Using The Yield Curve To Forecast Economic Growth

Parley Ruogu Yang[1]

UNIVERSITY OF OXFORD
DEPARTMENT OF STATISTICS

Modelling with Big Data and Machine Learning Conference

4-5 Nov 2019, Bank of England

[1]Contact: ruogu.yang@st-annes.ox.ac.uk

"

I do not define time, space, place and motion, as being well known to all

"

— Sir Issac Newton (1687)

Overview

- The yield curve has a well-performing ability to forecast the real GDP growth in the US, c.f. professional forecasters and pure ARIMA models.
- Results depend largely on the estimation and forecasting techniques employed.
- Statistical learning methods play a role in validating and choosing which particular model to use.
- Remark: this talk is leaning towards the statistical methods instead of the current concerns on recession. For this reason the motivation part contains a hands-on example which helps to motivate and introduce the methodology. (Click here to see an example)

Motivation

1. Macro & Finance Literature:

$$g_{t,t+k} = \alpha + \beta S_t + \varepsilon_t$$

    - Which k fits / forecasts better?
    - How to define S_t? — Variable selection

2. Time Series Literature:
    - Window-based estimation & forecasting

3. Statistical Learning Literature:
    - Bias-Variance trade-off in estimation
    - Model selection
    - Loss / learning function

An example: asymptotic analysis

Consider a Data Generating Process (DGP) over time $\{1, ..., T_2\} = \{1, ..., T_1\} \cup \{T_1 + 1, ..., T_2\}$, with ergodic time series $x_t, y_t \in \mathbb{R}\ \forall t$ with the following evolution:

$$
\begin{aligned}
\forall t, \forall j \in \{1, 2\} \qquad & \varepsilon_{j,t} \sim iidN(0, 1) && \text{(1a)}\\
\text{When } 1 \leq t \leq T_1 \qquad & y_t = \alpha_1 + \beta_1 x_t + \sigma_1 \varepsilon_{1,t} && \text{(1b)}\\
\text{When } T_1 + 1 \leq t \leq T_2 \qquad & y_t = \alpha_2 + \beta_2 x_t + \sigma_2 \varepsilon_{2,t} && \text{(1c)}
\end{aligned}
$$

We concern about the forecast $y_{t+1|t} := \mathbb{E}[y_{t+1} | x_{t+1}, y_t, x_t, y_{t-1}, x_{t-1}, ...]$.

We write the pooled OLS estimation at time t as β_t. When $t < T_1$, we have $\mathbb{E}[\hat{\beta}_t] = \beta_1$ and conveniently $\mathbb{E}[(y_{t+1} - y_{t+1|t})] = 0$ and $\mathbb{E}[(y_{t+1} - y_{t+1|t})^2] = \sigma_1^2$. However, when $t > T_1$, we have

$$\mathbb{E}[\hat{\beta}_t] = \frac{\beta_1 \sum_{\tau=1}^{T_1}(x_\tau - \bar{x})^2 + \beta_2 \sum_{\tau=T_1+1}^{t}(x_\tau - \bar{x})^2}{\sum_{\tau=1}^{t}(x_\tau - \bar{x})^2} \tag{2}$$

Thus

$$\mathbb{E}[(y_{t+1} - y_{t+1|t})] = \mathbb{E}[\alpha_2 - \hat{\alpha}_t] + \mathbb{E}[\beta_2 - \hat{\beta}_t]x_{t+1} \tag{3}$$

Now suppose $T_2 \to \infty$ with the process description 1, then $\mathbb{E}[\hat{\beta}_t] \to \beta_2$, assuming ergodicity. Thus $\mathbb{E}[(y_{t+1} - y_{t+1|t})] \to 0$ and $\mathbb{E}[(y_{t+1} - y_{t+1|t})^2] \to \sigma_2^2$.

- However, if we expand T_2 by admitting the change in the frequency of switching between regimes, then we probably would still have significant bias and larger-than-desired MSE.
- For example, let $T \to \infty$ with the set $\{1, ..., T\} = A \cup B$ where A contains some of the points and B contains the remaining of the points. While in A we have the DGP evolving equation 1b, and in B we have equation 1c as the evolution of the datapoint, then $\hat{\beta}_t \xrightarrow{p} a\beta_1 + (1-a)\beta_2$ where $\frac{|A|}{T} \xrightarrow{p} a$ is assumed to exist.

