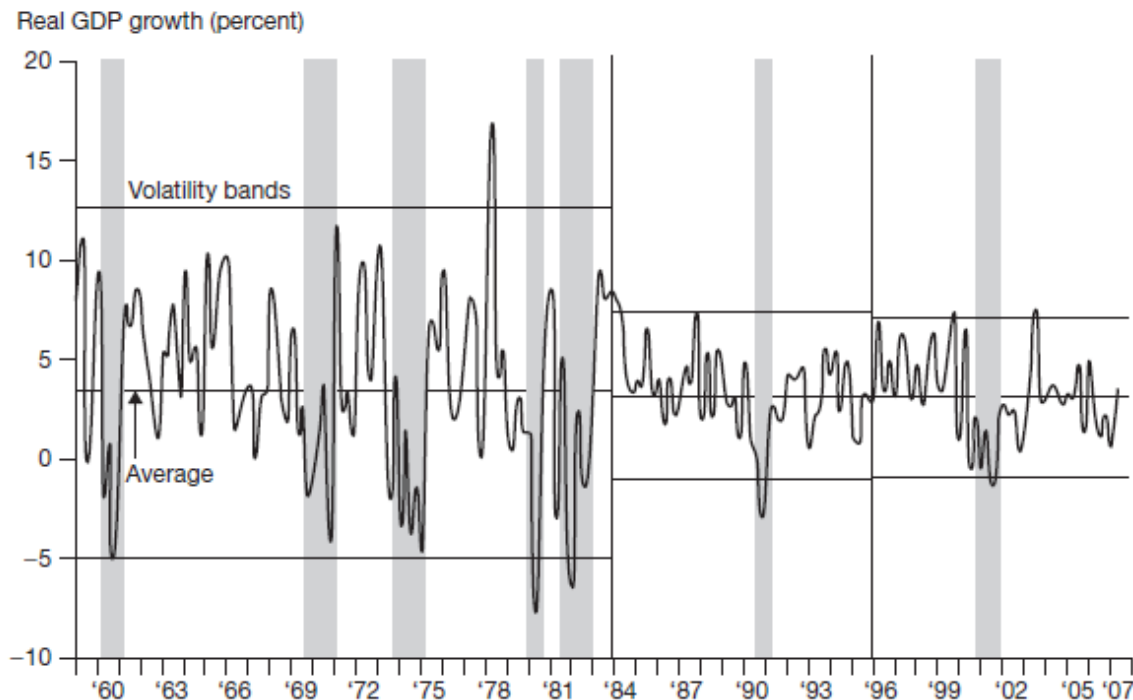


CHAPTER 13

FORECASTING VOLATILITY I

In ARMA models considered in this course we have assumed that volatility is constant



Note: Shaded areas denote recessions.

Figure 13.2 U.S. Real GDP with Volatility Bands

But there is evidence that for some financial series **volatility is time varying**

By **volatility** we mean variability: σ^2 , σ , MAD or other

These slides are based on:

González-Rivera: Forecasting for Economics and Business, Copyright © 2013 Pearson Education, Inc.

Slides adapted for this course. We thank Gloria González-Rivera and assume full responsibility for all errors due to our changes

