The Macroeconomic and Fiscal Implications of Inflation Forecast Errors

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Introduction

- Accurate inflation forecasts are essential to macroeconomic policy formulation

- This paper begins by analysing exactly why this is the case

- It then goes on to suggest a new approach to forecast combination which we believe will generally improve forecast accuracy, especially in a situation where structural breaks are endemic.

- An illustration is provided for the US and the EU

Theoretical Background

- There are at least three reasons why inflation forecast errors lead to inefficient policy formulation.

- 1. The Lucas Supply Curve

- $y(t) - y^*_{(t)} = \frac{\alpha}{1-\alpha}(\pi(t) - E_{t-1}\pi(t) \quad)$

- Inflation forecast errors thus lead to inefficient variation in GDP

Theoretic Background

- 2. Fiscal Implications of forecast errors
- This concerns asset pricing for assets with a fixed nominal rate of return (Canzoneri and Dellas(1998))
- We derive the following relationship
- $R_t^{-1} + \frac{\beta E_t \frac{C_{t+1}^{-\gamma} P_t}{C_t^{-\gamma} P_{t+1}}}{E_t \frac{P_t}{P_{t+1}}} = r_t^{-1} + \frac{\beta Cov_t(\frac{C_{t+1}^{-\gamma}}{C_t^{-\gamma}}, \frac{P_t}{P_{t+1}})}{E_t \frac{P_t}{P_{t+1}}}$
- Where the last term is the risk premium on nominal assets when inflation is not perfectly forecasted.

Theoretical Background

- The risk premium depends on the sign of the covariance between inflation and consumption. This can produce either a positive or negative risk premium on nominal assets.

- 3.Central Bank inflation targeting
- If the central bank has an inflation target then if its forecasts of inflation are inaccurate this will inevitably lead to sub optimal policy.

Analytical Motivation

- Two Strands of Literature brought together
- 1 Forcast combination
- 2 Forecasting in the presence of structural breaks

Analytical motivation (Forecast Combination)

- Two forecasters a and b and a combination c

$$\hat{y}^{c}{}_{t+h,t} = \alpha \hat{y}^{a}{}_{t+h,t} + (1-\alpha)\hat{y}^{b}{}_{t+h,t}$$

- Combined error $e^{c}{}_{t+h,t} = \alpha e^{a}{}_{t+h,t} + (1-\alpha)e^{b}{}_{t+h,t}$

- Variance will be $\sigma^{2}{}_{c} = \alpha^{2}\sigma^{2}{}_{a} + (1-\alpha)^{2}\sigma^{2}{}_{b} + 2\alpha(1-\alpha)\sigma_{ab}$

Analytical motivation (Forecast Combination)

- Optimal weights derived by OLS

$$y_{t+h,t} = \beta_0 + \beta_1 \hat{y}^a{}_{t+h,t} + \beta_2 \hat{y}^b{}_{t+h,t} + \varepsilon_{t+h}$$

- But often in practise equal weights perform just as well.

- This is a linear combination however and we argue that a non-linear combination must perform at least as well as this and should generally perform better.

Analytical motivation (Structural Breaks)

- An important recent research theme has been the use of rolling windows in forecasting to overcome the presence of structural breaks.
- Clements and Hendry (1996, 1998), Hendry (2000), Pesaran and Timmerman (2002), Goyal and Welch (2003), Pessaran, Pettenuzzzo and Timmerman (2006), Koop and Potter (2007), Castle Clements and Hendry (2013) and Rossie (2013a, b).

Analytical Motivation (together)

- We are bringing these two branches of the literature together
- We look at forecast combinations but allow explicitly for structural breaks by employing non-linear combination techniques

Analytical motivation

- Our suggestion a non-linear combination

$$\hat{y}^{c}{}_{t+h,t} = f(\hat{y}^{a}{}_{t+h,t}, \hat{y}^{b}{}_{t+h,t})$$

- But how to implement this,

- One way, the Swamy and Mehta theorem, TVC estimation

$$\hat{y}^{c}{}_{t+h,t} = \gamma_{0t} + \gamma_{1t}\hat{y}^{1}{}_{t+h,t} + \ldots + \gamma_{kt}\hat{y}^{k}{}_{t+h,t}$$

Kalman filter state space model

- Measurement equation

$$y_{t+h,t} = \gamma_{0t} + \gamma_{1t}\hat{y}^{1}_{t+h,t} + \ldots + \gamma_{kt}\hat{y}^{k}_{t+h,t}$$