Small window estimation:

- Transition Period $TP(w) := \{T_1 + 1, ..., T_1 + w\}$
- Stable Period $SP(w) := \{T_1 + w + 1, ..., T_2\}$
- When $t \in TP(w)$, we get

$$\mathbb{E}[\hat{\beta}_t] = \frac{\beta_1 \sum_{\tau=t-w}^{T_1} (x_\tau - \bar{x})^2 + \beta_2 \sum_{\tau=T_1+1}^{t} (x_\tau - \bar{x})^2}{\sum_{\tau=t-w}^{t} (x_\tau - \bar{x})^2} \quad (4)$$

- When $t \in SP(w)$ we get $\mathbb{E}[\hat{\beta}_t] = \beta_2$.

Large window estimation:

- $TP(w)$ covers almost all time.
- $SP(w)$ covers little time.

If we now expand T by admitting the change in the frequency of switching as previously described, then (with regularity assumption)

$$\left(\frac{nw}{T_n}\right)^{-1} \max(|\hat{\beta}_t - \beta_1|, |\hat{\beta}_t - \beta_2|) \xrightarrow{p} |\beta_1 - \beta_2| \qquad (5)$$

While the pooled OLS can only achieve

$$(\max(a, 1-a))^{-1} \max(|\hat{\beta}_t - \beta_1|, |\hat{\beta}_t - \beta_2|) \xrightarrow{p} |\beta_1 - \beta_2| \qquad (6)$$

An example: simulation

Consider $\{x_t, y_t\}_{t=1}^{T}$ to be drawn from the following distribution and relationship:

$$
\begin{aligned}
x_t &\sim N(5,1) && \forall t && \text{(7a)}\\
\varepsilon_{j,t} &\sim N(0,1) && \forall j,t && \text{(7b)}\\
y_t &= \alpha_1 + \beta_1 x_t + \sigma_1 \varepsilon_{1,t} && \text{when } t \in A && \text{(7c)}\\
y_t &= \alpha_2 + \beta_2 x_t + \theta x_t^2 + \sigma_2 \varepsilon_{2,t} && \text{when } t \in B && \text{(7d)}\\
y_t &= \alpha_3 + \delta x_t^3 + \sigma_3 \varepsilon_{3,t} && \text{when } t \in C && \text{(7e)}
\end{aligned}
$$

Here A, B, C are partition sets for $\{1, ..., T\}$.
Consider the following specific parameters: $T = 600$,
$\alpha = (2, -2, -1)$, $\beta = (1, -1)$, $\theta = 3$, $\delta = 1$, $\sigma = (10, 20, 20)$.

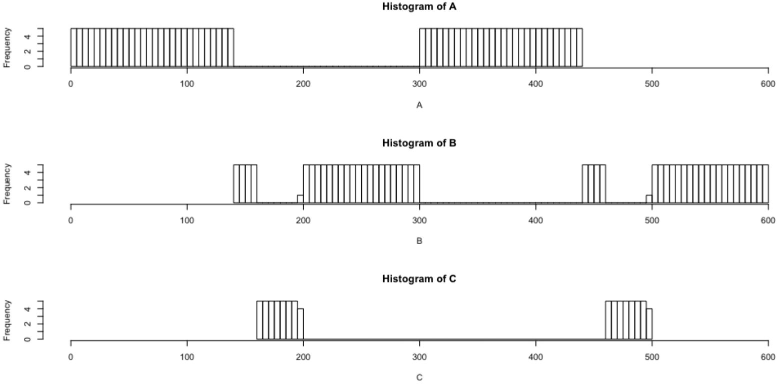


Figure: Partition of the dataset

We consider five models:

$$
\begin{aligned}
y_t =& \alpha + \beta x_t + \sigma \varepsilon_{1,t} && \text{(pooled OLS)} && \text{(8a)}\\
y_t =& \alpha + \beta x_t + \sigma \varepsilon_{2,t} && (w = 20) && \text{(8b)}\\
y_t =& \alpha + \beta x_t + \sigma \varepsilon_{3,t} && (w = 50) && \text{(8c)}\\
y_t =& \alpha + \beta x_t + \theta x_t^2 + \sigma \varepsilon_{4,t} && (w = 20) && \text{(8d)}\\
y_t =& \alpha + \beta x_t + \theta x_t^2 + \sigma \varepsilon_{5,t} && (w = 50) && \text{(8e)}
\end{aligned}
$$

At every time $t \in \{100, ..., T-1\}$, we estimate the five models and record their forecasts $y_{t+1|t}$. MAE and MSE are then recorded after the iterative process.