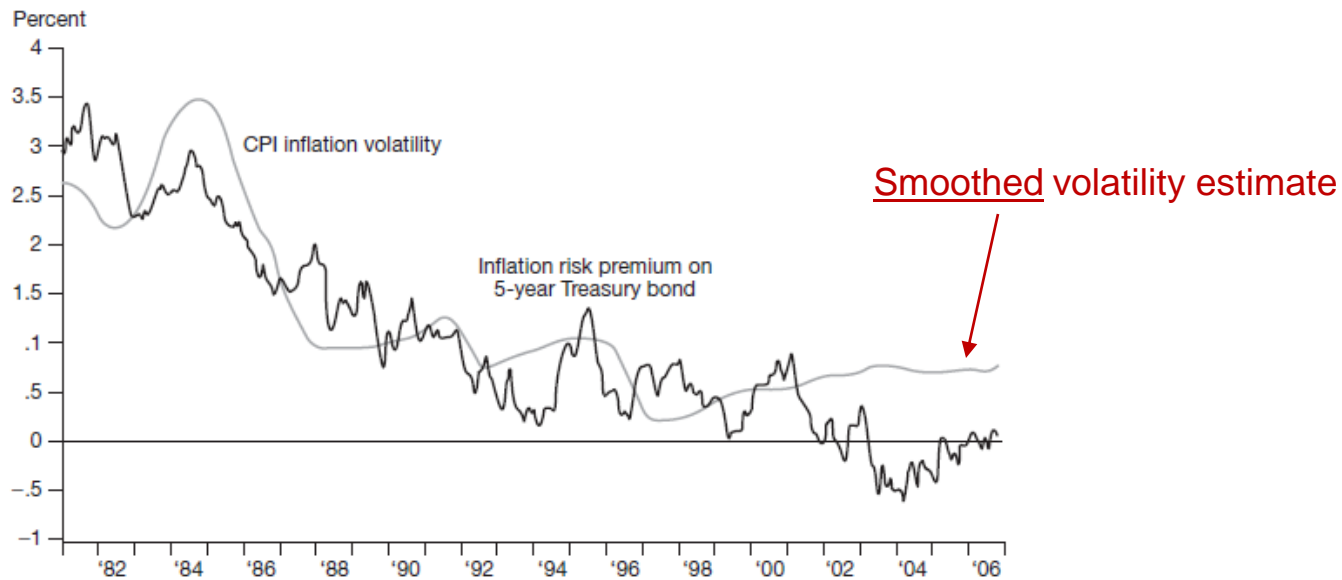


Figure 13.3 Volatility of Consumer Price Index Inflation

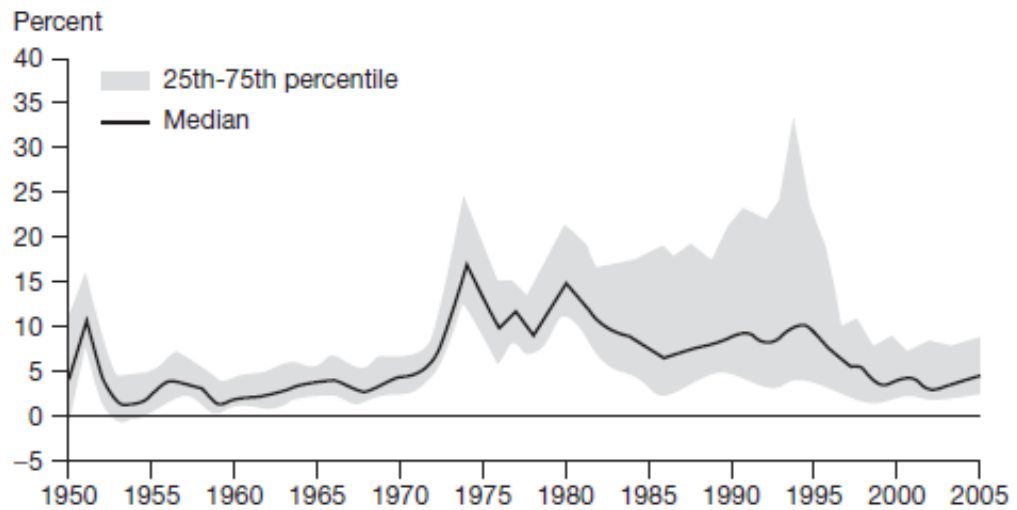


Figure 13.4 Global Inflation Rate

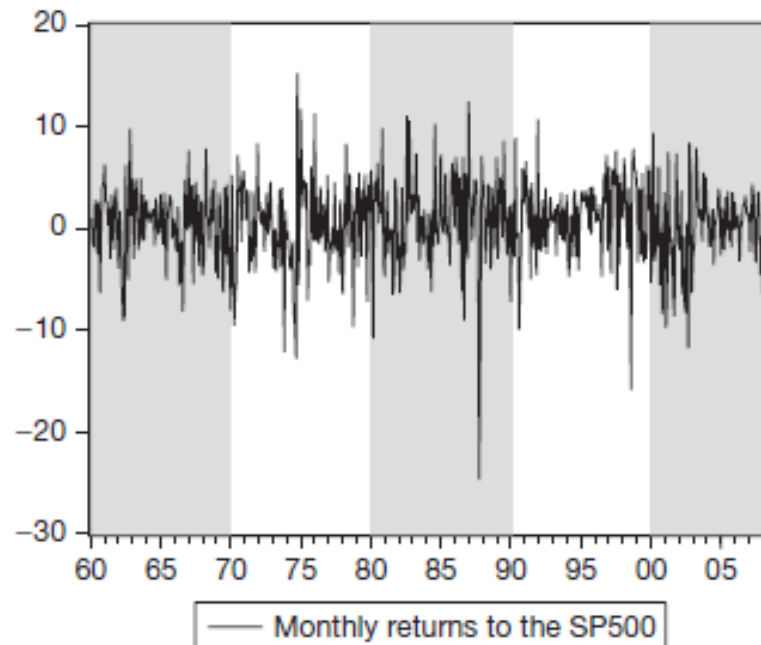


Figure 13.5 Monthly Returns of the SP500 Index

	1960–1969	1970–1979	1980–1989	1990–1999	2000–2008 (July)
Sample standard deviation	3.45%	4.59%	4.79%	3.88%	4.05%
Maximum	9.67%	15.10%	12.38%	10.58%	9.23%
Minimum	-8.99%	-12.71%	-24.54%	-15.76%	-11.65%
Range	18.66	27.81	36.92	26.34	20.88
Interquartile interval	(-1.62, 2.69)	(-2.21, 3.56)	(-1.42, 3.96)	(-1.00, 3.80)	(-2.03, 2.10)
Interquartile range	4.31	5.77	5.38	4.80	4.13

Table 13.1 Summary of the Dispersion in the Monthly Returns to the SP500

13.3 Is There Time Dependence in Volatility?

Figure 13.6 Time Series of SP500 Index, Yen/Dollar Exchange Rate, and 10-year Treasury Note Yield

