

# Volatility Forecasting

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# MIDAS RV Regression

The MIDAS RV regression is:

$$\hat{Q}_{\tau_h} = \mu_h + \beta_h \sum_{j=0}^{jmax} \omega_j(\theta_h) \hat{Q}_{t-j} + \epsilon_{\tau_h}$$

where  $\hat{Q}_{\tau_h}$  is  $h$ -period variance,  $\omega_j(\theta_h)$  - some parsimonious weighting function truncated at  $jmax$  and parameterized by a low-dimensional  $\theta_h$  parameter, and  $\hat{Q}_t$  are daily realized variances.

- Note that realized variance is an estimated quantity. We take 5-minute log-returns and compute the sum of squared returns over the day, i.e.  $\hat{Q}_t = \sum_{j=1}^m [r_{t-(j-1)/m}]^2$ .
- For multiperiod realized variances,  $\hat{Q}_{\tau_5}$ ,  $\hat{Q}_{\tau_{10}}$ , we compute a non-overlapping sum of daily realized variances.

# Volatility Forecasting Example

- This example shows how MIDAS regression could be applied in the context of multi-period realized volatility forecasting.
- 5-day and 10-day realized volatility regressed on daily data for several asset classes: equity (S&P 500), Treasury (30y treasury), currency (Euro), and commodity (gold, cocoa).
- Model specification: forecast horizons 5 days, 10 days, truncation value  $j_{max}$  - 126 days.
- Compare direct with different weights specifications: Beta density and exponential Almon.

# Volatility Forecasting Example

## Listing 1: Preliminaries

```
clear all;  
close all;  
  
%load in data  
load('example2.mat')
```

Check if data is loaded in your Matlab workspace.

You should see: AllclosingRet\_2018, Alldates\_2018, AllRV2018, Names

# Volatility Forecasting Example

Set options for lags and for horizons.

```
% General options
optionsmidas.aggrX=126; % no. of lags of RV
Horizons = [5 10]; % forecasting horizons
```

# Volatility Forecasting Example

- For this example we will rely on the RV example folder for all of our functions
- The folder holds the weight functions, the midas objective function, the midas filter, the data generation function and the optimization function

# Volatility Forecasting Example

Running the loop:

- Here, the outer loop goes through all 5 assets
- re-loads the data and pulls it
- sets the counter to 1

```
%% loop across assets
for countf = 1 : 5

    %load in data
    load('example2.mat')

    Rd = AllclosingRet_2018{countf,1};
    dates = Alldates_2018{countf,1};
    RV = AllRV_2018{countf,1};
    T = size(dates,1); % no of time-series obs

    counth = 1;
```

# Volatility Forecasting Example

Running the loop:

- Here, we loop through all of the horizons for each individual asset
- we display the asset count and horizon at the start of each iteration
- we set the aggregation equal to the horizon
- `datageneration_midas` function data transformation function for MiDaS regressions, non-overlapping sum of RV over the horizon  $h$

```
%% loop across horizons
for hhh = Horizons

    disp([countf hhh])
    optionsmidas.aggrY=hhh;

    [RVh,~,dates_hhh] = datageneration_midas(RV,optionsmidas,dates);
```



# Volatility Forecasting Example

Running the loop:

- midas\_optimization function runs the MIDAS RV regressions
- we run for beta and almon polynomial for each horizon

```
%%%      MIDAS on RV with beta weights
[theta_MIDAS_beta, ~, s2_MIDAS_beta]= midas_optimization(RV,
    optionsmidas, 'beta');
%%%      MIDAS on RV with exp weights
[theta_MIDAS_exp, objfn_MIDAS_exp, s2_MIDAS_exp]= midas_optimization(
    RV, optionsmidas, 'exp');
```

# Volatility Forecasting Example

## Running the loop:

- Here, we collect our forecasts made with beta weights and almon weights
- then we evaluate forecast performance

```
% collect forecasts ---  
%[first col is beta weight forecasts second is expalmon forecasts]  
Forecasts = [s2_MIDAS_beta s2_MIDAS_exp];  
  
% evaluate forecasts performance  
for fff = 1 : size(Forecasts,2)  
    errors2(:,fff) = (RVh - Forecasts(:,fff)).^2;  
    qlike(:,fff) = log(Forecasts(:,fff)+RVh./Forecasts(:,fff));  
    RMSFE(counth,fff,countf) = sqrt(mean(errors2(:,fff)));  
    QLIKE(counth,fff,countf) = mean(qlike(:,fff));  
end
```

