

# Materials 40 - Still trying to understand why not identified

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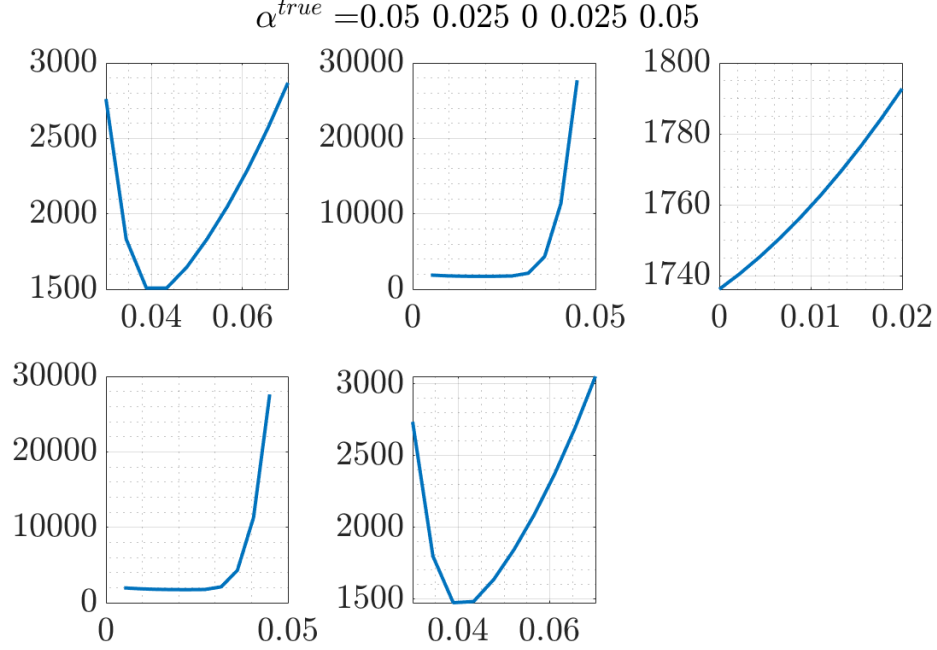
August 9, 2020

## Overview

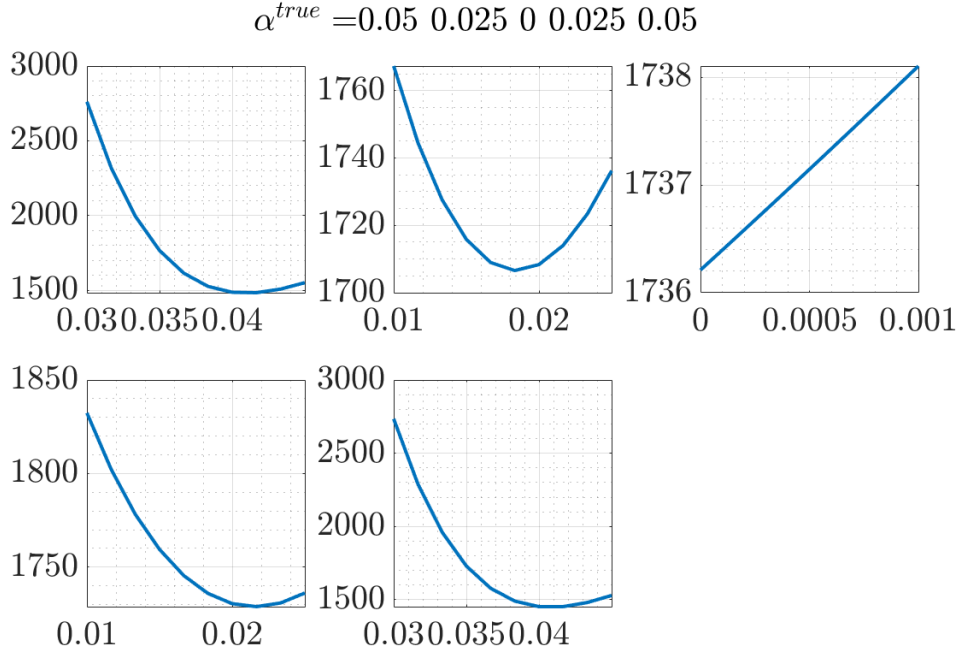
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# 1 Loss when varying one parameter, more details

**Figure 1:** Loss for  $N = 100$ , **NOT** using 1-step ahead forecasts of inflation, estimate mean moments once, imposing convexity with weight 100K, w/o measurement error, truth with  $nfe = 5, fe \in (-2, 2)$



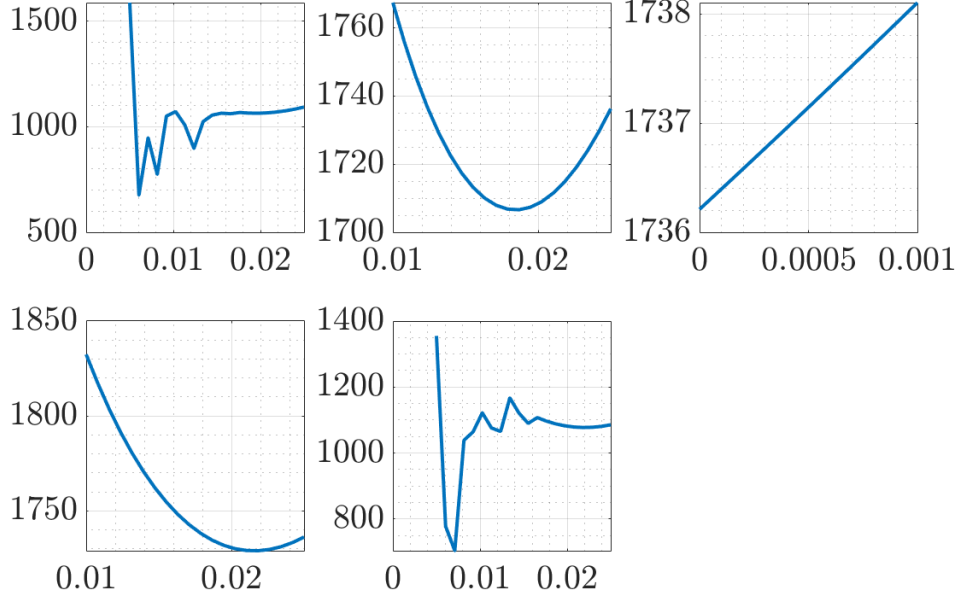
Reference figure from Materials 39: increment around true value 0.02



Minima: (0.041; 0.0187; 0; 0.0218; 0.041)