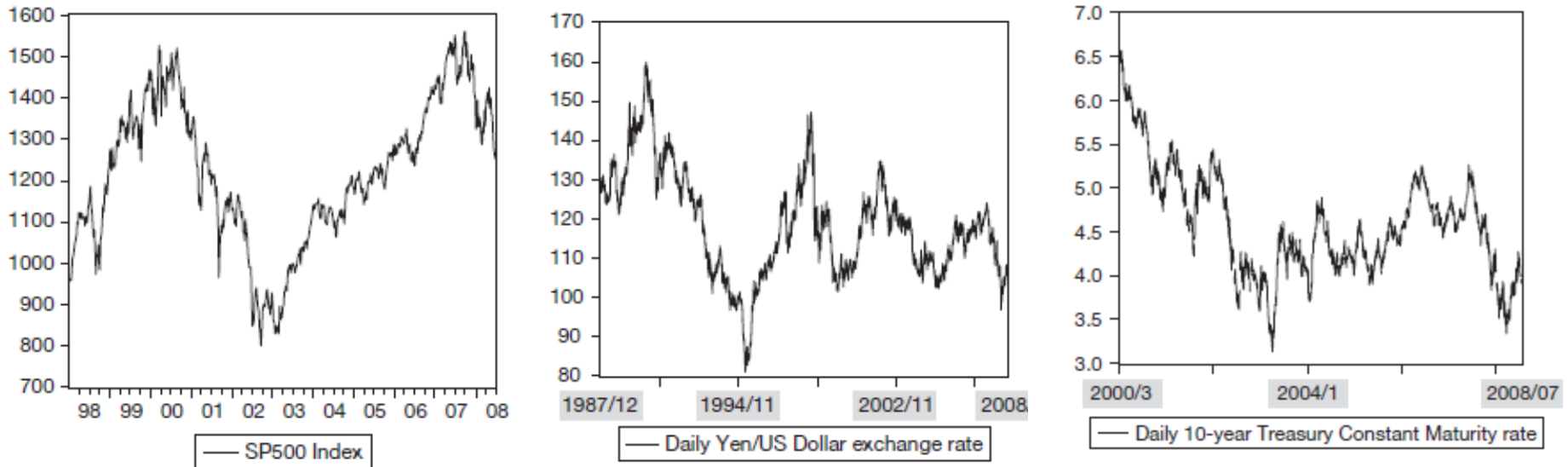
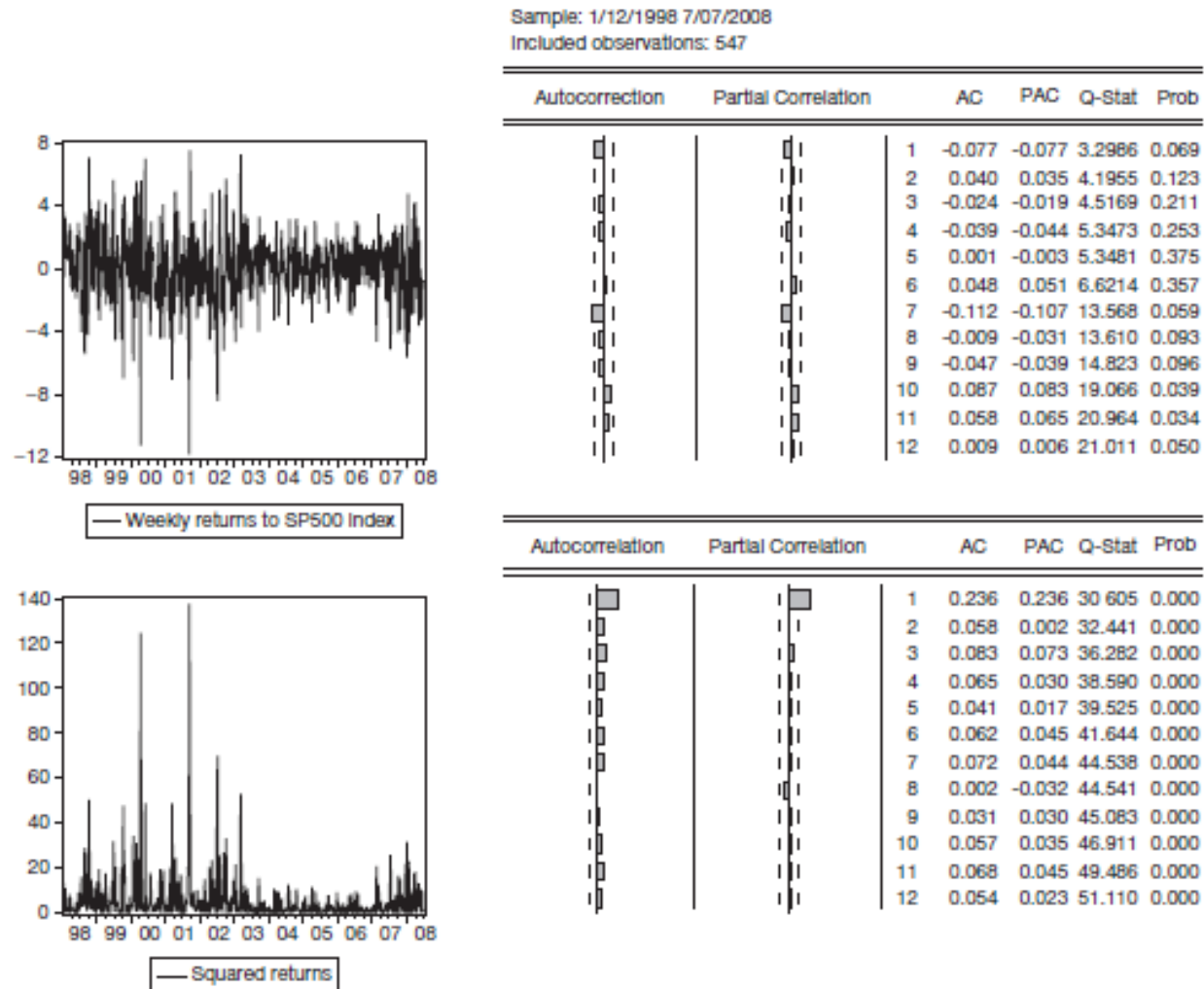


Table 13.2 Unit Root Testing: Value of the Dickey-Fuller Test

SP500 Index	Yen/Dollar exchange rate	10-year Treasury Note
-2.07	-2.69	-2.09
<i>p</i> -value = 0.25	<i>p</i> -value = 0.08	<i>p</i> -value = 0.24

The time series are nonstationary -> we proceed to take the first difference of each series (in logs) to get the returns r_t

Figure 13.7 Transformations of Weekly Returns to the SP500 Index and Their Autocorrelations



The series of returns does not display autocorrelation.
But the squared returns do.

The transformations r_t^2 , $|r_t|$ and $r_t^{HI} - r_t^{LO}$ have positive autocorrelations.

