Analysis and Forecasting of Financial Time Series

Analysis and Forecasting of Financial Time Series:

Selected Cases

^{By} Jaydip Sen

Cambridge Scholars Publishing



Analysis and Forecasting of Financial Time Series: Selected Cases

By Jaydip Sen

This book first published 2022

Cambridge Scholars Publishing

Lady Stephenson Library, Newcastle upon Tyne, NE6 2PA, UK

British Library Cataloguing in Publication Data A catalogue record for this book is available from the British Library

Copyright © 2022 by Jaydip Sen

All rights for this book reserved. No part of this book may be reproduced, stored in a retrieval system, or transmitted, in any form or by any means, electronic, mechanical, photocopying, recording or otherwise, without the prior permission of the copyright owner.

ISBN (10): 1-5275-8884-X ISBN (13): 978-1-5275-8884-4

Dedicated to my sister Nabanita who left us on September 27, 2021. Jaydip

TABLE OF CONTENTS

List of Figures
List of Tables xvi
About the Authorxxi
Preface xxii
Chapter 1
Chapter 2
Chapter 3
Chapter 4
Chapter 5
Chapter 6
Index

LIST OF FIGURES

Fig. 1-1. Time series of the mid-cap sector in the BSE of India	. 11
Fig. 1-2. Decomposition of the BSE mid-cap time series	. 12
Fig. 1-3. The actual and the predicted index using Method I	. 20
Fig. 1-4. The ACF plot of residuals of model of Method I	. 21
Fig. 1-5. Actual and predicted index using Method II	. 23
Fig. 1-6. The ACF plot of residuals of model of Method II	. 23
Fig. 1-7. Actual and predicted index using Method III	. 26
Fig. 1-8. First-order difference time series of mid-cap sector	
Fig. 1-9. ACF plot of stationary series of mid-cap sector	. 29
Fig. 1-10. PACF plot of stationary series of mid-cap sector	. 30
Fig. 1-11. ACF plot of residuals of the ARIMA model	. 30
Fig. 1-12. Actual & predicted index using Method IV	. 32
Fig. 1-13. Actual & predicted index using Method V	. 34
Fig. 1-14. ACF plot of residuals of model of Method V	. 35
Fig. 2-1. Architecture of LSTM model	. 51
Fig. 2-2. Loss convergence of LSTM model for Maruti Suzuki	. 53
Fig. 2-3. Actual vs predicted price of Maruti Suzuki stock	. 54
Fig. 2-4. Loss convergence of LSTM model for the HDFC Bank	. 55
Fig. 2-5. Actual vs predicted price of HDFC Bank stock	. 55
Fig. 2-6. Loss convergence of LSTM model for Titan Company	. 57
Fig. 2-7. Actual vs predicted price of Titan Company	. 57
Fig. 2-8. Loss convergence of LSTM model for ITC	. 58
Fig. 2-9. Actual vs predicted price of ITC	. 59
Fig. 2-10. Loss convergence of LSTM model for Sun Pharma	. 60
Fig. 2-11. Actual vs LSTM predicted price of Sun Pharma	. 60
Fig. 2-12. Loss convergence of LSTM model for Infosys	. 62
Fig. 2-13. Actual vs LSTM predicted price of Infosys	. 62
Fig. 2-14. Loss convergence of LSTM model for Zee Entertainment	
Fig. 2-15. Actual vs predicted price of Zee Entertainment	. 64
Fig. 2-16. Loss convergence of LSTM model for Tata Steel	. 65
Fig. 2-17. Actual vs LSTM predicted price for Tata Steel	. 65
Fig. 2-18. Loss convergence of LSTM model for Reliance Industries	. 67
Fig. 2-19. Actual vs predicted price of Reliance Industries	. 67
Fig. 2-20. Loss convergence of LSTM model for DLF	. 68
Fig. 2-21. Actual vs LSTM model-predicted price of DLF	. 69

Fig. 2-22. Loss convergence of LSTM for Larsen & Toubro	70
Fig. 2-23. Actual vs LSTM model-predicted price of DLF	70
Fig. 2-24. Loss convergence of LSTM model for Power Grid Corp	72
Fig. 2-25. Actual vs predicted price of Power Grid Corp	
Fig. 2-26. Loss convergence of LSTM model for ICICI Bank	74
Fig. 2-27. Actual vs predicted price of ICICI Bank	
Fig. 2-28. Loss convergence of LSTM model for State Bank of India	75
Fig. 2-29. Actual vs predicted price of State Bank of India	
Fig. 3-1. Daily log return plots of MSZ stock	
Fig. 3-2. Daily volatility plots of MSZ stock	. 105
Fig. 3-3. Stand resids and cond vol of const mean GARCH for MSZ	. 108
Fig. 3-4. Actual vs GARCH-predicted return for MSZ	
Fig. 3-5. Residuals of GARCH model for MSZ	
Fig. 3-6. Actual vs GARCH-fitted volatility for MSZ stock	. 113
Fig. 3-7. EGARCH forecasts of daily returns for MSZ	. 113
Fig. 3-8. Daily log return plots of HDB stock	
Fig. 3-9. Daily volatility plots of HDB stock	
Fig. 3-10. Stand resids and cond vol of const mean GARCH for HDB	. 120
Fig. 3-11. Actual vs GARCH-predicted return for HDB	
Fig. 3-12. Residuals of GARCH model for HDB	
Fig. 3-13. Actual vs GARCH-fitted volatility for HDB stock	
Fig. 3-14. EGARCH forecasts of daily returns for HDB	
Fig. 3-15. Daily log return plots of TTC stock	. 127
Fig. 3-16. Daily volatility plots of TTC stock	. 129
Fig. 3-17. Stand resids and cond vol of const mean GARCH for TTC .	. 131
Fig. 3-18. Actual vs GARCH-predicted return for TTC	
Fig. 3-19. Residuals of GARCH model for TTC	
Fig. 3-20. Actual vs GARCH-fitted volatility for TTC	
Fig. 3-21. EGARCH forecasts of daily returns for TTC	
Fig. 3-22. Daily log return plots of TCS stock	
Fig. 3-23. Daily volatility plots of TCS stock	
Fig. 3-24. Stand resids and cond vol of const mean GARCH for TCS	
Fig. 3-25. Actual vs GARCH-predicted return for TCS	
Fig. 3-26. Residuals of GARCH model for TCS	
Fig. 3-27. Actual vs GARCH-fitted volatility for TCS	
Fig. 3-28. EGARCH forecasts of daily returns for TCS	
Fig. 3-29. Daily log return plots of SPI stock	. 150
Fig. 3-30. Daily volatility plots of SPI stock	. 151
Fig. 3-31. Stand resids and cond vol of const mean GARCH for SPI	. 153
Fig. 3-32. Actual vs GARCH-predicted return for SPI	
Fig. 3-33. Residuals of GARCH model for SPI	. 155