- State equations 1

$$\gamma_{it} = \gamma_{it-1} + \varepsilon_{it} \quad i = 0,\ldots,k$$

- State equations 2

$$\gamma_{it} = \gamma_{it-1} + \gamma_{k+1+it-1} + \varepsilon_{it}$$

$$\gamma_{k+1+it} = \gamma_{k+1+it-1} \qquad i = 0,\ldots,k$$

Analytical Motivation

- Second approach
- An explicit non-linear estimation technique, Neural Nets

$$\hat{y}^{c}{}_{t+h,t} = f(\hat{y}^{a}{}_{t+h,t}, \hat{y}^{b}{}_{t+h,t})$$

- A simple Neural net

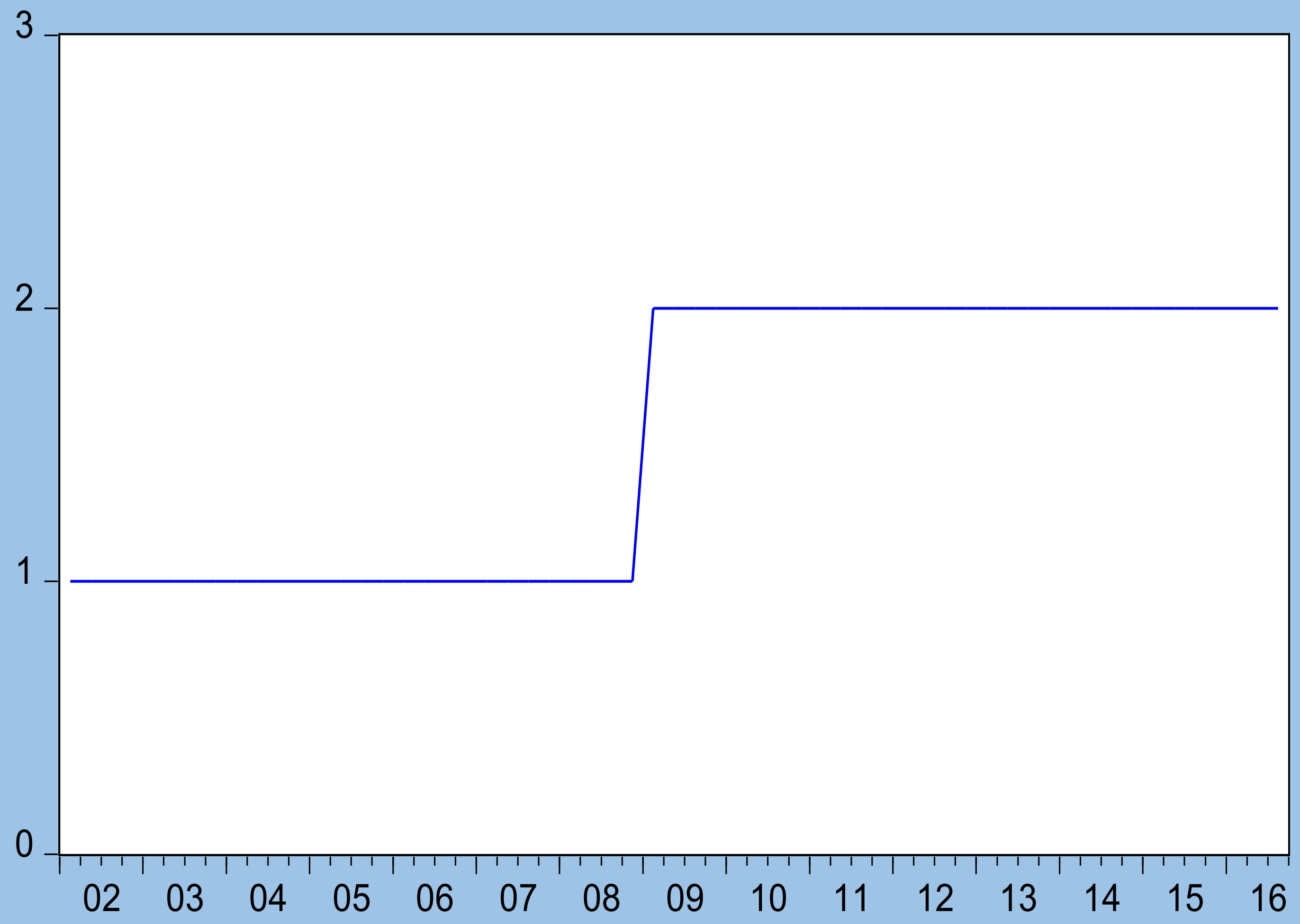
$$Y = h(\sum_{k=1}^{K} \alpha_k g(\sum_{j=1}^{J} \beta_{jk} X_j))$$