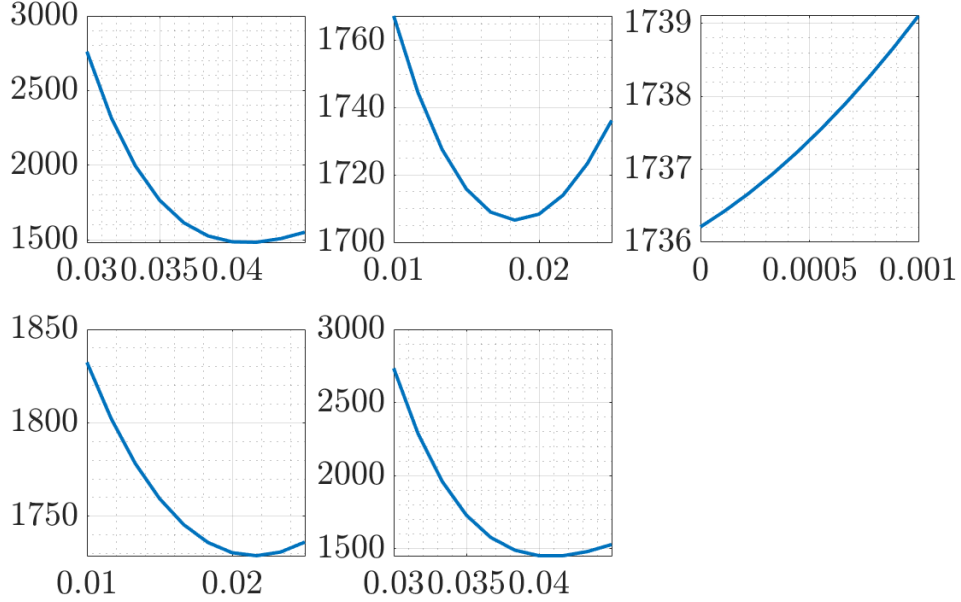
**Figure 2:** Variations I

$$\alpha^{true} = 0.05 \quad 0.025 \quad 0 \quad 0.025 \quad 0.05$$



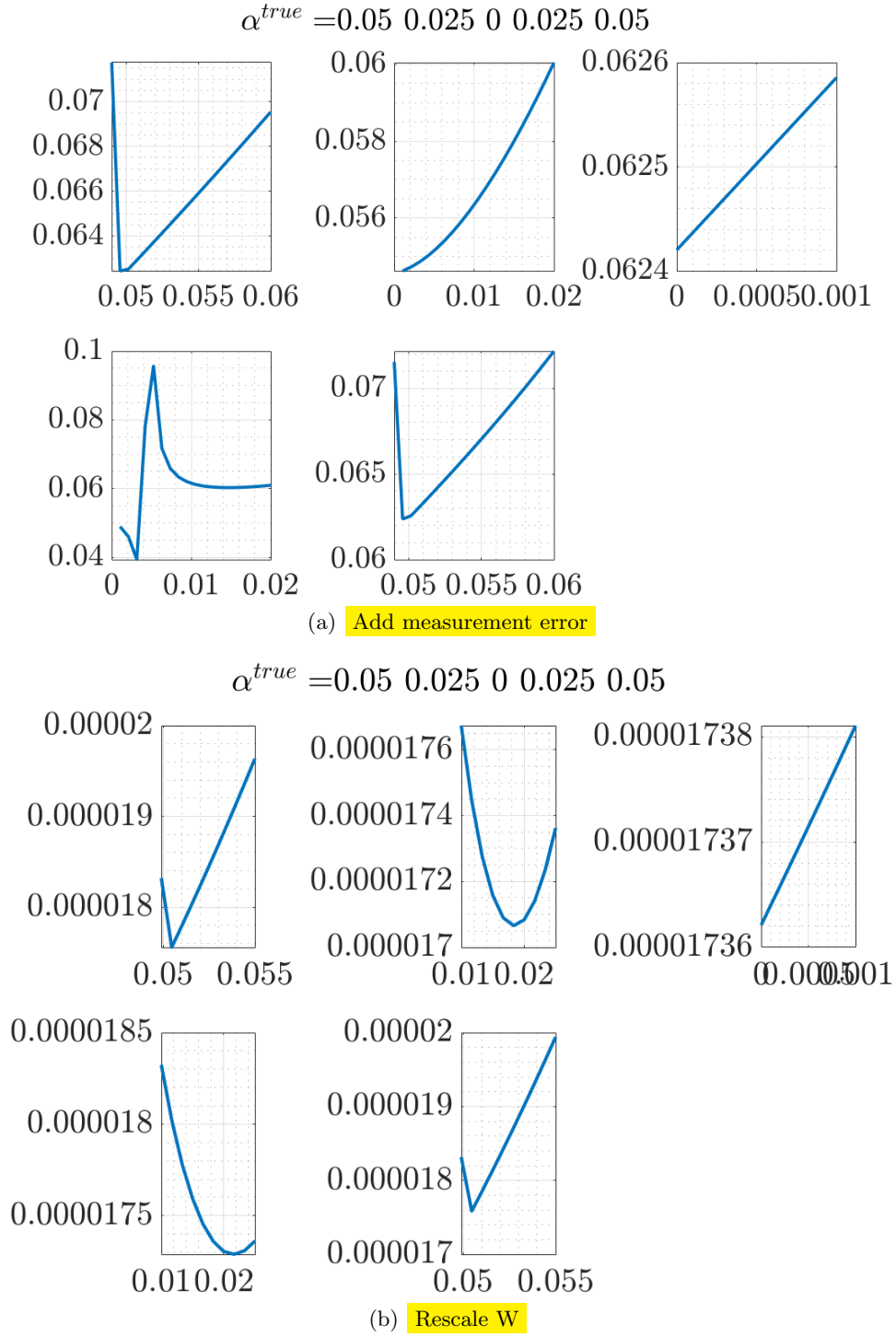
(a) Shutting of the convexity moment (weight 0)

$$\alpha^{true} = 0.05 \quad 0.025 \quad 0 \quad 0.025 \quad 0.05$$

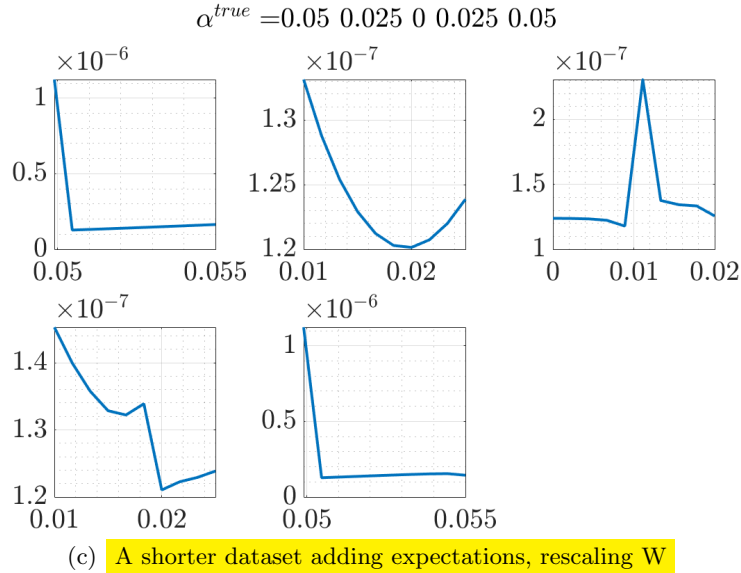
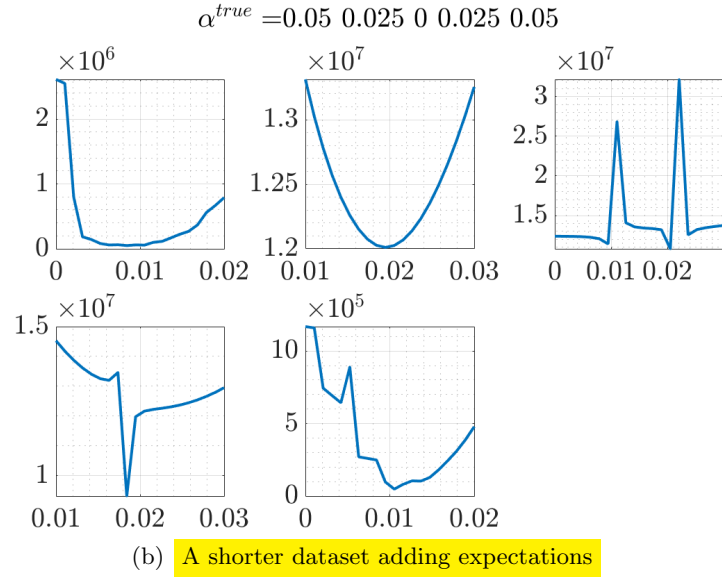
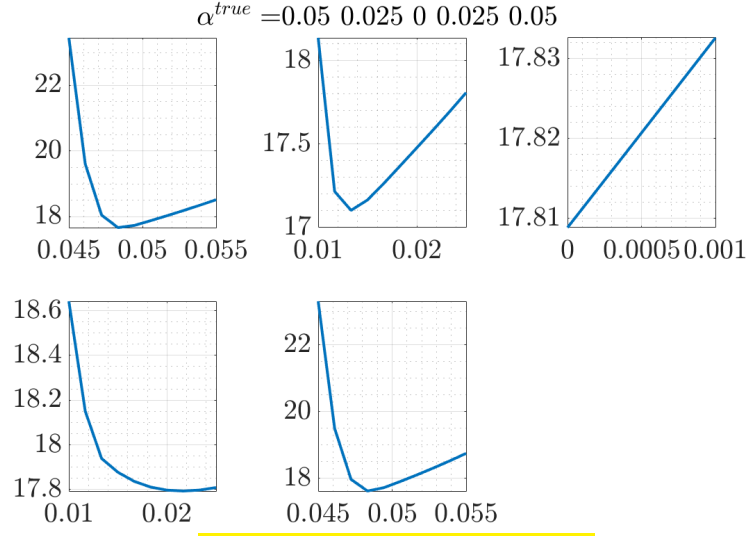


(b) Adding the 0 at 0 restriction (weight 1000)

