# Macro forecasting: ARDL-MIDAS regressions

August 29, 2019

# ARDL-MIDAS regression

 $\mathsf{ARDL} ext{-MIDAS}(p_y^Q, q_X^M) \mathsf{model}$ 

$$Y_{t+h}^{Q,h} = \mu_h + \sum_{j=0}^{p_y^Q - 1} \rho_{j+1}^h Y_{t-j}^Q + \beta^h \sum_{j=0}^{q_X^M - 1} \sum_{i=0}^{m-1} \omega_{i+j*m}(\theta_h) X_{m-i,t-j}^M + \epsilon_{t+h}^h$$
(1)

#### where

- ullet  $Y_{t+h}^{Q,h}$  low-frequency (quarterly) target variable
- $Y_{t+h}^{Q,h}$  low-frequency (quarterly) target variable  $X_{m-i,t-j}^{M}$  high-frequency (monthly) predictor variable
- $\omega_{i+j*m}(\theta_h)$  weight function
- $\Theta := (\mu_h, \rho_1, \dots, \rho_{\rho_v^Q}, \beta^h, \theta_h)$  model parameters estimated by NLS

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# Macro forecasting

#### Listing 1: Preliminaries

```
%clear workspace
clear all
%add MIDAS toolbox to filepath
addpath(genpath('MIDASv2.2/MIDASv2.2/privatex'));
% Load data for macro examples:
load('example1.mat')
```

Check if data is loaded in your Matlab workspace.

You should see: ads, cfnai, payems, rgdp.

# Macro forecasting

#### Listing 2: Transform payems and rgdp

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#### Listing 3: Transform dates to datetime format

### MIDAS in Matlab

- There are several MIDAS toolboxes for Matlab to run different MIDAS regressions.
- For this example we will rely on the MIDASv2 toolbox. Specifically, the MIDASADL function will be used.

First example is with Nonfarm Payrolls data Set initial and last date for in-sample estimation:

Listing 4: Set intial and last date for in-sample estimation:

```
% Specify start and end dates

EstStart = '1985-01-01';

EstEnd = '2009-01-01';
```

### Set options for MIDAS estimation:

#### Listing 5: Options

```
% Specify lag structure, horizon and method
Xlag = 9;
Ylag = 1;
Horizon = 3;
Method = 'fixedWindow';
% set data - x and y variables
DataX=logpayems;
DataY=logrgdp;
% set data dates
DataYdate = datergdp;
DataXdate = datepayems;
% set polynomial
poly='expAlmon';
```

Estimate ARDL-MIDAS regression using MIDAS ADL function from MIDAS package.

#### Listing 6: Estimating via MIDAS ADL function

```
[OutputForecast1, OutputEstimate1, MixedFreqData] = MIDAS_ADL(DataY, DataYdate, DataX, DataXdate,...
'Xlag', Xlag, 'Ylag', Ylag, 'Horizon', Horizon, 'EstStart', EstStart, 'EstEnd', EstEnd, 'Polynomial', poly, 'Method', Method, 'PlotWeights', 0);
```

Estimate ARDL regression model using time-averaged Nonfarm Payrolls data.

#### Listing 7: Estimating via time-averaged data

```
%now compare to time averaged employment data
%form X vars first from MixedFreqData structure
Xvars=[MixedFreqData.EstLagY, mean(MixedFreqData.EstX(:,1:3),2), mean(
MixedFreqData.EstX(:,4:6),2), mean(MixedFreqData.EstX(:,7:9),2)];
est_ta= fitlm(Xvars, MixedFreqData.EstY)
```

Compare in-sample performance. Grab MIDAS residuals from OutputEstimate1 structure and time-averaged from est ta.Residuals.

