Comparing SVR to LSTM ANN for Volatility Forecasting

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Abstract

Volatility modelling is an important problem in financial econmetrics. The recent prolierfation of powerful machine learning techniques offers a models that are well suited to this complex problem. In this paper volatility forecasting by Support Vector Regression (SVR) and Long-Short Term Memory Recurrent Neural Networks (LSTM) are compared. The JSE All Share index is used to compare. An EGARCH models is used as a baseline model. The LSTM model performed best at one-day ahead and three-day ahead forecasting.

1. Introduction

Volatility modelling is an important and complex problem in financial econometrics. The volatility the returns of an asset are an important measure for the risk of an asset. Volatility itself is a key factor in options pricing and in asset allocation. The Value-at-Risk calculations made for risk management rely on measures of volatility. There has been a recent proliferation of machine learning techniques that can greatly improve the precision of volatility forecasting. The traditional forecasting techniques build on the generalized autoregressive conditional heteroscedastic (GARCH) class of models are well suited for uncovering the true patterns of volatility. However, their ability to accurately forecast volatility is limited.

The use of machine learning techniques including Support Vector Regression (SVR) and artifical neural network models has grown in recent years with far superior performance (citation needed). Recently proposed volatility models using the long-short term memeroy recurrent neural network (LSTM) have futher improved forecasting precision(citation needed). While these models have been used to model volatility in the US, only the SVR and GARCH models have been applied to South African data.

The volatility of the JSE ALSI total returns index (TRI) is modelled. This paper finds that the GARCH models perform poorly on pure forecasting precision. The SVR and LSTM models perform similarly well on one-day ahead forecasting with the LSTM marginally better. On three-day ahead forecasting

The remainder of the paper is organised as follows: the data and methodology is described, the results

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are analysed followed by the conclusion.

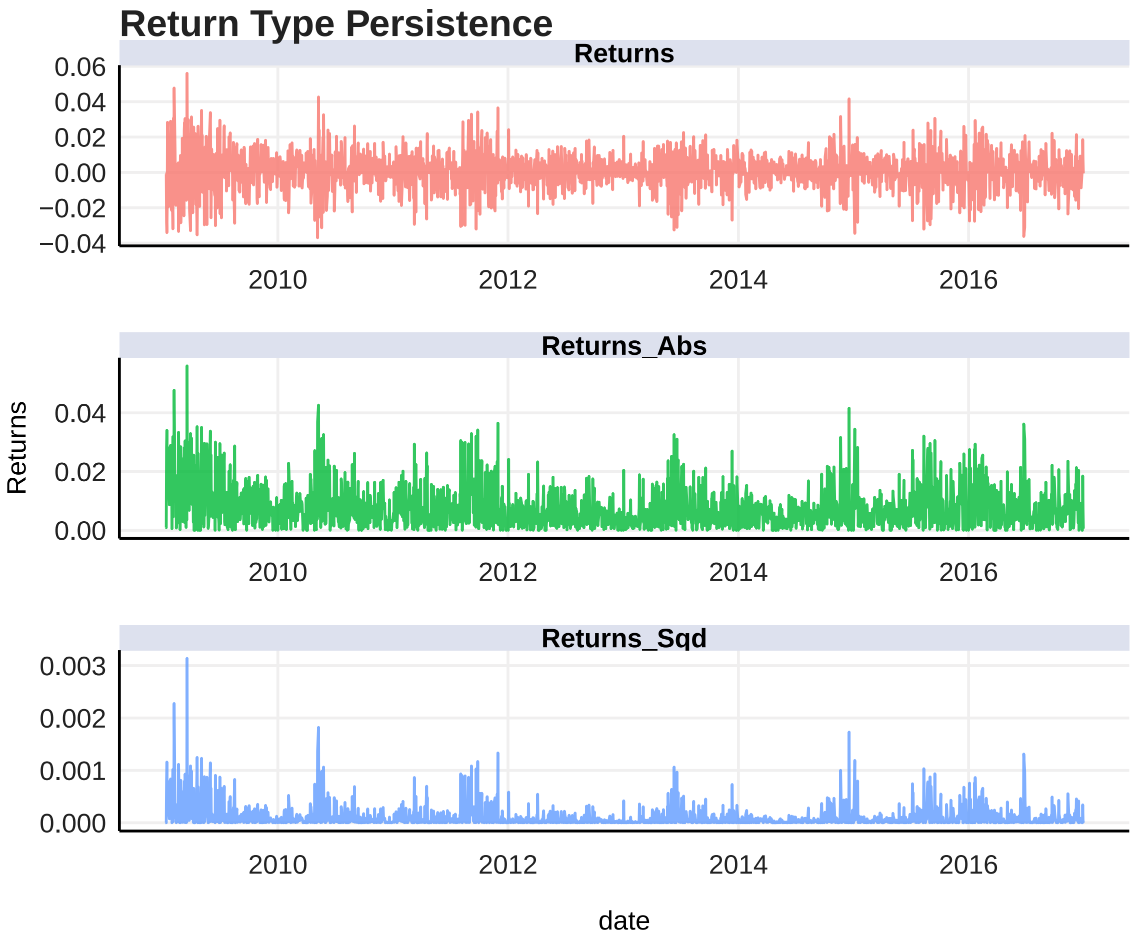
Data

The data used in this paper is the total return index (TRI) of the JSE ALSI. The TRI is price adjusted for dividends, stock splits and other corporate actions. The data is split into training, validation and test series. The training set is from 05-01-2009 to 30-12-2016, the validation set is from 03-01-2017 to 31-12-2018, and the test set is from 03-01-2019 to 31-12-2019. Returns, dlogret, are calculated using log difference of TRI, log(TRI) - log(lag(TRI)). The volatility, sigma, is calculated as dlogret^2.

