

Smooth Robust Multi-Horizon Forecasts: How have the OBR's productivity forecasts performed since the pandemic?

Andrew B. Martinez

with Jennifer L. Castle and David F. Hendry

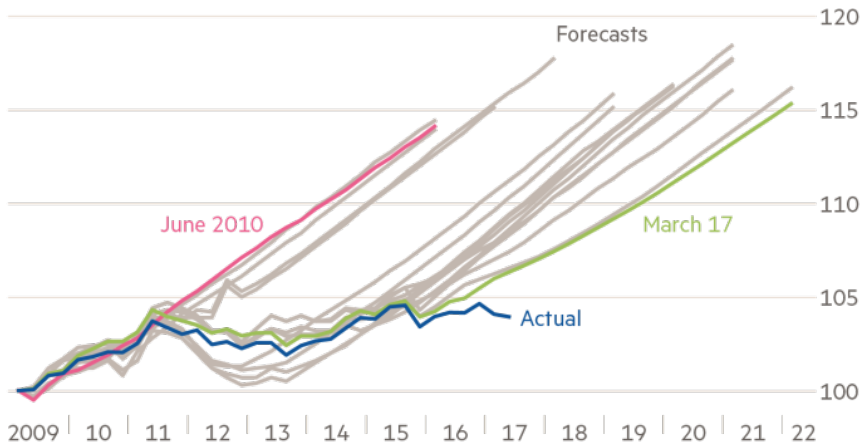
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Oslo

Motivation: Persistent Forecast Failure

Productivity growth has again fallen short of the OBR forecast

Output per hour, rebased (Q1 2009=100)



Sources: Office for Budget Responsibility; ONS

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 - ▶ Naive forecasts less susceptible but
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- ▶ How do we prevent persistent multi-horizon forecast failure?
- ▶ Forecast failure is often driven by a change in the long-run mean
 - ▶ Naive forecasts less susceptible but
 1. Exhibit much more volatility and
 2. Do not incorporate economic structure
- ▶ Reinterpret naive forecasts as local estimates of the long-run.
- ▶ Average local estimates to improve bias-variance trade-off.

1. Motivation
2. Forecast Failure and Naive Robust Forecasts
3. Smooth Robust Forecasts
4. Application: UK Productivity Forecasts
5. Application: Update of UK Productivity Forecasts since the pandemic
6. Conclusions

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$$x_t = \mu + \rho (x_{t-1} - \mu) + \epsilon_t$$

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How well can we forecast after the shift occurs?

Ignoring estimation uncertainty where the forecast for horizon h is:

$$\hat{x}_{T+b+h|T+b} = \mu + \rho (\hat{x}_{T+b+h-1|T+b} - \mu)$$

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$$\text{BIAS}_{AR} : \mathbb{E} [\hat{e}_{T+b+h|T+b}] \xrightarrow{h \rightarrow \infty} \mu^* - \mu = \nabla \mu^*$$

→ Systematic Forecast Failure

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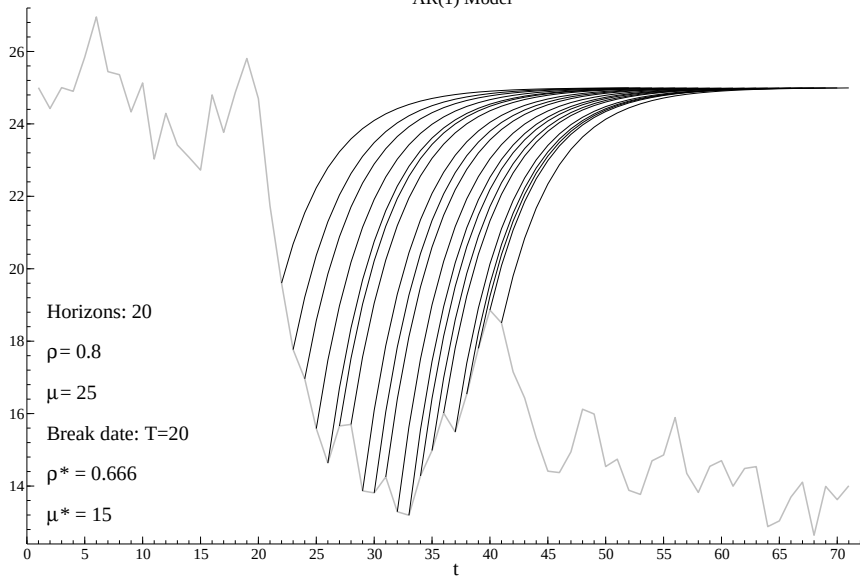
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$$\text{MSFE}_{AR} : \mathbb{E} [\hat{e}_{T+b+h|T+b}^2 | \rho^* = \rho] \xrightarrow{h \rightarrow \infty} (\nabla \mu^*)^2 + \frac{\sigma_\epsilon^2}{1 - \rho^2}$$

Illustration: AR Model

AR(1) Model



Often very difficult to beat a random walk:

$$\bar{x}_{T+b+h|T+b} = \bar{x}_{T+b+h-1|T+b}$$

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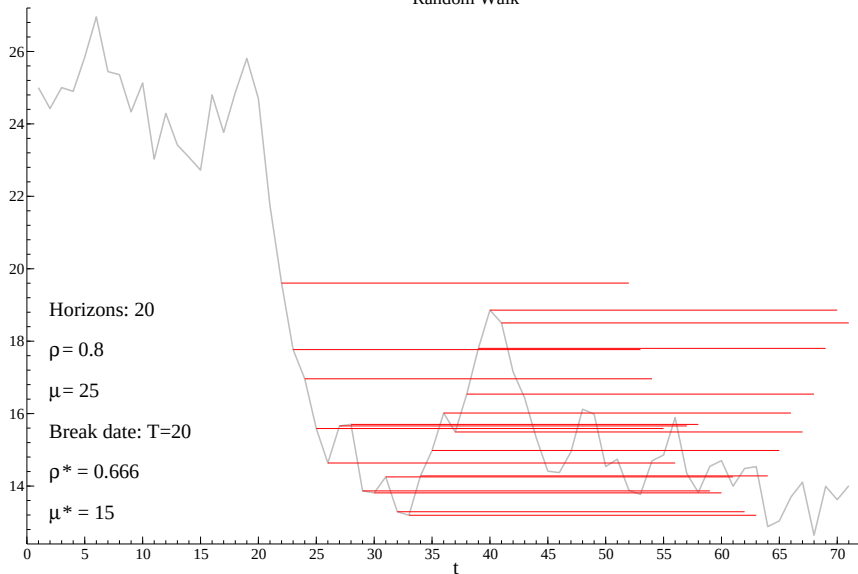
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→ Double the forecast error variance