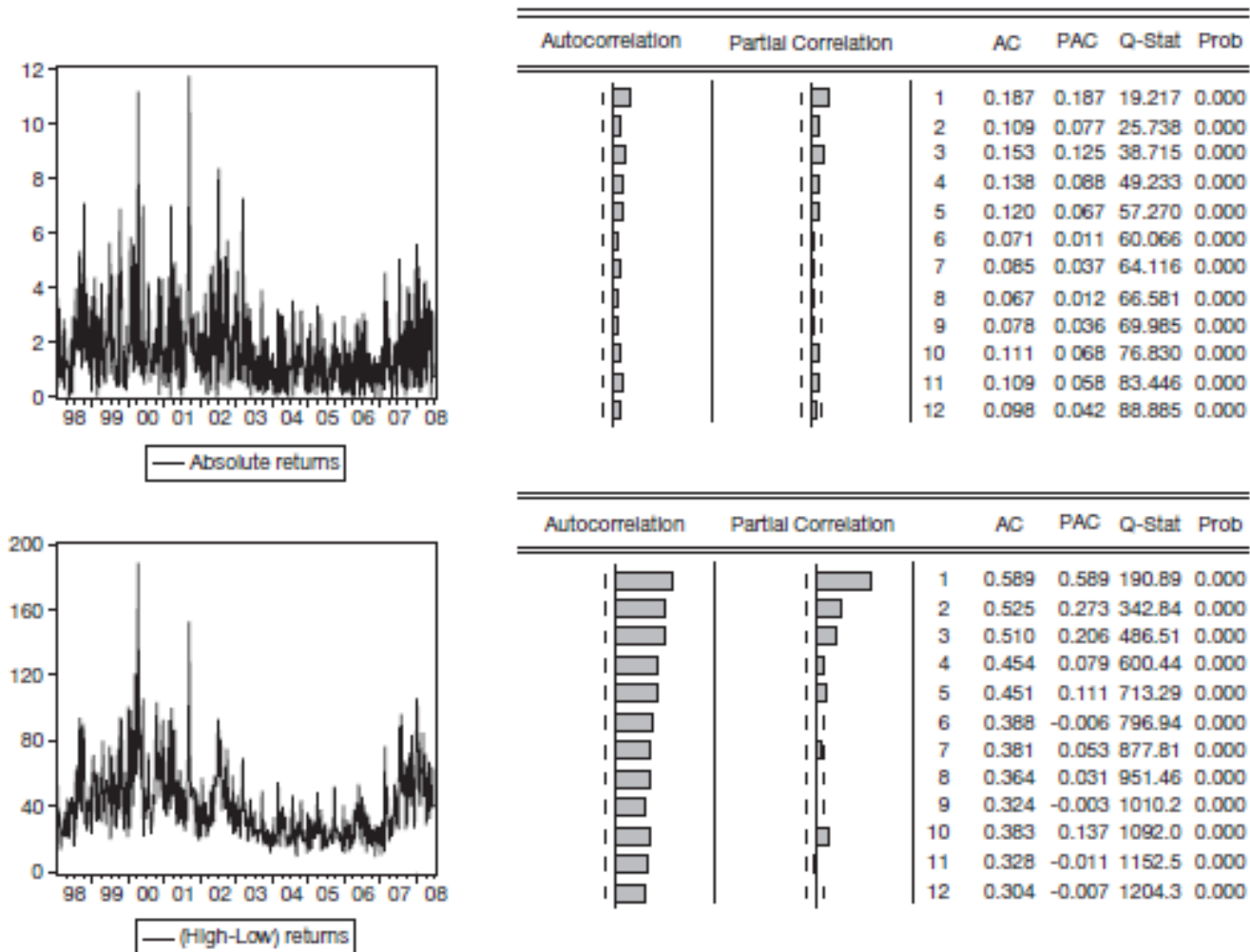
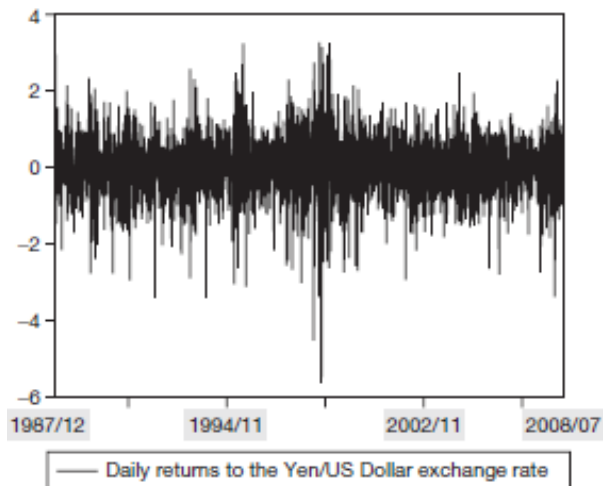


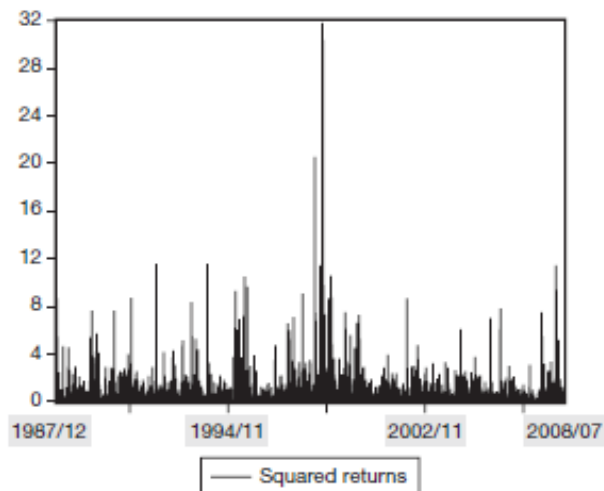
Figure 13.7 Transformations of Weekly Returns to the SP500 Index and Their Autocorrelations

Figure 13.8 Transformations of Daily Returns to Yen/Dollar Exchange Rate and Their Autocorrelations



Sample: 4251 9414
Included observations: 5164

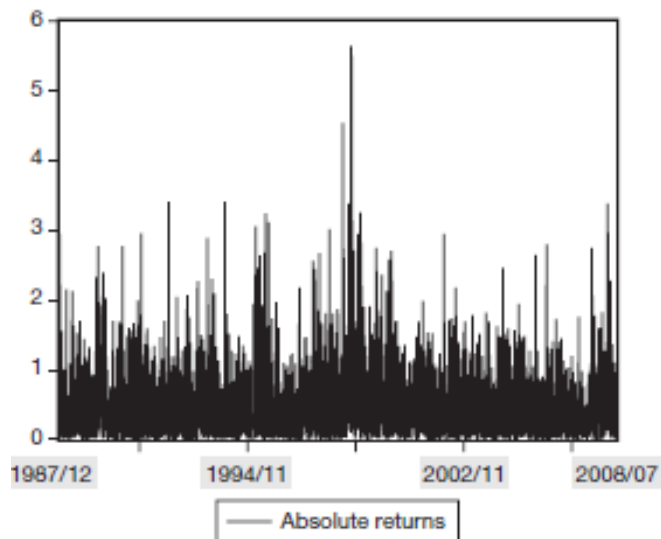
Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob	
		1	0.020	0.020	2.1653	0.141
		2	0.008	0.008	2.5119	0.285
		3	-0.027	-0.028	6.3895	0.094
		4	-0.001	0.000	6.3949	0.172
		5	0.004	0.005	6.4908	0.261
		6	-0.017	-0.018	7.9488	0.242
		7	0.018	0.019	9.6769	0.208
		8	-0.000	-0.001	9.6778	0.288
		9	0.004	0.003	9.7815	0.368
		10	0.032	0.033	15.050	0.130
		11	-0.008	-0.009	15.373	0.166
		12	0.016	0.015	16.641	0.164