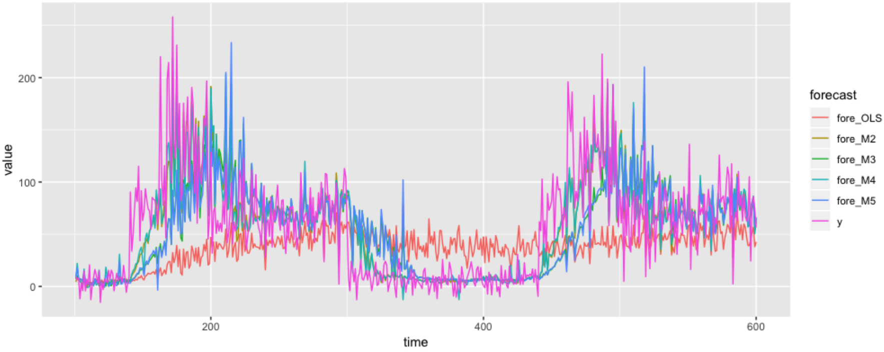


Figure: Forecasting result

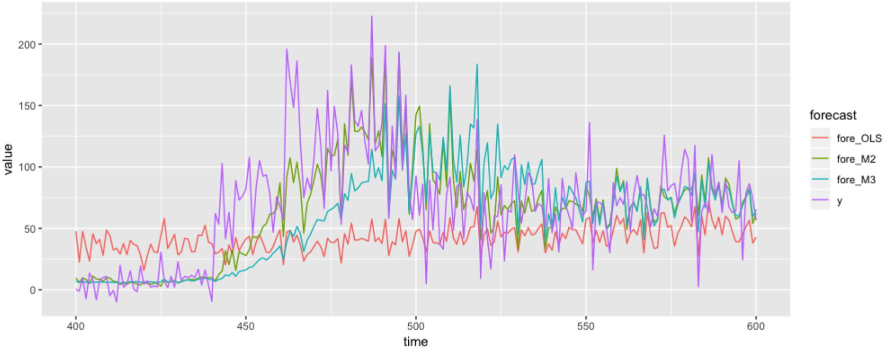


Figure: Forecasting result (models b and c)

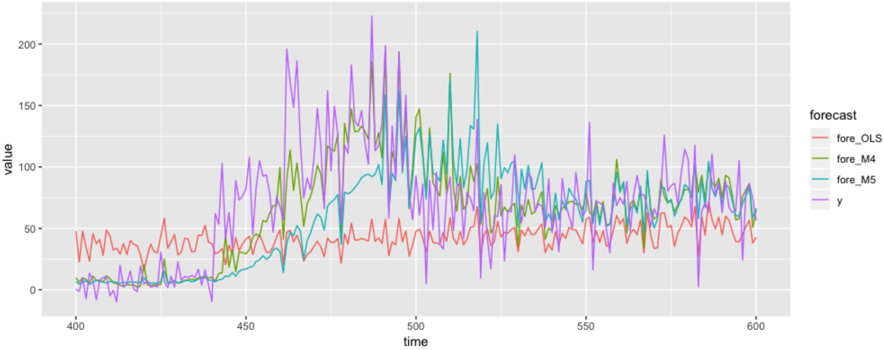


Figure: Forecasting result (models d and e)

Model selection over time

- For each $t \geq 100$, repeat:
  - Run the five models, collect the output of loss function for each model.
  - Pick the model which minimises the loss function at time t and call such a forecast the forecast from the learning model at time t.