Fig. 3-34. Actual vs GARCH-fitted volatility for SPI	157
Fig. 3-35. EGARCH forecasts of daily returns for SPI	158
Fig. 4-1. Dendrogram of auto sector stocks	175
Fig. 4-2. Weight allocation by MVP & HRP for auto sector stocks	175
Fig. 4-3. Returns of MVP & HRP for auto sector stocks on trng data	176
Fig. 4-4. Returns of MVP & HRP to auto sector on test data	177
Fig. 4-5. Dendrogram of banking sector stocks	
Fig. 4-6. Weight allocation by MVP & HRP to banking sector stocks	178
Fig. 4-7. Returns of MVP & HRP for banking sec stocks on trng data	179
Fig. 4-8. Returns of MVP & HRP to banking sector on test data	
Fig. 4-9. Dendrogram of cons durab sector stocks	
Fig. 4-10. Weight alloc by MVP & HRP to cons durab sector stocks	
Fig. 4-11. Returns of MVP & HRP to cons durab stocks on trng data	
Fig. 4-12. Returns of MVP & HRP to cons durab stocks on test data	
Fig. 4-13. Dendrogram of FMCG sector stocks	
Fig. 4-14. Weight allocation by MVP & HRP to FMCG sector stocks	
Fig. 4-15. Ret of MVP & HRP to FMCG stocks on trng data	
Fig. 4-16. Ret of MVP & HRP to FMCG sector stocks test data	
Fig. 4-17. Dendrogram of IT sector stocks	
Fig. 4-18. Weight allocation by MVP & HRP for IT sector stocks	
Fig. 4-19. Returns of MVP & HRP for IT sector stocks on trng data	
Fig. 4-20. Returns of MVP & HRP for IT sector stocks on test data	
Fig. 4-21. Dendrogram of pharma sector stocks	
Fig. 4-22. Weight allocation by MVP & HRP to pharma sector stocks	
Fig. 4-23. Ret of MVP & HRP for pharma sec stocks on trng data	
Fig. 4-24. Ret of MVP & HRP for pharma sec stocks on test data	
Fig. 4-25. Dendrogram of realty sector stocks	
Fig. 4-26. Weight allocation by MVP & HRP to realty sector stocks	
Fig. 4-27. Return of MVP & HRP for realty sector stocks on trng data	
Fig. 4-28. Return of MVP & HRP for realty sector stocks on test data	
Fig. 4-29. Dendrogram of metal sector stocks	
Fig. 4-30. Weight allocation by MVP & HRP to metal sector stocks	
Fig. 4-31. Return of MVP & HRP for metal sector stocks on trng data	
Fig. 4-32. Return of MVP & HRP for metal sector stocks on test data	
Fig. 4-33. Dendrogram of oil & gas sector stocks	
Fig. 4-34. Weight allocation by MVP & HRP to oil & gas sector	
Fig. 4-35. Return of MVP & HRP for oil & gas sector on trng data	
Fig. 4-36. Return of MVP & HRP for oil & gas sector on test data	
Fig. 4-37. Dendrogram of media sector stocks	
Fig. 4-38. Weight allocation by MVP & HRP to media sector stocks	
Fig. 4-39. Return of MVP & HRP for media sector on trng data	203

Fig. 4	4-40. Return of MVP & HRP for media sector on test data	204
Fig. 4	4-41. Dendrogram of private banks sector stocks	205
Fig. 4	4-42. Weight allocation by MVP & HRP to pvt sec banks stocks	205
Fig. 4	4-43. Return of MVP & HRP for pvt sec bank stocks on trng data	206
Fig. 4	4-44. Return of MVP & HRP for pvt sec bank stocks on test data .	207
	4-45. Dendrogram of PSU banks sector stocks	
Fig. 4	4-46. Weight allocation by MVP & HRP to PSU banks sector	208
Fig. 4	4-47. Return of MVP & HRP for PSU banks on trng data	209
Fig. 4	4-48. Return of MVP & HRP for PSU banks on test data	210
Fig. 4	4-49. Dendrogram of financial services sector	211
Fig.	4-50. Weight allocation by MVP & HRP to fin serv sector	211
Fig.	4-51. Return of MVP & HRP for fin serv sector on trng data	212
	4-52. Return of MVP & HRP for fin serv sector on test data	
	4-53. Dendrogram of NIFTY 50 stocks	
Fig.	4-54. Weight allocation by MVP & HRP to NIFTY 50 stocks	214
	4-55. Return of MVP & HRP for NIFTY 50 on trng data	
	4-56. Return of MVP & HRP for NIFTY 50 on test data	
	5-1. Portfolio of auto sector with max Sharpe ratio	
	5-2. Portfolio of auto sector with max Sortino ratio	
	5-3. Portfolio of auto sector with max Calmar ratio	
	5-4. Portfolio compositions for auto sector stocks	
	5-5. Cumulative returns of auto sector portfolios on training data	
Fig. :	5-6. Cumulative returns of auto sector portfolios on test data	236
	5-7. Portfolio of banking sector with max Sharpe ratio	
	5-8. Portfolio of banking sector with max Sortino ratio	
	5-9. Portfolio of banking sector with max Calmar ratio	
	5-10. Portfolio compositions for banking sector stocks	
Fig. :	5-11. Cumulative returns of banking sec portfolios on trng data	240
	5-12. Cumulative returns of banking sec portfolios on test data	
Fig. :	5-13. Portfolio of cons durb sector with max Sharpe ratio	241
Fig. :	5-14. Portfolio of cons durb sector with max Sortino ratio	242
	5-15. Portfolio of cons durb sector with max Calmar ratio	
	5-16. Portfolio compositions for cons durb sector	
Fig. :	5-17. Cumulative returns of cons durb sec portfolios on trng data	244
	5-18. Cumulative returns of cons durb sec portfolios on test data	
	5-19. Portfolio of FMCG sector with max Sharpe ratio	
	5-20. Portfolio of FMCG sector with max Sortino ratio	
	5-21. Portfolio of FMCG sector with max Calmar ratio	
	5-22. Portfolio compositions for FMCG sector	
	5-23. Cumulative returns of FMCG sector on trng data	
	5-24. Cumulative returns of FMCG sector on test data	
-		