- Where X is a vector of individual forecasts

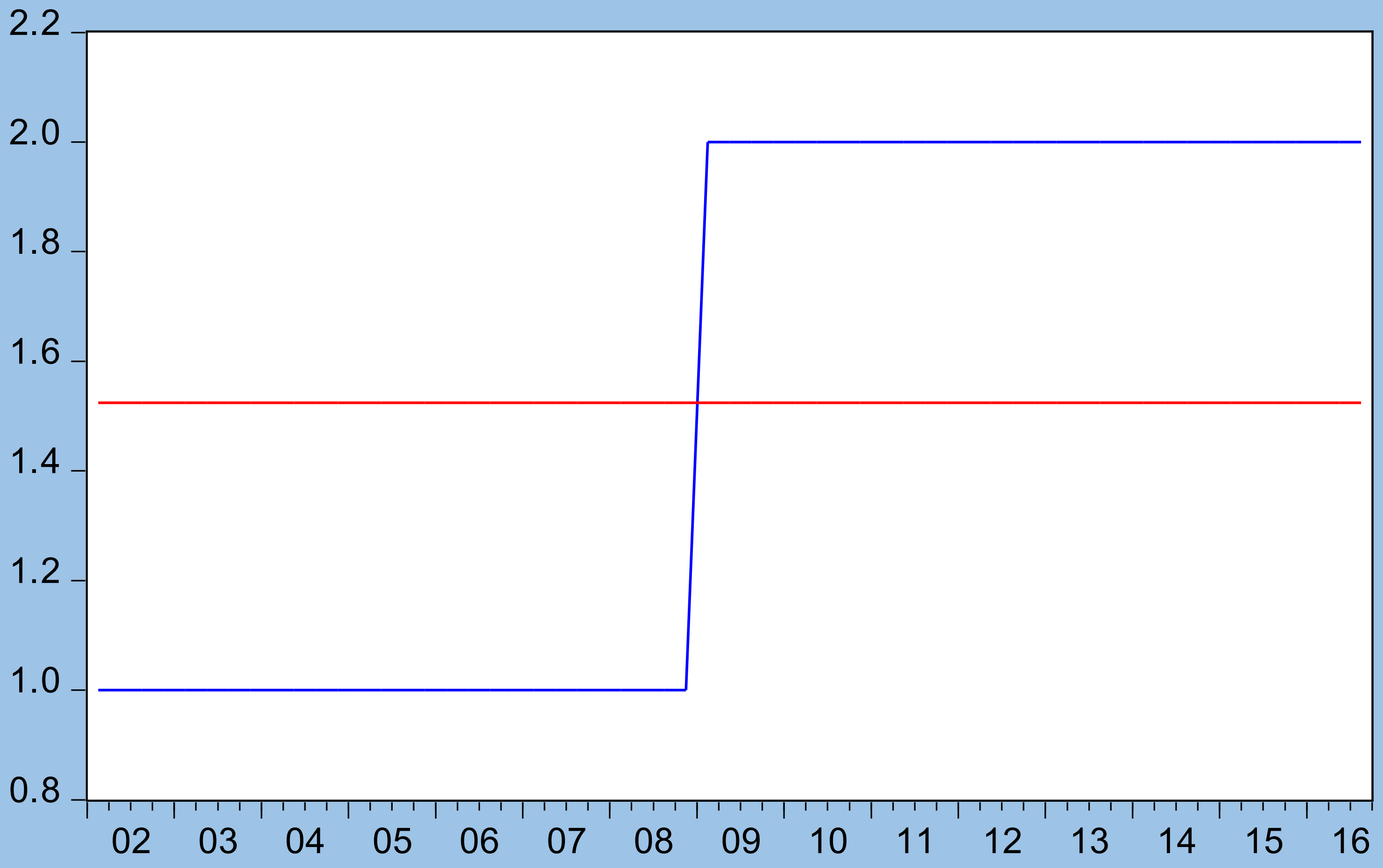
So the basic idea

- We believe a non-linear forecast combination must in general be superior.
- If the neural net captures the non-linearity without any structural breaks then this is probably the best technique.
- If structural breaks are hard to capture for the net then the Kalman filter model should do better.