Specification of the learning function $L(\{|y_{\tau+1|\tau} - y_\tau|\}_{100 \leq \tau \leq t-1})$:

$$L(\{x_\tau\}_{100 \leq \tau \leq t-1}) = \sum_{100 \leq \tau \leq t-1} \lambda^{t-1-\tau} l(x_\tau) \tag{9}$$

where

$$l(x) = l_{\delta,\epsilon}(x) = \begin{cases} (\epsilon - \delta)x + \frac{\delta^2 - \epsilon^2}{2} & \text{if } x > \epsilon \\ \frac{(x-\delta)^2}{2} & \text{if } \delta < x \leq \epsilon \\ 0 & \text{if } x \leq \delta \end{cases} \tag{10}$$

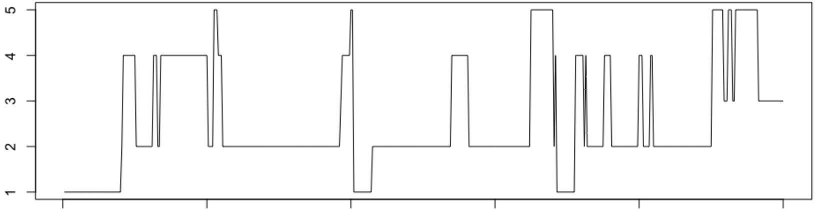


Figure: Model selection over time

Results:

Model	8a	8b	8c	8d	8e
MAE	40.3	**19.6**	28.6	20.2	29.0
MSE	2828.4	**817.2**	1662.0	848.7	1706.5

Model	$\lambda = 0.9, \delta = 20, \epsilon = 50$	$\lambda = 0.7, \delta = 5, \epsilon = 25$
MAE	19.0	16.8
MSE	728.5	574.3

Data

- Time indexing: $\{1976Q3, ..., 2019Q1\} \cong \{1, ..., T\}$ with $T = 171$.
- Interest rate vector $x_t \in \mathbb{R}^9$ contains:
  - Effective Federal Funds Rate and 3-month US Interbank Rate.
  - US Treasury yields of the following durations: 3, 12, 24, 36, 60, 84, and 120 months.
- Growth rate of GDP defined as: $k \in \{1, ..., 12\}$,

$$g_{t,t+k} = \frac{GDP_{t+k} - GDP_t}{GDP_t} \times \frac{400}{k}$$

- For a given k, an information set up to time t is $\Phi_t = \{\mathbf{x}_\tau | 1 \leq \tau \leq t\} \cup \{g_{\tau,\tau+k} | 1 \leq \tau \leq t-k\}$.
- Dickey-Fuller Test (individually) checked for stationarity.
- Comparing the results against SPF forecasts. (k up to 5)

General setting

- Ultimate aim: $\hat{g}_{t,t+k} = f(\Phi_t; \theta_t, \eta_t)$
- $M = \{f(\cdot; \theta, \eta) | \theta \in \Theta, \eta \in H\}$ is then a collection of functions that f can choose from.
  - Model groups 1 to 6: H is a singleton and $\Theta = \mathbb{R}^n$
  - Model groups 7 to 9: H finite and Θ depends on the specification of $\eta \in H$
- Estimation (M_1 to M_6): OLS to estimate the fit

$$g_{\tau,\tau+k} = f(\theta) + \varepsilon_\tau, \quad \varepsilon_\tau \sim iidN(0, \sigma^2), \quad p \leq \tau \leq t - k$$

  Then take the estimated θ as θ_t.
  N.B. p depends on the window method specification.
- Assess the forecasts by MAE and MSE.

Methodology (M_1 & $M_{2,w}$)

- Equation of interest for model groups 1 and 2:

$$f(\Phi_t; \alpha_t, \beta_t) = \alpha_t + \beta_t S_t \tag{11}$$

  - M_1 : expanding window size estimation & forecast for $t \geq 61$.
  - $M_{2,w}$: fixed window size estimation for $w \in \{20, 28, ..., 124, 132\}$, and forecast during $t \in \{w + k + 1, ..., 171 - k\}$.