2. Methodology

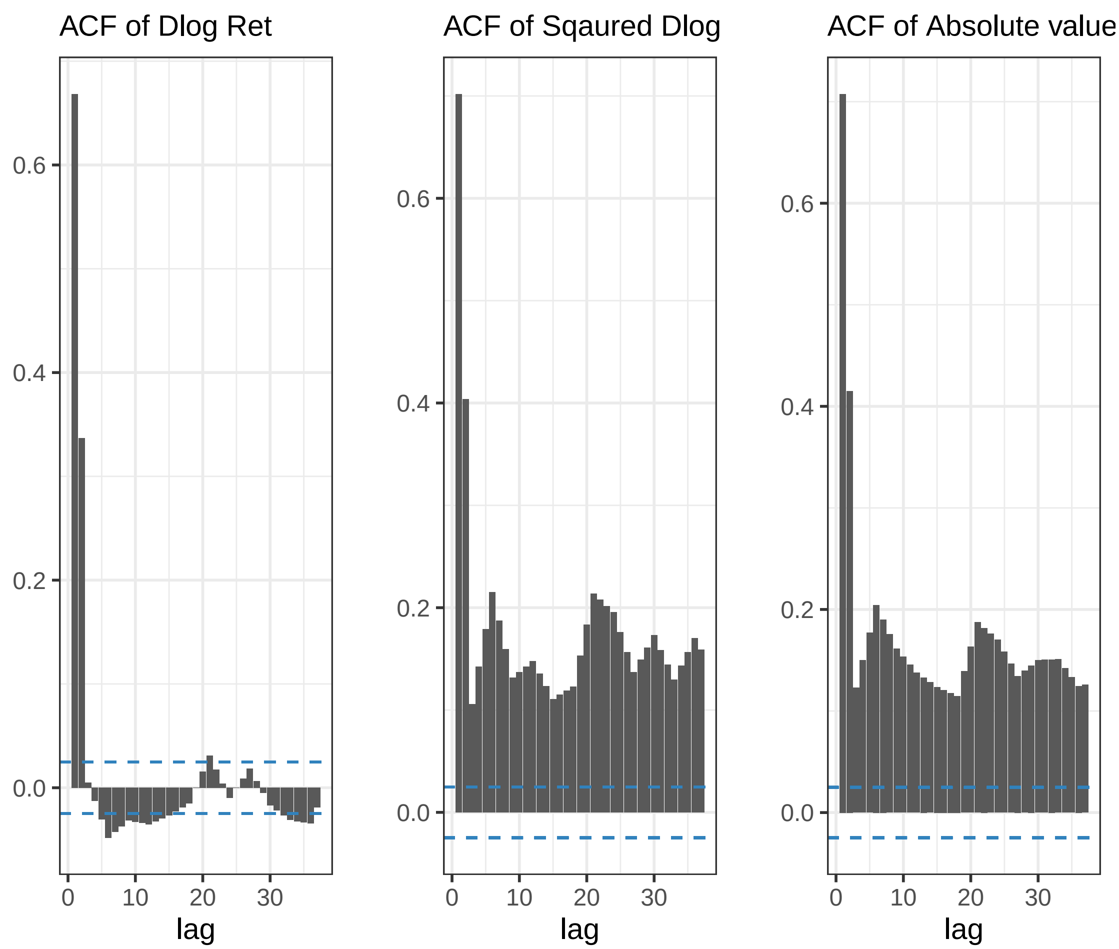
3. Results

```
## $`Return Plots`
```



Return Type Persistence
Returns
0.06
0.04
0.02
0.00
−0.02
−0.04
2010
2012
2014
2016
Returns_Abs
0.04
0.02
0.00
Returns
Returns_Sqd
0.003
0.002
0.001
0.000
date


```
##
## $`ACF Plots`
```




```
##
## $`Box Statistics`
##
##  Box-Ljung test
##
## data:  data$dlogret^2
## X-squared = 632.57, df = 12, p-value < 2.2e-16
```

```
##                 sGARCH  gjrGARCH    eGARCH    apARCH
## Akaike       -6.452107 -6.482330 -6.490124 -6.476212
## Bayes        -6.438554 -6.466067 -6.473860 -6.457238
## Shibata      -6.452119 -6.482347 -6.490140 -6.476235
## Hannan-Quinn -6.447141 -6.476371 -6.484164 -6.469259
```

```
##             Estimate   Std. Error       t value     Pr(>|t|)
## mu      0.0003515747 2.130849e-04     1.6499274 9.895778e-02
## ar1     0.0125580135 3.000059e-02     0.4185922 6.755142e-01
## omega  -0.1158799416 3.678887e-03   -31.4986395 0.000000e+00
## alpha1 -0.1229697781 1.276882e-02    -9.6304719 0.000000e+00
## beta1   0.9876109595 3.831107e-05 25778.7351700 0.000000e+00
## gamma1  0.0827979223 8.778569e-03     9.4318240 0.000000e+00
## shape  11.8303799861 2.471258e+00     4.7871886 1.691339e-06
```

```
##             Estimate   Std. Error      t value     Pr(>|t|)
## mu      0.0002864073 0.0003012782    0.9506407 3.417868e-01
## ar1     0.0264570892 0.0442049551    0.5985096 5.495000e-01
## omega  -0.3238038491 0.0070088366  -46.1993718 0.000000e+00
## alpha1 -0.1486355485 0.0223898006   -6.6385383 3.168088e-11
## beta1   0.9667674863 0.0001089335 8874.8383943 0.000000e+00
## gamma1  0.0614327405 0.0272134808    2.2574378 2.398073e-02
## shape   8.2762798876 2.8918533902    2.8619293 4.210709e-03
```

```
## [1] 0.003458062
```

```
## [1] 0.009582018
```