5-25.	Portfolio of IT sector with max Sharpe ratio	251
5-26.	Portfolio of IT sector with max Sortino ratio	251
5-27.	Portfolio of IT sector with max Calmar ratio	252
5-29.	Cumulative returns of IT sec portfolios on trng data	253
5-30.	Cumulative returns of IT sec portfolios on test data	254
5-31.	Portfolio of pharma sector with max Sharpe ratio	255
5-32.	Portfolio of pharma sector with max Sortino ratio	256
5-33.	Portfolio of pharma sector with max Calmar ratio	256
5-34.	Portfolio compositions for pharma sector	257
5-35.	Cumulative returns of pharma sec portfolios on trng data	258
5-36.	Cumulative returns of pharma sec portfolios on test data	258
5-37.	Portfolio of realty sector with max Sharpe ratio	259
5-50.	Portfolio of oil & gas sector with max Sortino ratio	269
5-65.	Cumulative returns for pvt banks sec on trng data	279
	5-26. 5-27. 5-28. 5-29. 5-30. 5-31. 5-32. 5-33. 5-34. 5-35. 5-36. 5-37. 5-38. 5-39. 5-40. 5-41. 5-42. 5-43. 5-44. 5-45. 5-44. 5-45. 5-50. 5-51. 5-52. 5-55. 5-55. 5-55. 5-56. 5-57. 5-58. 5-59. 5-60. 5-61. 5-62. 5-64. 5-64.	 5-25. Portfolio of IT sector with max Sharpe ratio

Fig. 5-66. Cumulative returns for pvt banks sec on test data...... 280 Fig. 5-69. Portfolio of PSU banks sec with max Calmar ratio...... 282 Fig. 5-71. Cumulative returns for PSU banks sec on trng data...... 284 Fig. 5-72. Cumulative returns for PSU banks sec on test data...... 284 Fig. 6-3. OLS regression model for AL and BF close prices...... 303 Fig. 6-4. Residual plot of the AL-BF OLS regression model 304 Fig. 6-7. Daily value of BF-AL pair portfolio over test period 306 Fig. 6-11. Residual plot of the SB-IF OLS regression model...... 309 Fig. 6-15. The matrix of the cointegration tests for cons durb sector 312 Fig. 6-22. The matrix of the cointegration tests for FMCG sector 316 Fig. 6-29. The matrix of the cointegration tests for IT sector stocks 321 Fig. 6-31. OLS regression model for CF and TC close prices...... 322 Fig. 6-32. Residual plot of the TC-CF OLS regression model 323 Fig. 6-33. Z-values of the ratio series of TC-CF pair 323 Fig. 6-34. The pair-trading signals for TC and CF 324

Fig.	6-35.	Daily value of TC-CF pair portfolio over test period	324
Fig.	6-36.	The matrix of the cointegration tests for pharma sector	326
Fig.	6-37.	Daily close prices of LP and AK stocks	327
Fig.	6-38.	OLS regression model for AK and LP close prices	327
Fig.	6-39.	Residual plot of the LP-AK OLS regression model	328
		Z-values of the ratio series of LP-AK pair	
Fig.	6-41.	The pair-trading signals for LP and AK	329
Fig.	6-42.	Daily value of LP-AK pair portfolio over test period	329
Fig.	6-43.	The matrix of the cointegration tests for realty sector	331
		Daily close prices of OR and PE stocks	
Fig.	6-45.	OLS regression model for PE and OR close prices	332
		Residual plot of the OR-PE OLS regression model	
		Z-values of the ratio series of OR-PE pair	
		The pair-trading signals for OR and PE	
		Daily value of OR-PE pair portfolio over test period	
		The matrix of the cointegration tests for metal sector	
		Daily close prices of HI and JS stocks	
		OLS regression model for JS and HI close prices	
		Residual plot of the HI-JS OLS regression model	
		Z-values of the ratio series of HI-JS pair	
		The pair-trading signals for HI and JS	
		Daily value of HI-JS pair portfolio over test period	
		The matrix of the cointegration tests for oil & gas	
		Daily close prices of GA and IG stocks	
		OLS regression model for IG and GA close prices	
		Residual plot of the GA-IG OLS regression model	
		Z-values of the ratio series of GA-IG pair	
Fig.	6-62.	The pair-trading signals for GA and IG	343
Fig.	6-63.	Daily value of GA-IG pair portfolio over test period	344
		The matrix of the cointegration tests for media sec	
		Daily close prices of ZE and DT stocks	
		OLS regression model for DT and ZE close prices	
		Residual plot of the ZE-DT OLS regression model	
		Z-values of the ratio series of ZE-DT pair	
		The pair-trading signals for ZE and DT	
Fig.	6-70.	Daily value of ZE-DT pair portfolio over test period	348
Fig.	6-71.	The matrix of the cointegration tests for pvt bank sec	350
		Daily close prices of IN and IF stocks	
		OLS regression model for IF and IN close prices	
		Residual plot of the IN-IF OLS regression model	
Fig.	6-75.	Z-values of the ratio series of IN-IF pair	353

