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$$egin{aligned} \mathbb{E}_{t+1}[a_i] &= \mathbb{E}_t[a_i] rac{\sigma_arepsilon^2}{\sigma_arepsilon^2 + \mathbb{V}_t[a_i]} + S_{it} rac{\mathbb{V}_t[a_i]}{\sigma_arepsilon^2 + \mathbb{V}_t[a_i]} \ \mathbb{V}_{t+1}[a_i] &= \mathbb{V}_t[a_i] rac{\sigma_arepsilon^2}{\sigma_arepsilon^2 + \mathbb{V}_t[a_i]} \end{aligned}$$

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$$\mathbb{V}_{t+1}[a_i] = \mathbb{V}_t[a_i] \frac{\sigma_{\varepsilon}^2}{\sigma_{\varepsilon}^2 + \mathbb{V}_t[a_i]}$$

• $\mathbb{E}_{t+1}[a_i]$ and $\mathbb{V}_{t+1}[a_i]$ are referred to as the posterior beliefs

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These properties may not always be desirable, but they are intrinsic to Bayesianism