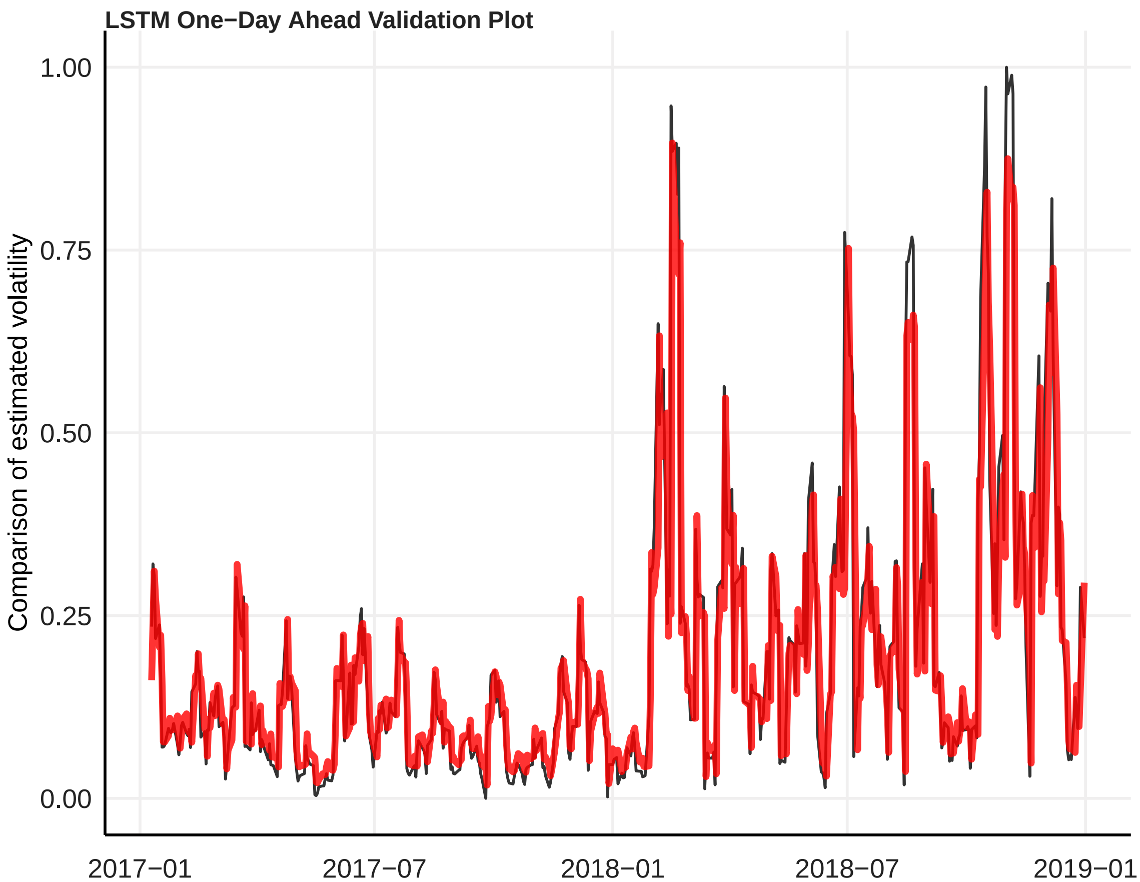


Figure 3.1: LSTM One-Day Ahead Validation Forecast

```
## [1] 0.01517164
```

```
## [1] 0.04770794
```

```
## [1] "1 DONE!!"
## [1] "DONE!!"
```

```
## # A tibble: 1 x 3
##    gamma lambda     mse
##    <dbl>  <dbl>   <dbl>
## 1 0.0821 0.0821 0.00342
```

```
## # A tibble: 1 x 3
##    gamma lambda     mse
##    <dbl>  <dbl>   <dbl>
## 1 0.0821 0.0821 0.00968
```

```
## [1] "1 DONE!!"
## [1] "DONE!!"
```

```
## # A tibble: 1 x 3
##    gamma lambda     mse
##    <dbl>  <dbl>   <dbl>
## 1 0.0821 0.0821 0.00813
```

```
## # A tibble: 1 x 3
##    gamma lambda    mse
##    <dbl>  <dbl>  <dbl>
## 1 0.0821 0.0821 0.0462
```

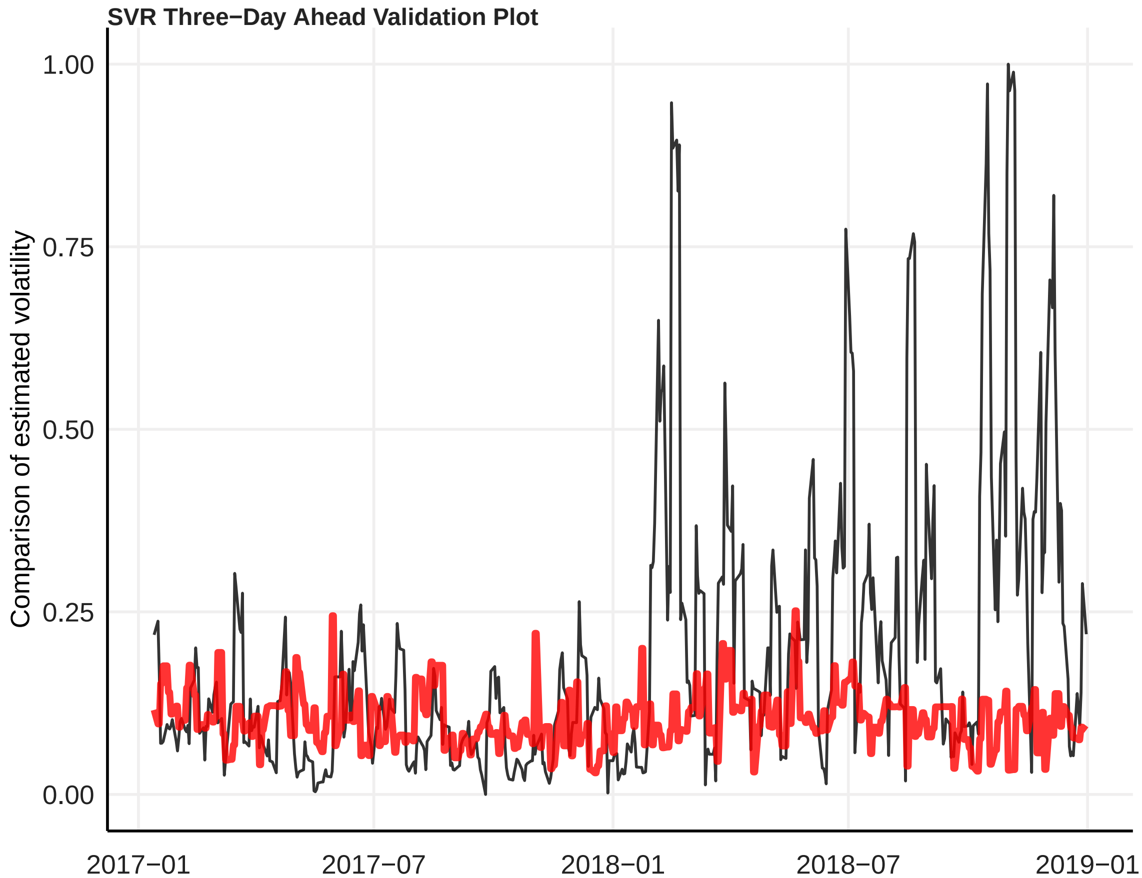


Figure 3.2: SVR Three-Day Ahead Validation Forecast

```
## [1] 0.003129262
```

```
## [1] 0.01206342
```