Result (M_1 & $M_{2,w}$)

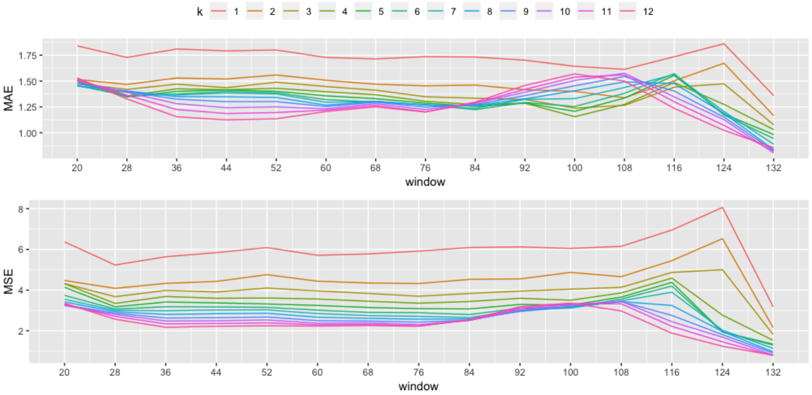


Figure: MAE (top) and MSE (bottom) for different window sizes (w) and lags (k) in the model group 2.

k	$MAE(M_1)$	$MAE(M_2)$		$MSE(M_1)$	$MSE(M_2)$	
		minimum	mean		minimum	mean
1	1.77	1.36	1.72	6.10	3.19	5.94
2	1.67	1.17	1.47	5.29	2.16	4.53
3	1.64	1.08	1.38	5.23	1.82	3.94
4	1.67	1.03	1.33	5.28	1.53	3.48
5	1.72	0.98	1.32	5.19	1.34	3.19
6	1.69	0.94	1.31	4.98	1.30	3.01
7	1.64	0.89	1.32	4.65	1.14	2.88
8	1.55	0.84	1.32	4.15	0.97	2.74
9	1.45	0.83	1.31	3.61	0.91	2.61
10	1.37	0.81	1.30	3.13	0.81	2.52
11	1.27	0.82	1.28	2.68	0.79	2.45
12	1.19	0.86	1.26	2.30	0.80	2.35

Table: MAE (columns 2 to 4) and MSE (columns 5 to 7) for different k from model group 1 and 2. Columns 3 and 6 take the minimum over 15 window sizes and columns 4 and 7 take the mean over 15 window sizes in model group 2.

Methodology ($M_{3,i,j,w}$ to $M_{6,i,j,w}$)

- Define vector $\textbf{short}_t$ as a vector of short term interest rates, in particular, the Federal Funds Rate, 3-month Interbank Rate, 3-month, 12-month, and 24-month Treasury yields.
- Define vector $\textbf{long}_t$ as a vector of long term interest rates consisted of 120-, 84-, 60-, and 36-month Treasury yields.

Models 3 to 6:

$$f(\Phi_t;\alpha_t,\beta_{1,t},\beta_{2,t}) = \alpha_t + \beta_{1,t}\textbf{long}_{t,j} + \beta_{2,t}\textbf{short}_{t,i}$$

$$\begin{aligned} f(\Phi_t;\alpha_t,\beta_{1,t},\beta_{2,t},\phi_t) =& \frac{\alpha_t(1-\phi_t^k)}{1-\phi_t} \\ &+ \sum_{l=0}^{k-1}\left(\beta_{1,t}\phi_t^l\textbf{long}_{t-l,j} + \beta_{2,t}\phi_t^l\textbf{short}_{t-l,i}\right) \\ &+ \phi_t^k g_{t-k,t} \end{aligned}$$

$$f(\Phi_t;\alpha_t,\beta_{1,t},\beta_{2,t}) = \alpha_t + \beta_{1,t}\textbf{long}_{t-1,j} + \beta_{2,t}\textbf{short}_{t-1,i}$$

$$\begin{aligned} f(\Phi_t;\alpha_t,\beta_{1,t},\beta_{2,t},\phi_t) =& \frac{\alpha_t(1-\phi_t^k)}{1-\phi_t} \\ &+ \sum_{l=0}^{k-1}\left(\beta_{1,t}\phi_t^l\textbf{long}_{t-l-1,j} + \beta_{2,t}\phi_t^l\textbf{short}_{t-l-1,i}\right) \\ &+ \phi_t^k g_{t-k,t} \end{aligned}$$

Results ($M_{3,i,j,w}$ to $M_{6,i,j,w}$)

Present $\min_{\iota,i,j} MAE(M_{\iota,i,j,w})$ for each k, w; likewise for MSE.