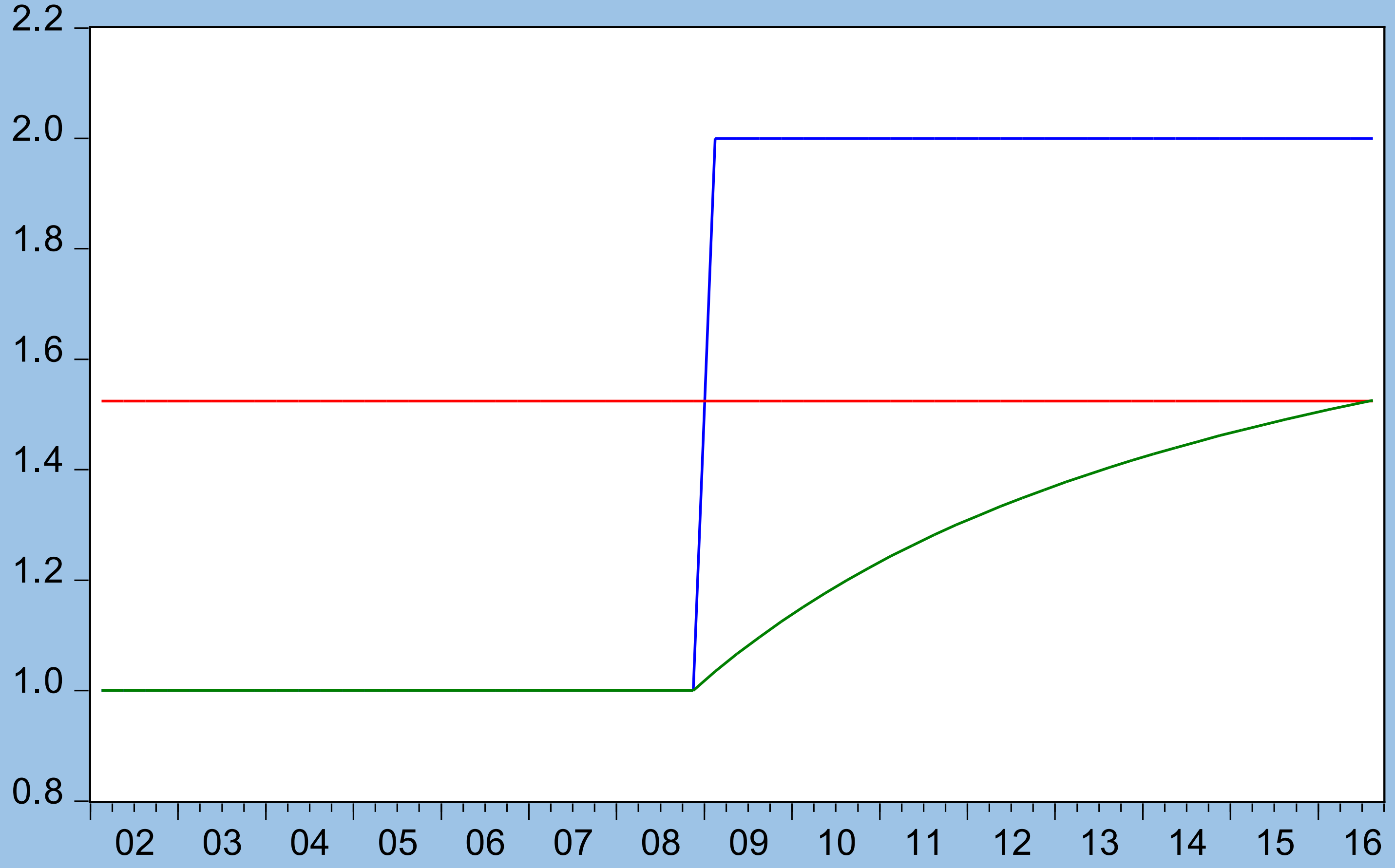
Intuition



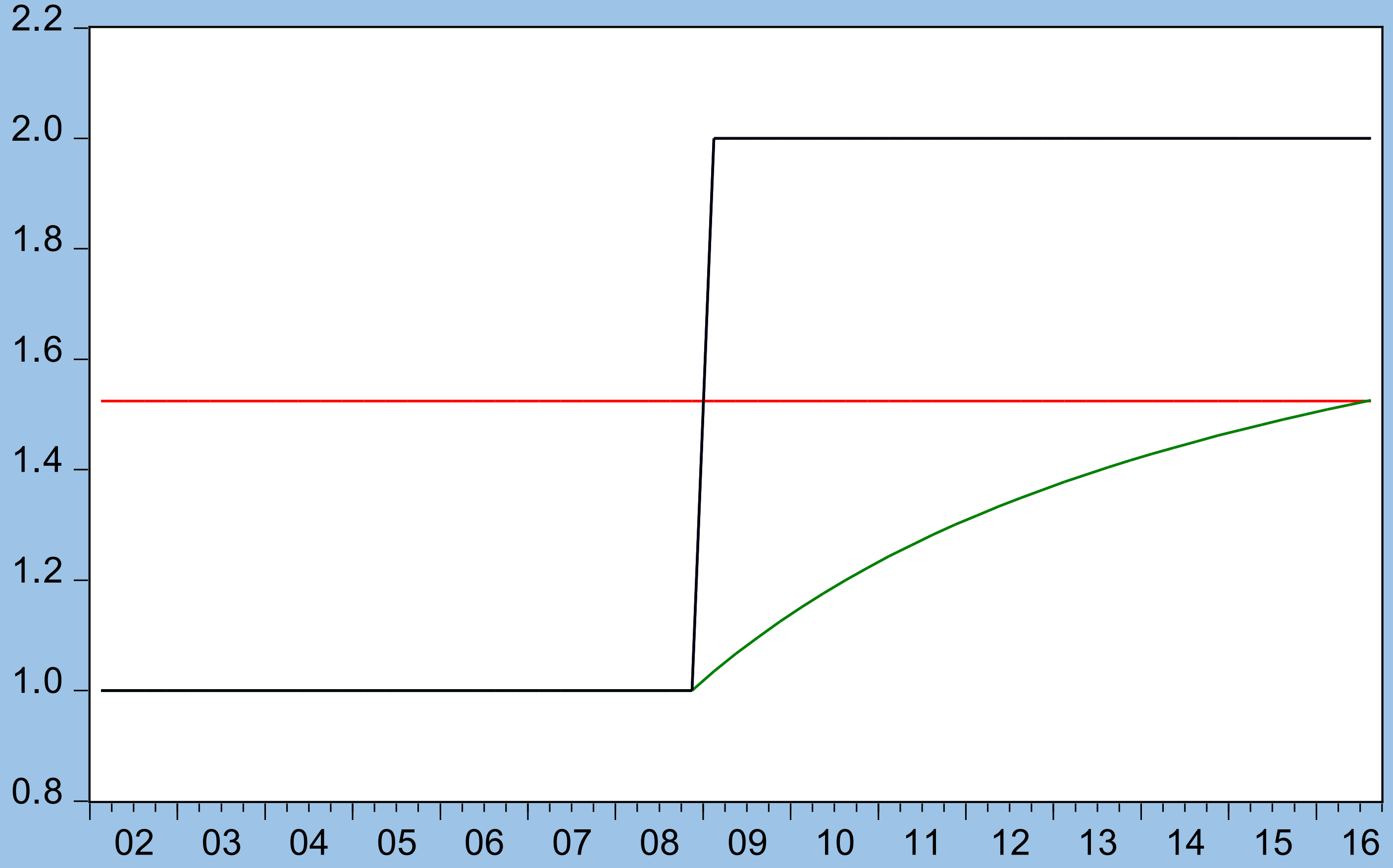
What does OLS do