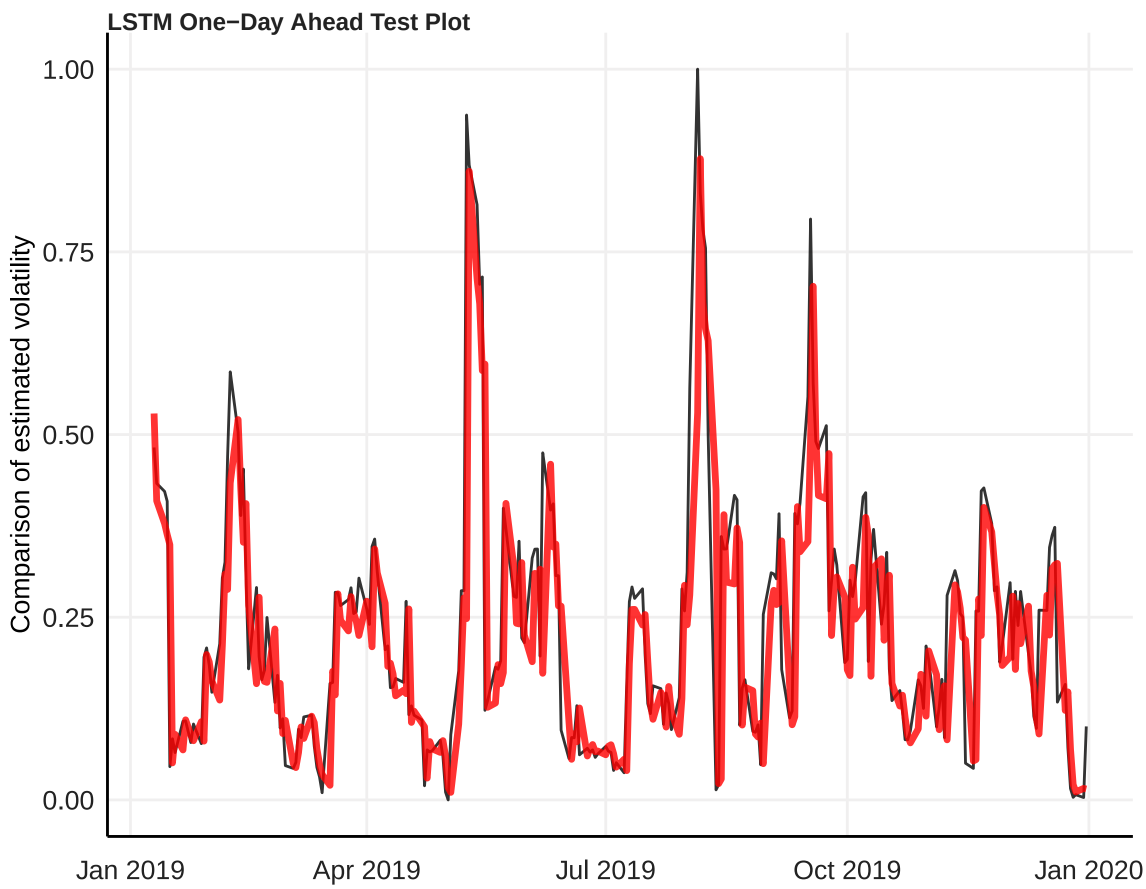


Figure 3.3: LSTM One-Day Ahead Test Forecast

```
## [1] "1 DONE!!"
## [1] "DONE!!"
```

```
## # A tibble: 1 x 3
##    gamma lambda     mse
##    <dbl>  <dbl>   <dbl>
## 1 0.0821 0.0821 0.00372
```

```
## # A tibble: 1 x 3
##    gamma lambda    mse
##    <dbl>  <dbl>  <dbl>
## 1 0.0821 0.0821 0.0523
```

