CHAPTER 4
TOOLS OF THE FORECASTER

4.1 The Information Set

4.1.1 Some Information Sets Are More Valuable than Others

Table 4.1 OLS Regression Results: House Prices and Mortgages Rates

Model (i)

Dependent Variable: DP
Method: Least Squares
Sample (adjusted): 1974 2007
Included observations: 34 after adjustments
Newey-West HAC Standard Errors & Covariance (lag truncation=3)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.507576	0.772012	3.248103	0.0028
DP(-1)	0.949125	0.158163	6.000914	0.0000
DP(-2)	-0.380643	0.207324	-1.835982	0.0760

R-squared	0.512796	Mean dependent var	6.152156
Adjusted R-squared	0.481363	S.D. dependent var	3.436283
S.E. of regression	2.474689	Akaike info criterion	4.734204
Sum squared resid	189.8467	Schwarz criterion	4.868883
Log likelihood	-77.48147	F-statistic	16.31416
Durbin-Watson stat	1.906822	Prob(F-statistic)	0.000014

Model (ii)

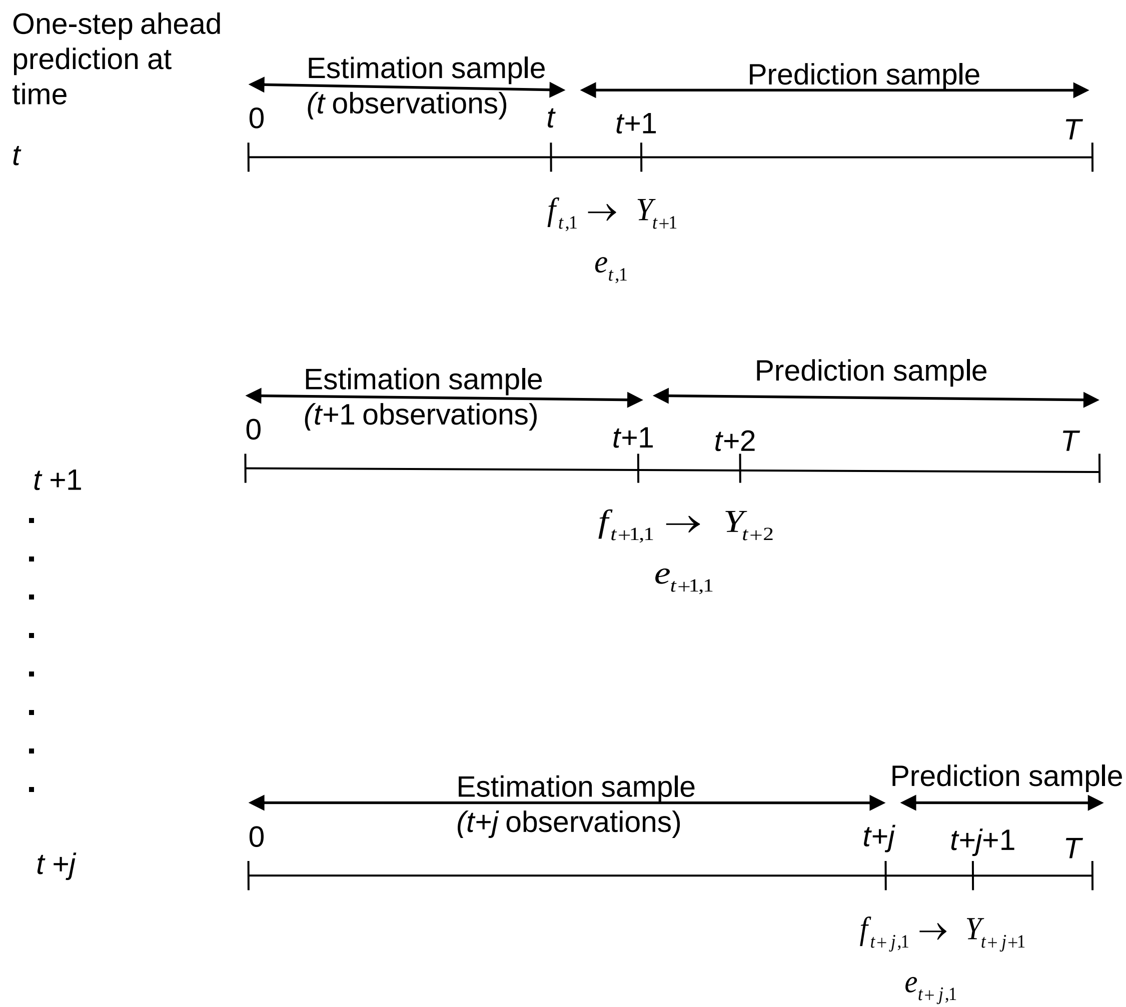
Dependent Variable: DP
Method: Least Squares
Sample (adjusted): 1974 2007
Included observations: 34 after adjustments
Newey-West HAC Standard Errors & Covariance (lag truncation=3)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.220667	0.939448	2.363800	0.0250
DP(-1)	0.914249	0.187557	4.874509	0.0000
DP(-2)	-0.303738	0.276051	-1.100296	0.2803
DR(-1)	-0.227373	0.373079	-0.609449	0.5470
DR(-2)	-0.155855	0.295756	-0.526970	0.6022