Illustration: Random Walk

Random Walk



Proposed by Castle et al. (2015a) for 1-step-ahead forecasts. Starts with quasi-differenced AR model:

$$\tilde{x}_{T+b+h|T+b} = \tilde{x}_{T+b+h-1|T+b} + \rho \Delta \tilde{x}_{T+b+h-1|T+b}$$

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$$\tilde{x}_{T+b+h|T+b} = x_{T+b} + (1 - \rho^h) \frac{\rho}{1 - \rho} \Delta x_{T+b}$$

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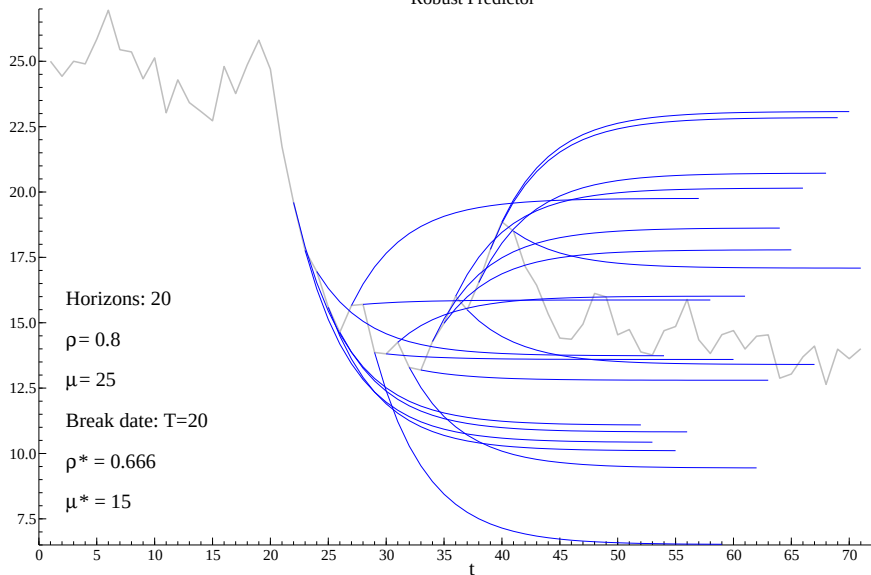
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$$\text{MSFE}_{\text{RP}} : \mathbb{E} \left[\tilde{e}_{T+b+h|T+b}^2 | \rho^* = \rho \right]_{h \rightarrow \infty} \rightarrow \left(\frac{2}{1 - \rho} \right) \frac{\sigma_{\epsilon}^2}{1 - \rho^2}$$

→ No bias if $\rho = \rho^*$ but large variance

Illustration: Robust Predictor

Robust Predictor



Reinterpreting Robust Forecasts

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⇒ High variance since local estimates rely on a single observation.

A Generalized Robust Predictor

$$\hat{x}_{T+b+1|T+b} = \mu + \sum_{j=1}^p \rho_j (x_{t+b+1-j} - \mu) + \sum_{k=1}^q \theta_k \epsilon_{t+b+1-k}$$

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- Local estimator of Generalized Robust Predictor is the Beveridge-Nelson (BN) trend of ARIMA(p,1,q):

$$\hat{\mu}_{GRP} = \frac{\theta(1)\rho(L)}{\rho(1)\theta(L)} x_{t+b}$$

where $\rho(L) = 1 - \sum_{j=1}^p \rho_j L^j$ and $\theta(L) = 1 + \sum_{s=1}^q \theta_s L^s$

A Generalized Robust Predictor

$$\hat{x}_{T+b+1|T+b} = \mu + \sum_{j=1}^p \rho_j (x_{t+b+1-j} - \mu) + \sum_{k=1}^q \theta_k \epsilon_{t+b+1-k}$$

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- Substituting in $x_{t+b} = \mu + \frac{\theta(L)}{\rho(L)} \epsilon_{t+b}$ implies

$$\hat{\mu}_{GRP} = \mu + \frac{\theta(1)}{\rho(1)} \epsilon_{t+b}$$

→ generalized mean correction.

- ▶ Hendry (2006): Double-Differenced Predictors

- ▶ Double Differenced Predictor (DD):

$$\mu_{DD} = x_t + \left(\frac{h}{1 - \rho^h} \right) \Delta x_t$$

- ▶ Double Robust Predictor (DR):

$$\mu_{DR} = x_t + \left(\frac{h}{1 - \rho^h} \right) \Delta x_t + \left(\frac{\sum_{j=1}^h (1 - \rho^j)}{1 - \rho^h} \right) \Delta^2 x_t$$