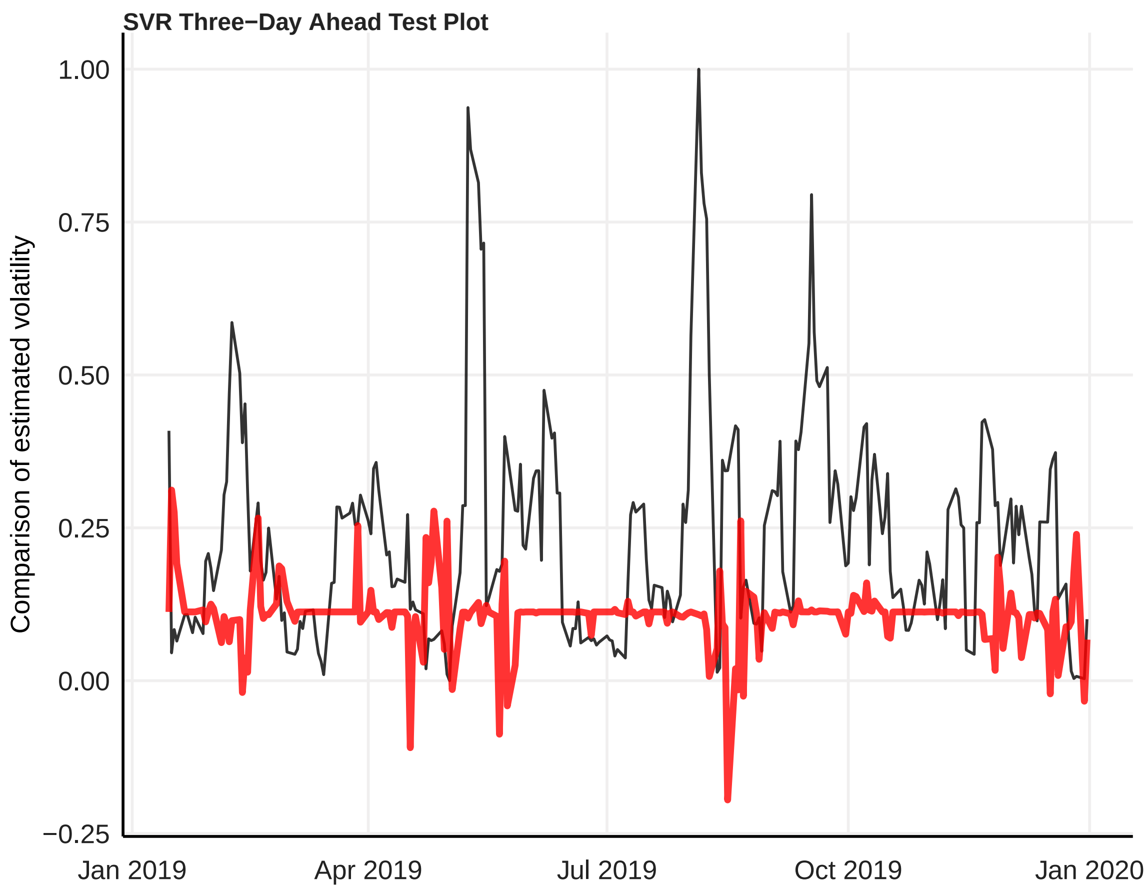


Figure 3.4: LSTM Three-Day Ahead Test Forecast

4. Conclusion

References

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Appendix

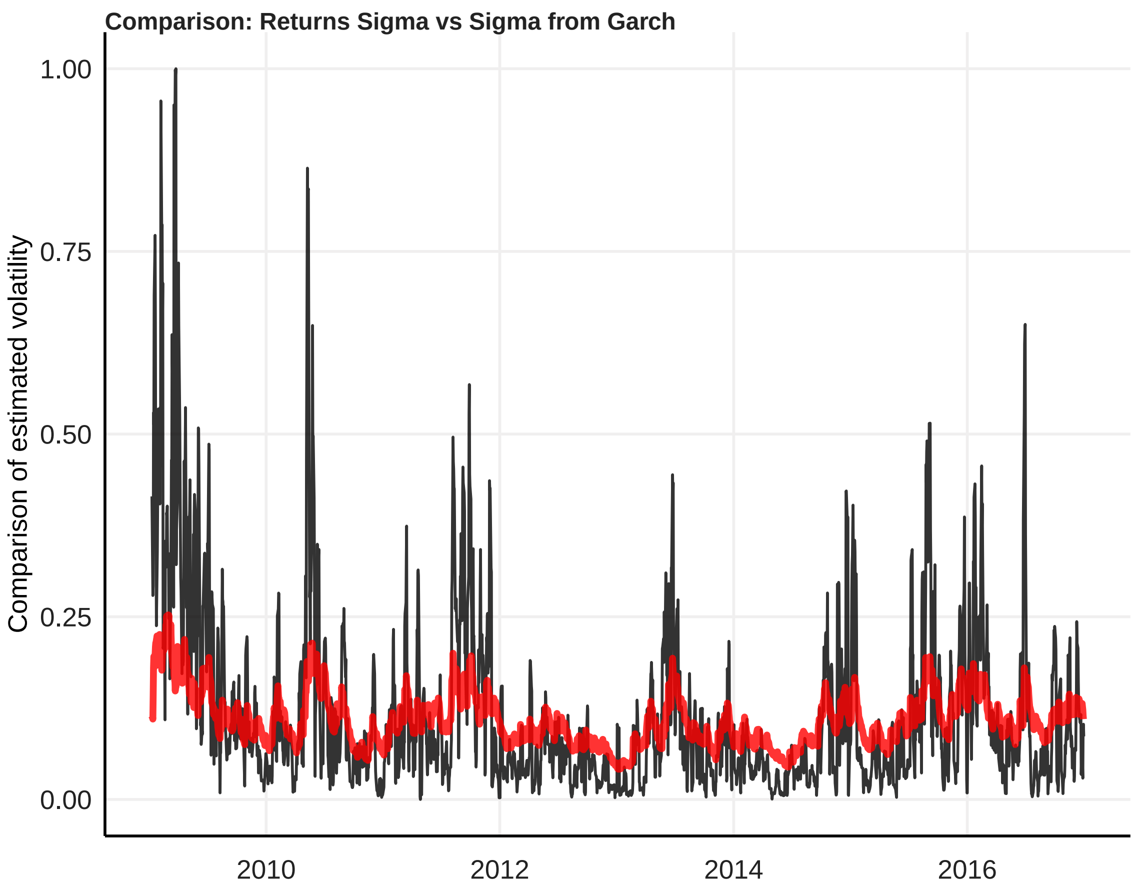

Figure 4.1: EGARCH(1,1) One-Day Ahead Training Forecast