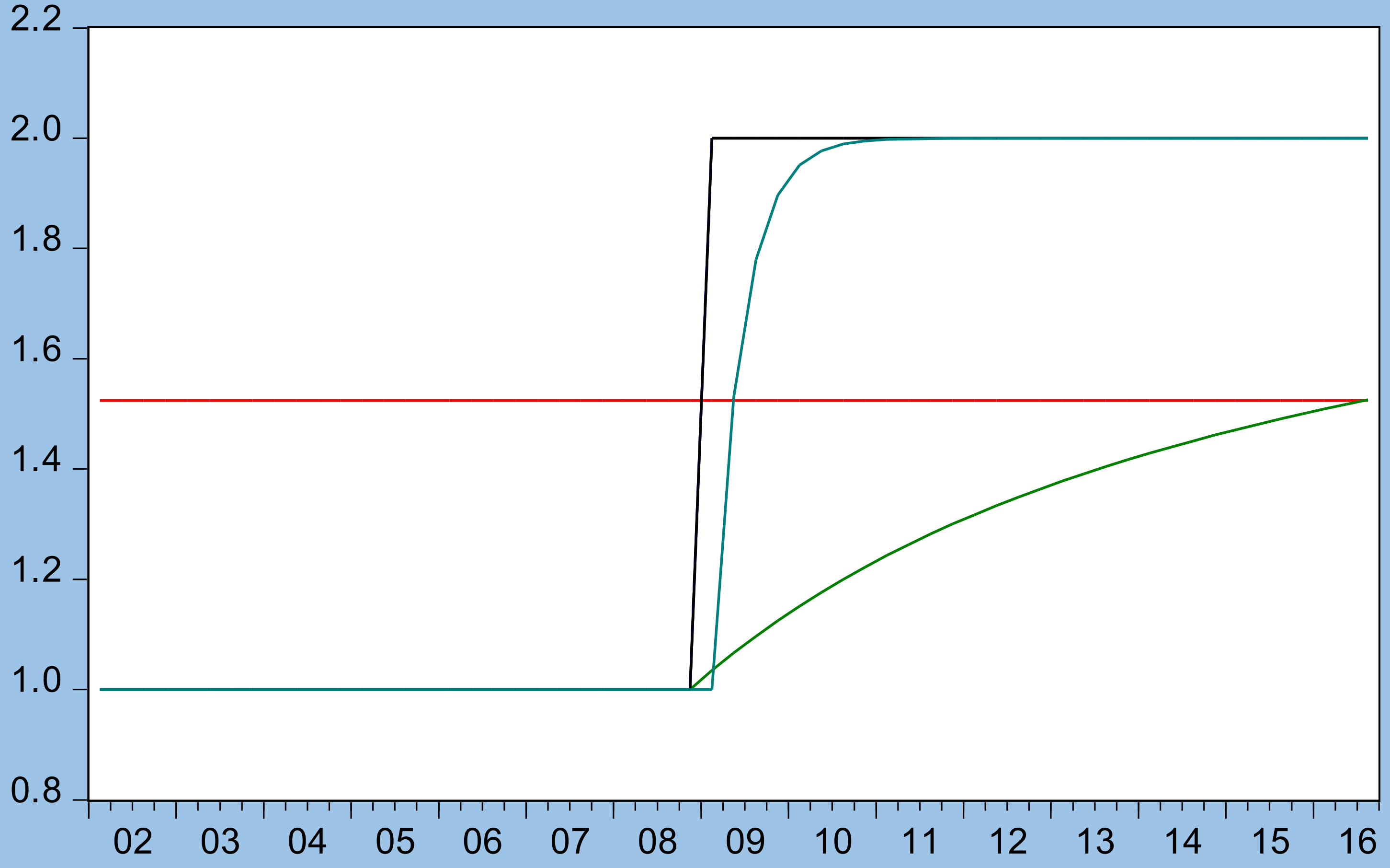
Recursive OLS



Smoothed Kalman Filter



Kalman Filter Predicted (past information)