- ▶ Higher variance but protection against broken trends

$$\hat{x}_{T+b+h|T+b} = \mu + \rho^h (x_{T+b} - \mu)$$

$$\hat{\mu}_{SRW} = \frac{1}{n} \sum_{i=0}^{n-1} x_{T+b-i}$$

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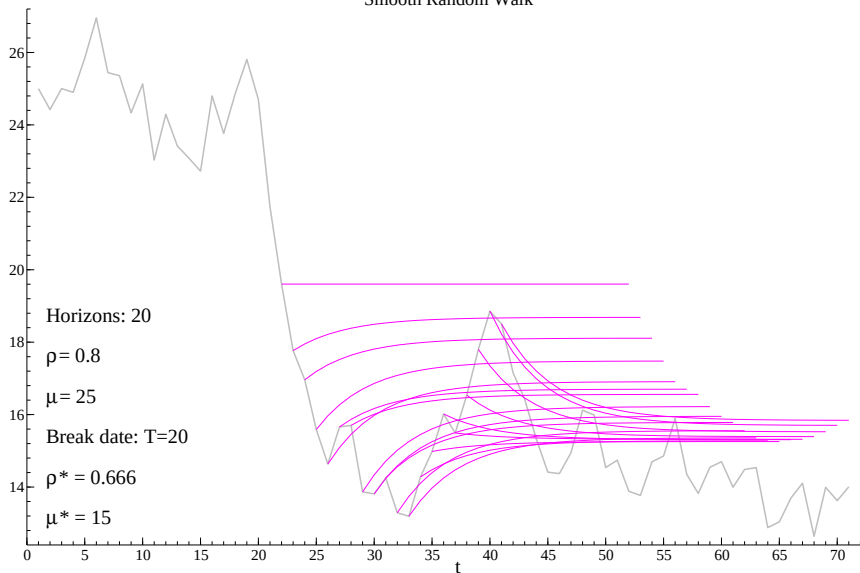
For $n \leq b$:

$$\text{BIAS}_{SRW} \xrightarrow{h \rightarrow \infty} \left(\frac{1}{n} \sum_{i=0}^{n-1} \rho^{*-i} \right) \rho^{*b} \nabla \mu^*$$

$$\text{MSFE}_{SRW} \xrightarrow{h \rightarrow \infty} \left\{ \frac{1}{n} \sum_{i=0}^{n-1} \rho^{-i} \right\}^2 \left(\rho^b \nabla \mu^* \right)^2 + \mathbb{V} \left[\frac{1}{n} \sum_{i=0}^{n-1} x_{T+b-i} \right] + \frac{\sigma_{\epsilon}^2}{1 - \rho^2}$$

Illustration: Smooth RW

Smooth Random Walk



$$\hat{x}_{T+b+h|T+b} = \mu + \rho^h (x_{T+b} - \mu)$$

$$\hat{\mu}_{SRP} = \frac{1}{n} \sum_{i=0}^{n-1} \left(x_{T+b-i} + \frac{\rho}{1-\rho} \Delta x_{T+b-i} \right)$$

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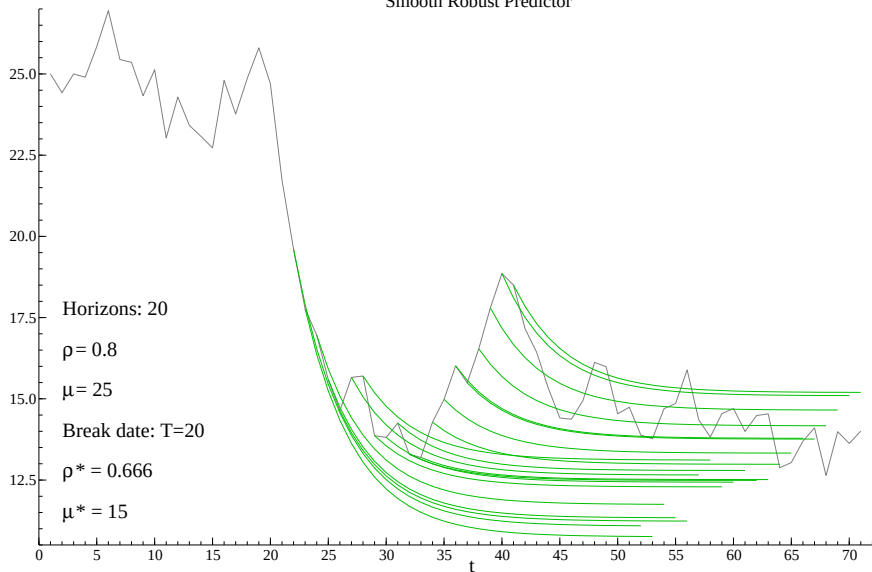
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$$\text{MSFE}_{SRP} \xrightarrow{h \rightarrow \infty} \left[1 + \frac{1}{n} \left(\frac{1+\rho}{1-\rho} \right) \right] \frac{\sigma_{\epsilon}^2}{1-\rho^2}$$

Illustration: Smooth RP

Smooth Robust Predictor



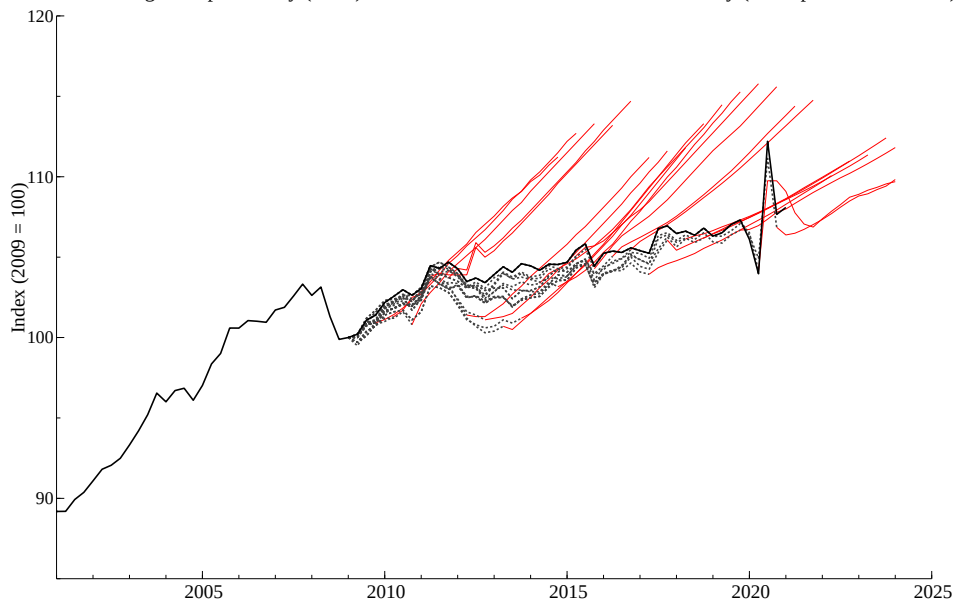
How to choose the estimation window?