Sample: 4251 9414
Included observations: 5164

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob	
		1	0.198	0.198	201.84	0.000
		2	0.113	0.077	268.31	0.000
		3	0.088	0.054	307.91	0.000
		4	0.069	0.037	332.92	0.000
		5	0.103	0.076	387.32	0.000
		6	0.090	0.049	428.94	0.000
		7	0.090	0.049	470.50	0.000
		8	0.094	0.051	515.75	0.000
		9	0.089	0.044	556.38	0.000
		10	0.032	-0.019	561.60	0.000
		11	0.071	0.041	587.55	0.000
		12	0.041	-0.001	596.28	0.000

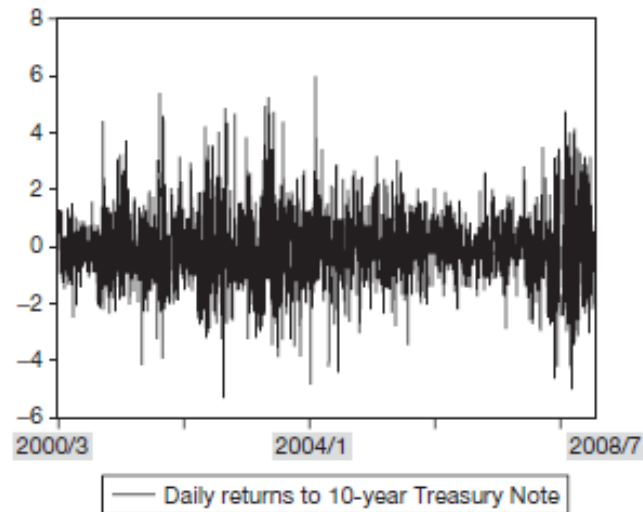
Figure 13.8 Transformations of Daily Returns to Yen/Dollar Exchange Rate and Their Autocorrelations



Sample: 4251 9414
Included observations: 5164

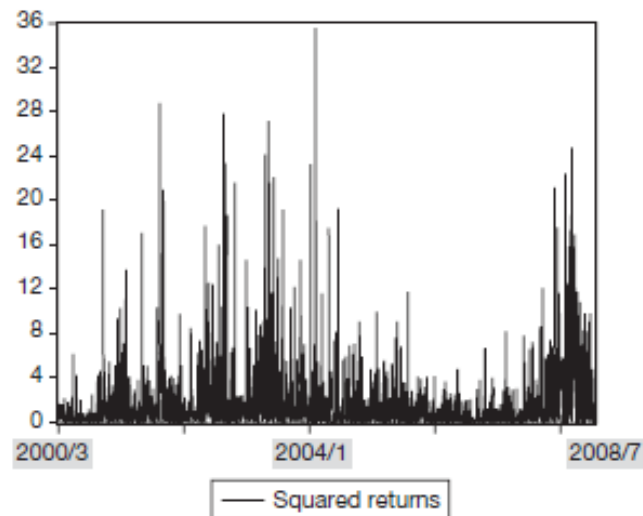
Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob	
		1	0.122	0.122	76.904	0.000
		2	0.107	0.093	135.78	0.000
		3	0.102	0.081	189.60	0.000
		4	0.104	0.077	245.41	0.000
		5	0.111	0.079	309.65	0.000
		6	0.100	0.061	361.14	0.000
		7	0.104	0.063	417.35	0.000
		8	0.087	0.040	456.12	0.000
		9	0.104	0.058	511.96	0.000
		10	0.067	0.015	535.09	0.000
		11	0.088	0.040	575.23	0.000
		12	0.065	0.013	596.87	0.000

Figure 13.9 Transformations of Daily Returns to the 10-Year Treasury Notes and Their Autocorrelations