# Volatility Forecasting Example

Running the loop, evaluating forecast performance:

- Here, we compute our squared forecast error.
- Forecasts is from our MIDAS forecasts and RVh is the actual realized volatility

```
errors2(:, fff) = (RVh - Forecasts(:, fff)).^2;
```

# Volatility Forecasting Example

Running the loop:

- Here, we compute the QLIKE criterion at a given horizon for each model (beta and almon polynomial)

$$QLIKE(V_{s,k}^F, \hat{Q}_s) = \log(V_{s,k}^F) + \frac{\hat{Q}_s}{V_{s,k}^F}$$

where  $s$  denotes the time of the forecast,  $\hat{Q}_s$  is the realized variance,  $k$  is the horizon and  $F$  is the model which generates forecasts  $V_{s,k}^F$ .

```
qlike(:, fff) = log( Forecasts(:, fff) ) + RVh ./ Forecasts(:, fff);
```

# Volatility Forecasting Example

Running the loop:

- Now we compute the RMSFE using the squared forecast errors from before.

```
RMSFE(counth, fff, countf) = sqrt(mean(errors2(:, fff)));
```

# Volatility Forecasting Example

Running the loop:

- We take the mean of the QLIKE criterion.
- The forecast performance can be ranked by this value.
- The lower the value the better the performance.

```
QLIKE(counth, fff, countf) = mean(qlike(:, fff));
```

# Volatility Forecasting Example

Running the loop:

- We store the date, which is the first date of the forecasted, non-overlapping period
- We store the estimated coefficients for each horizon and asset for beta polynomial and for almon polynomial
- We store the forecasts

```
Dates{countf,counth}=dates_hhh; % where it is stored the first date of the
    forecasted, non-overlapping period
    Theta_MIDAS_exp(:,counth,countf) = theta_MIDAS_exp;
    Theta_MIDAS_beta(:,counth,countf) = theta_MIDAS_beta;
    MIDAS-forecasts{countf,counth}=Forecasts;
```

# Volatility Forecasting Example

Running the loop:

- We clear certain variables in our workspace because they will be calculated at each horizon
- we add one to the counter

```
clear s2* theta_* RVh dates_hhh hhh_* errors2* qlike* obj* dates_*  
    counth = counth+1;  
end
```



# Volatility Forecasting Example

Running the loop:

- We clear more variables here to clean up our workspace
- at this point we have looped through all horizons for one asset
- we go back and loop through another asset

```
clear s2* theta_* RVh dates_hhh hhh_* errors2* qlike* obj* dates_*  
    counth = counth+1;  
end
```

# Volatility Forecasting Example

## QLIKE Criteria for each asset, horizon and MIDAS model

$\text{val}(:, :, x)$  where  $x$  is the asset number

row is horizon, first is  $h=5$ , second is  $h=10$

column 1 is beta polynomial, column 2 is exponential almon

$\text{val}(:, :, 1) =$

-6.5096	-6.6146
-5.8347	-5.8520

$\text{val}(:, :, 2) =$

-7.7229	-7.7235
-7.0226	-7.0231

$\text{val}(:, :, 4) =$

-5.6316	-5.6325
-4.9309	-4.9309

$\text{val}(:, :, 3) =$

-6.5667	-6.5677
-5.8576	-5.8573

$\text{val}(:, :, 5) =$

-7.3427	-7.3442
-6.6376	-6.6391

# Volatility Forecasting Example

## RMSFE Criteria for each asset, horizon and MIDAS model

`val(:, :, x)` where `x` is the asset number

row is horizon, first is `h=5`, second is `h=10`

column 1 is beta polynomial, column 2 is exponential almon

```
val(:, :, 1) =
```

0.0015	0.0015
0.0021	0.0022

```
val(:, :, 2) =
```

```
1.0e-03 *
```

0.1032	0.1029
0.1850	0.1842

```
val(:, :, 4) =
```

0.0006	0.0006
0.0011	0.0011

```
val(:, :, 3) =
```

```
1.0e-03 *
```

0.4778	0.4775
0.8567	0.8567

```
val(:, :, 5) =
```

```
1.0e-03 *
```

0.1313	0.1305
0.2308	0.2294

# The End