- ▶ Rule-of-thumb:
 - ▶ Hendry (2006): $n = 4$ works well for quarterly data
 - ▶ Higher order differencing requires larger windows to have better estimates.
- ▶ Alternative approaches:
 - ▶ Optimal Estimation Windows for unknown number of breaks at unknown periods: Pesaran and Timmermann (2007), Pesaran et al. (2013), Giraitis et al. (2013) and Inoue et al. (2017)
 - ▶ Saturation methods to detect breaks and choose estimation window simultaneously; see Castle et al. (2015b).

Simulation Results

OBR's Forecasts of UK Productivity

Office of Budget Responsibility (OBR) Semi-Annual Forecasts of UK Productivity (GVA per hours worked)



Estimate an AR(1) model with a constant and a linear trend from 1997-Q2 through to 2007-Q4:

$$\hat{x}_t = \underset{(10.6)}{36.6} + \underset{(0.08)}{0.25} t + \underset{(0.13)}{0.54} x_{t-1}$$

$$\hat{\sigma}_x = 0.53 \quad R^2 = 0.99$$

$$F_{ar}(2, 38) = 2.698[0.080], \quad F_{arch}(1, 41) = 0.663[0.420]$$

$$\chi^2_{nd}(2) = 4.709[0.095], \quad F_{het}(4, 38) = 0.155[0.960]$$

$$F_{reset}(2, 55) = 2.001[0.149]$$

→ Model is reasonably well-specified

Long-run trend: $\frac{0.25}{1-0.54} * 4 = 2.2 \rightarrow$ **similar to OBR assumption: 2%**

Extend estimates of model through to 2020-Q1:

$$\hat{x}_t = \underset{(1.86)}{2.82} - \underset{(0.006)}{0.001}t + \underset{(0.02)}{0.97}x_{t-1}$$

$$\hat{\sigma}_x = 0.63 \quad R^2 = 0.99$$

$$F_{ar}(5, 84) = 0.834[0.529], \quad F_{arch}(4, 84) = 0.551[0.699]$$

$$\chi_{nd}^2(2) = 2.675[0.263], \quad F_{het}(4, 87) = 0.521[0.760]$$

$$F_{reset}(2, 87) = 5.855[0.004]**$$

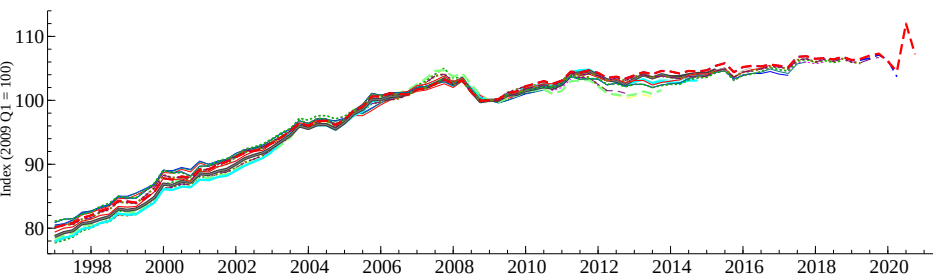
Large changes in coefficients: Trend flips sign and insignificant

→ Looks like a random walk with drift

→ Ramsey RESET test indicates model is now misspecified

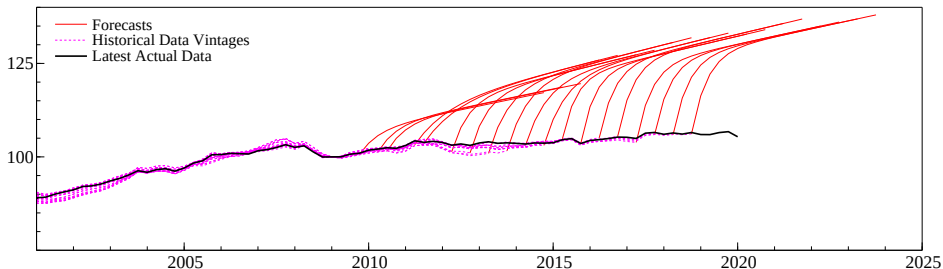
Real-time vintages of UK Productivity

Calculate real-time vintages of UK productivity starting in 2009 for each March and October to mimic OBR information set:

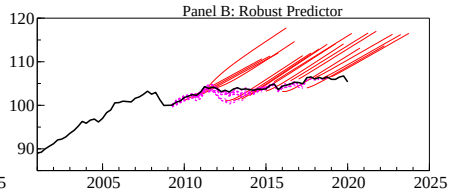
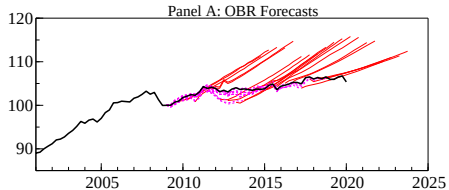


Forecasting UK Productivity

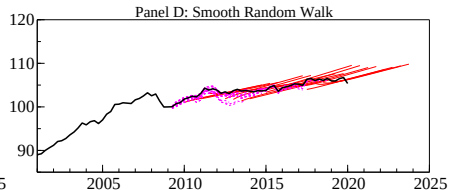
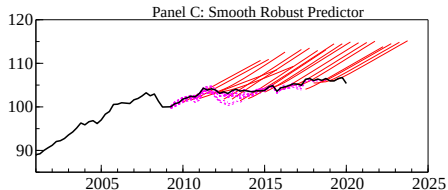
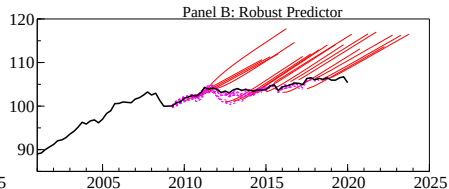
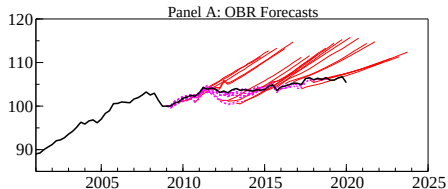
Forecast AR(1) using real-time vintages of data starting in 2009 with fixed parameter estimates as of 2007-Q4 ignoring breaks:



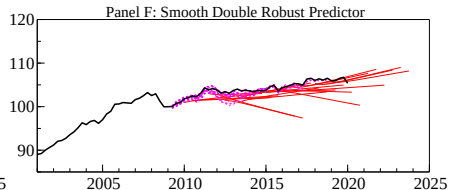
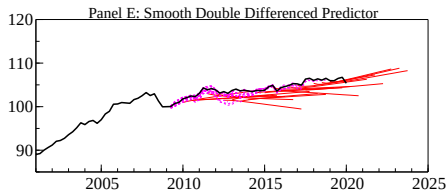
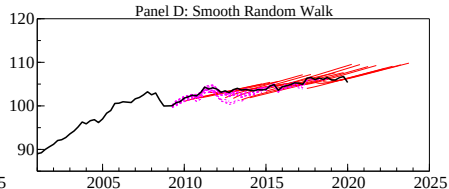
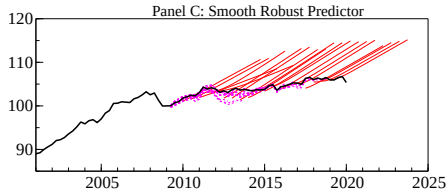
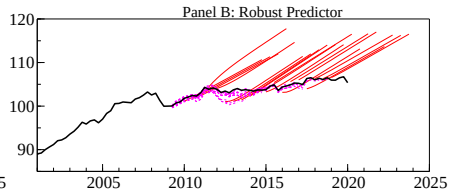
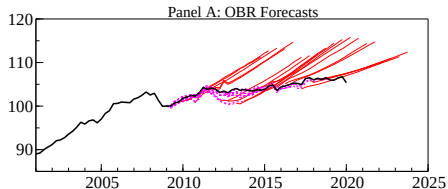
The Forecasts



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The Forecasts



Comparing Forecast Performance

	RMSE	relative RMSE
h	OBR	
1	1.34	
2	1.42	
3	1.28	
4	1.24	
5	1.25	
6	1.43	
7	1.62	
8	2.02	
9	2.42	
10	2.93	
11	3.37	
12	3.97	
13	4.54	
14	4.91	
15	5.51	
16	6.00	
17	6.58	
18	6.95	
19	7.50	
20	7.78	
Ave.	3.63	

Comparing Forecast Performance

h	RMSE	relative RMSE	
	OBR	RP	RW
1	1.34	0.95	0.90
2	1.42	1.00	0.93
3	1.28	1.06	0.88
4	1.24	1.36	0.96
5	1.25	1.46	0.87
6	1.43	1.47	0.79
7	1.62	1.55	0.71
8	2.02	1.41	0.51
9	2.42	1.37	0.50
10	2.93	1.26	0.33
11	3.37	1.23	0.35
12	3.97	1.19	0.32
13	4.54	1.15	0.33
14	4.91	1.11	0.26
15	5.51	1.09	0.29
16	6.00	1.05	0.25
17	6.58	1.03	0.24
18	6.95	1.07	0.22
19	7.50	1.05	0.23
20	7.78	1.04	0.17
Ave.	3.63	1.13	0.30

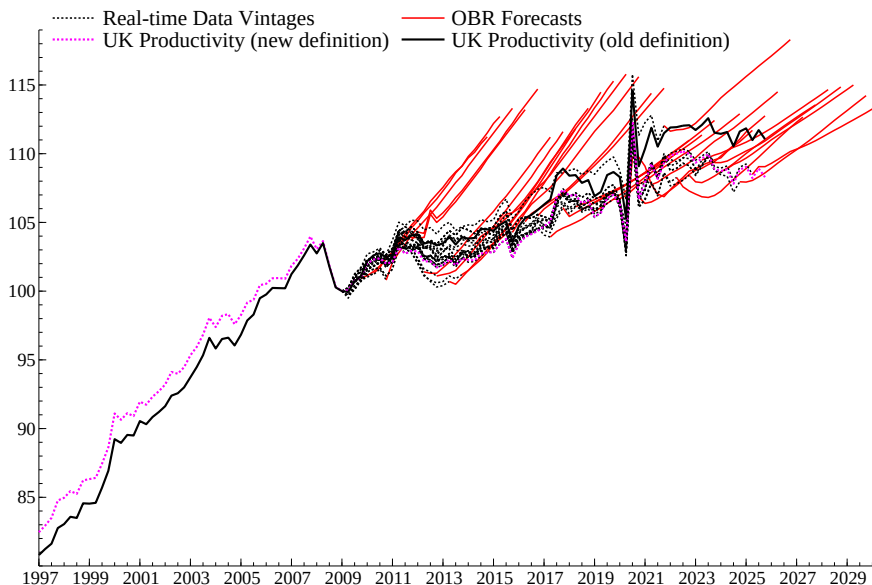
Comparing Forecast Performance

h	RMSE	relative RMSE					
	OBR	RP	RW	SRP	SRW	SDD	SDR
1	1.34	0.95	0.90	0.84	0.86	0.97	0.98
2	1.42	1.00	0.93	0.75	0.85	1.03	1.02
3	1.28	1.06	0.88	0.55	0.80	1.14	1.16
4	1.24	1.36	0.96	0.60	0.84	1.28	1.31
5	1.25	1.46	0.87	0.58	0.67	1.24	1.29
6	1.43	1.47	0.79	0.76	0.67	1.20	1.28
7	1.62	1.55	0.71	0.86	0.45	1.06	1.16
8	2.02	1.41	0.51	0.88	0.33	0.86	0.95
9	2.42	1.37	0.50	0.93	0.25	0.76	0.86
10	2.93	1.26	0.33	0.92	0.15	0.64	0.75
11	3.37	1.23	0.35	0.93	0.17	0.57	0.67
12	3.97	1.19	0.32	0.91	0.18	0.54	0.65
13	4.54	1.15	0.33	0.90	0.19	0.48	0.59
14	4.91	1.11	0.26	0.91	0.19	0.45	0.57
15	5.51	1.09	0.29	0.91	0.22	0.44	0.56
16	6.00	1.05	0.25	0.89	0.19	0.43	0.53
17	6.58	1.03	0.24	0.89	0.21	0.40	0.50
18	6.95	1.07	0.22	0.90	0.18	0.39	0.49
19	7.50	1.05	0.23	0.90	0.19	0.37	0.45
20	7.78	1.04	0.17	0.89	0.16	0.38	0.46
Ave.	3.63	1.13	0.30	0.87	0.24	0.58	0.66