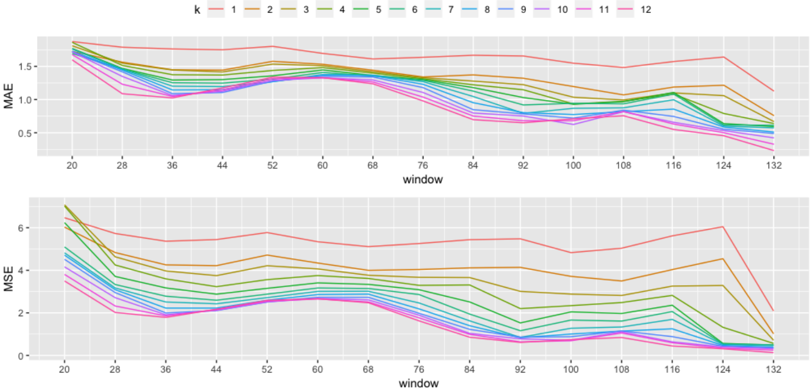


Figure: MAE (top) and MSE (bottom) for different window sizes and different k for the best models in model groups 3 to 6.

Comparison against model group 2.

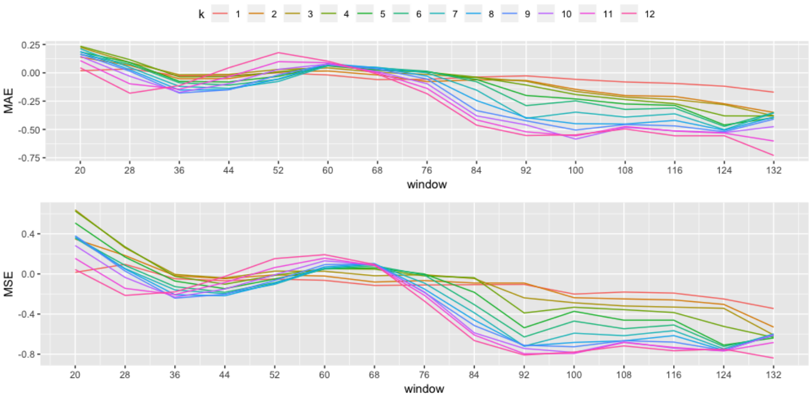


Figure: Proportional comparison of the MAE (top) and MSE (bottom) obtained by models in groups 2 and 3-6, across different k and w. A negative number means the model from groups 3-6 yields lower MAE or MSE compared to group 2, and vice versa.

Comparison against SPF.

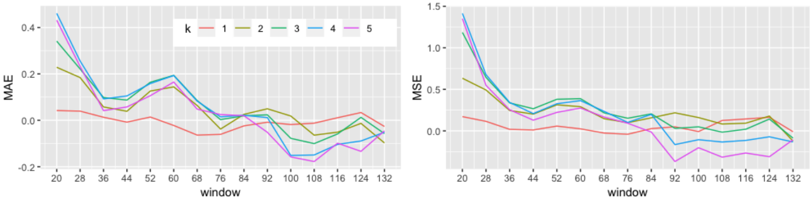


Figure: Proportional comparison of the MAE (top) and MSE (bottom) obtained by the best model in groups 3-6 and the SPF, across different k and w.

Methodology (M_7 to M_9)

- Two main questions:
  - How to ensure we pick the "right" or "almost right" model so that we achieve the minimum?
  - Can we do better? Dynamically picking up models that do well historically?
- For any given (k, w), at any time $t \geq w + 2k + 1$, there are 4 model groups available, each containing 20 models given by (i, j). Now, for these total of 80 models which generate forecasts, an assessment is made at time t. Call such assessment $L(\{g_{\tau,\tau+k} - \hat{g}_{\tau,\tau+k}\}_{w+k+1 \leq \tau \leq t-k})$ a loss function. Optimisation is then done through minimising the loss function, and thereafter forecast.