Strategy

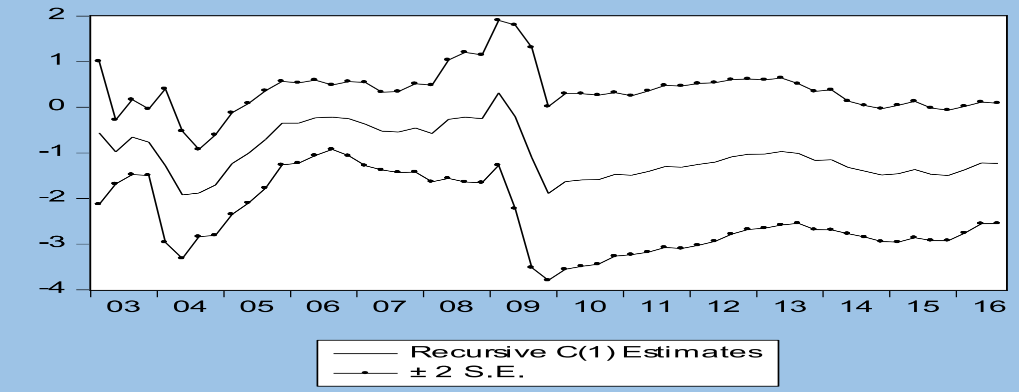
- 1. first do recursive estimation of the combination weights to asses how much of a problem breaks are
- Then do recursive OLS combination, equal weight combination and full sample OLS.
- Then compare with TVC weights (filtered) and recursive neural net combinations

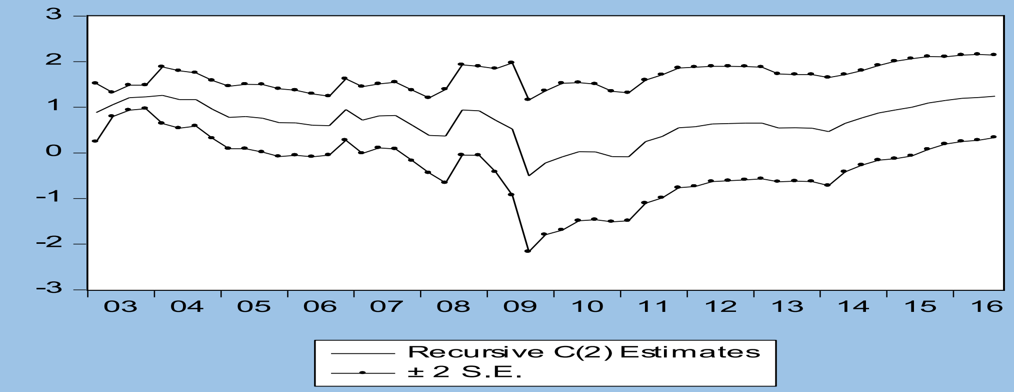
Application

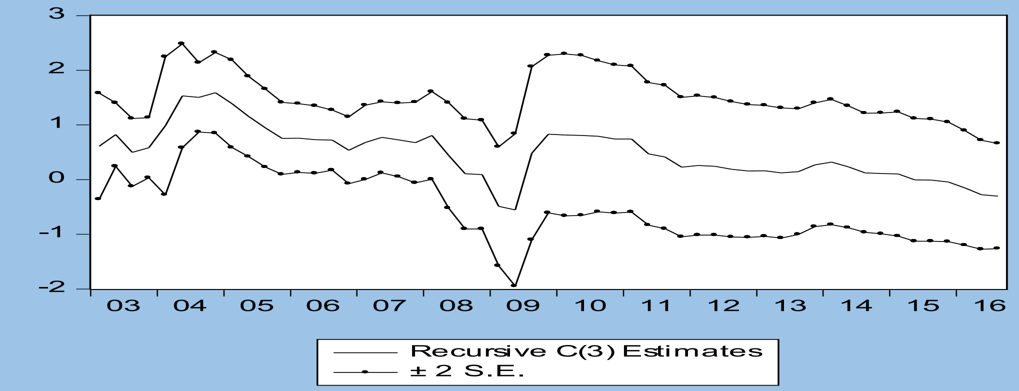
- We use data from ECB's quarterly report, *Survey of Professional Forecasters and for the US, the* Federal Reserve Bank of Philadelphia, *Survey of Professional Forecasters. For inflation forecasts, one quarter ahead for US and four quarter ahead for EU.*

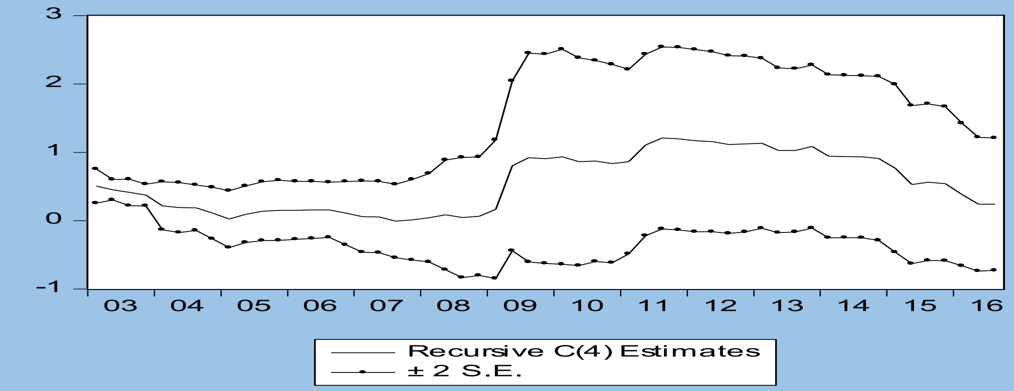
- *Lots of missing data etc. 6 forecasters for the EU, 4 for the US*