Fig. 6-76. The pair-trading signals for IN and IF	222
Fig. 6-77. Daily value of IN-IF pair portfolio over test period	354
Fig. 6-78. The matrix of the cointegration tests for PSU bank sec	355
Fig. 6-79. Daily close prices of PN and BI stocks	356
Fig. 6-80. OLS regression model for BI and PN close prices	356
Fig. 6-81. Residual plot of the PN-BI OLS regression model	357
Fig. 6-82. Z-values of the ratio series of PN-BI pair	358
Fig. 6-83. The pair-trading signals for PN and BI	358
Fig. 6-84. Daily value of PN-BI pair portfolio over test period	359

LIST OF TABLES

Table 1-1. Decomposition of the Indian mid-cap sector index	13
Table 1-2. The HoltWinters model of forecasting using Method I	
Table 1-3. Error computation of the model built using Method I	20
Table 1-4. The Ljung-Box test results of Method I	
Table 1-5. The error computation of Method II	22
Table 1-6. Forecast error of the model built using Method III	24
Table 1-7. The output of the auto.arima function	26
Table 1-8. Forecast error of the model built using Method IV	32
Table 1-9. Details of each iteration of modelling using Method V	33
Table 1-10. Forecast error of the model built using Method V	34
Table 1-11. The Ljung-Box test results of Method V	36
Table 1-12. Comparative performance of the models	36
Table 2-1. The results of the auto sector stocks	
Table 2-2. The results of the banking sector stocks	54
Table 2-3. The results of the consumer durables sector stocks	56
Table 2-4. The results of the FMCG sector stocks	
Table 2-5. The results of the healthcare sector stocks	
Table 2-6. The results of the IT sector stocks	
Table 2-7. The results of the media sector stocks	63
Table 2-8. The results of the metal sector stocks	
Table 2-9. The results of the oil & gas sector stocks	66
Table 2-10. The results of the realty sector stocks	68
Table 2-11. The results of the infrastructure sector stocks	
Table 2-12. The results of the energy sector stocks	71
Table 2-13. The results of the private banks sector stocks	73
Table 2-14. The results of the PSU banks sector stocks	75
Table 2-15. The summary results of the sectors	
Table 2-16. The LSTM model performance for the auto sector	
Table 2-17. The LSTM model performance for the banking sector	
Table 2-18. The LSTM model for the consumer durables sector	
Table 2-19. The LSTM model performance for the FMCG sector	79
Table 2-20. The LSTM model performance for the healthcare sector	79
Table 2-21. The LSTM model performance for the IT sector	
Table 2-22. The LSTM model performance for the media sector	80
Table 2-23. The LSTM model performance for the metal sector	81

Table 2-24. The LSTM model performance for the oil & gas sector 81 Table 3-1. The Hurst exponents and volatilities of the auto sector...... 103 Table 3-2. The daily log return series of the auto sector stocks...... 105 Table 3-4. Constant mean GARCH (1,1) model for the auto sector...... 107 Table 3-5. Normal error GARCH (1,1) for the auto sector...... 107 Table 3-6. The best-fit SARIMAX models for the auto sector stocks.... 109 Table 3-7. GARCH models on ARIMA residuals for auto sector 111 Table 3-8. Constant mean GJR-GARCH for the auto sector 111 Table 3-10. BIC values of the GARCH models for the auto sector...... 112 Table 3-11. EGARCH performance on the auto sector stocks 114 Table 3-12. The Hurst exponents of the banking sector 115 Table 3-13. The daily log return of the banking sector stocks...... 115 Table 3-15. Constant mean GARCH (1, 1) for the banking sector...... 118 Table 3-16. Normal error GARCH (1, 1) for the banking sector...... 119 Table 3-17. The best-fit SARIMAX models for the banking sector...... 121 Table 3-18. GARCH models on ARIMA residuals for banking sector .. 123 Table 3-19. Constant mean GJR-GARCH for the banking sector 123 Table 3-20. Constant mean EGARCH for the banking sector 124 Table 3-21. BIC values of the GARCH models for banking sector 125 Table 3-22. EGARCH performance on the banking sector 126 Table 3-23. The Hurst exponents of the consumer durable sector...... 127 Table 3-24. The daily log return of the consumer durable sector 128 Table 3-27. Normal error GARCH (1, 1) for the cons. durb. sector 130 Table 3-28. The best-fit SARIMAX models for cons. durb. sector 132 Table 3-29. GARCH models on ARIMA resid for cons. durb. sec 134 Table 3-30. Constant mean GJR-GARCH for the cons. durb. sec...... 134 Table 3-31. Constant mean EGARCH for the cons. durb. sec...... 135 Table 3-32. BIC values of GARCH models for cons. durb. sec 136 Table 3-33. EGARCH performance on cons. durb. sec...... 137 Table 3-34. The Hurst exponents of the IT sector 138