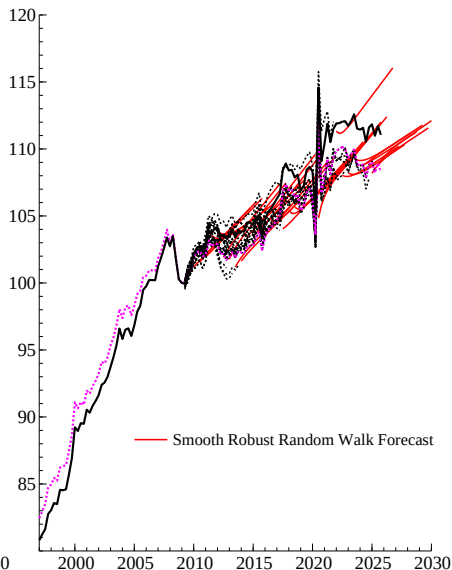
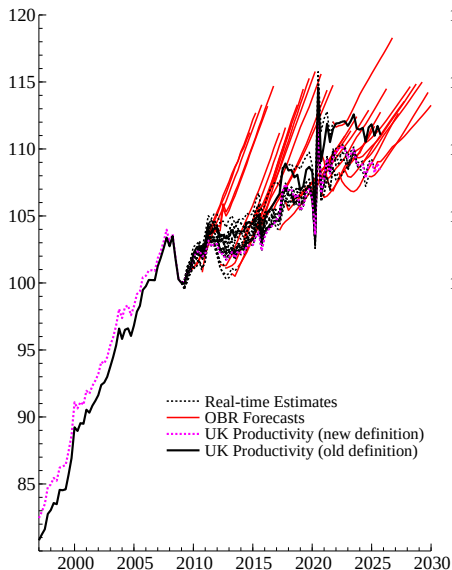
Comparing Forecast Performance

h	RMSE		relative RMSE							
	OBR	RP	RW	SRP	SRW	SDD	SDR	Ave _{SRW,SRP}	Ave _{SDD,SDR}	Ave _{SRW,SDD}
1	1.34	0.95	0.90	0.84	0.86	0.97	0.98	0.84	0.98	0.92
2	1.42	1.00	0.93	0.75	0.85	1.03	1.02	0.79	1.02	0.93
3	1.28	1.06	0.88	0.55	0.80	1.14	1.16	0.65	1.15	0.96
4	1.24	1.36	0.96	0.60	0.84	1.28	1.31	0.66	1.29	1.04
5	1.25	1.46	0.87	0.58	0.67	1.24	1.29	0.47	1.26	0.92
6	1.43	1.47	0.79	0.76	0.67	1.20	1.28	0.56	1.23	0.89
7	1.62	1.55	0.71	0.86	0.45	1.06	1.16	0.49	1.10	0.71
8	2.02	1.41	0.51	0.88	0.33	0.86	0.95	0.50	0.90	0.53
9	2.42	1.37	0.50	0.93	0.25	0.76	0.86	0.52	0.80	0.44
10	2.93	1.26	0.33	0.92	0.15	0.64	0.75	0.52	0.69	0.32
11	3.37	1.23	0.35	0.93	0.17	0.57	0.67	0.54	0.61	0.27
12	3.97	1.19	0.32	0.91	0.18	0.54	0.65	0.54	0.58	0.26
13	4.54	1.15	0.33	0.90	0.19	0.48	0.59	0.55	0.53	0.23
14	4.91	1.11	0.26	0.91	0.19	0.45	0.57	0.55	0.50	0.19
15	5.51	1.09	0.29	0.91	0.22	0.44	0.56	0.56	0.49	0.21
16	6.00	1.05	0.25	0.89	0.19	0.43	0.53	0.55	0.47	0.18
17	6.58	1.03	0.24	0.89	0.21	0.40	0.50	0.56	0.44	0.17
18	6.95	1.07	0.22	0.90	0.18	0.39	0.49	0.55	0.43	0.18
19	7.50	1.05	0.23	0.90	0.19	0.37	0.45	0.55	0.40	0.16
20	7.78	1.04	0.17	0.89	0.16	0.38	0.46	0.54	0.41	0.16
Ave.	3.63	1.13	0.30	0.87	0.24	0.58	0.66	0.55	0.61	0.33

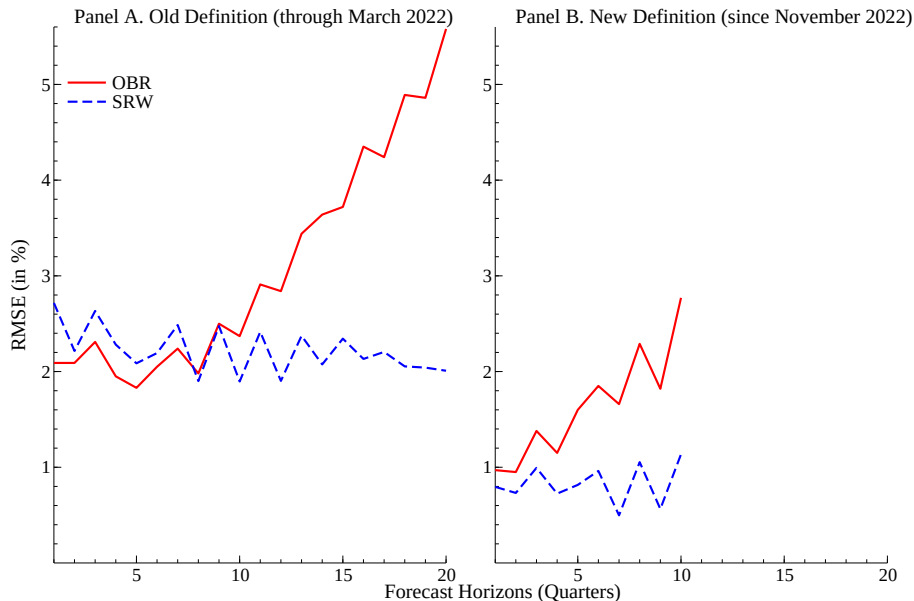
How have OBR forecasts done through the pandemic?