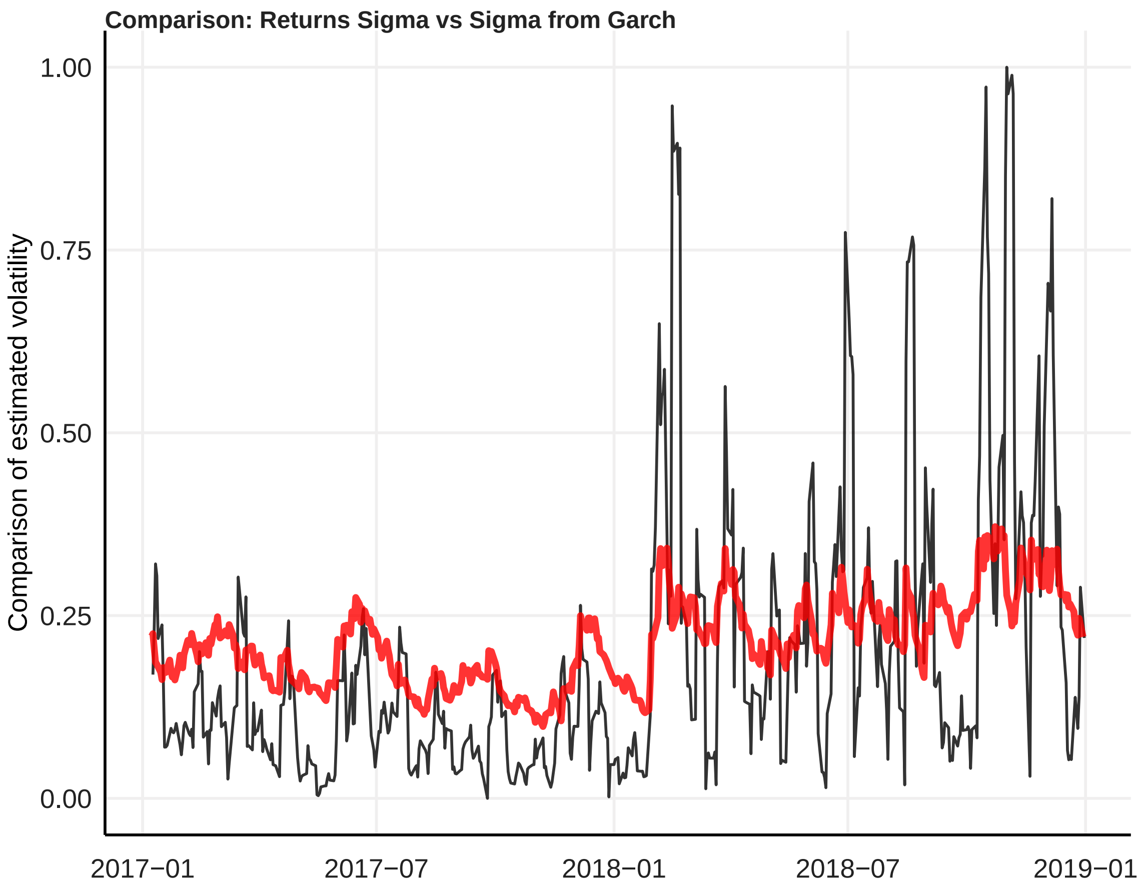

Figure 4.2: EGARCH(1,1) One-Day Ahead Validation Forecast

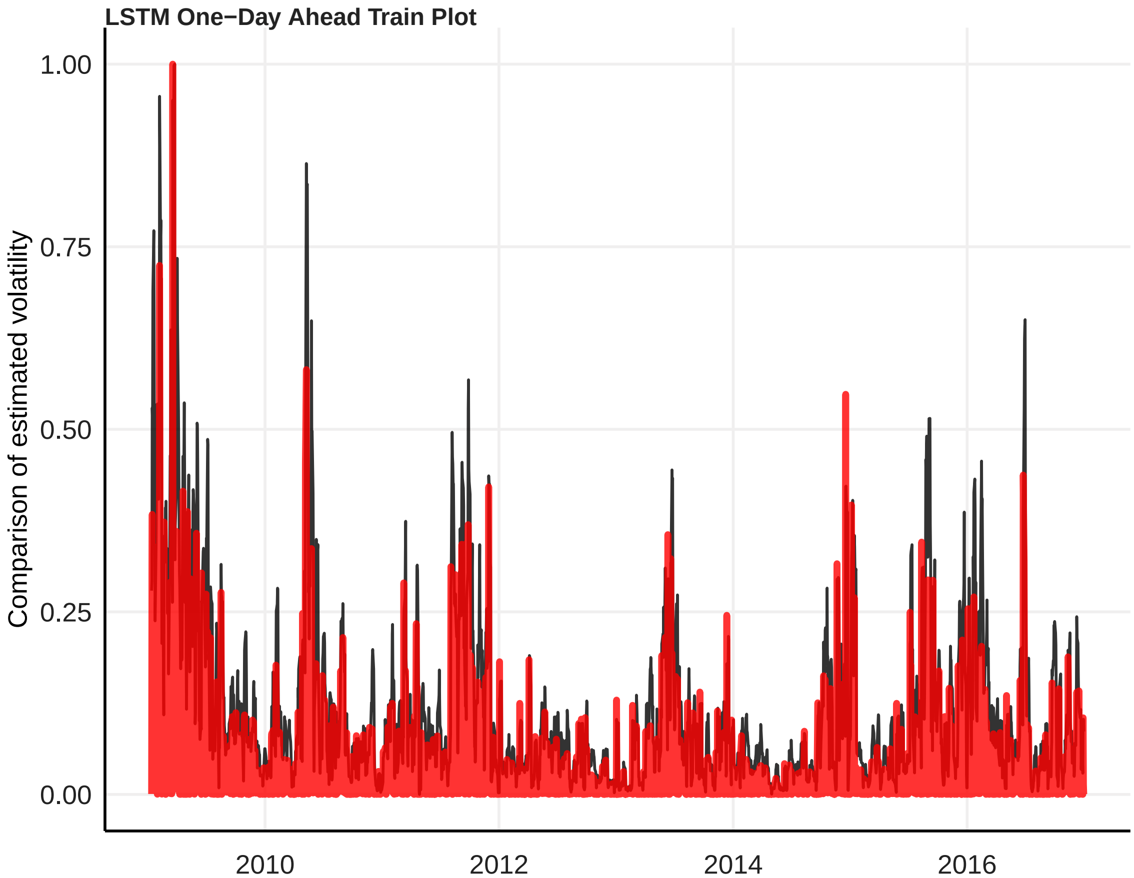

Figure 4.3: LSTM One-Day Ahead Training Forecast

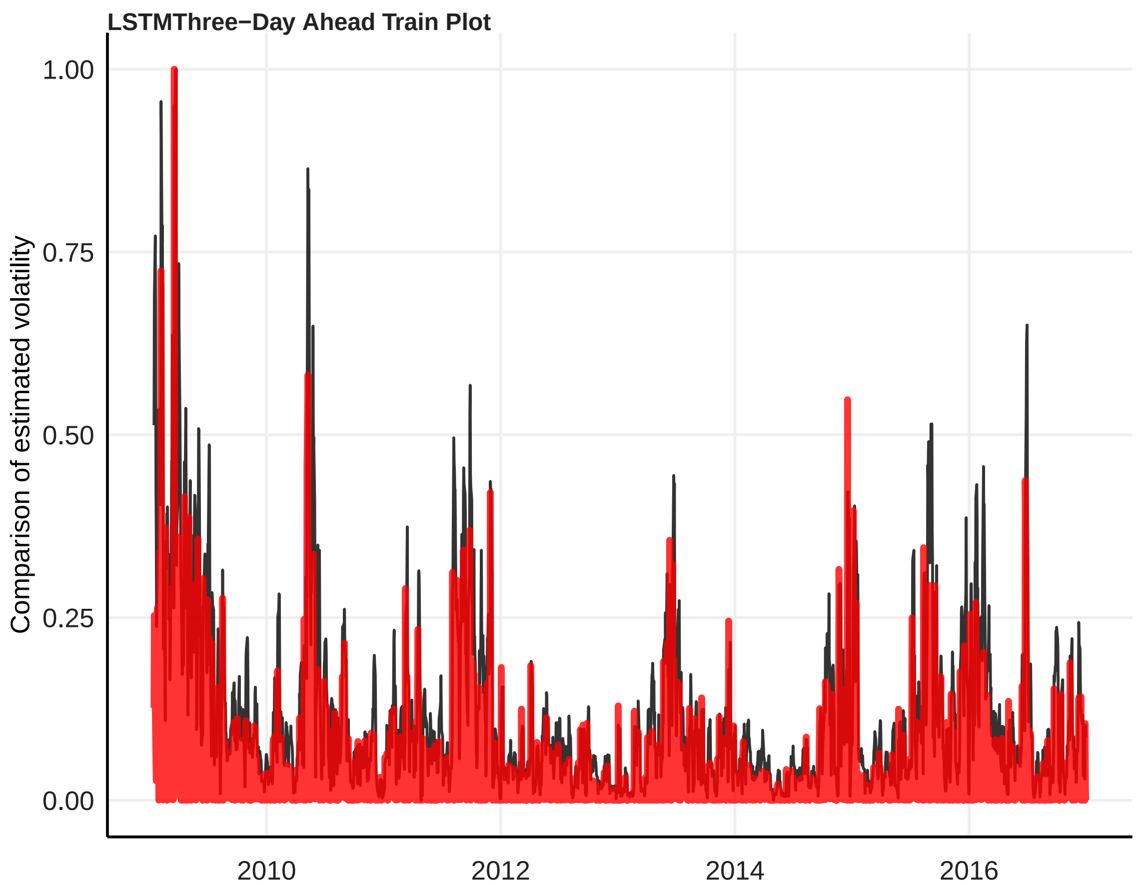