Table 3-36. The daily volatility of the IT sector	140
Table 3-37. Constant mean GARCH (1, 1) for IT sector stocks	141
Table 3-38. Normal error GARCH (1, 1) model for IT sector	141
Table 3-39. The best-fit SARIMAX models for IT sector	143
Table 3-40. GARCH models on ARIMA residuals for IT sector	145
Table 3-41. Constant mean GJR-GARCH for IT sector	145
Table 3-42. Constant mean EGARCH for IT sector	145
Table 3-43. BIC values of GARCH models for IT sector	147
Table 3-44. EGARCH performance on IT sector	
Table 3-45. The Hurst exponents of the pharma sector	149
Table 3-46. The daily log return of pharma sector	
Table 3-47. The daily volatility of pharma sector	150
Table 3-48. Constant mean GARCH (1, 1) for pharma sector	
Table 3-49. Normal error GARCH (1, 1) model for pharma sector	
Table 3-50. The best-fit SARIMAX models for the pharma sector	
Table 3-51. GARCH models on ARIMA residuals for pharma sec	155
Table 3-52. Constant mean GJR-GARCH for the pharma sector	156
Table 3-53. Constant mean EGARCH for pharma sector	156
Table 3-54. BIC values of GARCH models for pharma sector	158
Table 3-55. EGARCH performance on pharma sector	159
Table 4-1. The portfolio compositions of auto sector	176
Table 4-2. The performance results auto sector portfolios	177
Table 4-3. The portfolio compositions of banking sector	179
Table 4-4. The performance results of banking sector portfolios	180
Table 4-5. The portfolio compositions of cons. durb. sector	182
Table 4-6. The performance results of cons. durb. sec portfolios	183
Table 4-7. The portfolio compositions of FMCG sector	185
Table 4-8. The performance results of FMCG sector portfolios	186
Table 4-9. The portfolio compositions of IT sector	188
Table 4-10. The performance results of IT sector portfolios	189
Table 4-11. The portfolio compositions of pharma sector	191
Table 4-12. The performance results of pharma sector portfolios	192
Table 4-13. The portfolio compositions of realty sector	
Table 4-14. The performance results of realty sector portfolios	
Table 4-15. The portfolio compositions of metal sector	197
Table 4-16. The performance results of metal sector portfolios	198
Table 4-17. The portfolio compositions of oil & gas sector	200
Table 4-18. The performance results of oil & gas sector portfolios	201
Table 4-19. The portfolio compositions of media sector	203
Table 4-20. The performance results of media sector portfolios	204
Table 4-21. The portfolio compositions of private banks	

Table 4-22. The performance results of private banks sector	207
Table 4-23. The portfolio compositions of PSU banks	209
Table 4-24. The performance results of PSU banks sector	210
Table 4-25. The portfolio compositions of fin. ser. sector	212
Table 4-26. The performance results of fin. serv. sector	213
Table 4-27. The portfolio compositions of NIFTY 50 stocks	215
Table 4-28. The performance results of NIFTY 50 portfolios	
Table 5-1. The portfolio compositions for the auto sector	235
Table 5-2. The auto sector portfolio cumulative returns	236
Table 5-3. The portfolio compositions for the banking sector	239
Table 5-4. The banking sector portfolio cumulative returns	241
Table 5-5. Portfolio compositions for cons durb. sec	
Table 5-6. The cons. durb sector portfolio cumulative returns	
Table 5-7. The portfolio compositions for the FMCG sector	248
Table 5-8. The FMCG sector portfolio cumulative returns	250
Table 5-9. The portfolio compositions for the IT sector	253
Table 5-10. The IT sector portfolio cumulative returns	254
Table 5-11. The portfolio compositions for pharma sector	257
Table 5-12. The pharma sector portfolio cumulative returns	259
Table 5-13. The portfolio compositions for the realty sector	262
Table 5-14. The realty sector portfolio cumulative returns	263
Table 5-15. The portfolio compositions for the metal sector	
Table 5-16. The metal sector portfolio cumulative returns	
Table 5-17. The portfolio compositions for the oil & gas sector	270
Table 5-18. The oil & gas sector portfolio cumulative returns	272
Table 5-19. The portfolio compositions for the media sector	274
Table 5-20. The media sector portfolio cumulative returns	276
Table 5-21. The portfolio compositions for private banks sector	279
Table 5-22. The private banks sector portfolio cumulative returns	280
Table 5-23. The portfolio compositions for PSU banks sector	283
Table 5-24. The PSU banks sector portfolio cumulative returns	285
Table 5-25. Summary of the performance results of the portfolios	285
Table 6-1. Returns of the auto sector pair-trading portfolios	306
Table 6-2. Returns of banking sector pair-trading portfolios	
Table 6-3. Returns of cons. durb. sec. pair-trading portfolios	
Table 6-4. Returns of FMCG sector pair-trading portfolios	
Table 6-5. Returns of IT sector pair-trading portfolios	
Table 6-6. Returns of pharma sector pair-trading portfolios	
Table 6-7. Returns of realty sector pair-trading portfolios	335
Table 6-8. Returns of metal sector pair-trading portfolios	
Table 6-9. Returns of oil & gas sector pair-trading portfolios	344

List of Tables

Table 6-10. Returns of media sector pair-trading portfolios	
Table 6-11. Returns of private banks pair-trading portfolios	
Table 6-12. Returns of PSU banks pair-trading portfolios	
Table 6-13. Summary results of pair trading portfolios	

ABOUT THE AUTHOR



Jaydip Sen has experience in research, teaching, and industry over a span of 27 years. He had worked in reputed organizations like Oil and Natural Gas Corporation Ltd, India, Oracle India Pvt Ltd, Akamai Technology Pvt Ltd, Tata Consultancy Services Ltd and National Institute of Science and Technology, India, and Calcutta Business School, India. Currently, he is associated with Praxis Business School, Kolkata, INDIA, as a professor in the department of Data Science and Artificial Intelligence. His research areas include security in wired and wireless networks, intrusion detection systems, secure routing protocols in wireless ad hoc and sensor networks, trust, and reputation-based systems, privacy issues in ubiquitous and pervasive communication and the Internet of Things, machine learning, deep learning, and artificial intelligence in the financial domain. He has more than 200 publications in reputed international journals and referred conference proceedings and 20 book chapters in books published by internationally renowned publishing houses like Springer, CRC press, IGI-Global, etc. He has also authored two books which are published by two internationally reputed publishing houses. He has been listed among the top 2% of scientists in the world for the last three consecutive years 2019-2021, as per studies conducted by Stanford University, USA. Prof. Sen serves on the editorial board of three prestigious international journals and on the technical program committee in several international conferences of repute. Prof. Sen is a senior member of IEEE and ACM, USA.