**Figure 3:** Variations II

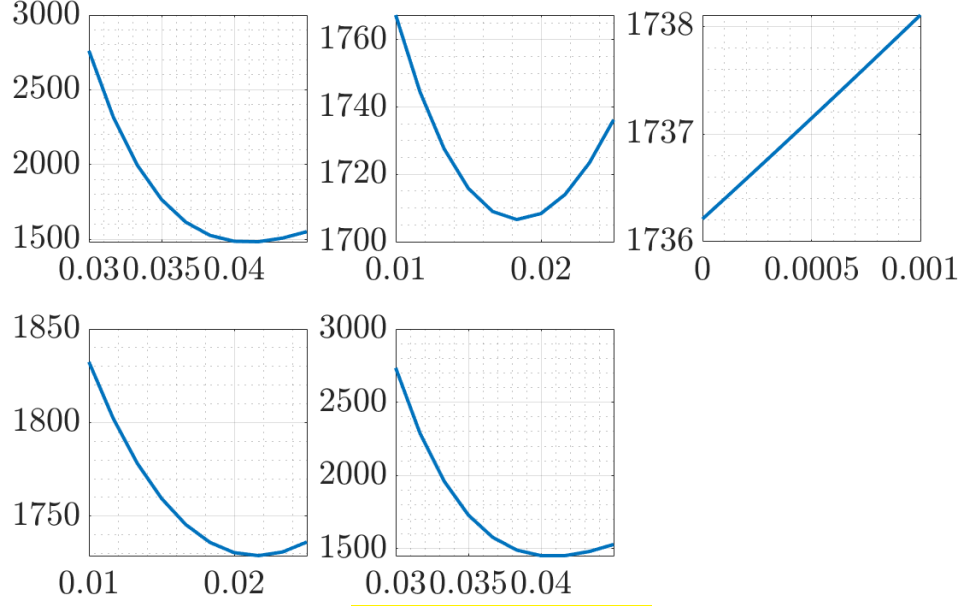


**Figure 4: Variations III**



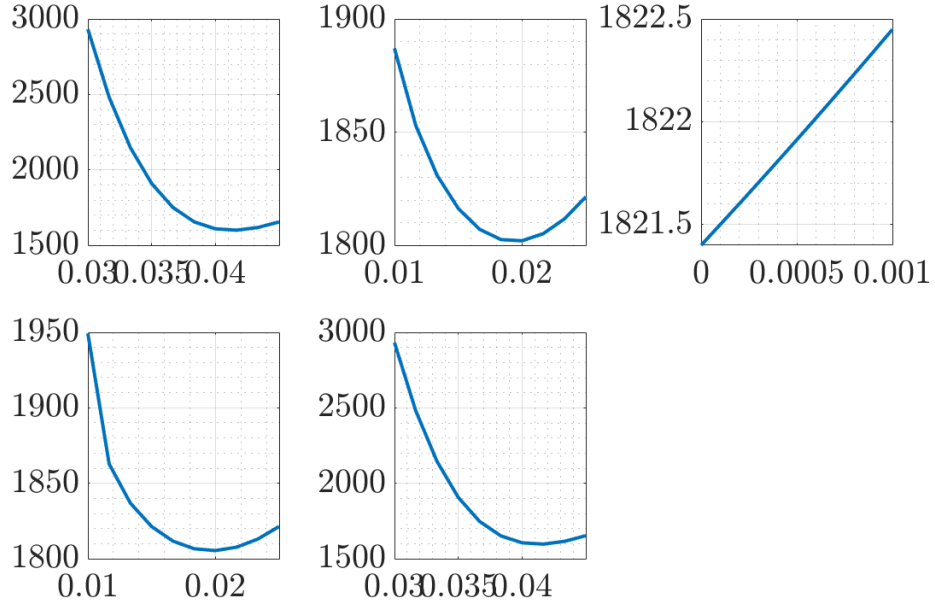
**Figure 5:** Variations IV

$$\alpha^{true} = 0.05 \quad 0.025 \quad 0 \quad 0.025 \quad 0.05$$



(a) Reproduces Fig 1, Panel b

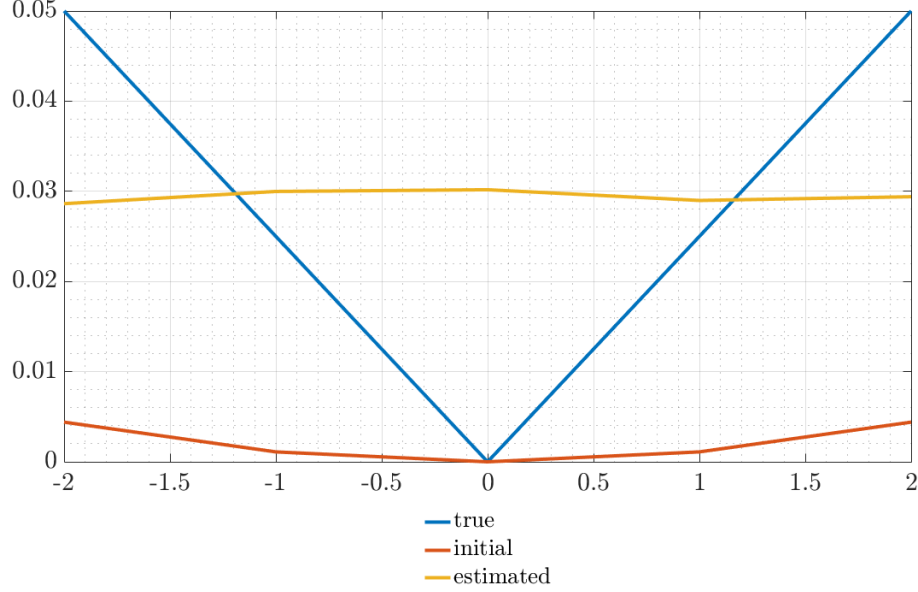
$$\alpha^{true} = 0.05 \quad 0.025 \quad 0 \quad 0.025 \quad 0.05$$



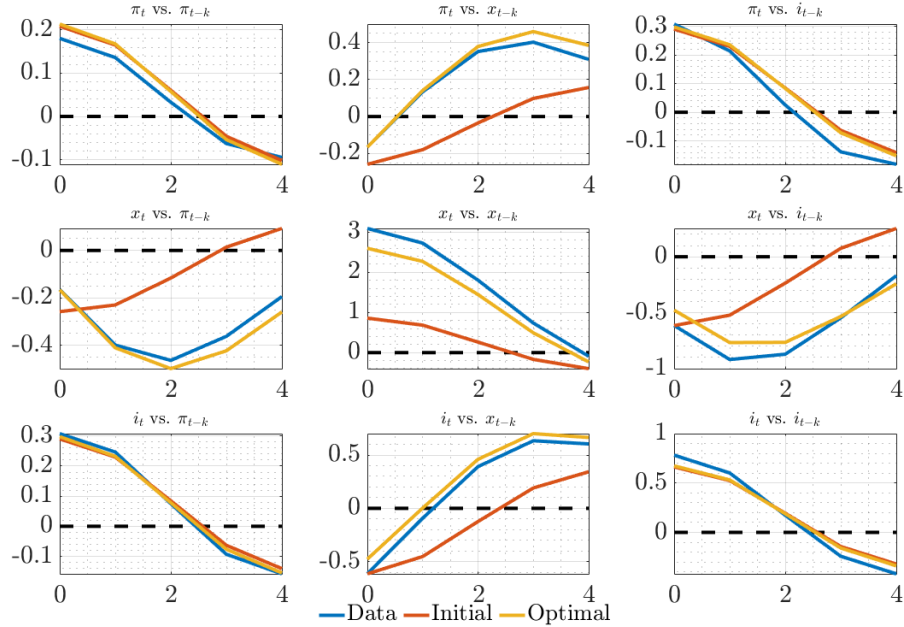
(b)  $N=1000$

1.1  $N = 1000$  for  $N$  simulations, one estimation

**Figure 6:** NOT using 1-step ahead forecasts of inflation, estimate mean moments once, imposing convexity with weight 100K, w/o measurement error, truth with  $nfe = 5, fe \in (-2, 2)$



