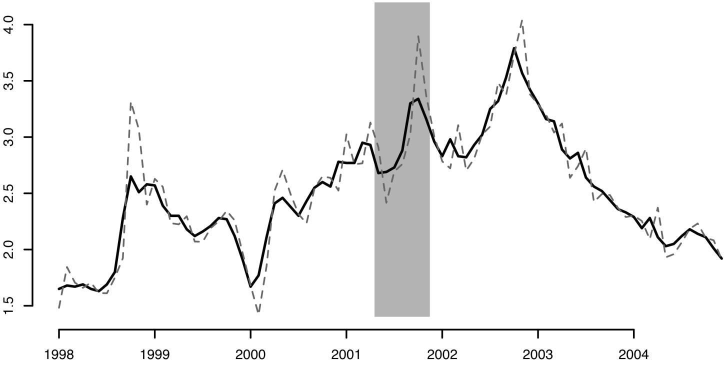

Figure 2: Baa spread 1998 – 2004 and its diagnostic expectations.

Bayesian Threshold Vector Autoregression

Non-linear M-dimensional VAR of $\{\mathbf{Y}_t\}_{t=1}^{T}$:

$$\mathbf{Y}_t = \begin{cases} \mathbf{c}_1 + \sum_{j=1}^{p} \mathbf{A}_{1j} \mathbf{Y}_{t-j} + \mathbf{\Lambda}_1 \mathbf{e}_t, & \text{if } S_t = 1, \\ \mathbf{c}_2 + \sum_{j=1}^{p} \mathbf{A}_{2j} \mathbf{Y}_{t-j} + \mathbf{\Lambda}_2 \mathbf{e}_t, & \text{if } S_t = 2, \end{cases} \tag{3}$$

with

- $\mathbf{Y}_t = \{\omega_t, y_t, L_t, \pi_t, i_t\}$,
- $\mathbf{c}_i$ is a $M \times 1$ intercept vector for regime i,
- $\mathbf{A}_{ij}$ is a $M \times M$ coefficient matrix of lag j for regime i,
- $\mathbf{\Lambda}_i$ is the lower triangular Cholesky factor of regime i where $\mathbf{\Sigma}_i = \mathbf{\Lambda}_i \mathbf{\Lambda}_i^T$ holds,
- $\mathbf{e}_t \sim \mathcal{N}_M(\mathbf{0}, \mathbf{I}_M)$,
- $\{S_t\}_{t=1}^{T}$ is a latent indicator vector.

Data & Threshold Variable

Time series process $\mathbf{Y}_t = \{\omega_t, y_t, L_t, \pi_t, i_t\}$ with sample period 1968M1 – 2015M12.

- 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:

$$\begin{aligned} S_t = 1 &\iff \omega_{t-d} \leq \gamma, \\ S_t = 2 &\iff \omega_{t-d} > \gamma, \end{aligned} \tag{4}$$

- with latent threshold parameter γ and
- delay parameter d.

Identification based on External Instruments

Approach by Mertens and Ravn (2013) and Gertler and Karadi (2015) with the following assumptions for the structural shocks

$$\begin{aligned} \mathbb{E}(\mathbf{Z}_t e_t^{\omega \intercal}) &= \mathbf{\Phi}, \\ \mathbb{E}(\mathbf{Z}_t e_t^{-\omega \intercal}) &= \mathbf{0}. \end{aligned} \tag{5}$$

We use the fitted values from regressing the instrument on the reduced form errors

$$\varepsilon_t^{-\omega} = \beta \hat{\varepsilon}_t^{\omega} + \nu_t, \quad \nu_t \sim N(0, \sigma_\varepsilon^2). \tag{6}$$

We use news on the financial market as external instrument:

- Z_t is the realized forecast error of the predicted credit market sentiment,
- expectation formation mechanism:
  - diagnostic expectations,
  - rational expectations,
  - a set of heuristics (Anufriev and Hommes, 2012).

Prior setup

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

$$
\begin{aligned}
\beta_{ij} \mid \psi_{ij}, \lambda_j^2 &\sim N(0, \frac{2}{\lambda_j^2}\psi_{ij}),\\
\psi_{ij} &\sim G(\vartheta, \vartheta), \quad \vartheta \sim Exp(1),\\
\lambda_j^2 &= \prod_{k=1}^{j} \zeta_k, \quad \zeta_k \sim G(0.01, 0.01).
\end{aligned} \tag{7}
$$

MCMC algorithm relies on data augmentation

- conditional on the regime allocation we draw the VAR coefficients regime-wise using the triangular algorithm (Carriero et al., 2019)
- conditional on the parameters we draw the threshold parameter γ using an adaptive RW-MH step (Haario et al., 2001)
- draw the delay parameter d using an independent MH step (Chen and Lee, 1995)

Regime Allocation

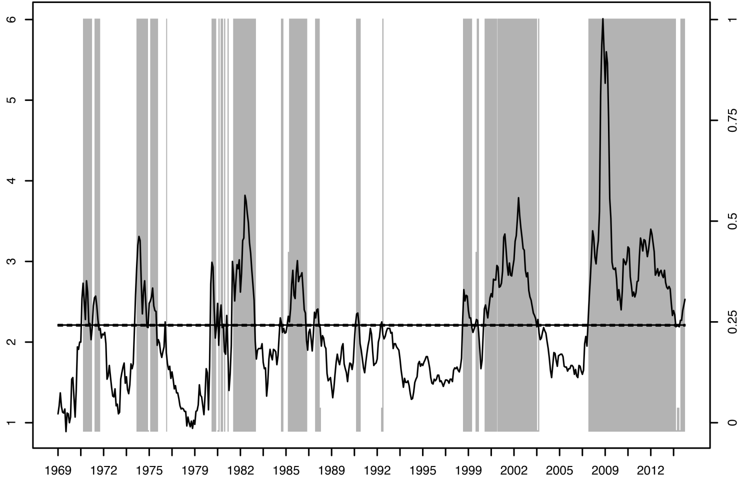

Figure 3: Regime allocation probabilities

Threshold VAR

(unexpected 100 basis point Baa spread increase → news shock)