PREFACE

The subject of financial time series analysis has attracted substantial attention in the last two decades, especially after Professors Robert Engle and Clive Granger won the Nobel awards. At the same time, this field has undergone rapid evolution and developments, especially in high-frequency finance, stochastic volatility, and the availability of sophisticated software and tools. While at a basic level, financial time series analysis is concerned with the theory and practice of asset valuation over time, at a broader level it includes diverse topics such as analysis of high-frequency price observations, arbitrage pricing theory, asset price dynamics, optimal asset allocation, cointegration, capital asset price models, and value at risk. It is a highly empirical discipline, but like other scientific fields theory forms the foundation for making inferences.

There is, however, a key feature that distinguishes financial time series analysis from other time series analyses. Both financial theory and its empirical time series contain an element of uncertainty. For example, there are various definitions of asset volatility, and for a stock return series, the volatility is not directly observable. As a result of the added uncertainty, statistical and econometric theories, and methods play an important role in financial time series analysis.

The chapters in the volume present several techniques of financial time series analysis and forecasting based on statistical and econometric approaches. The historical stock prices and sectoral index values for important stocks and sectors listed on the National Stock Exchange (NSE) of India and the Bombay Stock Exchange (BSE) are used in building financial models which are used to predict the future values of the index and stock prices. The statistical and econometric methods discussed in the chapters of this book include exponential smoothing, Holt and Winter trend and seasonality method, time series decomposition, autoregressive integrated moving average (ARIMA) method, ordinary least square regression (OLS), generalized autoregressive conditional heteroscedasticity (GARCH), and cointegration.

Chapter 1 titled A Robust and Accurate Predictive Framework for the Indian Mid-Cap Sector Index presents a time series decomposition-based approach for analyzing the salient characteristics of the time series of the mid-cap sector of the Indian economy from January 2010 to December 2021. The time series of the mid-cap sector index is decomposed into its three components - trend, seasonal, and random. Based on the decomposition results several interesting characteristics of the time series are identified. The month of March is found to exhibit the highest level of seasonality for the mid-cap time series, while July experiences the lowest seasonality effect. The time series is found to consist of a very moderate random component with the mean value of the percentage of the random component to the time series' aggregate value being as low as 4.73. The time series was found to be dominated by its trend component. Further, five predictive models are proposed for forecasting the future index values of the time series. Using the five models and based on the training data of the mid-cap sector's monthly index values from January 2010 to December 2021, the monthly index values for the year 2021 are forecasted. The models are compared based on their forecast accuracies.

Chapter 2 titled A Deep Learning Model for Sectoral Profitability Study of the Indian Stock Market presents an LSTM model for predicting future stock prices. The model is optimized with suitably designed layers and regularized using the dropout regularization method. The historical stock prices for 140 stocks from fourteen sectors listed in NSE, India are extracted from the web from January 1, 2010, to July 13, 2022. The model is used for predicting future stock prices with a forecast horizon of one day and based on the predicted output of the model, buy/sell decisions of the stocks are taken. The total profit earned from the buy/sell transactions for a stock is normalized by its mean price over the entire period to arrive at the profitability measure of the stock. The profitability figures of all stocks of a sector are summed up to derive the overall profitability index of the sector. It is observed that while the fast-moving consumer goods (FMCG) sector is the most profitable one, the *realty* sector has the lowest profitability index. The accuracy of the LSTM model is measured using three metrics, Huber loss, mean absolute error (MAE), and the accuracy score. It is observed that the LSTM model is highly accurate.

Chapter 3 titled *Sectoral Volatility Analysis of the Indian Stock Market using GARCH*, illustrates the design and analysis of several volatility models based on different variants of GARCH have been presented. The models are built on the historical stock prices from five important sectors listed on the NSE of India from January 1, 2010, to April 30, 2022. From each of the five sectors, the top ten stocks are selected based on the report published by the NSE on December 31, 2021. The five sectors are auto, banking, consumer durables, information technology, and pharma. The GARCH models are fine-tuned and then backtested on the out-of-sample data to estimate their accuracies in the prediction of future volatility of the

stocks. While it is observed that asymmetric GARCH models outperform their symmetric counterparts, EGARCH is found to have yielded the most accurate results for all the stocks analyzed in this work.

Chapter 4 titled *Portfolio Design using Mean-Variance Optimization and Hierarchical Risk Parity Approach* presents portfolio design approaches for stocks chosen from thirteen sectors and NIFTY 50 stocks on the National Stock Exchange of India. Based on the historical prices of the ten stocks with the largest free-float market capitalization from each sector and the 50 stocks in the NIFTY group, the *mean-variance portfolio* (MVP) and the *hierarchical risk parity* (HRP) portfolios are designed. The portfolios are backtested on both training and the test data to identify the portfolio with the higher cumulative return and higher Sharpe Ratio for each sector. It is found that while on the training data, the MVP portfolio yielded the higher cumulative returns for seven among the fourteen sectors, the return yielded by the HRP portfolio is found to be higher for eleven sectors on the test data. Since for a portfolio, its performance on the test data is what matters to the investors, the results of the study indicate that the HRP portfolio is a better choice over the MVP for the investors of the Indian stock market.