Sample: 10000 12136
Included observations: 1960

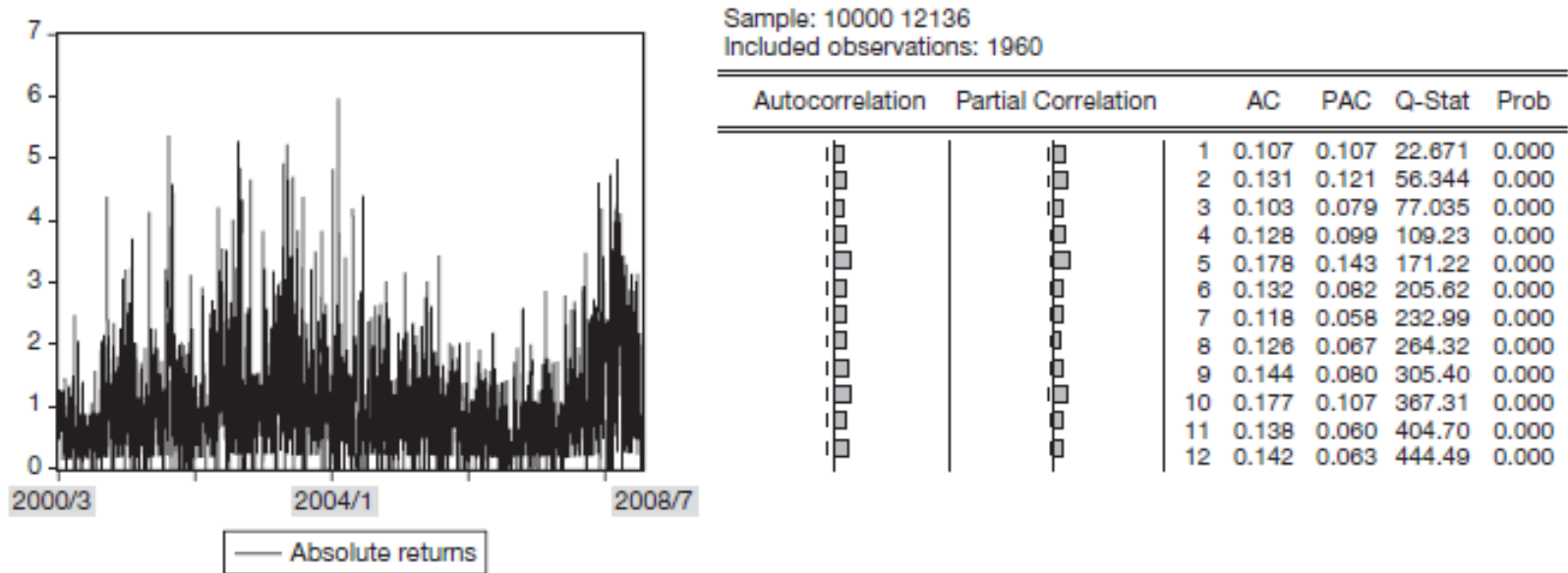
	Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
1			0.004	0.004	0.0262	0.872
2			-0.062	-0.062	7.5887	0.022
3			-0.020	-0.020	8.3849	0.039
4			0.003	0.001	8.3979	0.078
5			0.040	0.038	11.518	0.042
6			0.025	0.024	12.710	0.048
7			0.056	0.061	18.905	0.008
8			-0.008	-0.004	19.031	0.015
9			-0.035	-0.027	21.463	0.011
10			-0.027	-0.028	22.902	0.011
11			0.013	0.006	23.217	0.016
12			0.037	0.027	25.850	0.011



Sample: 10000 12136
Included observations: 1960

	Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
1			0.089	0.089	15.563	0.000
2			0.096	0.089	33.691	0.000
3			0.067	0.052	42.535	0.000
4			0.121	0.105	71.317	0.000
5			0.186	0.163	139.06	0.000
6			0.109	0.069	162.55	0.000
7			0.111	0.068	186.85	0.000
8			0.090	0.045	202.79	0.000
9			0.126	0.072	234.20	0.000
10			0.154	0.093	280.80	0.000
11			0.129	0.067	313.52	0.000
12			0.128	0.066	345.92	0.000

Figure 13.9 Transformations of Daily Returns to the 10-Year Treasury Notes and Their Autocorrelations



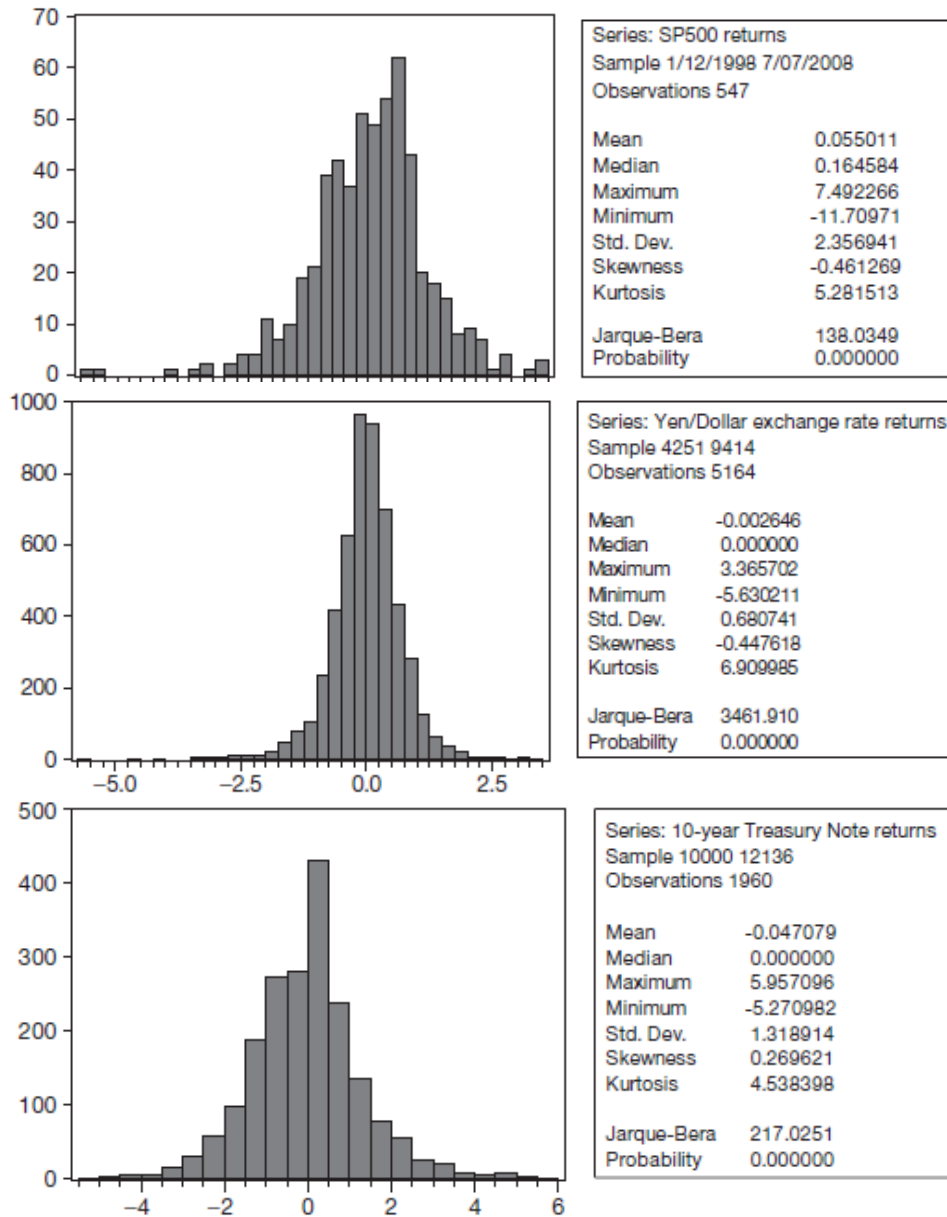
Volatility is time varying and exhibits time dependence.