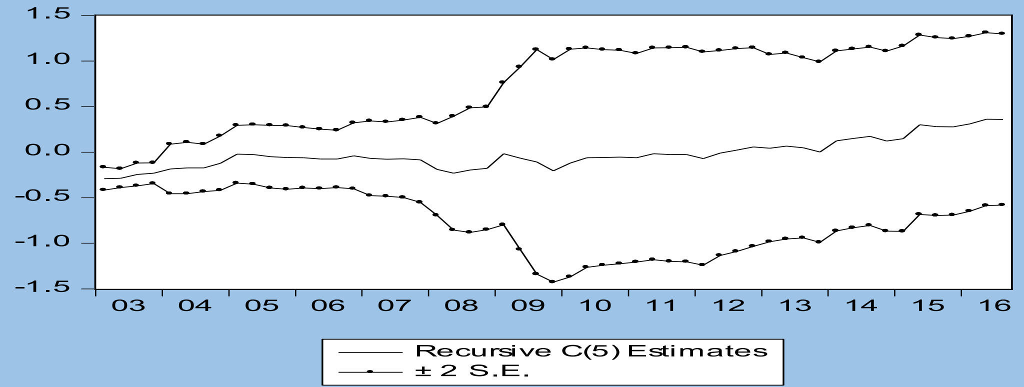
EU example Recursive OLS weights

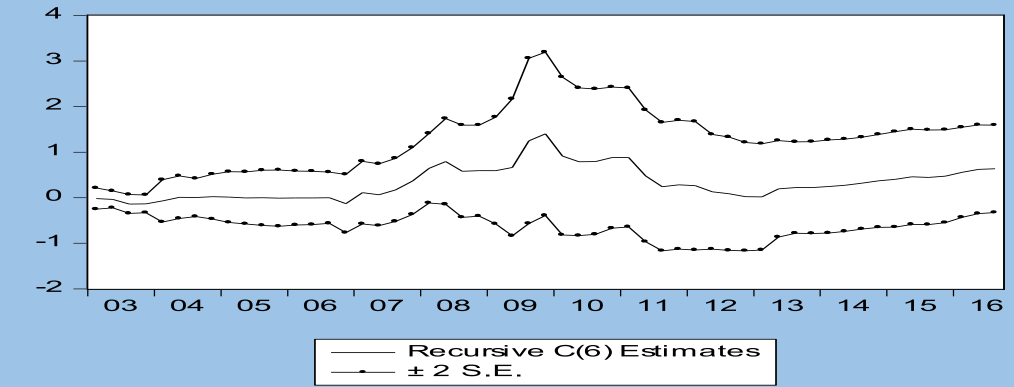












EU Cusum squared test

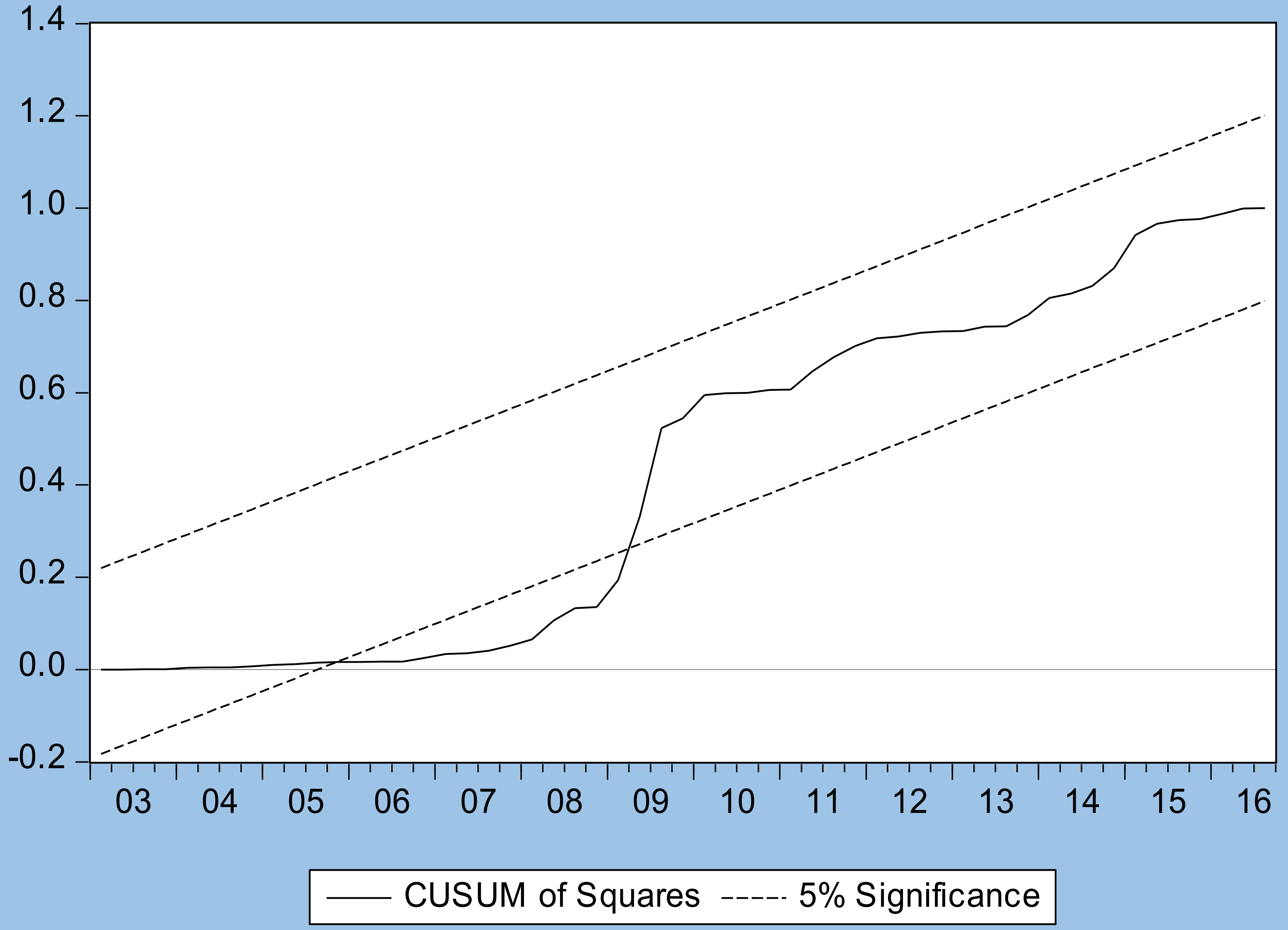


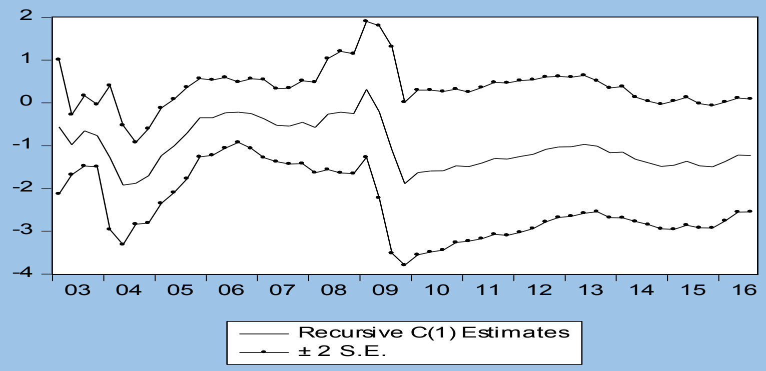
Table 1 EU, individual forecaster and standard combinations

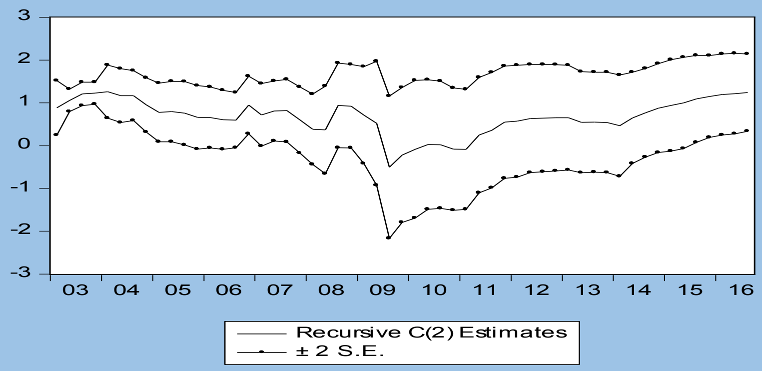
	1	2	3	4	5	6	Equal weights	OLS weights	RLS weights
RMSE	1.029	0.942	1.008	1.019	0.943	0.951	0.982	0.839	1.305
MAE	0.850	0.740	0.827	0.845	0.762	0.767	0.787	0.616	1.089
MAPE	240.1	177.4	258.2	288.2	240.1	216.5	240.7	135.5	153.4

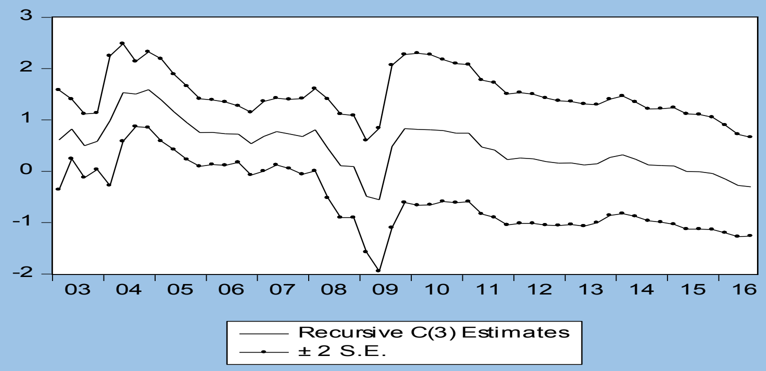
Table 2 EU, Nonlinear combinations

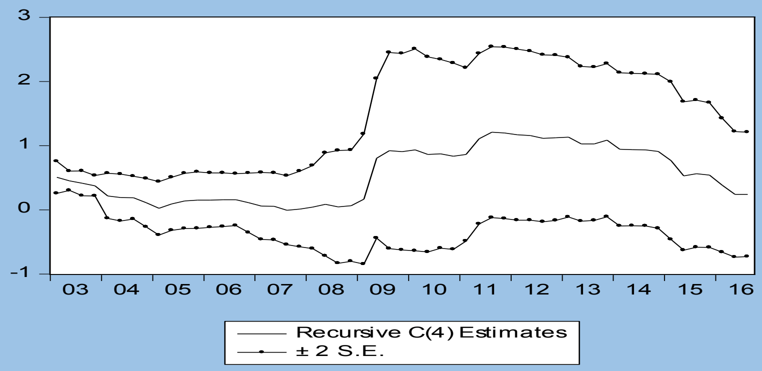
	TVC1	TVC2	Neural Net
RMSE	0.488	0.574	1.275
MAE	0.357	0.460	0.958
MAPE	79.1	119.1	157.6