Chapter 5 titled A Comparative Study of Performance Metrics in Mean-Variance Portfolio Optimization illustrates three different approaches to portfolio design based on the maximization of three ratios – the Sharpe ratio, the Sortino ratio, and the Calmar ratio. Twelve important sectors listed on the National Stock Exchange of India are first selected, and portfolios are designed based on the three approaches for ten stocks from each sector on the historical stock prices from January 1, 2017, to December 31, 2020. The performances of the portfolios are evaluated based on their cumulative returns for the period January 1, 2021, to December 31, 2021. It is observed that, for the test period, the cumulative returns of portfolios built on the maximization of the Sharpe ratio are the highest for eight sectors of the twelve sectors studied in the work. The results demonstrate the superiority of the Sharpe ratio as the metric in portfolio optimization.

Chapter 6 titled *A Cointegration-Based Approach to Pair Trading of Stocks from Selected Sectors of the Indian Stock Market* presents a cointegration-based pair-trading approach that identifies stock pairs that exhibit robust cointegration in their prices over three years from January 1, 2018, to December 31, 2020. The stocks are chosen from twelve sectors listed on the National Stock Exchange of India. Once the cointegrated pairs are identified, the pair-trading portfolios are formed and the performance of the portfolios is observed over a test period of one year from January 1, 2021, to December 31, 2021. Suitable trigger points are identified so that the short and the long positions for both stocks are identified accurately. The realty and the PSU bank sectors are found to have produced the best results as all the cointegrated pairs from these two sectors yielded positive returns. However, four pairs from the auto sector out of a total of ten pairs yielded negative returns.

While the chapters in this volume do not cover the basic theories of the topics involved, all the relevant principles and fundamentals are discussed in brief in the chapters for the sake of completeness. Hence, even if some background knowledge of statistics and econometrics may be useful, the readers are not expected to have advanced knowledge in those fields. I am sure that the volume will be a valuable resource to anybody interested in gaining knowledge in financial time series analysis. However, the primary target reader groups for the book are the advanced postgraduate and doctoral students of finance, econometrics, management, data science, computer science, and information technology. Further, faculty members of graduate schools and universities, and practitioners in the industry working in the areas of financial analytics, risk management, security analysis, and portfolio management, are also expected to find the book quite useful.

I express our sincere thanks to all without whose help and support this project would not have been a success. Special thanks are due to Adam Rummens, Commissioning Editor, Amanda Miller, Typesetting Manager, and Courtney Dixon, Designer of Cambridge Scholars Publishing for their support and cooperation. The members of my family have always been the sources of motivation and inspiration for all my scholastic and academic works of mine. I dedicate my work to my beloved sister Ms. Nabanita Sen, who, unfortunately, left us on 27th September 2021, due to the deadly disease of cancer. My sister was always the pillar of strength for me, and she was the primary source of support and motivation for my effort toward this volume. Last but not the least, I gratefully acknowledge the immense support and motivation I received from my wife Ms. Nalanda Sen, my daughter Ms. Ritabrata Sen, and my mother Ms. Krishna Sen. Without their sacrifice and support, the publication of this volume would not have been possible. Many thanks to all of them!

Jaydip Sen Praxis Business School Kolkata, INDIA

Program Codes: The program codes associated with the chapters of this book are available at the following GitHub link:

https://github.com/JaydipSen/Analysis-and-Forecasting-of-Financial-Time-Series-Selected-Cases

CHAPTER 1

A ROBUST AND ACCURATE PREDICTIVE FRAMEWORK FOR THE INDIAN MID-CAP SECTOR INDEX

Introduction

Developing an accurate and efficient forecasting framework for the robust prediction of stock prices has been one of the most exciting yet complex challenges researchers face in machine learning and analytics. Researchers have proposed numerous technical, fundamental, and statistical indicators for accurately predicting the prices of stocks. Sen and Datta Chaudhuri proposed a novel approach based on time series decomposition and analysis for efficient portfolio diversification and prediction of stock prices (Sen, 2022; Sen, 2018b; Sen, 2018c; Sen, 2017a; Sen, 2017b; Sen & Datta Chaudhuri, 2018; Sen & Datta Chaudhuri, 2017a; Sen & Datta Chaudhuri, 2017b; Sen & Datta Chaudhuri, 2017c; Sen & Datta Chaudhuri, 2016a; Sen & Datta Chaudhuri, 2016b; Sen & Datta Chaudhuri, 2016c; Sen & Datta Chaudhuri, 2016d; Sen & Datta Chaudhuri, 2016e). The authors hypothesized that all sectors of an economy do not exhibit a similar pattern of variations in their stock prices. It is more usual to find that various sectors exhibit different patterns in their trend, different characteristics in their seasonality behavior, and varying degrees of randomness in their time series values. While on the one side, the efficient market hypothesis has argued for the randomness aspect of stock price movements. On the other side, there are propositions to counter the hypothesis by delving into various fundamental characteristics of different sectors and different stocks in those sectors. We argue that in addition to the differences in the fundamental attributes among stocks belonging to multiple companies, the performances of different stocks are also very much dependent on and coupled to the sectors to which the stocks belong. Since the behavior of each sector of the economy is influenced by its unique set of factors, the pattern of the price movement of stocks belonging to various sectors is also determined and influenced by these factors.

Chapter 1

In this chapter, our goal is to study the behavioral pattern exhibited by the time series of the *mid-cap* sector of India so that the salient properties of that sector can be better understood. By its definition, a *mid-cap* company has a market capitalization between Indian Rupees (INR) 50 billion to INR 200 billion. For our study, the monthly average index values of the mid-cap sector are used for the period January 2010 - December 2016 as per the Bombay Stock Exchange (BSE). The monthly time series data is decomposed into its three components using functions defined in the R programming language. Based on the decomposition results, we demonstrate how several exciting characteristics of the time series can be extracted to gain valuable insights into its behavioral pattern. We particularly illustrate how a more indepth analysis of the trend, seasonal and random components, provides us with helpful information about the growth pattern, seasonal properties, and randomness exhibited by the time series index values. For predicting future behavioral patterns, we also propose an extensive framework for time series forecasting consisting of five methods of prediction of time series index values. The five forecasting methods are critically analyzed in terms of forecasting accuracy.