Algorithm for the models. (Labelled as Algo 3.3 in the paper)

Algorithm 3.3: Model groups 7 to 9

1. For $k \in \{1, ..., 5\}$, $w \in \{20, 28, ..., 132\}$, repeat:
   (a) For each $t \in \{w + 2k + 1, ..., 171 - k\}$, repeat:
      i. For each $\iota \in \{3, 4, 5, 6\}$, $i \in \{1, 2, 3, 4, 5\}$, $j \in \{1, 2, 3, 4\}$, repeat:
         A. Over the period $\{w + k + 1, ..., t - k\}$, run the required OLS estimation such that the forecast based on the model $M_{\iota,i,j,w}$, can be generated, then forecast.
         B. Compute the output of loss function for each $M_{\iota,i,j,w}$.
      ii. Pick the model, say M^* which minimises the loss function.
      iii. Use M^* as the model to make forecast at time t, [a] and call such a forecast the forecast from the learning model at time t.
   (b) Collect the MAE and MSE for the overall forecasts from the learning model.

[a] Running the relevant OLS regression prior to the forecast of M^* is also required.

- M_7: A relatively naïve way:

$$L(\{g_{\tau,\tau+k} - \hat{g}_{\tau,\tau+k}\}_{w+k+1\leq\tau\leq t-k}) = |g_{t-k,t} - \hat{g}_{t-k,t}|$$

- M_8: Full-history learning:

$$L(\ldots) = \sum_{w+k+1\leq\tau\leq t-k} l(|g_{\tau,\tau+k} - \hat{g}_{\tau,\tau+k}|)$$

- M_9: Discounted-history learning:

$$L(\ldots) = \sum_{w+k+1\leq\tau\leq t-k} \lambda^{t-k-\tau} l(|g_{\tau,\tau+k} - \hat{g}_{\tau,\tau+k}|)$$

where $\lambda \in (0, 1]$

The design of $l(\cdot)$:

- Vapnik (2000): $j \in \{1, 2\}$

$$l(x) = l_\epsilon(x) = \mathbb{1}[x > \epsilon](x - \epsilon)^j$$

- Huber (1964):

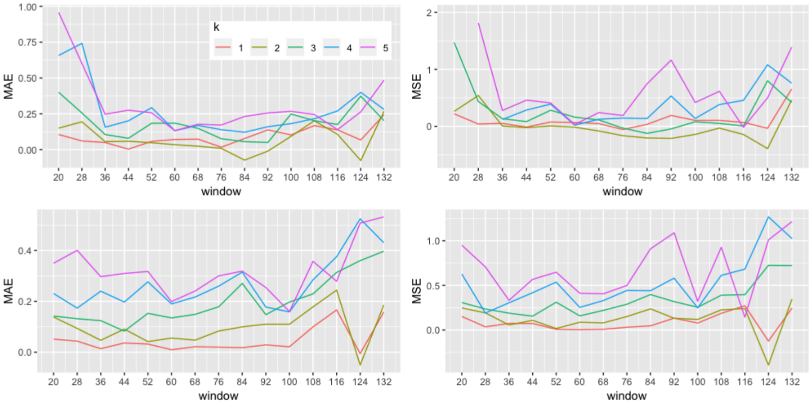
$$l(x) = l_{H,\epsilon}(x) = \begin{cases} \epsilon x - \frac{\epsilon^2}{2} & \text{if } x > \epsilon \\ \frac{x^2}{2} & \text{if } x \leq \epsilon \end{cases}$$

- Another way (introduced in the motivation section):

$$l(x) = l_{\delta,\epsilon}(x) = \begin{cases} (\epsilon - \delta)x + \frac{\delta^2 - \epsilon^2}{2} & \text{if } x > \epsilon \\ \frac{(x-\delta)^2}{2} & \text{if } \delta < x \leq \epsilon \\ 0 & \text{if } x \leq \delta \end{cases}$$

Results (M_9)