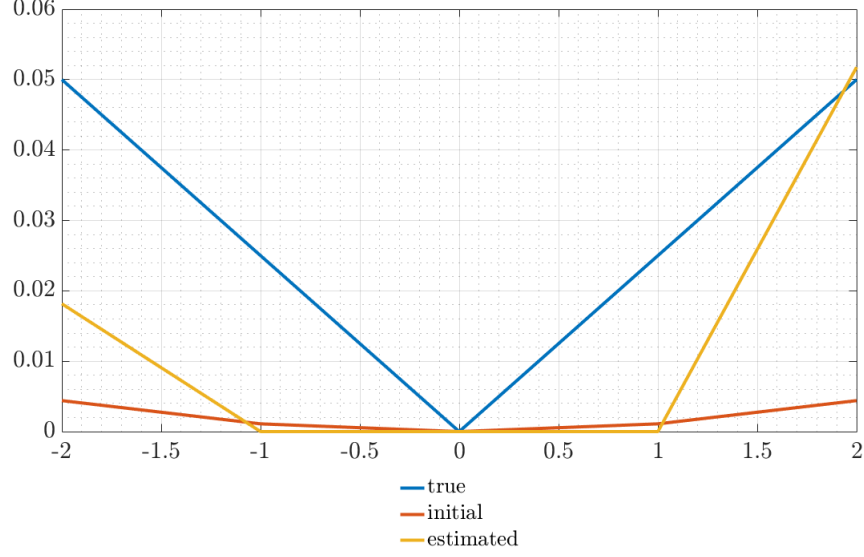
(a) Estimated parameters



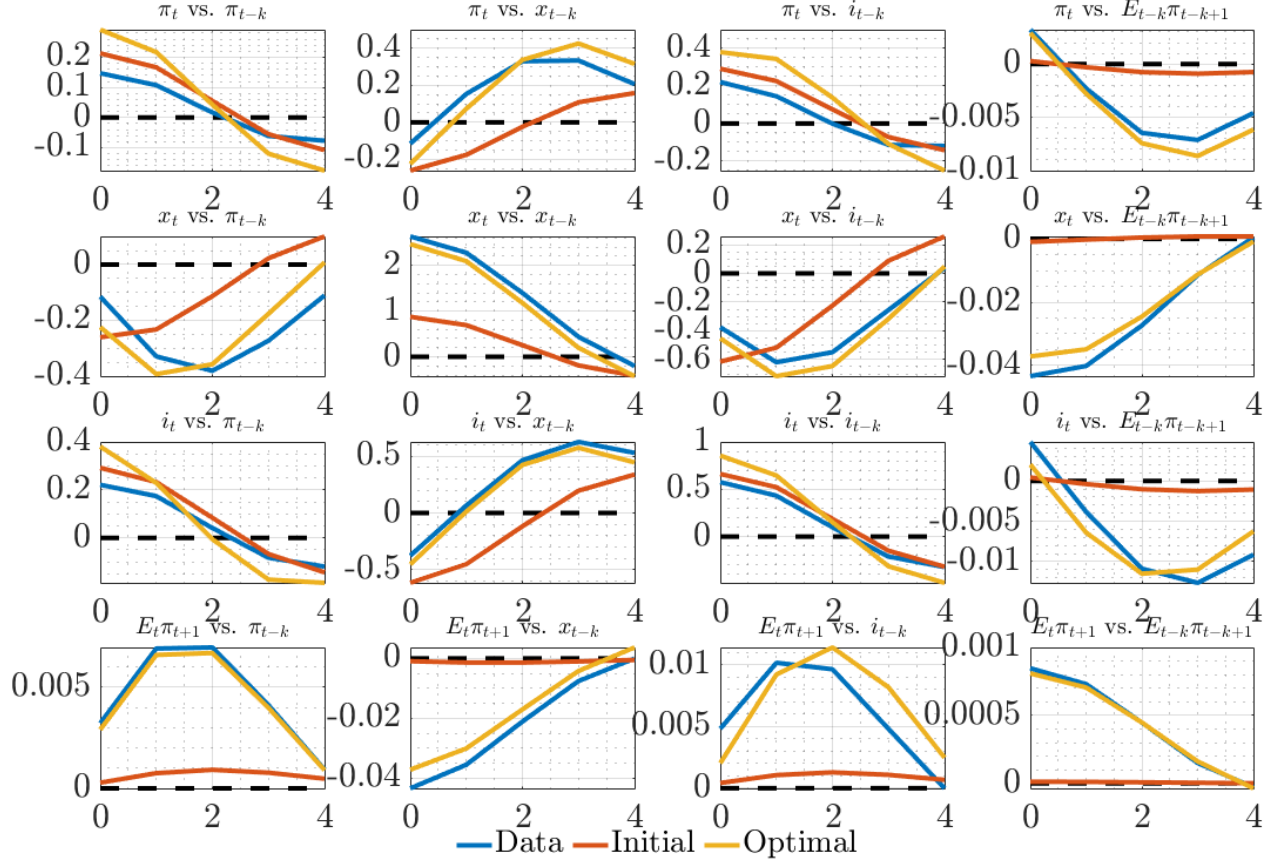
(b) Autocovariogram

## 1.2 Expectations

**Figure 7:** using 1-step ahead forecasts of inflation, estimate mean moments once, imposing convexity with weight 100K, w/o measurement error, truth with  $nfe = 5, fe \in (-2, 2)$



(a) Estimated parameters

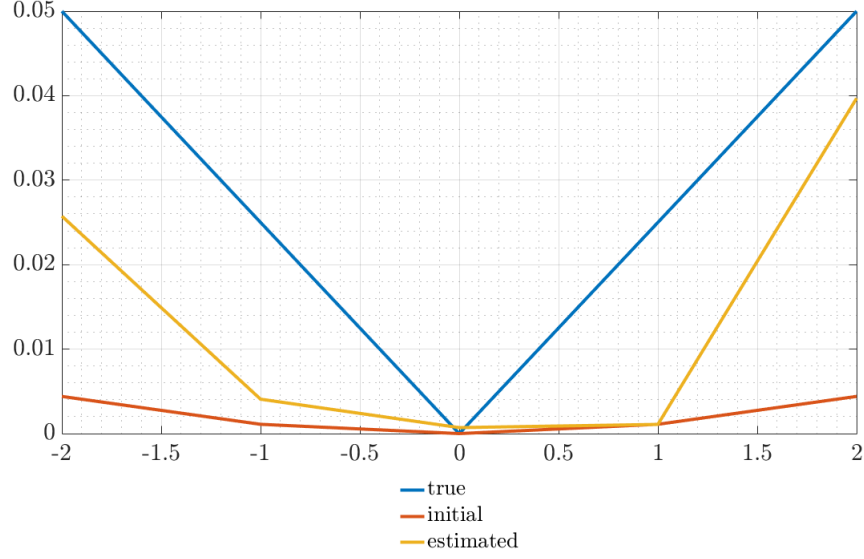


(b) Autocovariogram

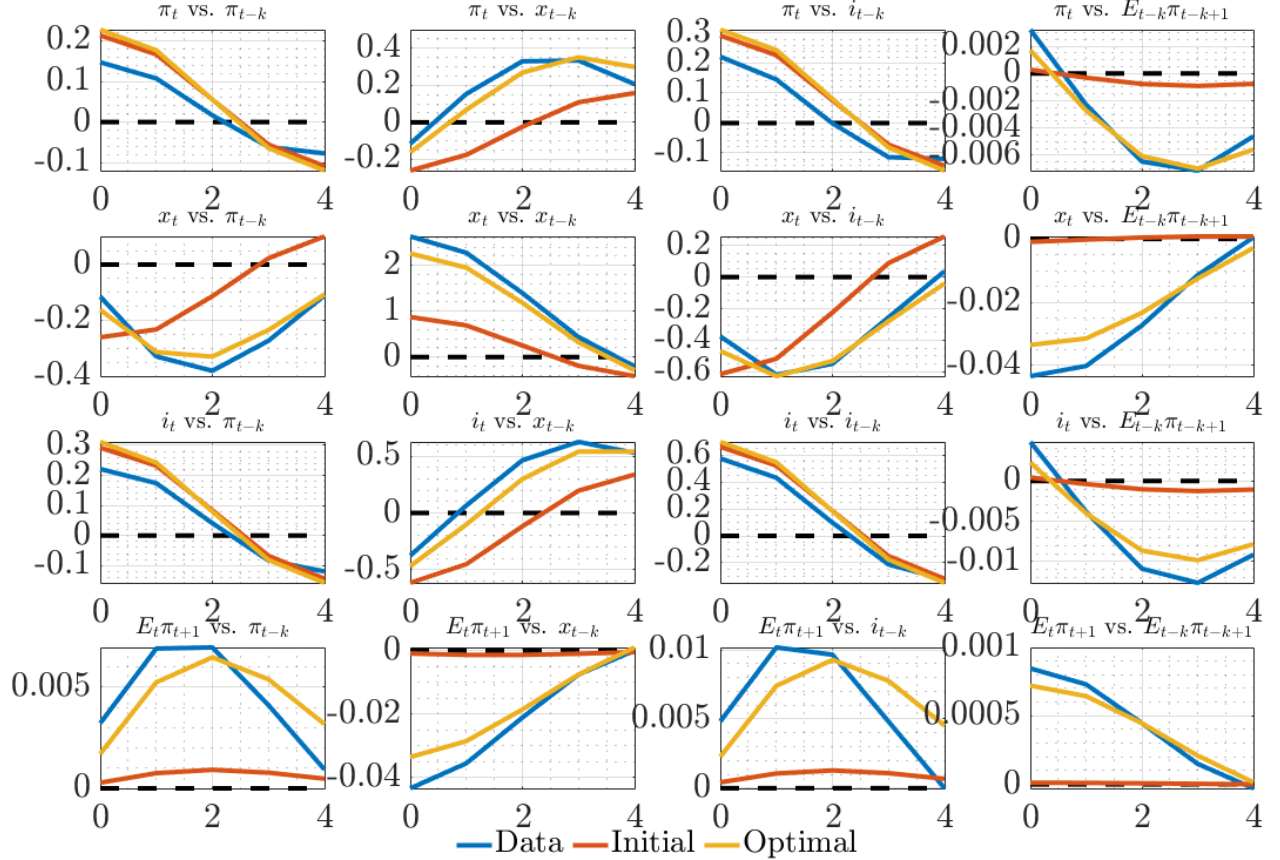


### 1.3 Expectations and rescaling

**Figure 8:** using 1-step ahead forecasts of inflation, rescaling  $W$ , estimate mean moments once, imposing convexity with weight 100K, w/o measurement error, truth with  $nfe = 5$ ,  $fe \in (-2, 2)$