#### Listing 8: In sample of MIDAS model

```
%compare in sample performance sqrt(mean(OutputEstimate1.resid.^2))
```

ans = 0.5103

#### Listing 9: In sample of time-averaged model

```
sqrt(mean(table2array(est_ta.Residuals(:,1)).^2))
```

Compare out-of-sample performance. Grab MIDAS RMSE from OutputForecast1.RMSE. Forecast out time-averaged using MixedFreqData structure to grab data first.

#### Listing 10: Out-of-sample time-averaged model and MIDAS RMSE

ans = 0.4461

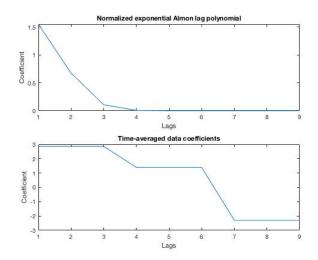
#### Listing 11: Calculate time-averaged out-of-sample RMSE

```
ta_oos_rmse = sqrt(mean((ta_oos-MixedFreqData.OutY).^2))
```

#### Plot lag polynomials.

#### Listing 12: Collect time-averaged weights

```
%set lags
lags = 1:9:
%time averaged weights
ta_weights = [repelem(table2array(est_ta.Coefficients(3,1)),3) repelem(
     table2array(est_ta.Coefficients(4,1)),3) repelem(table2array(est_ta.
     Coefficients (5,1)),3)|';
%now plots . . .
    subplot (2,1,1)
    plot(lags, OutputEstimate1.estWeights)
    xlabel('Lags');
    vlabel('Coefficient'):
    title ('Normalized exponential Almon lag polynomial'):
    subplot (2,1,2)
    plot(lags,ta_weights)
    xlabel('Lags');
    vlabel('Coefficient');
    title ('Time-averaged data coefficients'):
```



We will compare fixed, rolling, expanding windows predictions of GDP using these two models. For MIDAS our previous settings should be saved.

#### Listing 13: Fixed Window MIDAS

```
[OutputForecast1_Fixed,OutputEstimate1_Fixed,MixedFreqData_Fixed] = MIDAS_ADL (DataY,DataYdate,DataX,DataXdate,...
'Xlag',Xlag',Ylag',Ylag',Horizon',Horizon,'EstStart',EstStart,'EstEnd',
EstEnd,'Polynomial','expAlmon','Method',Method,'PlotWeights',0);
```

Use the structure MixedFreqData Fixed as inputs for time-averaged model.

Listing 14: Fixed Window time-averaged

Recall, we have already compared predictions for fixed scheme above.

### Set Method to Rolling Window.

#### Listing 15: Rolling Window MIDAS

```
%rolling windows
Method='RollingWindow';
[OutputForecast1_Roll, OutputEstimate1_Roll, MixedFreqData_Roll,
ExtendedForecast_Roll] = MIDAS_ADL(DataY, DataYdate, DataX, DataXdate,...
'Xlag', Xlag', Ylag', Ylag', Horizon', Horizon', EstStart', EstStart', EstEnd',
EstEnd, 'Polynomial', 'expAlmon', 'Method', Method);
```

#### Listing 16: Rolling Window time-averaged

```
%rolling time averaged
nobs=length (MixedFreqData_Roll.EstY);
nforecast=length (MixedFreqData_Roll.OutY);
nroll=nforecast;
Xvars_TA=[MixedFreqData_Roll.EstLagY, mean(MixedFreqData_Roll.EstX(:,1:3),2),
     mean (MixedFreqData_Roll.EstX(:,4:6),2), mean (MixedFreqData_Roll.EstX
     (:,7:9),2):
Xnew_TA_Roll=|MixedFreqData_Roll.OutLagY, mean(MixedFreqData_Roll.OutX(:,1:3)
     ,2), mean(MixedFreqData_Roll.OutX(:,4:6),2), mean(MixedFreqData_Roll.OutX
     (:,7:9),2):
Xvars_temp = [Xvars_TA: Xnew_TA_Roll]:
Yvars_temp = [MixedFreqData_Roll.EstY; MixedFreqData_Roll.OutY];
for t=1: nroll
    Xvars_TA_Roll = Xvars_temp(t:nobs-1+t,:);
    Yvars_Roll = Yvars_temp(t:nobs-1+t,:);
    est_ta_Roll = fitlm(Xvars_TA_Roll, Yvars_Roll);
    Xvars_OOS_Roll = Xnew_TA_Roll(t,:);
    ta_oos_Roll(t,:) = predict(est_ta_Roll, Xvars_OOS_Roll);
end
```

Compare out-of-sample performance for rolling window.