Figure 4.4: LSTM Three-Day Ahead Training Forecast

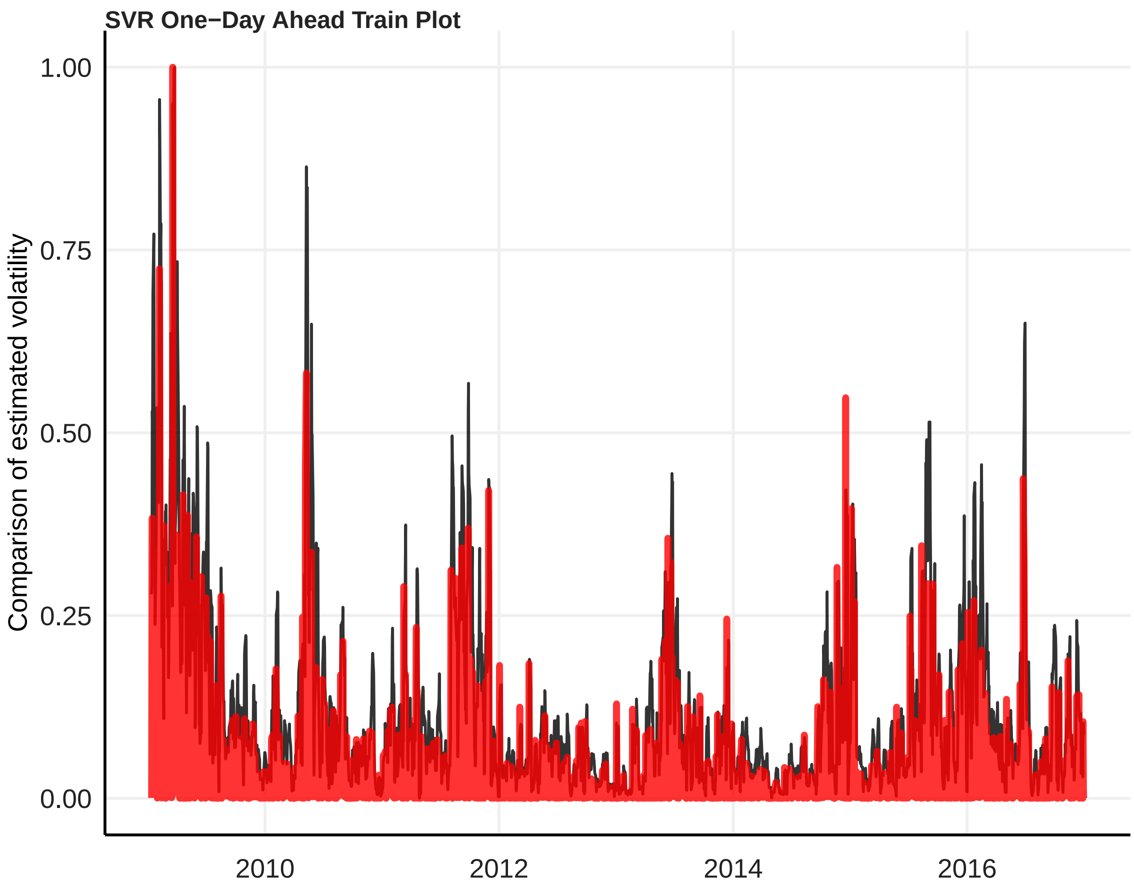

Figure 4.5: SVR One-Day Ahead Training Forecast

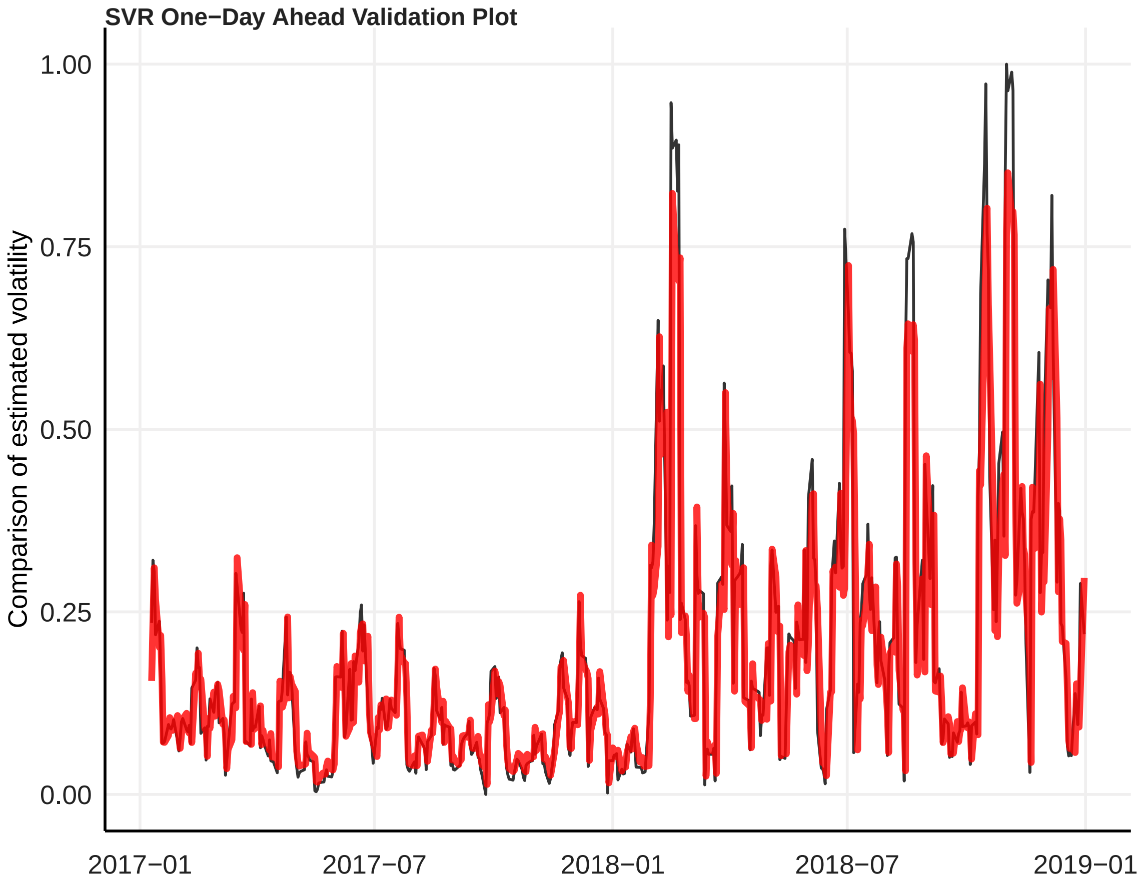

Figure 4.6: SVR One-Day Ahead Validation Forecast

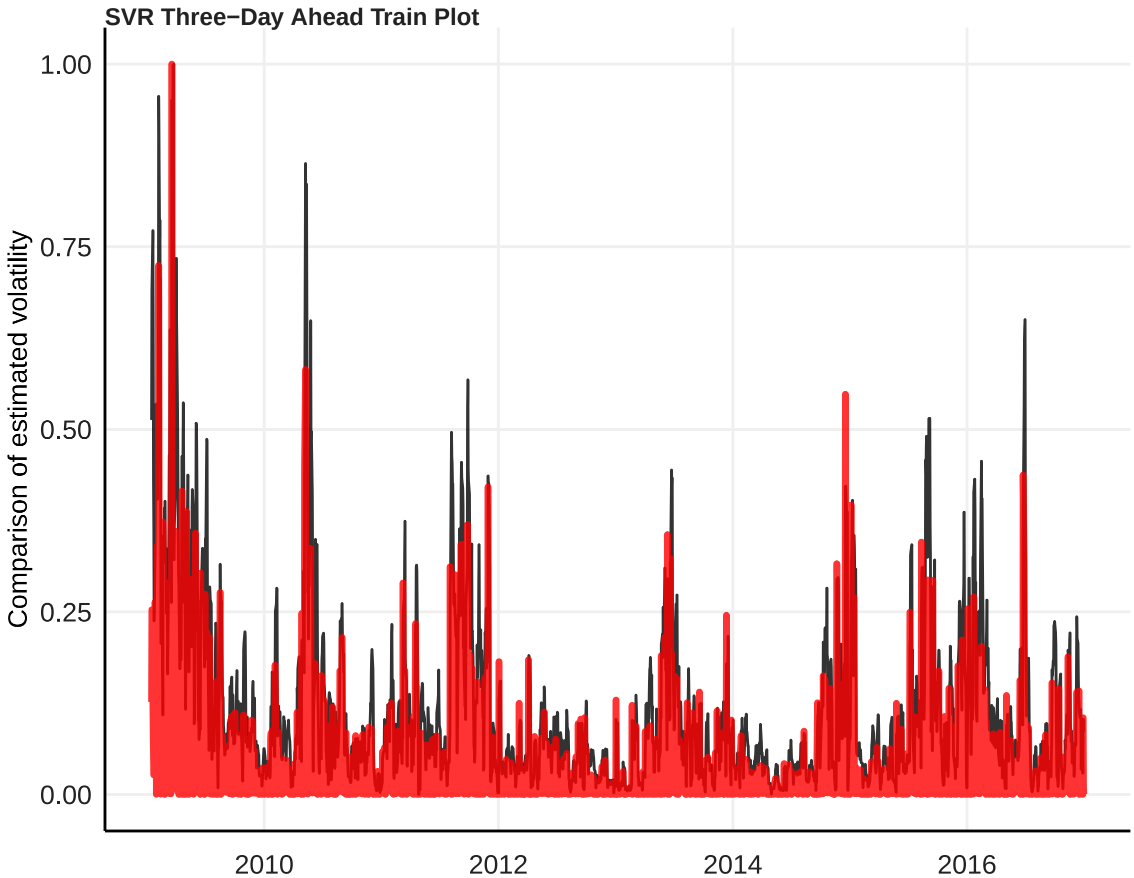