How have OBR forecasts done through the pandemic?



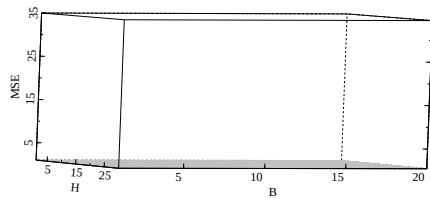
Comparing Forecast Performance

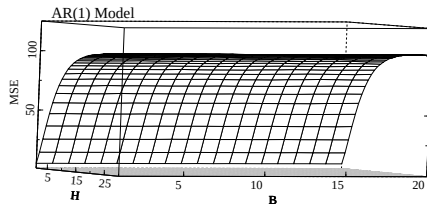


- ▶ Naive forecast methods are local estimators of the long-run
 - ▶ Exhibit different bias-variance tradeoffs
- ▶ Smoothing estimators over observations changes these tradeoffs
- ▶ Embedding smooth naive methods within economic models can improve forecasts while retaining structure.

THANK YOU

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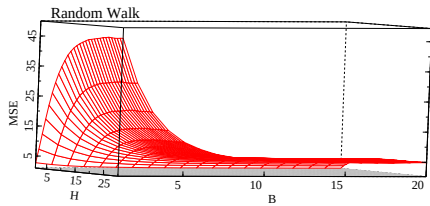
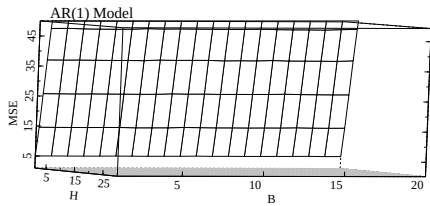


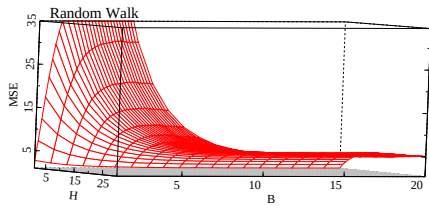
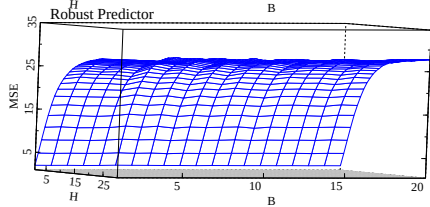
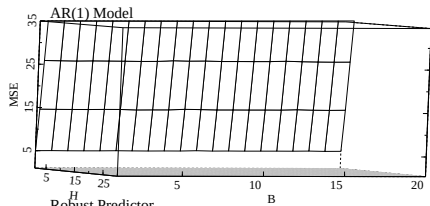