R-squared	0.520419	Mean dependent var	6.152156
Adjusted R-squared	0.454270	S.D. dependent var	3.436283
S.E. of regression	2.538503	Akaike info criterion	4.836079
Sum squared resid	186.8759	Schwarz criterion	5.060544
Log likelihood	-77.21334	F-statistic	7.867378
Durbin-Watson stat	1.867714	Prob(F-statistic)	0.000201

4.2.1 Forecasting Environments

Figure 4.1 Forecasting Environments: <u>**Recursive Scheme**</u>



Update the estimation sample with new observations as they become available

Figure 4.2 Forecasting Environments: **Rolling Scheme**

Doesn't enlarge the estimation sample as new observations become available, as old observations should not have much weight (breaks, evolving dynamics)

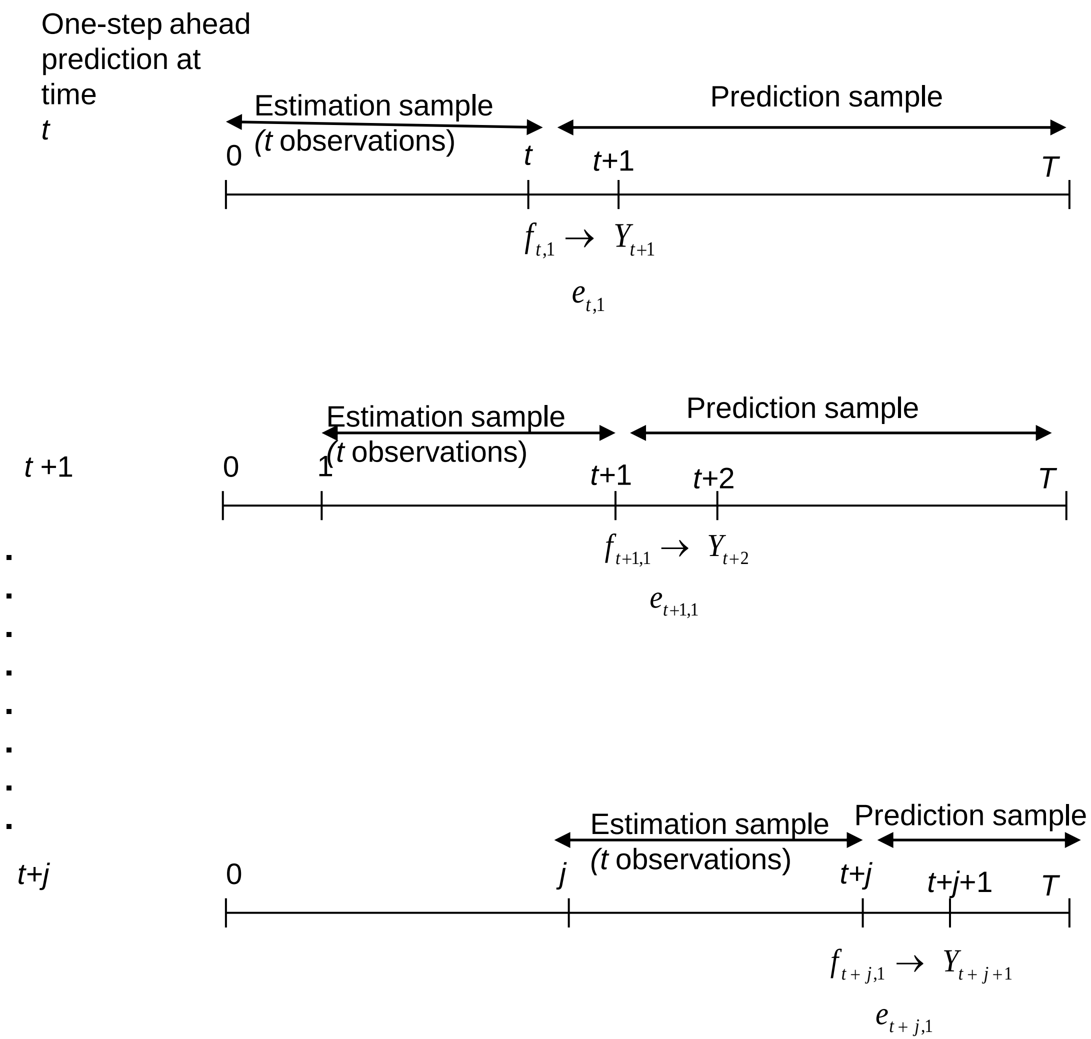
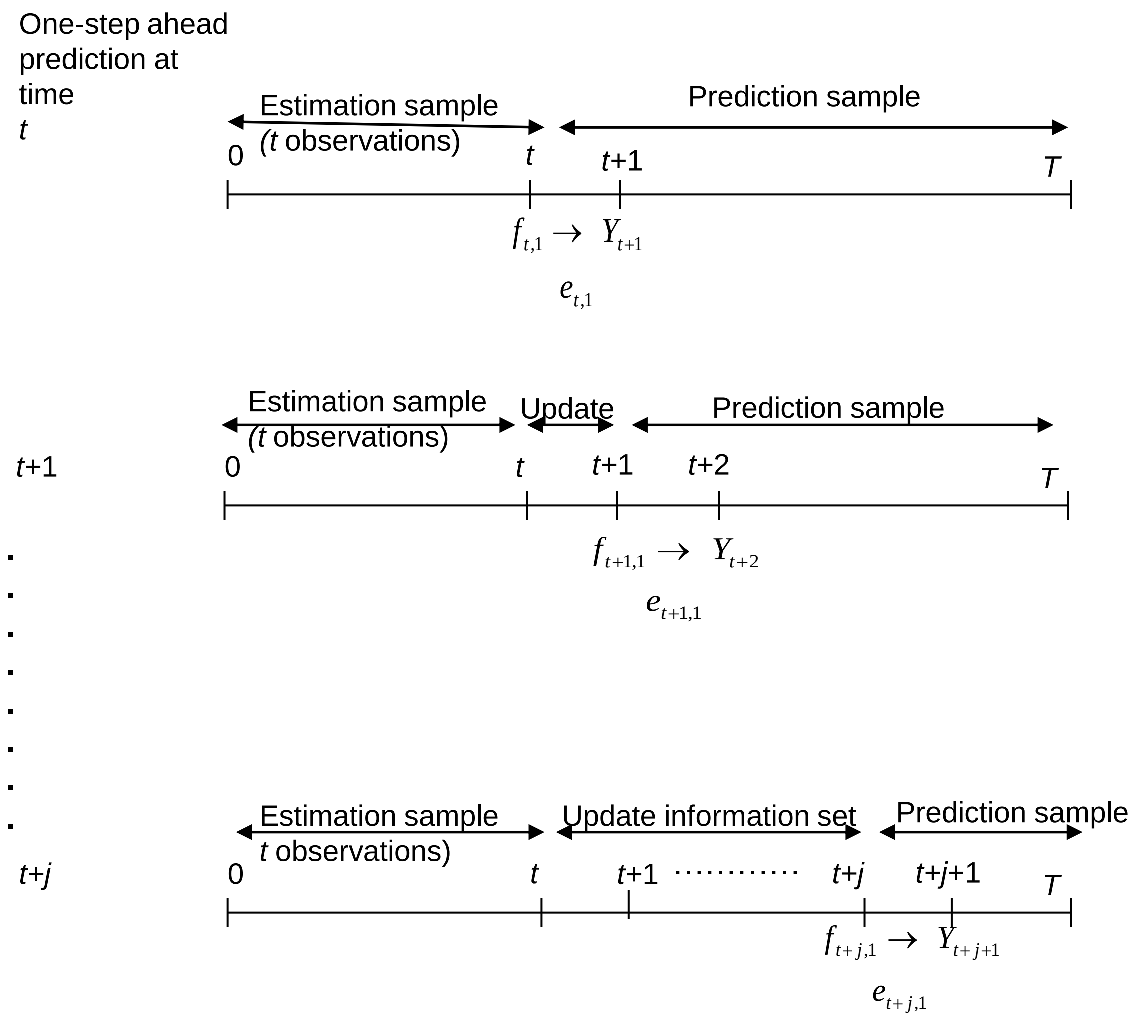