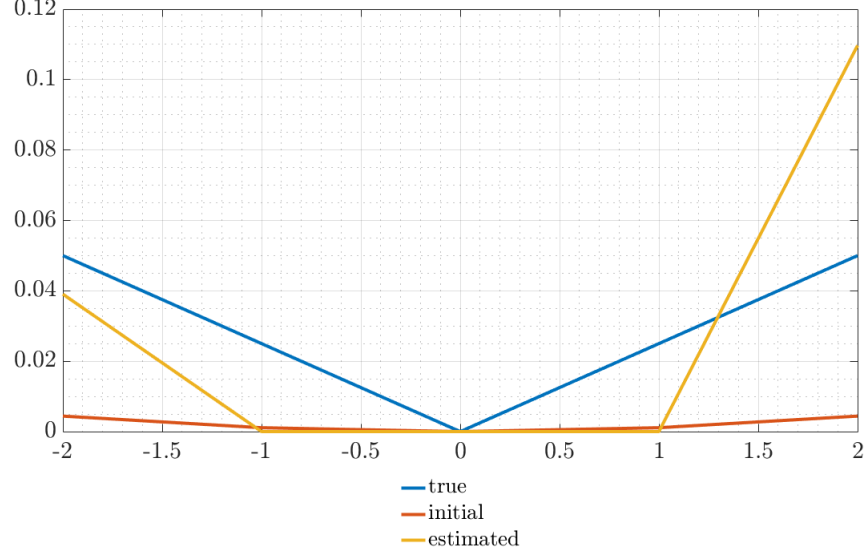
(a) Estimated parameters



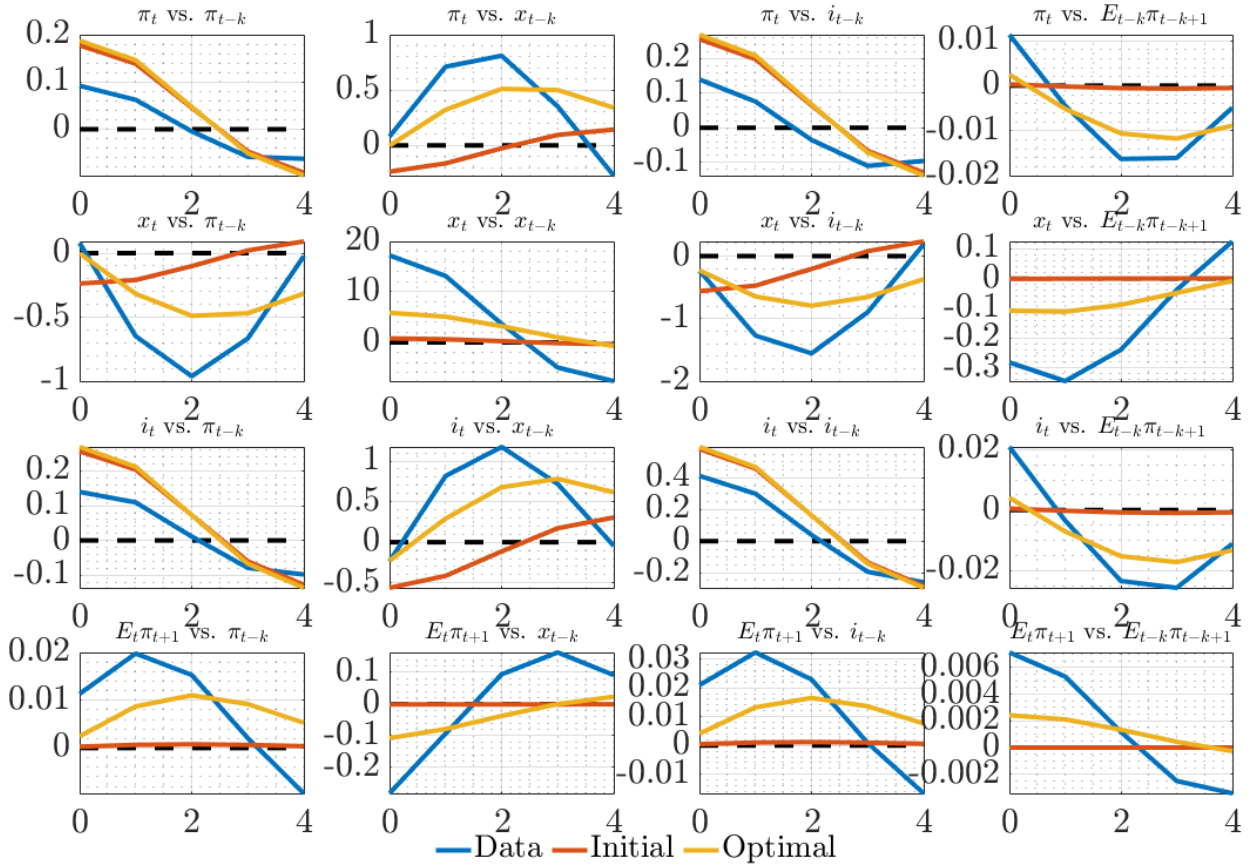
(b) Autocovariogram

## 1.4 Expectations and ridge

**Figure 9:** using 1-step ahead forecasts of inflation, ridge regression for data generation and estimation, estimate mean moments once, imposing convexity with weight 100K, w/o measurement error, truth with  $nfe = 5, fe \in (-2, 2)$