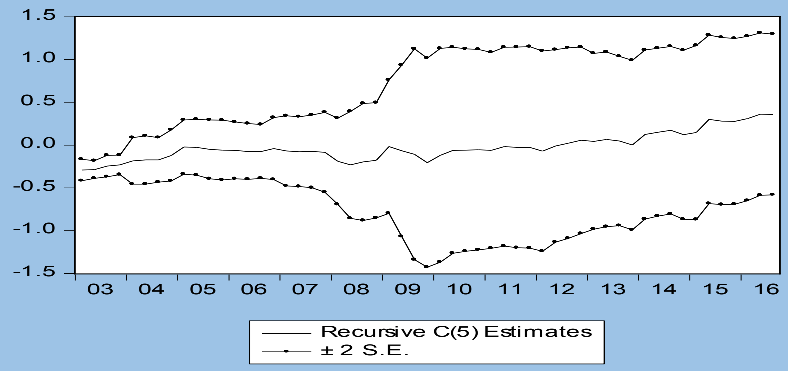
US recursive OLS

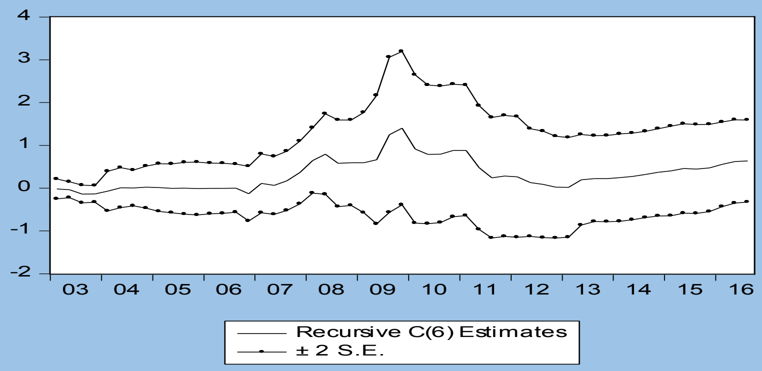












US CUSUM of Squares test

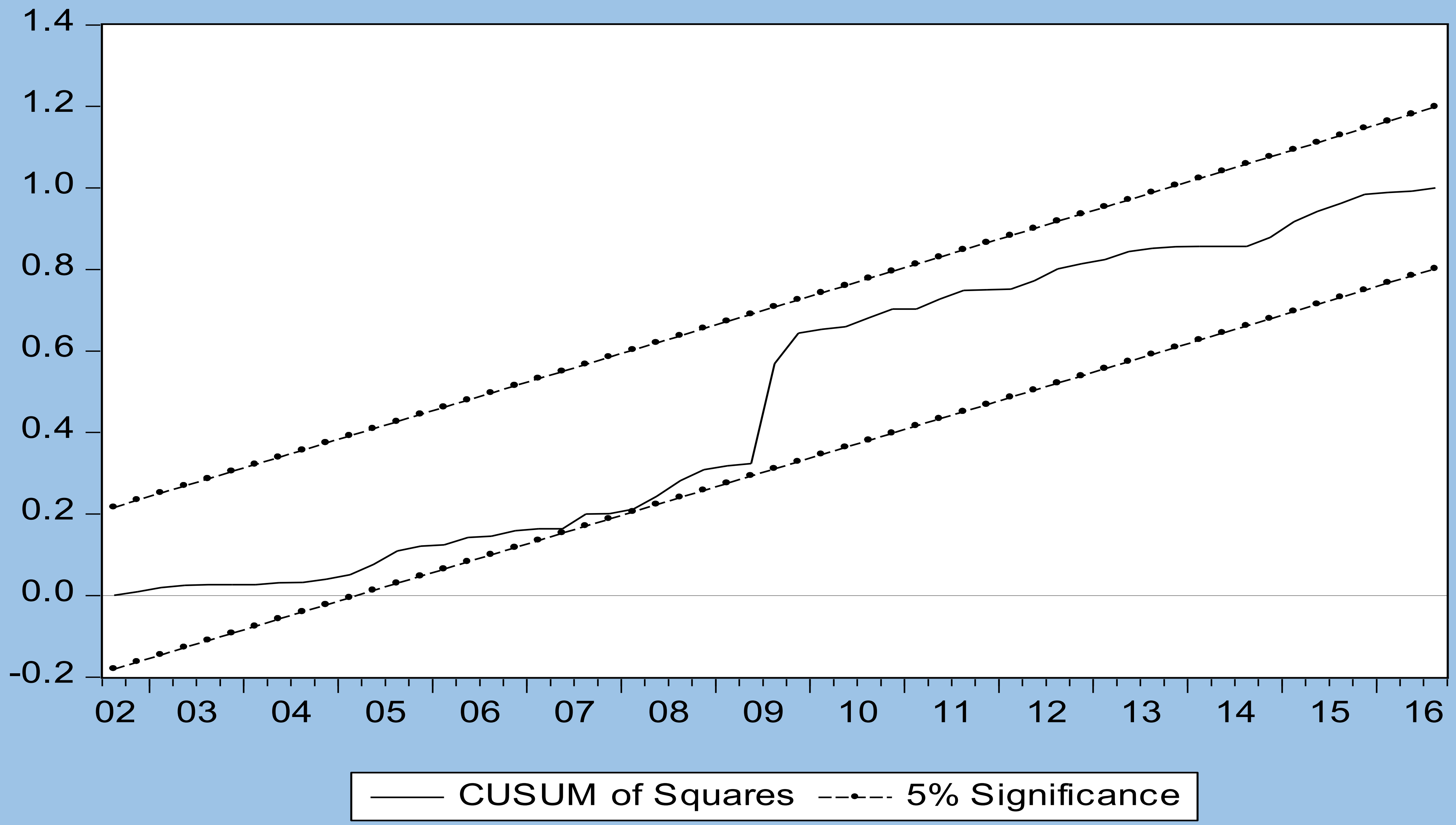


Table 3: United States: Forecasts based on simple averages and OLS weights

	1	2	3	4	Equal weights	OLS weights	RLS Weights
RMSE	1.291	1.045	1.285	1.588	1.143	0.931	1.110
MAE	0.983	0.837	0.987	1.307	0.947	0.689	0.909
MAPE	271.0	163.7	239.8	261.9	136.6	124.1	170.1

Table 4: United States: nonlinear results

	TVC 1	TVC2	Neural net
RMSE	0.897	0.997	0.832
MAE	0.620	0.703	0.546
MAPE	60.0	50.0	61.88

Economic Value of the improvement

- We attempt to quantify the value to the economy of this degree of forecast improvement by putting this within the context of a simple, calibrated economic model.

- We find that the gains in forecasting accuracy for the EU would be worth something of the order of 0.7 percent of total consumption

Conclusion

- Inflation forecast errors represent a significant cost to the economy.
- We have suggested a way of extending standard forecast combination technology so as to allow for structural breaks using a Kalman filter TVC model and a neural net.
- The evidence from our two examples suggests that considerable gains for the new combinations. When there is substantial structural breaks the TVC performs best. In the other case the neural net performs best.