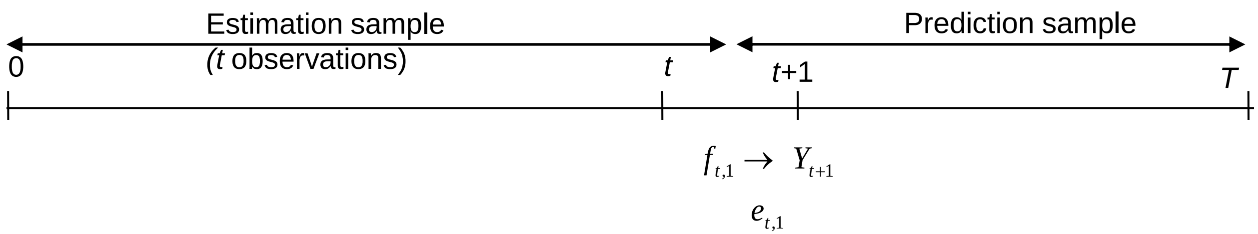
Figure 4.3 Forecasting Environments: **Fixed Scheme**

Doesn't enlarge the estimation sample for model parameters as new observations become available.

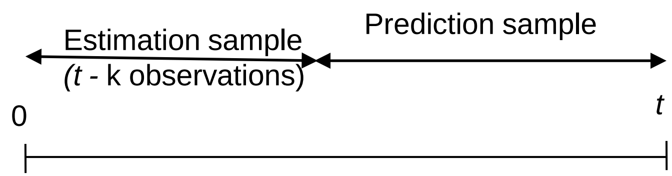
New observations are used with the same model estimated at time *t*