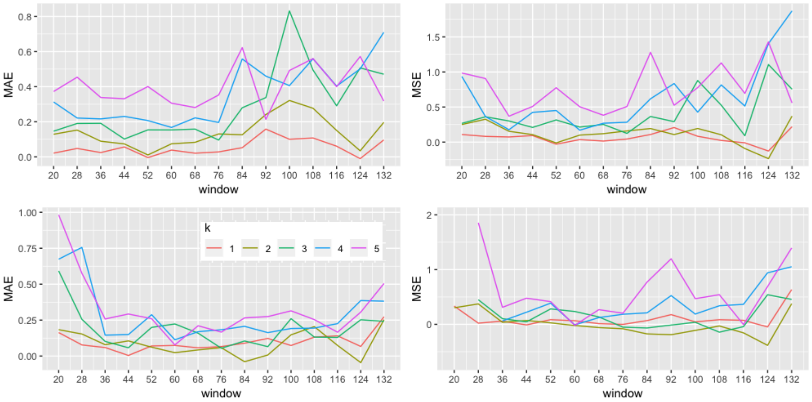
- M_7 and M_8 work badly, minor achievement can be seen occasionally.
- Let $M_{9,1,w}(\lambda, \epsilon)$ to be the model which employs $I_{H,\epsilon}$ as the specification of I.
- Let $M_{9,2,w}(\lambda, \epsilon, \delta)$ to be the model which employs $I_{\delta,\epsilon}$ as the specification of I.



Left to right: Proportional comparison of the MAE (left) and MSE (right) obtained by each model and the best model from groups 3-6, across different k and w.

Top to bottom: $M_{9,1}(0.5, 0.5)$ and $M_{9,1}(0.9, 0.5)$.

Note: three outliers in the top right plot are dropped.



Left to right: Proportional comparison of the MAE (left) and MSE (right) obtained by each model and the best model from groups 3-6, across different k and w.

Top to bottom: $M_{9,2}(0.75, 2.5, 0.5)$ and $M_{9,2}(0.7, 2, 0.7)$.

Improvement counts

	k	1	2	3	4	5
$M_{9,1}(0.5, 0.5)$	MAE	0	3	0	0	0
	MSE	3	10	3	0	1
$M_{9,1}(0.9, 0.5)$	MAE	1	1	0	0	0
	MSE	1	1	0	0	0

	k	1	2	3	4	5
$M_{9,2}(0.75, 2.5, 0.5)$	MAE	2	0	0	0	0
	MSE	3	3	0	0	0
$M_{9,2}(0.7, 2, 0.7)$	MAE	0	2	0	0	0
	MSE	3	9	5	1	2

Example output

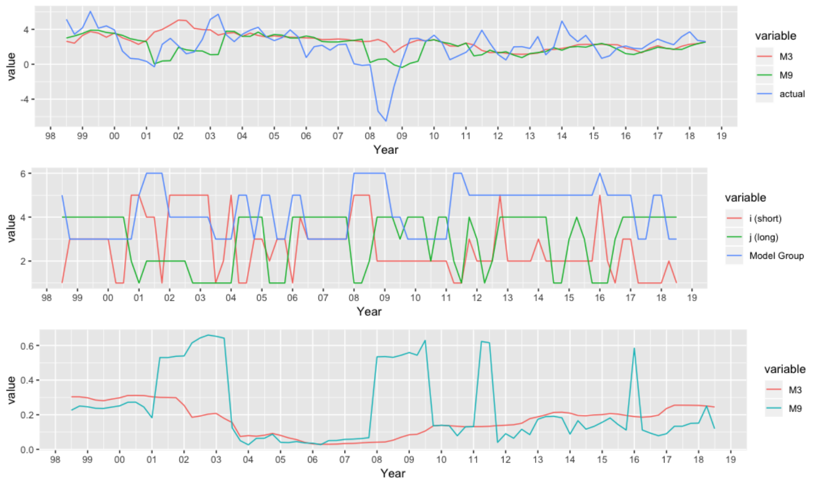


Figure: From top to bottom: $\hat{g}_{t,t+2}$ from different models and the actual $g_{t,t+2}$; the corresponding model that model 9 chooses over time; R^2 for the estimations of different models at each time.

Conclusion

1. Which k?
    - The larger the k, the less forecasting error it makes.
    - Small k can well outperform SPF forecasts.
    - Learning functions help to reduce "structural break" in the betterment.
2. Estimation and forecasting methods:
    - Variety in variable selection & window size methods bear fruit to the improvement.
    - Workhorse to the learning algorithms.
3. Future:
    - Engagement with macro & finance literature for variable selection and functional forms.
    - Asymptotics for learning function choices. (Harder ones than the initial example).

"

The only function of economic forecasting is to make astrology look respectable.

"

— Professor Ezra Solomon (1985)