(a) Estimated parameters



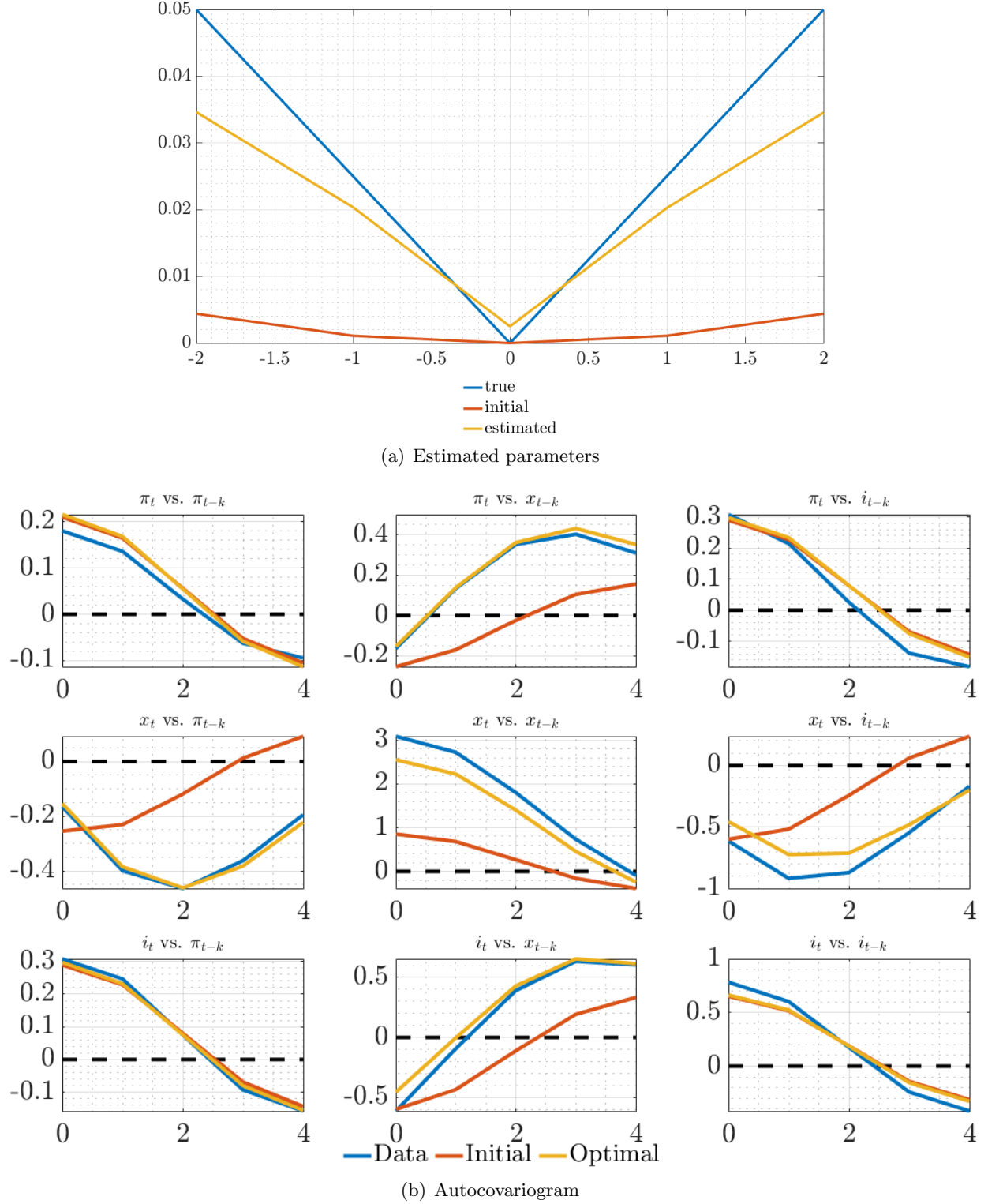
(b) Autocovariogram

## 1.5 Take a deep breath: what have I learned?

1. Some indication that the measurement error is screwed up, but I can bypass it, so ignore for now.
2. Rescaling might exit too soon. Main problem is it shouldn't change the *shape* of the loss function, but does. Yet no indication of numerical matrix inversion problems. I don't understand.
3. Indication that something is screwed up with the expectations, potentially connected with the rescaling. Ridge didn't really help either.
4. Loss function indicates that the parameters *are* identified. However, since loss is greater at true values than at estimated ones, it seems that the truth is a local, not a global min. I need to i) use some tricks to find this min ii) understand why this min isn't the global. I have a hypothesis: I think expectations in the true data aren't very large, and thus also aren't fluctuating enough. This screws up the moments somehow, but it also means that the estimation wants to set the  $\alpha$ s corresponding to large forecast errors to a low value, b/c otherwise it would cause fluctuations that aren't there in the data. Combined with the zero-neighborhood problem, the flat estimate is the result.

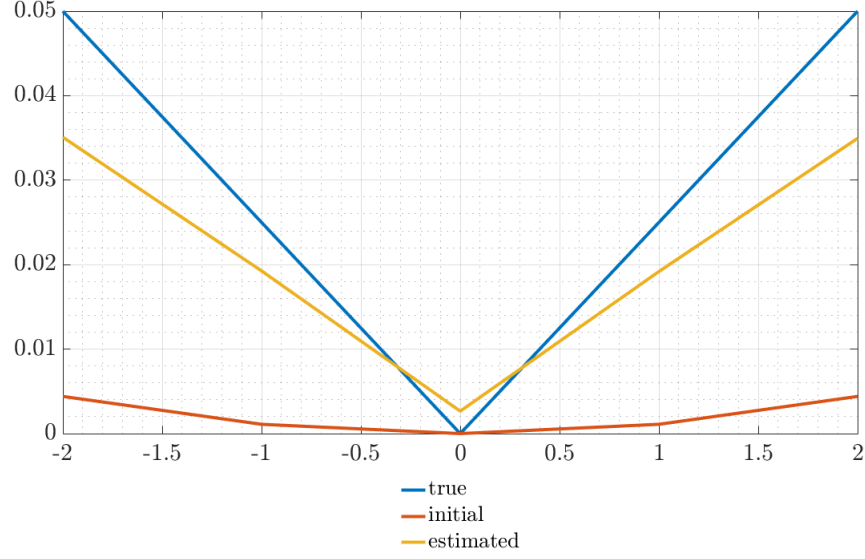
## 1.6 0 at 0

**Figure 10:** 0 at 0 imposed with weight 1000 not using 1-step ahead forecasts of inflation, not rescaling W, estimate mean moments once, imposing convexity with weight 100K, w/o measurement error, truth with  $nfe = 5$ ,  $fe \in (-2, 2)$

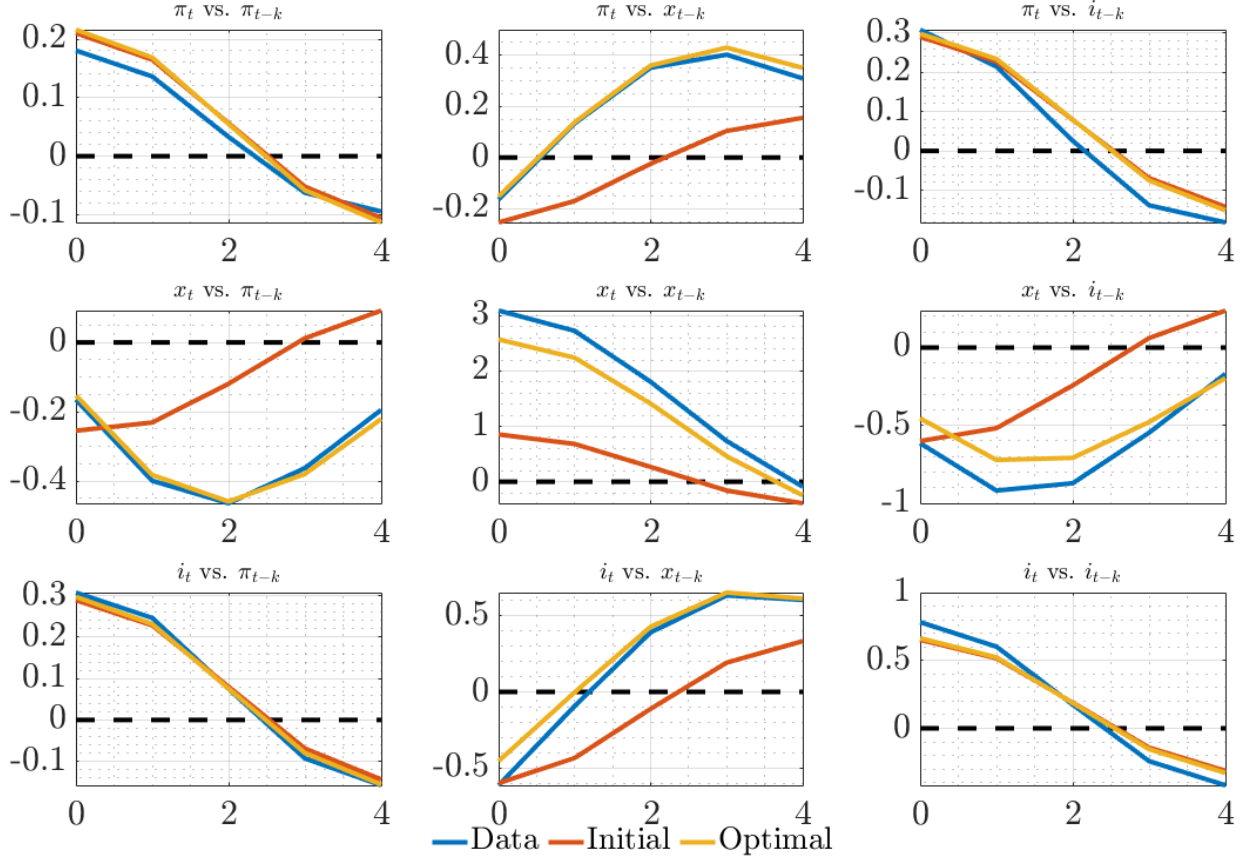


## 1.7 0 at 0, more convexity

**Figure 11:** 0 at 0 imposed with weight 1000 not using 1-step ahead forecasts of inflation, not rescaling W, estimate mean moments once, imposing convexity with weight 1000K, w/o measurement error, truth with  $nfe = 5, fe \in (-2, 2)$