Ex-ante forecasting



Ex-post forecasting



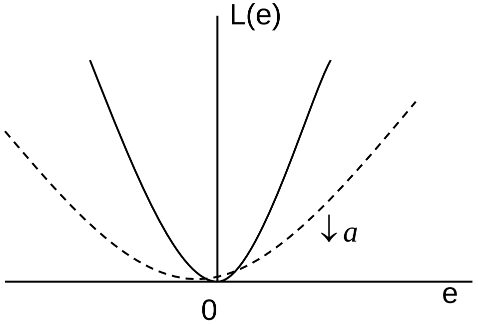
4.3 The Loss Function

4.3.2 Examples

Figure 4.4 Symmetric Loss Functions

Quadratic loss function

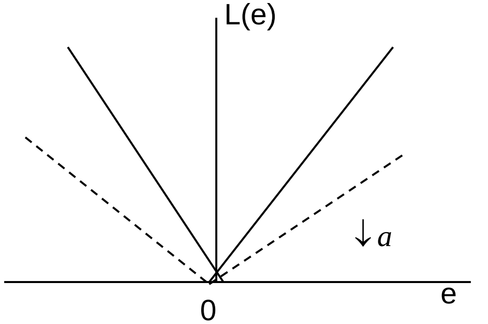
$$L(e) = ae^2, \quad a > 0$$



$$L(e) = L(-e)$$

Absolute value loss function

$$L(e) = a\,|\,e\,|, \quad a > 0$$

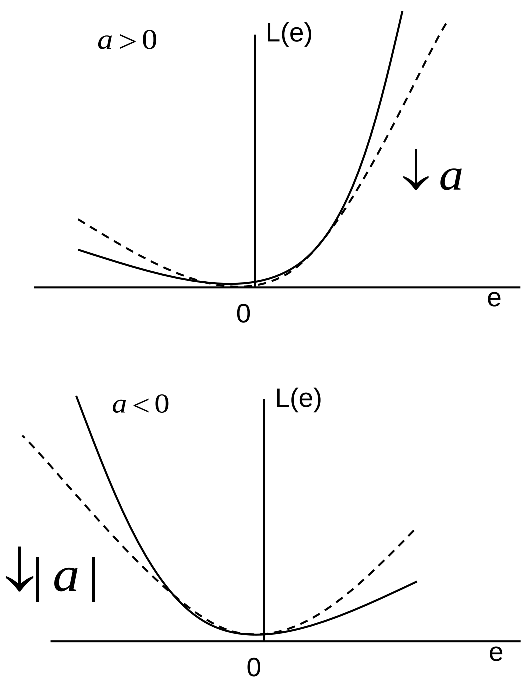


$$L(e) = L(-e)$$

Figure 4.5 Asymmetric Loss Functions

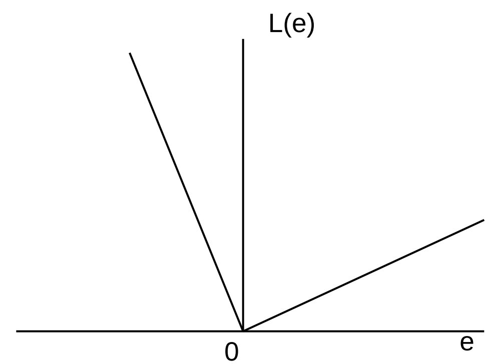
Linex function

$$L(e) = \exp(ae) - ae - 1, \quad a \neq 0$$



Lin-lin function

$$L(e) = \begin{cases} a\,|e| & e > 0 \\ b\,|e| & e \leq 0 \end{cases}$$



$b > a \rightarrow L(-e) > L(e)$

4.3.3 Optimal Forecast: An Introduction

Figure 4.6 The Forecasting Problem

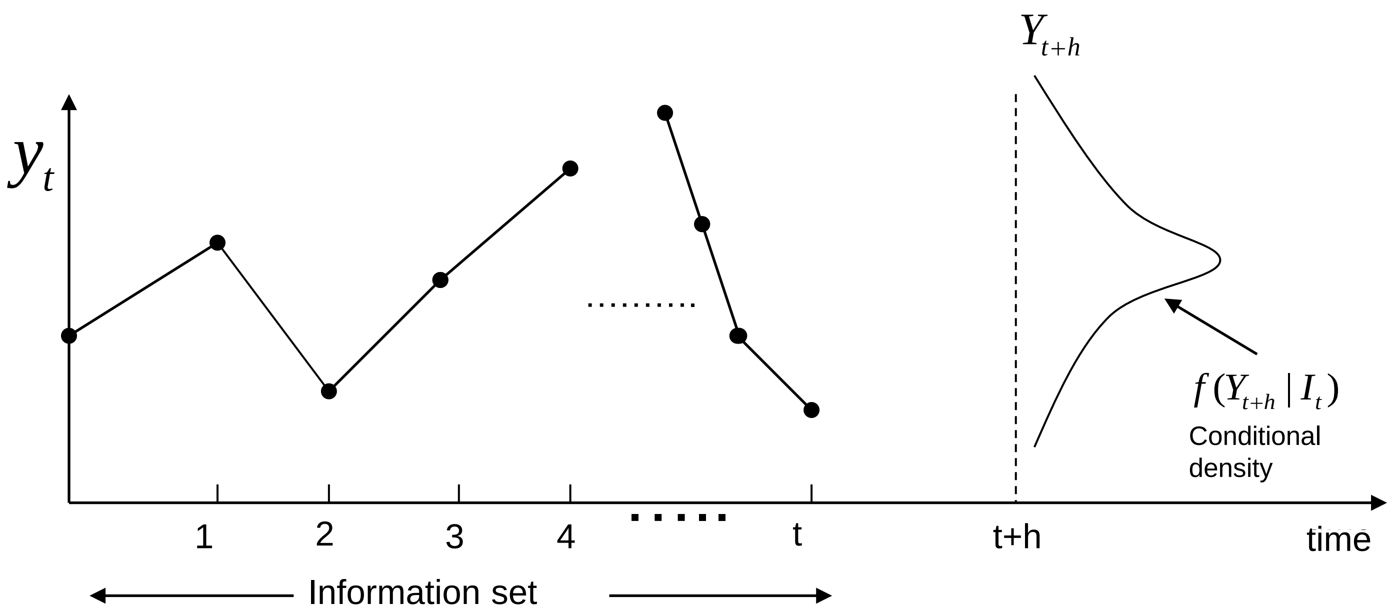