As Mandelbrot (1963) pointed out:

“large changes tend to be followed by large changes, of either sign, and small changes tend to be followed by small changes.”

A phenomenon called “volatility clustering”

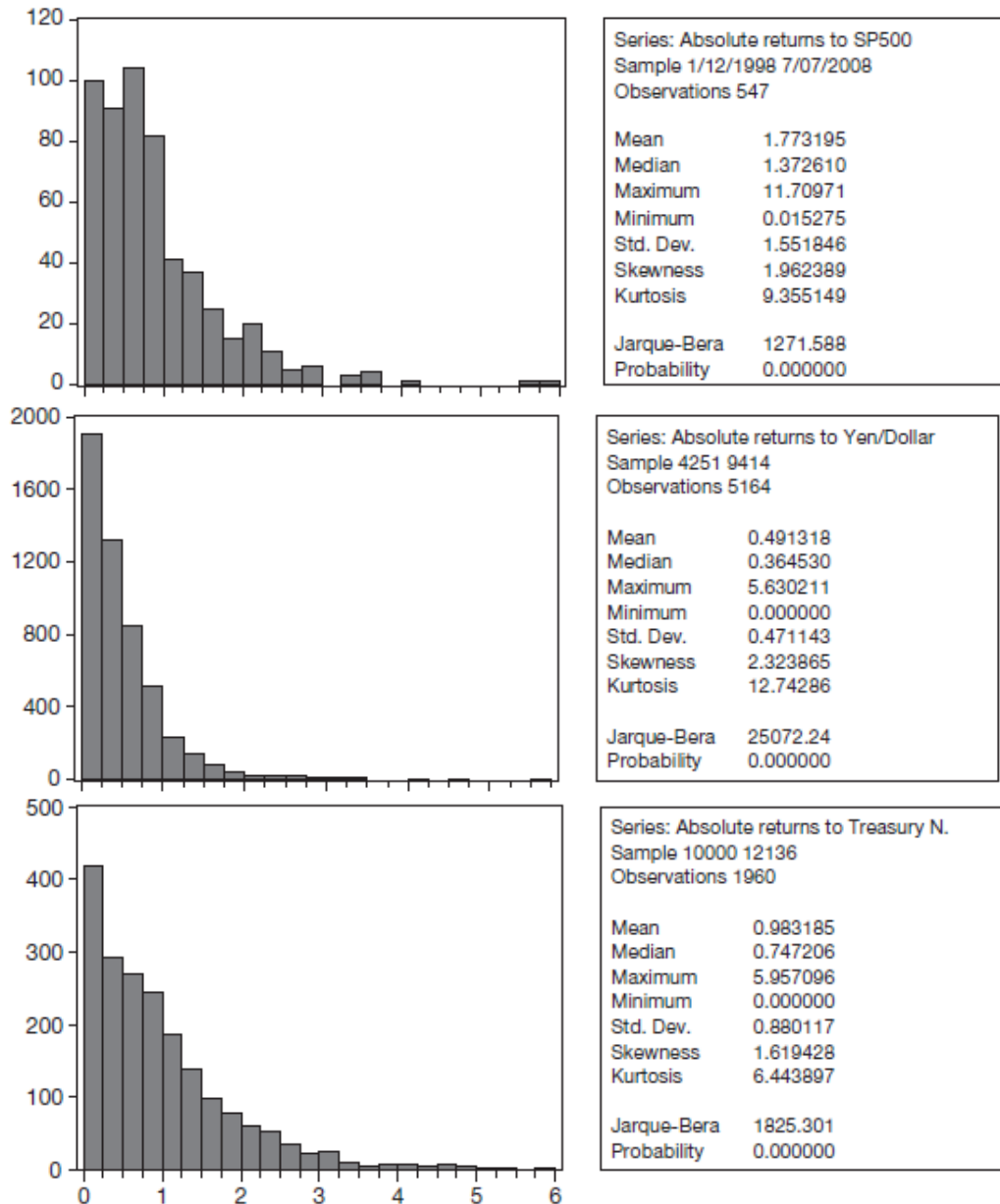
Figure 13.10 Unconditional Histograms of SP500, Exchange Rate, and 10-Year Treasury Returns



Not normally distributed:
 skewness (asymmetry) $\neq 0$
 kurtosis > 3 (heavy tails)
 Jarque-Bera test rejects H_0 : Normal

Returns are leptokurtic: they have **fat tails**, i.e., extreme events occur with large probability

Figure 13.10 Unconditional Histograms of SP500, Exchange Rate, 10-Year Treasury Returns (continued)



NOW MUCH MORE:

Not normally distributed:
 skewness (asymmetry) $\neq 0$
 kurtosis > 3 (heavy tails)
 Jarque-Bera test rejects H_0 : Normal

Volatility is strongly skewed to the right

Stylized facts of financial time series:

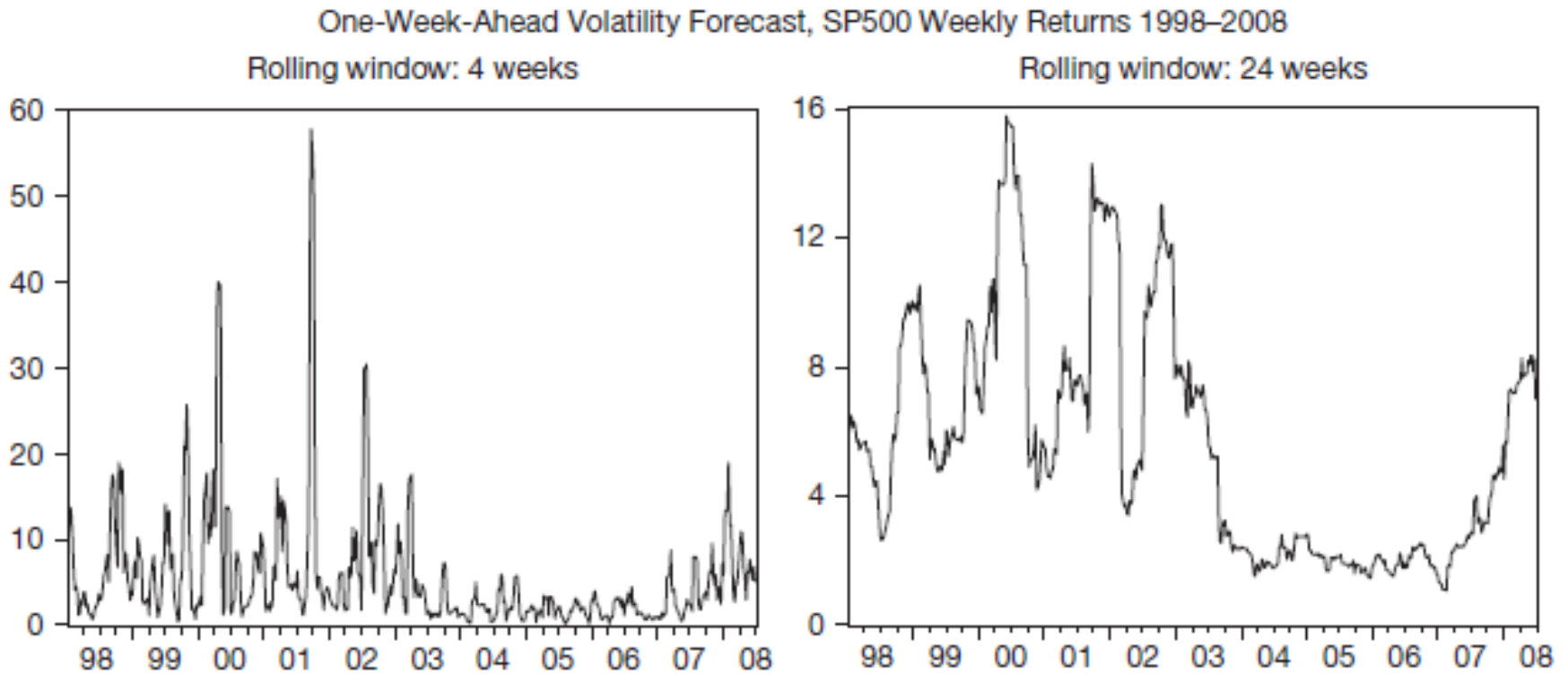
- **Nonstationarity:** Stock prices, exchange rates, interest rates, etc., have stochastic trends - unit root behavior;
- **Returns are uncorrelated:** white noise behavior;
- **Returns have time varying-volatility;**
- **Volatility Clustering:** large (small) movements tend to be followed by large (small) movements;
- **Returns are non normally distributed (fat tails) :** they are leptokurtic with kurtosis coefficient larger than 3;
- **Asymmetry and Leverage effect:** negative price movements (negative shocks) have a higher impact on volatility than positive surprises (positive shocks);

13.5.1 Rolling Window Volatility

$$\hat{\sigma}_t^2 |_{t-1} = \frac{1}{n} \sum_{i=1}^n (r_{t-i} - \mu)^2$$

The estimator can be considered as a *moving average* in which all the components of the moving average have the same weight $1/n$

Figure 13.11 Rolling Window Volatility Forecast

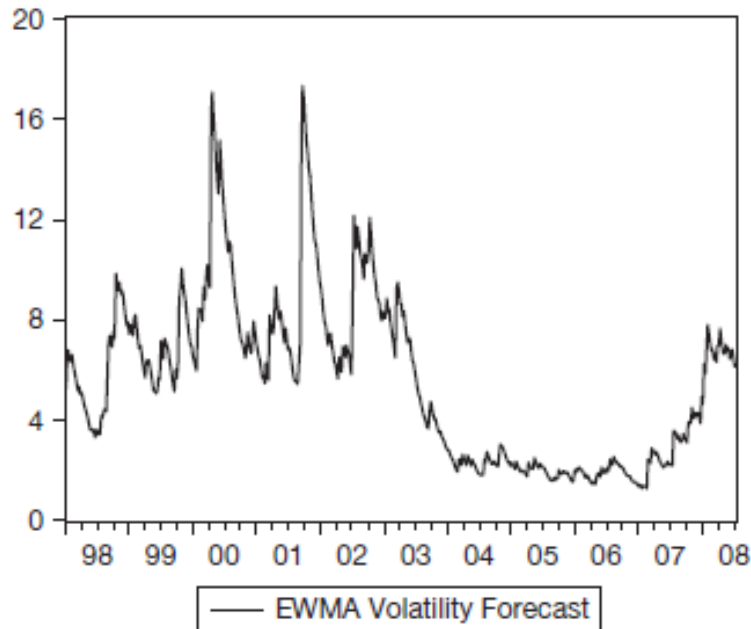


13.5.2 Exponentially Weighted Moving Average (EWMA) Volatility

If instead of equally weighting past squared realizations, we assign more weight to the most recent realizations, then we can define another estimator of the conditional variance as:

$$\hat{\sigma}_{t|t-1}^2 = (1 - \lambda) \sum_{i=1}^{t-1} \lambda^{i-1} (r_{t-i} - \mu)^2 \quad \text{for } \lambda \in (0,1)$$

One-Week-Ahead Volatility Forecast, SP500 Weekly Returns 1998–2008



When the sample size is large, this estimator can be approximated by the recursive formula:

$$\hat{\sigma}_{t|t-1}^2 = \lambda \hat{\sigma}_{t-1|t-2}^2 + (1 - \lambda)(r_{t-1} - \mu)^2$$

Of course, this is the EWMA:
The **exponential smoothing** method

Figure 13.12 EWMA Volatility Forecast