#### Listing 17: MIDAS Rolling window RMSE

```
%compare forecasts of rolling
% compare RMSE
% grab MIDAS RMSE
OutputForecast1_Roll.RMSE
```

ans = 0.4284

#### Listing 18: Time-averaged Rolling window RMSE

```
% compute rolling rmse sqrt(mean((ta_oos_Roll-MixedFreqData_Roll.OutY).^2))
```

#### Set Method to Recursive.

#### Listing 19: Expanding Window MIDAS

#### Listing 20: Expanding Window time-averaged

```
% Expanding time averaged
nobs=length (MixedFreqData_Exp.EstY):
nforecast=length (MixedFreqData_Exp.OutY);
Xvars_TA_Exp = [MixedFreqData_Exp. EstLagY, mean(MixedFreqData_Exp. EstX(:,1:3)
     ,2), mean(MixedFreqData_Exp.EstX(:,4:6),2), mean(MixedFreqData_Exp.EstX
     (:,7:9),2);
Xnew_TA_Exp=[MixedFreqData_Exp.OutLagY, mean(MixedFreqData_Exp.OutX(:,1:3),2)
     . mean (MixedFregData_Exp.OutX(:,4:6),2), mean (MixedFregData_Exp.OutX
     (:.7:9).2)1:
Xvars_temp_Exp = [Xvars_TA_Exp; Xnew_TA_Exp];
Yvars_temp_Exp = [MixedFreqData_Exp. EstY: MixedFreqData_Exp. OutY]:
for t=1:nroll
    Xvars_TA_Exp = Xvars_temp_Exp(1:nobs-1+t,:);
    Yvars_Exp = Yvars_temp_Exp(1:nobs-1+t,:);
    est_ta_Exp = fitlm(Xvars_TA_Exp, Yvars_Exp);
    Xvars_OOS_Exp = Xnew_TA_Exp(t.:):
    ta_oos_Exp(t,:) = predict(est_ta_Exp, Xvars_OOS_Exp);
end
```

Compare out-of-sample performance for expanding window.

#### Listing 21: MIDAS expanding window RMSE

```
% compare forecasts of rolling
% compare RMSE
% grab MIDAS RMSE
OutputForecast1_Exp.RMSE
```

ans = 0.4296

### Listing 22: Time-averaged expanding window RMSE

```
% compute expanding rmse sqrt(mean((ta_oos_Exp-MixedFreqData_Exp.OutY).^2))
```

First convert CFNAI dates to datetime format. Then set estimation dates, horizon, x and y variables, lags, etc.

Listing 23: Set options for MIDAS estimation

Estimate CFNAI example with exponential almon and u-midas polynomials. Compare the results.

#### Listing 24: Set polynomials and estimate MIDAS regressions

### Compare in-sample RMSE performance.

#### Listing 25: Exponential Almon polynomial

```
%compare in sample performance sqrt(mean(OutputEstimate1.resid.^2))
```

ans = 0.4849

#### Listing 26: U-MIDAS polynomial

```
% compare in sample performance  \mathtt{sqrt} \, (\, \mathtt{mean} \, (\, \mathtt{OutputEstimate\_U} \, . \, \, \mathtt{resid} \, . \, \, \hat{} \, \, 2 \, ) \, )
```