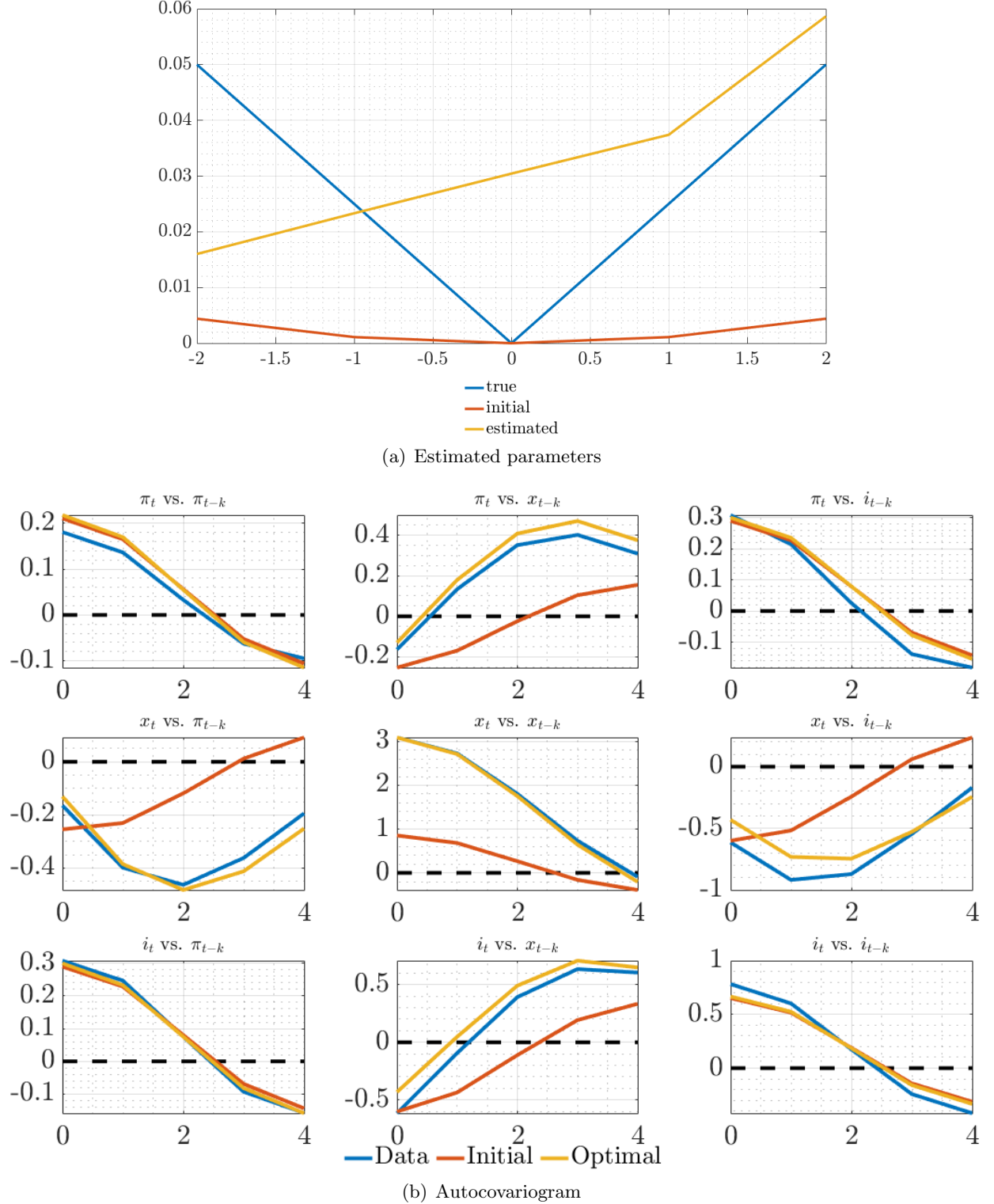
(a) Estimated parameters



(b) Autocovariogram

## 1.8 Identity weighting matrix

**Figure 12:** identity weighting matrix, not using 1-step ahead forecasts of inflation, not rescaling W, estimate mean moments once, imposing convexity with weight 1000K, w/o measurement error, truth with  $nfe = 5, fe \in (-2, 2)$





## A Model summary

$$x_t = -\sigma i_t + \hat{\mathbb{E}}_t \sum_{T=t}^{\infty} \beta^{T-t} ((1-\beta)x_{T+1} - \sigma(\beta i_{T+1} - \pi_{T+1}) + \sigma r_T^n) \quad (\text{A.1})$$

$$\pi_t = \kappa x_t + \hat{\mathbb{E}}_t \sum_{T=t}^{\infty} (\alpha\beta)^{T-t} (\kappa\alpha\beta x_{T+1} + (1-\alpha)\beta\pi_{T+1} + u_T) \quad (\text{A.2})$$

$$i_t = \psi_\pi \pi_t + \psi_x x_t + \bar{i}_t \quad (\text{if imposed}) \quad (\text{A.3})$$

$$\text{PLM:} \quad \hat{\mathbb{E}}_t z_{t+h} = a_{t-1} + b h_x^{h-1} s_t \quad \forall h \geq 1 \quad b = g_x h_x \quad (\text{A.4})$$

$$\text{Updating:} \quad a_t = a_{t-1} + k_t^{-1} (z_t - (a_{t-1} + b s_{t-1})) \quad (\text{A.5})$$

$$\text{Anchoring function:} \quad k_t^{-1} = \rho_k k_{t-1}^{-1} + \gamma_k f e_{t-1}^2 \quad (\text{A.6})$$

$$\text{Forecast error:} \quad f e_{t-1} = z_t - (a_{t-1} + b s_{t-1}) \quad (\text{A.7})$$

$$\text{LH expectations:} \quad f_a(t) = \frac{1}{1-\alpha\beta} a_{t-1} + b(\mathbb{I}_{nx} - \alpha\beta h)^{-1} s_t \quad f_b(t) = \frac{1}{1-\beta} a_{t-1} + b(\mathbb{I}_{nx} - \beta h)^{-1} s_t \quad (\text{A.8})$$

This notation captures vector learning ( $z$  learned) for intercept only. For scalar learning,  $a_t = (\bar{\pi}_t \ 0 \ 0)'$  and  $b_1$  designates the first row of  $b$ . The observables  $(\pi, x)$  are determined as:

$$x_t = -\sigma i_t + \begin{bmatrix} \sigma & 1-\beta & -\sigma\beta \end{bmatrix} f_b + \sigma \begin{bmatrix} 1 & 0 & 0 \end{bmatrix} (\mathbb{I}_{nx} - \beta h_x)^{-1} s_t \quad (\text{A.9})$$

$$\pi_t = \kappa x_t + \begin{bmatrix} (1-\alpha)\beta & \kappa\alpha\beta & 0 \end{bmatrix} f_a + \begin{bmatrix} 0 & 0 & 1 \end{bmatrix} (\mathbb{I}_{nx} - \alpha\beta h_x)^{-1} s_t \quad (\text{A.10})$$

## B Target criterion

The target criterion in the simplified model (scalar learning of inflation intercept only,  $k_t^{-1} = \mathbf{g}(f e_{t-1})$ ):

$$\pi_t = -\frac{\lambda_x}{\kappa} \left\{ x_t - \frac{(1-\alpha)\beta}{1-\alpha\beta} \left( k_t^{-1} + ((\pi_t - \bar{\pi}_{t-1} - b_1 s_{t-1})) \mathbf{g}_\pi(t) \right) \right. \\ \left. \left( \mathbb{E}_t \sum_{i=1}^{\infty} x_{t+i} \prod_{j=0}^{i-1} (1 - k_{t+1+j}^{-1} - (\pi_{t+1+j} - \bar{\pi}_{t+j} - b_1 s_{t+j}) \mathbf{g}_{\bar{\pi}}(t+j)) \right) \right\} \quad (\text{B.1})$$

where I'm using the notation that  $\prod_{j=0}^0 \equiv 1$ . For interpretation purposes, let me rewrite this as follows:

$$\pi_t = -\frac{\lambda_x}{\kappa} x_t + \frac{\lambda_x}{\kappa} \frac{(1-\alpha)\beta}{1-\alpha\beta} \left( k_t^{-1} + f e_{t|t-1}^{eve} \mathbf{g}_\pi(t) \right) \mathbb{E}_t \sum_{i=1}^{\infty} x_{t+i} \\ - \frac{\lambda_x}{\kappa} \frac{(1-\alpha)\beta}{1-\alpha\beta} \left( k_t^{-1} + f e_{t|t-1}^{eve} \mathbf{g}_\pi(t) \right) \left( \mathbb{E}_t \sum_{i=1}^{\infty} x_{t+i} \prod_{j=0}^{i-1} (k_{t+1+j}^{-1} + f e_{t+1+j|t+j}^{eve} \mathbf{g}_{\bar{\pi}}(t+j)) \right) \quad (\text{B.2})$$