Figure 4.7: SVR Three-Day Ahead Training Forecast

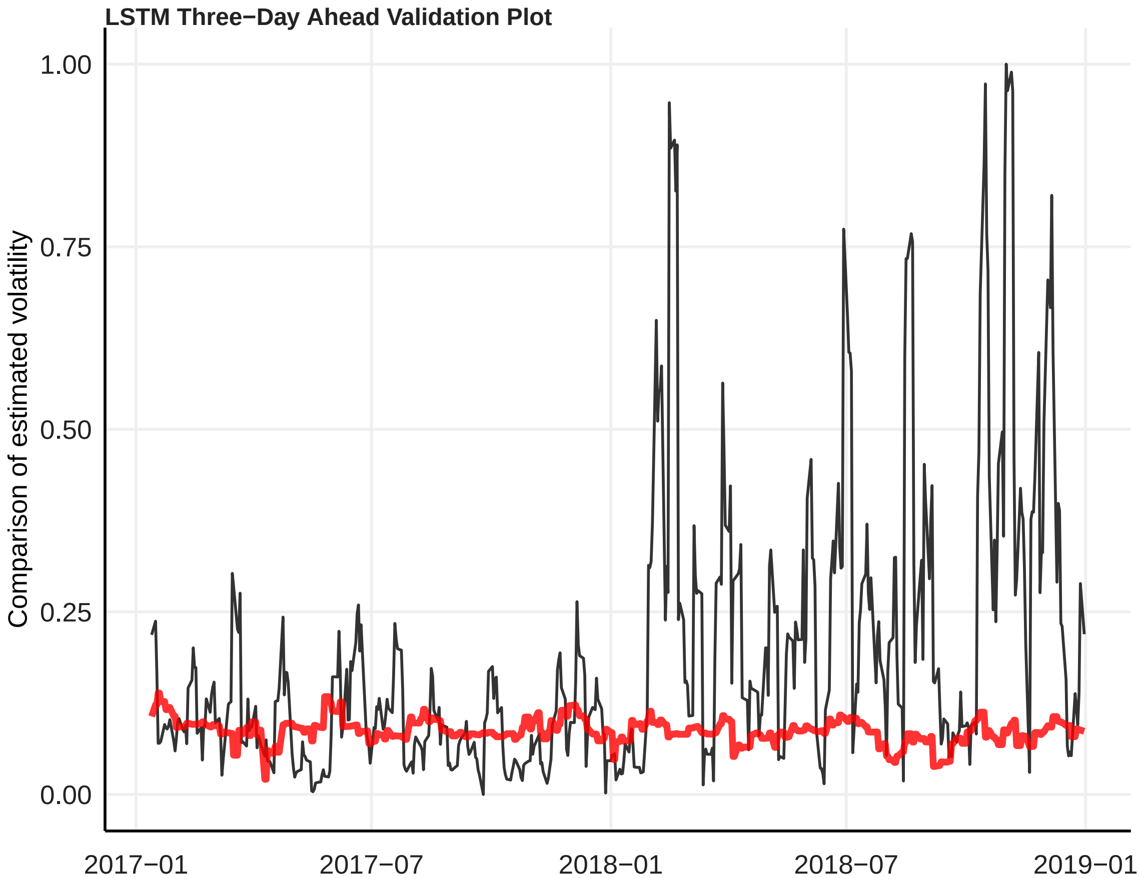

Figure 4.8: LSTM Three-Day Ahead Validation Forecast

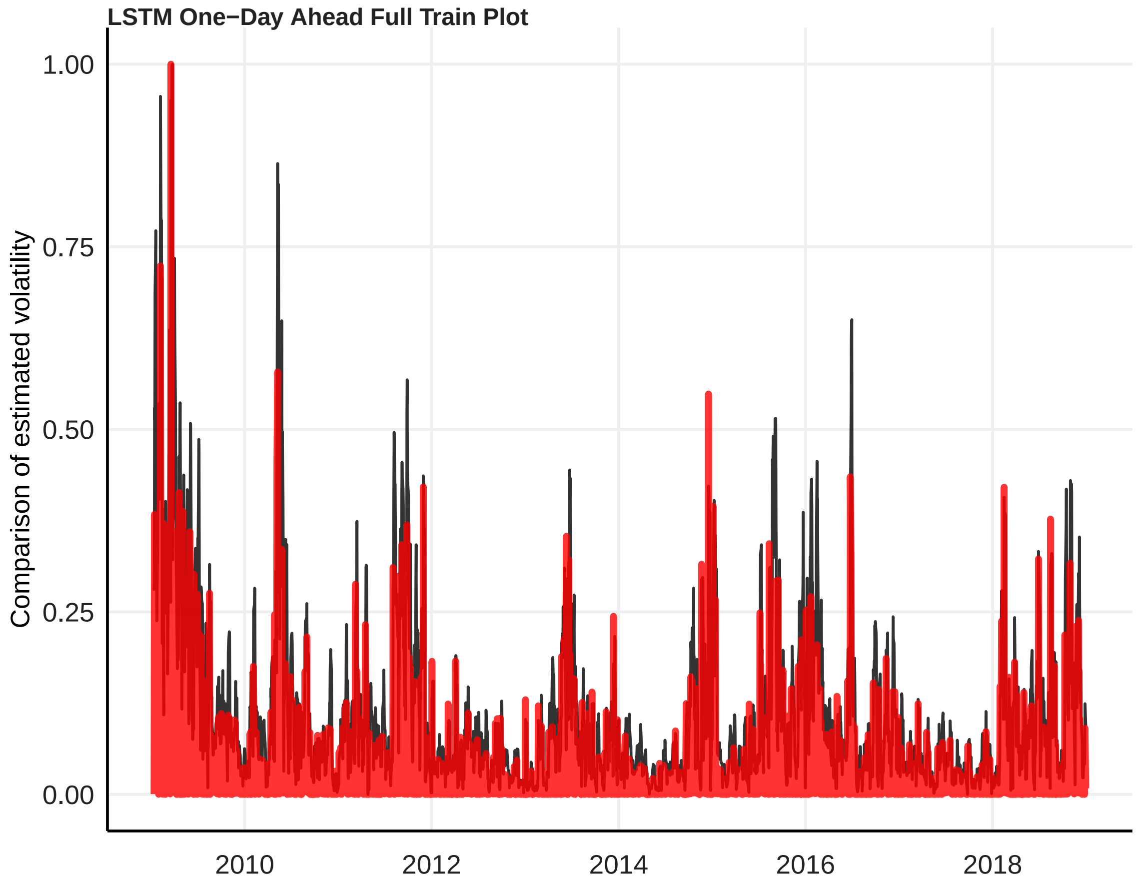

Figure 4.9: LSTM One-Day Ahead Full Training Forecast

```
## NULL
```