The organization of the chapter is as follows. The section titled *Related* Work presents a brief literature survey on some of the current work on time series analysis and forecasting. In the section titled *Methodology*, we present a detailed description of the methodology we followed in this work. We discuss in detail the method of decomposition of the *mid-cap* sector time series into its various components. The section titled Time Series Decomposition Results presents extensive decomposition results of the time series values into its trend, seasonal and random components. The decomposition results are analyzed in-depth to understand several essential characteristics and behavior revealed by the time series. In the section titled Proposed Forecasting Methods, we propose a set of five forecasting methods for predicting the future values of the time series. In the section titled *Forecasting Results*, we provide results on the performance of five forecasting methods on the *mid-cap* sector time series data. Each of the proposed algorithms is evaluated and compared based on two performance metrics. The first metric is based on the computation of the root mean square error (RMSE). However, to express the RMSE as the percentage of the mean value of the target variable, we design a derived metric that is computed as the ratio of the RMSE to the mean values of the target variable. The second metric used for comparing the performance of the predictive model is mean absolute percentage error (MAPE). Finally, in the section titled Conclusion, we conclude the chapter and highlight some future directions of work.

A Robust and Accurate Predictive Framework for the Indian Mid-cap Sector Index

Related Work

In the literature, researchers have proposed several approaches and techniques for forecasting the daily prices of stocks and index values of various sectors of the economy. Neural network-based approaches are the most popular among these propositions.

Mostafa presented a method of forecasting the movement of stock prices in Kuwait that utilized the concepts of *artificial neural networks* (ANNs) (Mostafa, 2010). The author used historical stock price records from the Kuwait Stock Exchange (KSE) from 2001 to 3003 and builds two models, (i) a multi-layer perceptron (MLP) and (ii) a generalized regression neural network, for predicting the close price of the stocks listed in KSE. The results show that the generalized regression neural network is more accurate in forecasting future stock prices.

Kimoto et al. proposed neural network models based on historical accounting data and various macroeconomic factors. The neural network models were found to be accurate in predicting the movement patterns in several stock returns (Kimoto et al., 1990).

Leigh et al. illustrated various approaches to predicting stock prices and stock market index movements in the New York Stock Exchange (NYSE) from January 1981 to December 1999 (Leigh et al., 2005). The authors used linear regression and simple neural network models in developing their proposed approaches.

Hammad et al. demonstrated how the output of an ANN model can be forced to converge after executing a finite number of iterations and then producing highly accurate predicted values of stock prices (Hammad et al., 2007).

Dutta et al. designed predictive models using ANNs for forecasting the closing index values of the BSE from January 2002 to December 2003 (Dutta et al., 2006).

Tsai and Wang carried out a study investigating how and why the forecasting accuracy produced by a BN-based approach usually is higher than that yielded by a traditional regression and neural network-based method (Tsai & Wang, 2009).

Tseng et al. showed how techniques like traditional time series decomposition, HoltWinters models, Box-Jenkins method, and artificial neural networks can be applied in predicting the prices of a randomly selected set of 50 stocks from September 1998 to December 2010 (Tseng et al., 2012). The authors observed that the forecasting errors were minor for the Box-Jenkins method, HoltWinters model, and normalized neural

network model. However, higher error values were observed in the time series decomposition method and non-normalized neural network model.

Moshiri and Cameron proposed a *backpropagation network* (BPN) with econometric models for predicting the inflation level of the economy using the following techniques: (i) Box-Jenkins Autoregressive Integrated Moving Average (BJARIMA) model, (ii) Vector Autoregressive (VAR) model, and (ii) Bayesian Vector Autoregressive (BVAR) model (Moshiri & Cameron, 2010).

Thenmozhi demonstrated how the chaos theory can be applied to identifying the pattern of changes in stock prices in the Bombay Stock Exchange (BSE) from August 1980 to September 1997. The author discovered that the daily and weekly returns of the BSE index exhibited non-linear trends, while the BSE index showed a weakly chaotic movement pattern (Thenmozhi, 2006).

Hutchinson proposed a novel approach based on the principle of learning networks for accurately predicting the price of a derivative (Hutchinson et al., 1994).

Mehtab and Sen presented a series of work on the design of predictive models for the future stock price and index values and movements based on innovative machine learning and deep learning architectures (Sen, 2021; Sen, 2018a; Sen & Mehtab, 2022; Mehtab & Sen, 2022; Mehtab & Sen, 2021; Mehtab & Sen, 2020a; Mehtab & Sen, 2020b; Mehtab & Sen, 2020c; Mehtab & Sen. 2019; Mehtab et al., 2021; Mehtab et al., 2020). The models proposed by the authors used historical stock prices and stock index values at daily intervals or 5 minutes intervals. The power of convolutional neural networks (CNNs) and long- and short-term memory (LSTM) networks was exploited for achieving a very high level of accuracy in the out-of-sample of data. The authors proposed four CNN models and six LSTM models that differ in architecture and input data (i.e., univariate or multivariate time series data and the size of the input data). The models were compared on their root mean square error (RMSE) values. The results elicited two interesting observations: (i) the performances of the CNN models are superior to that of the LSTM models, and (ii) the models based on the univariate data yield more accurate forecasting. In another set of papers, Sen et al. proposed further variants of CNN and LSTM-based models for predicting future stock price values and stock price movements for designing optimum portfolios of stocks (Sen & Datta Chaudhuri, 2018; Sen et al., 2021a; Sen et al., 2021b; Sen et al., 2021c; Sen & Mehtab, 2021d; Sen et al., 2021e; Sen et al., 2021f; Sen & Mehtab, 2021g; Sen et al., 2020). The authors reported extensive results for comparing the performance of the models.