### Compare out-of-sample RMSE performance.

#### Listing 27: Exponential Almon polynomial

```
%compare OOS performance now
%grab MIDAS RMSE
midas_oos_rmse = OutputForecast1.RMSE
```

 $\begin{array}{l} \mathsf{ans} = \\ 0.3155 \end{array}$ 

### Listing 28: U-MIDAS polynomial

```
umidas_oos_rmse = OutputForecast_U.RMSE
```

ans =

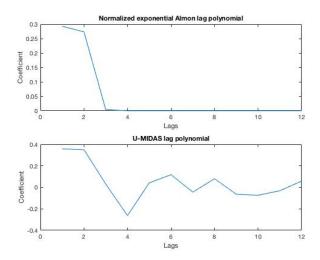
Plot the different weighting schemes.

Listing 29: Plot weights for both polynomials.

```
%plot weights and compare
%set lags
lags = 1:12;

subplot(2,1,1)
plot(lags, OutputEstimate1.estWeights)
xlabel('Lags');
ylabel('Coefficient');
title('Normalized exponential Almon lag polynomial');

subplot(2,1,2)
plot(lags, OutputEstimate_U.estWeights)
xlabel('Lags');
ylabel('Coefficient');
title('U-MIDAS lag polynomial');
```



Estimate ADS example with exponential almon and u-midas polynomials. Compare the results. We will focus on nowcasting vs. out-of-sample forecasting.

First convert ADS dates to datetime format. Then set estimation dates, horizon,  $\times$  and y variables, lags, etc.

Listing 30: Set options for MIDAS estimation

```
%Third Example now with ADS data
dateads= datetime(ads(1:end,1), 'ConvertFrom', 'datenum', 'Format', 'yyyy-MM-dd')
;

% Specify lag structure and sample size
Xlag = 66;
Ylag = 1;
Horizon = 66;
EstStart = '1987-01-01';
EstEnd = '2011-12-01';
Method = 'fixedWindow';

DataYdate = datergdp;
DataX=ads(:,2);
DataX=ads(:,2);
DataY=logrgdp;
```

### Estimate ADS example with forecasting, horizon was set to 66.

#### Listing 31: Estimate MIDAS regressions

### Estimate ADS example with nowcasting. Set horizon = 22

#### Listing 32: Estimate MIDAS regressions

Compare out-of-sample RMSE performance when forecasting with horizon set to 66.

#### Listing 33: Exponential Almon polynomial

```
%forecasts OOS
midas_oos_rmsefix = OutputForecast1.RMSE
```

 $\begin{array}{l} \mathsf{ans} = \\ 0.3096 \end{array}$ 

#### Listing 34: U-MIDAS polynomial

```
umidas_oos_rmsefix = OutputForecast_U.RMSE
```

Compare out-of-sample RMSE performance when nowcasting with horizon set to 22.

#### Listing 35: Exponential Almon polynomial

%nowcasts
midas\_oos\_rmsenow = OutputForecast1\_Now.RMSE

ans = 0.3486

#### Listing 36: U-MIDAS polynomial

umidas\_oos\_rmsenow = OutputForecast\_UNow.RMSE

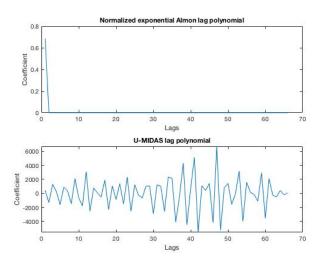
Plot polynomial weights for forecasting when horizon set to 66.

Listing 37: U-MIDAS polynomial

```
%plot weights and compare
%set lags
lags = 1:66;

subplot(2,1,1)
plot(lags, OutputEstimate1.estWeights)
xlabel('Lags');
ylabel('Coefficient');
title('Normalized exponential Almon lag polynomial');

subplot(2,1,2)
plot(lags, OutputEstimate_U.estWeights)
xlabel('Lags');
ylabel('Coefficient');
title('U-MIDAS lag polynomial');
```



# The End