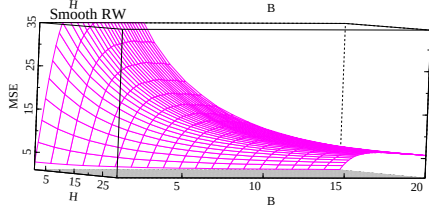
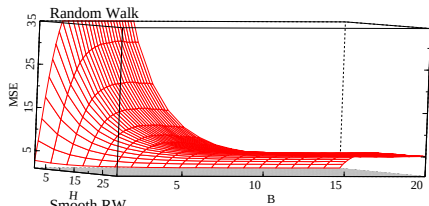
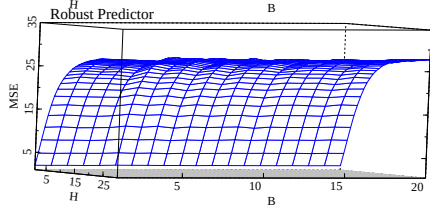
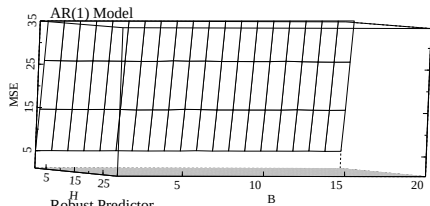
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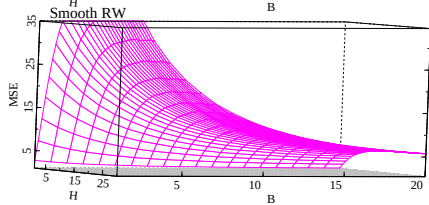
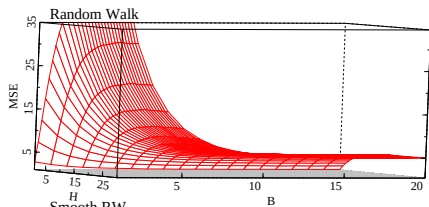
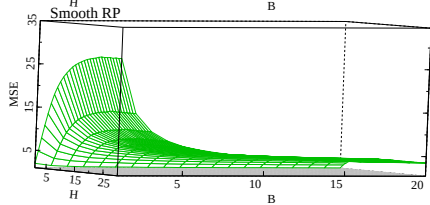
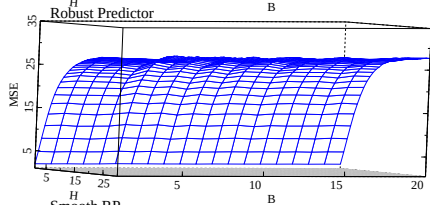
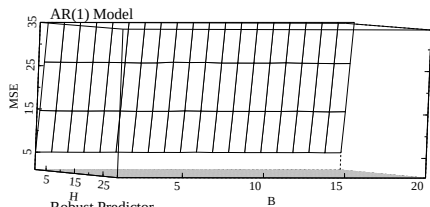
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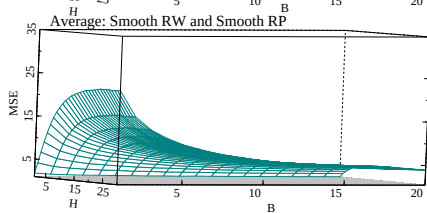
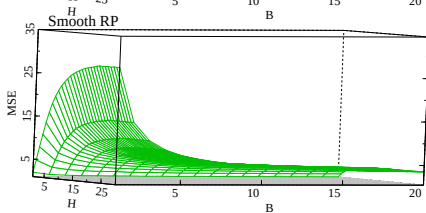
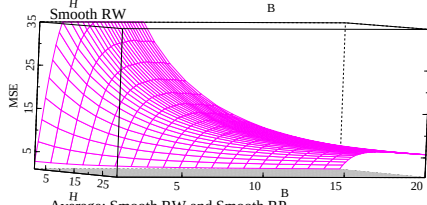
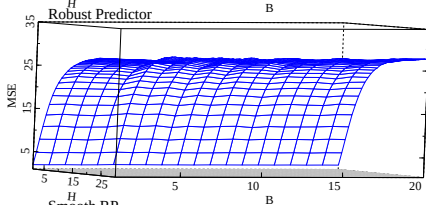
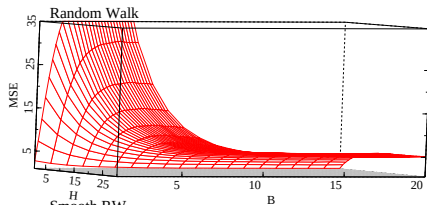
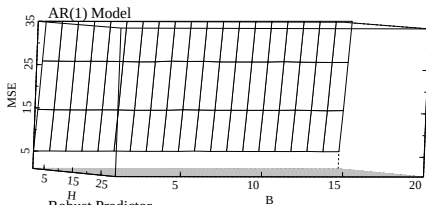
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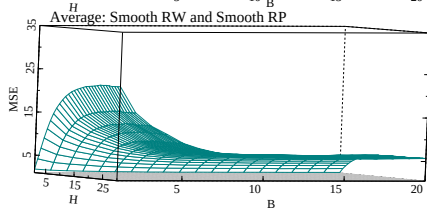
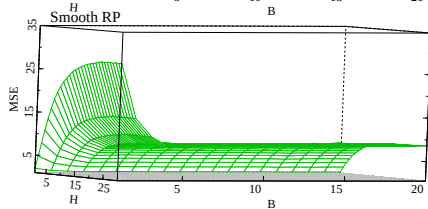
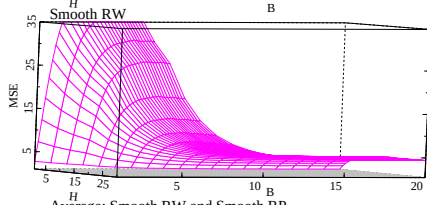
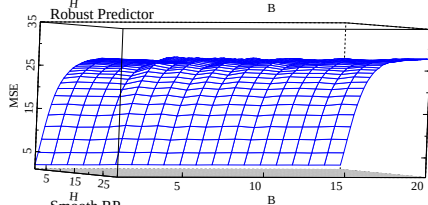
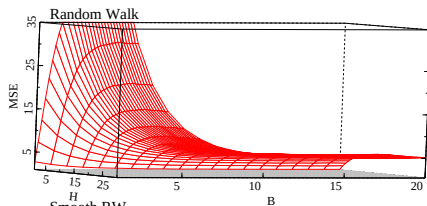
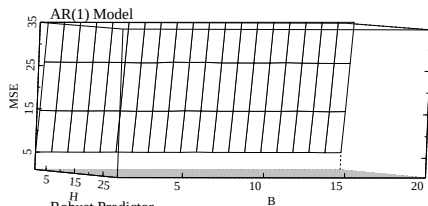




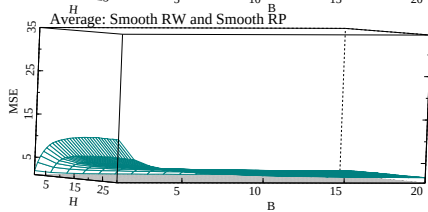
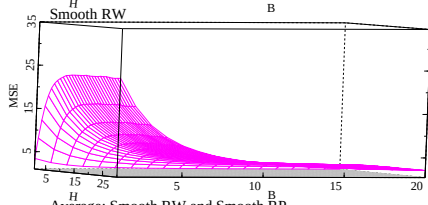
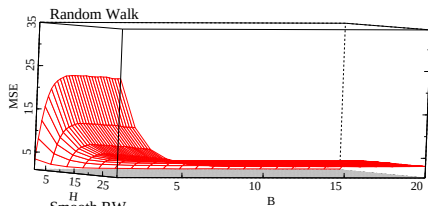
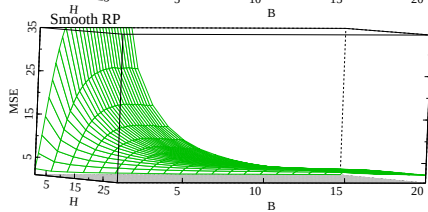
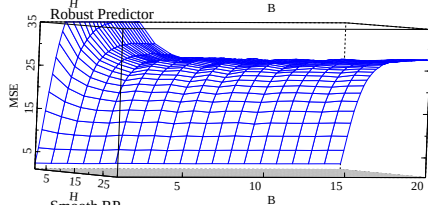
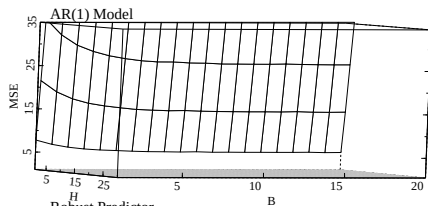




$n = 4$



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$n = 4$