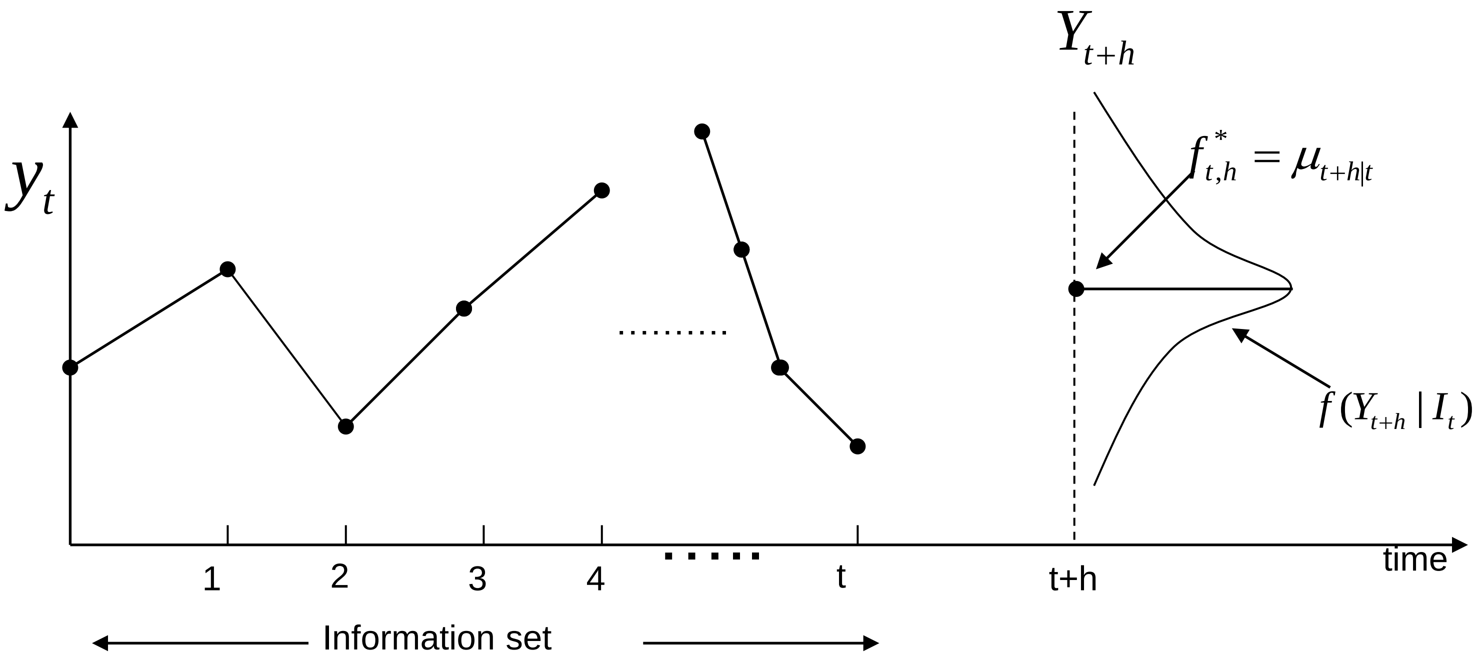


Figure 4.7 Optimal Forecast Under Quadratic Loss



4.3.3.2 Functional Form of the Loss Function: The Case of a Quadratic Loss

Suppose that the forecaster has a symmetric quadratic loss function $L(e_{t,h}) = ae_{t,h}^2$ for $a > 0$. Let us construct the expected value of the loss,

$$E(L(e_{t,h}) \mid I_t) = aE(e_{t,h}^2) = aE(y_{t+h} - f_{t,h})^2 = aE(y_{t+h}^2 - 2f_{t,h}\,y_{t+h} + f_{t,h}^2)$$
$$= a(E(y_{t+h}^2) - 2f_{t,h}\,E(y_{t+h}) + f_{t,h}^2)$$

$$\frac{\partial\, E(L(e_{t,h} \mid I_t)}{\partial\, f_{t,h}} = -2aE(y_{t+h} \mid I_t) + 2af_{t,h} = 0 \quad \Rightarrow f_{t,h}^* = E(y_{t+h} \mid I_t)$$

$$f_{t,h}^* = E(y_{t+h} \mid I_t) \equiv \mu_{t+h|t}$$

Distinguish between unconditional expectation and *conditional expectation*