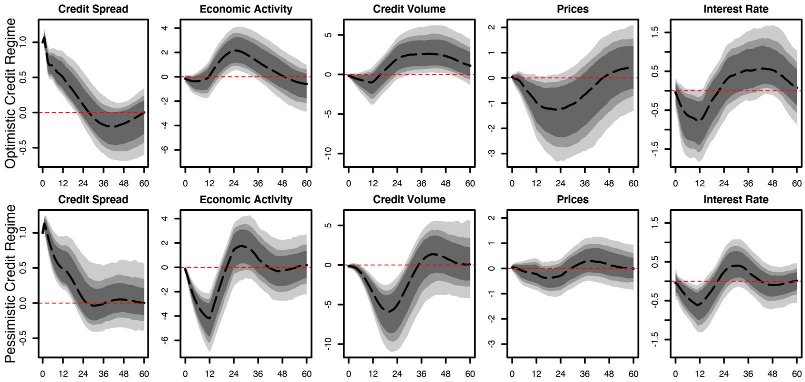

Figure 4: Identification based on the External Instrument.

Concluding 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 are an interesting tool for macroeconometric analysis.

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Normal-Gamma prior

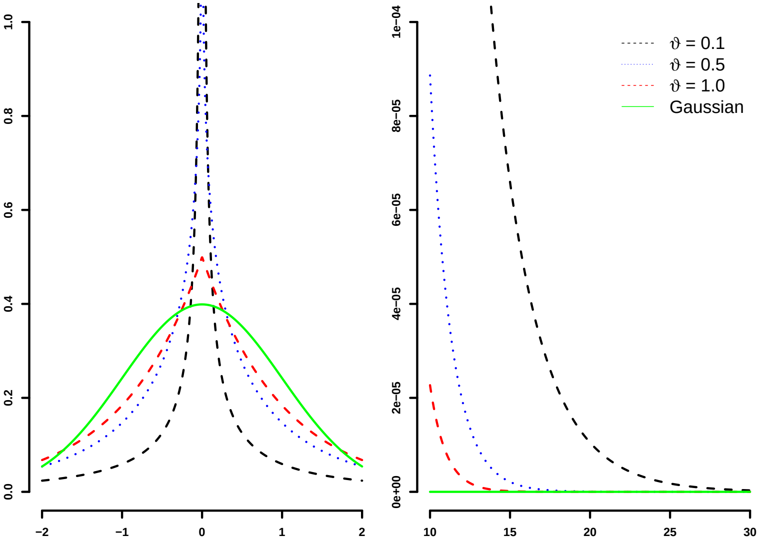

Figure 5: Normal-Gamma prior with varying degrees of shrinkage.

Standard VAR without threshold

(unexpected 100 basis point Baa spread increase → news shock)

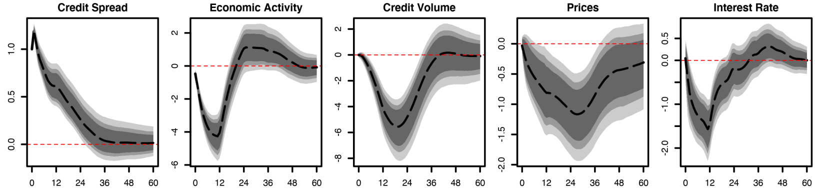

Figure 6: Identification based on the External Instrument.

Alternative belief formation mechanisms

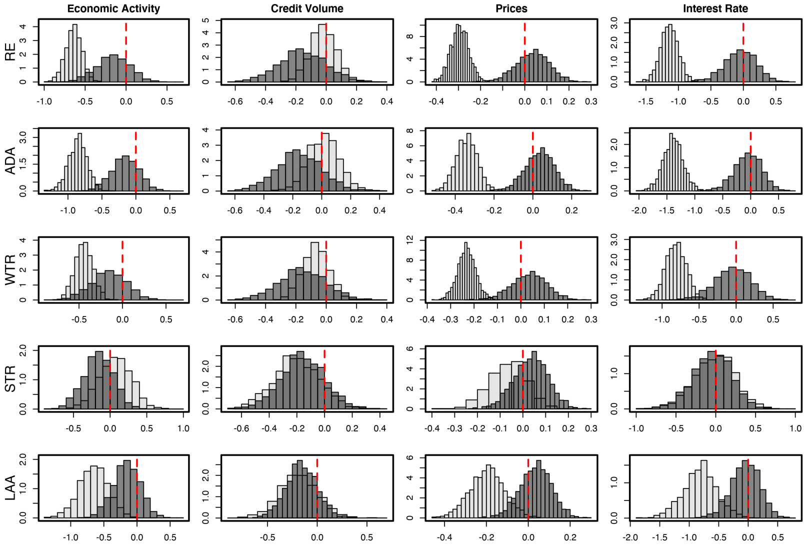

Figure 7: Identification via different heuristics (light gray) compared to identification via diagnostic expectations (dark gray) and the resulting overlap (medium gray).

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

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