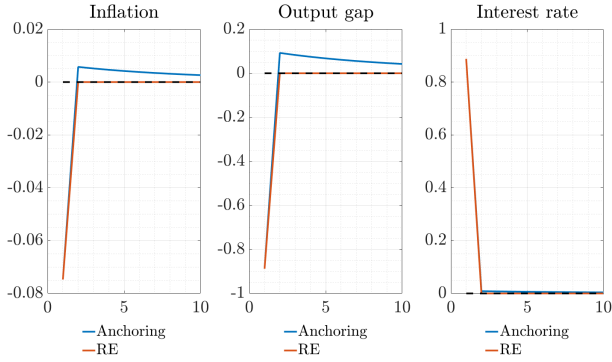
Interpretation: **tradeoffs from discretion in RE** + **effect of current level and change of the gain on future tradeoffs** + **effect of future expected levels and changes of the gain on future tradeoffs**



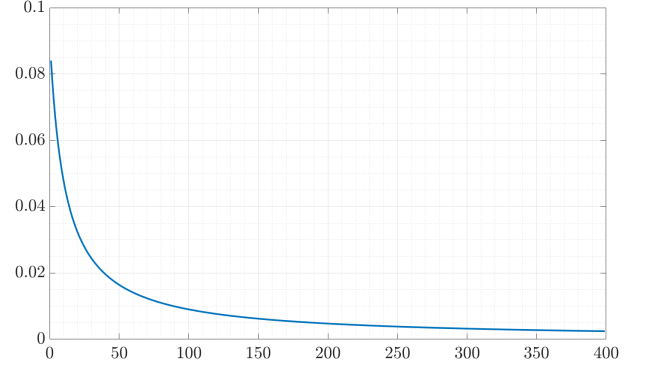
## C Impulse responses to iid monpol shocks across a wide range of learning models

$T = 400, N = 100, n_{drop} = 5$ , shock imposed at  $t = 25$ , calibration as above, Taylor rule assumed to be known, PLM = learn constant only, of inflation only.

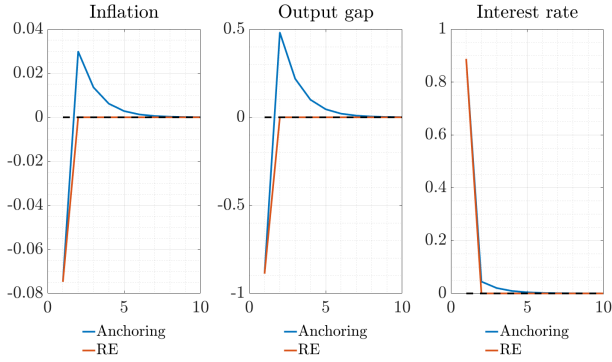
**Figure 13:** IRFs and gain history (sample means)



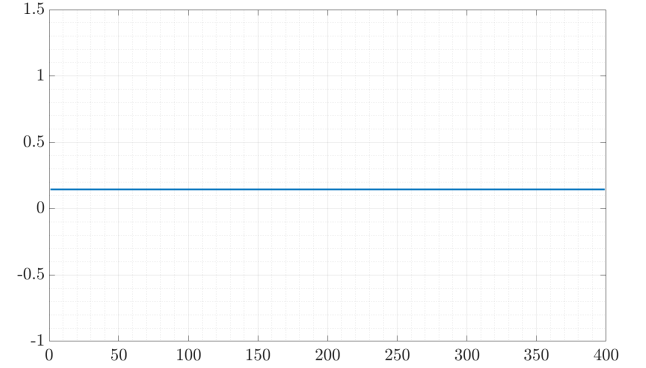
(a) Decreasing gain learning



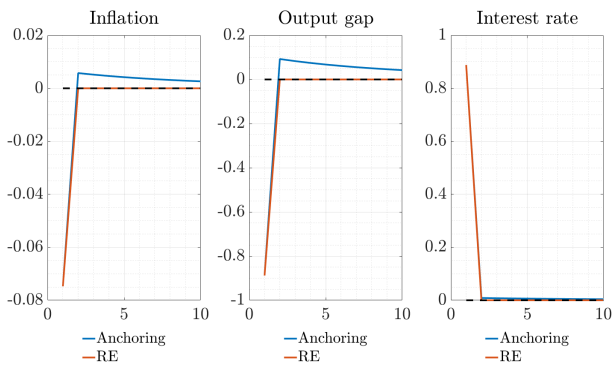
(b) Mean gain



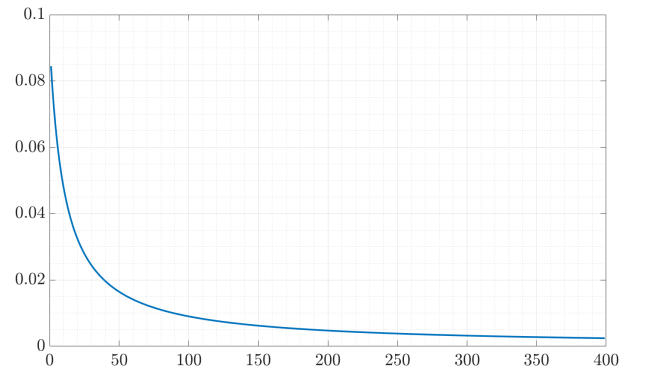
(c) Constant gain learning



(d) Mean gain

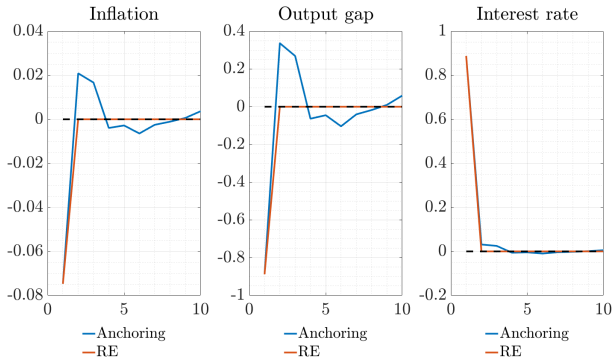


(e) CEMP criterion (vector)

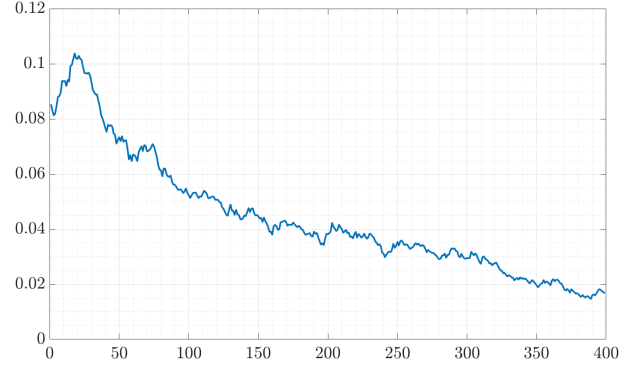


(f) Mean gain

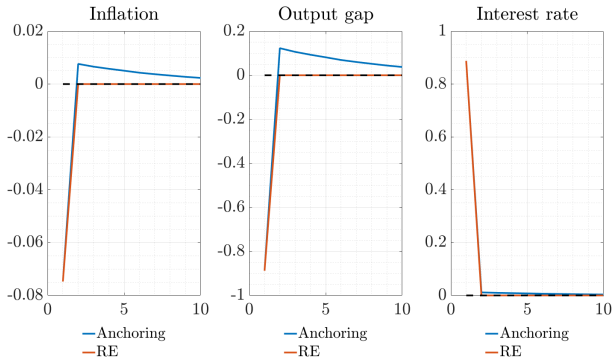
**Figure 14:** IRFs and gain history (sample means), continued



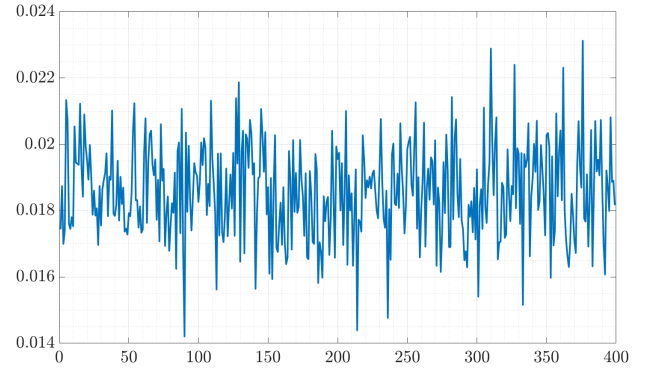
(a) CUSUM criterion (vector)



(b) Mean gain



(c) Smooth criterion, approximated, using  $\alpha^{true} = (0.05; 0.025; 0; 0.025; 0.05)$ , on  $fe \in (-2, 2)$ .



(d) Mean gain