Measuring GDP Growth Data Uncertainty

Ana Beatriz Galvão and James Mitchell

University of Warwick
Funding by ESCOE is gratefully acknowledged.

May 2018

Uncertainty

- Many measures of uncertainty are correlated with business cycles: stock market volatility, macroeconomic forecasting uncertainty, professional forecasters disagreement and economic policy uncertainty (Bachman et al , 2013; Jurado et al, 2015; Baker et al, 2016; Rossi et al, 2016; surveyed by Bloom (2014)).

Uncertainty

- Many measures of uncertainty are correlated with business cycles: stock market volatility, macroeconomic forecasting uncertainty, professional forecasters disagreement and economic policy uncertainty (Bachman et al , 2013; Jurado et al, 2015; Baker et al, 2016; Rossi et al, 2016; surveyed by Bloom (2014)).
- Economic statistics uncertainty has two components (Manski, 2014). *Transitory statistical uncertainty*, early data releases that are revised as new information arrives; and *permanent statistical uncertainty* from data incompleteness or the inadequacy of data collection which does not diminish over time.

GDP Data Revisions and Data Uncertainty

- For GDP growth, we are mainly concerned about the transitory uncertainty.

GDP Data Revisions and Data Uncertainty

- For GDP growth, we are mainly concerned about the transitory uncertainty.
- Data uncertainty arises from the fact that macroeconomic aggregates are initially released by statistical agencies based on incomplete datasets and are subject to many rounds of data revisions.

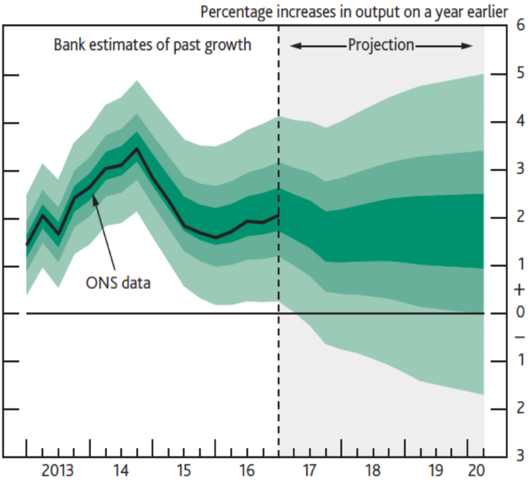
GDP Data Revisions and Data Uncertainty

- For GDP growth, we are mainly concerned about the transitory uncertainty.
- Data uncertainty arises from the fact that macroeconomic aggregates are initially released by statistical agencies based on incomplete datasets and are subject to many rounds of data revisions.
- Data uncertainty may affect policy decisions by adding a layer of uncertainty on the measurement of the current state of the economy.

Communication of UK GDP Growth Data Revision Uncertainty

- While the Office for National Statistics emphasise the uncertainty of early GDP data releases by indicating that their data will be revised, it is the Bank of England that provide quantitative estimates of GDP data uncertainty, as perceived by their Monetary Policy Committee.

Communication of UK GDP Growth Data Revision Uncertainty: Inflation Report Fan Chart June 2017.



Communication of UK GDP Growth Data Revision Uncertainty

- The fan charts shows "how the MPC's best collective judgement of the most likely path for the mature estimate of GDP growth, and the uncertainty around it, both over the past and into the future."
- "To the left of the first vertical dashed line, the centre of the darkest band of the fan chart gives the Committee's best collective judgement of the most likely path for GDP growth once the revisions process is complete. The estimate is based on an analysis of business surveys and the past pattern of official data revisions."

In this paper,

- we propose a new measure of data uncertainty that exploits mismeasurements between the Bank of England's *ex ante* probabilistic backcasts and actual revised GDP growth estimates to isolate the *unexpected component of data revisions*.

In this paper,

- we propose a new measure of data uncertainty that exploits mismeasurements between the Bank of England's *ex ante* probabilistic backcasts and actual revised GDP growth estimates to isolate the *unexpected component of data revisions*.
- we provide evidence that the ONS data revision process has changed since 1980: measurement error variance has decreased over time but there was a large and unexpected sign-switch in the revision bias at the onset of the 2008 recession.

In this paper,

- we propose a new measure of data uncertainty that exploits mismeasurements between the Bank of England's *ex ante* probabilistic backcasts and actual revised GDP growth estimates to isolate the *unexpected component of data revisions*.
- we provide evidence that the ONS data revision process has changed since 1980: measurement error variance has decreased over time but there was a large and unexpected sign-switch in the revision bias at the onset of the 2008 recession.
- we evaluate the accuracy of the Bank of England MPC's probabilistic backcasts over the 2007-2013 period.

In this paper,

- we propose a new measure of data uncertainty that exploits mismeasurements between the Bank of England's *ex ante* probabilistic backcasts and actual revised GDP growth estimates to isolate the *unexpected component of data revisions*.
- we provide evidence that the ONS data revision process has changed since 1980: measurement error variance has decreased over time but there was a large and unexpected sign-switch in the revision bias at the onset of the 2008 recession.
- we evaluate the accuracy of the Bank of England MPC's probabilistic backcasts over the 2007-2013 period.
- we propose a test that compares differences between *observed and expected* predictive performance, which is applied to MPC's backcasts.

UK Y-on-Y Growth Data Revisions Characteristics

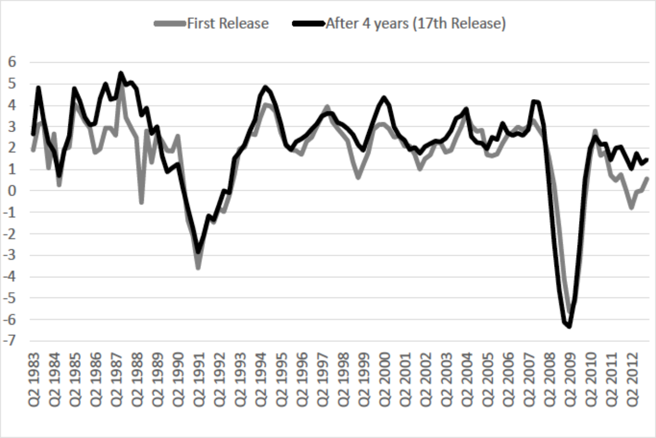
Data after 3 years, y_t^{t+13}, is a popular measure of 'mature' data in the US data revision literature, but results below suggest that data after 4 years, y_t^{t+17}, may be a better measure for the UK.

	$y^{17}-y^{1}$		$y^{17}-y^{13}$		$y^{latest}-y^{17}$	
Obs Period:	mean	std	mean	std	mean	std
1983Q2-2013Q1	**0.462**	0.906	0.065	0.451	**0.231**	0.709
1993Q2-2013Q1	**0.358**	0.807	**0.112**	0.483	0.066	0.646
2007Q3-2013Q1	0.306	1.328	0.229	0.836	0.001	0.600

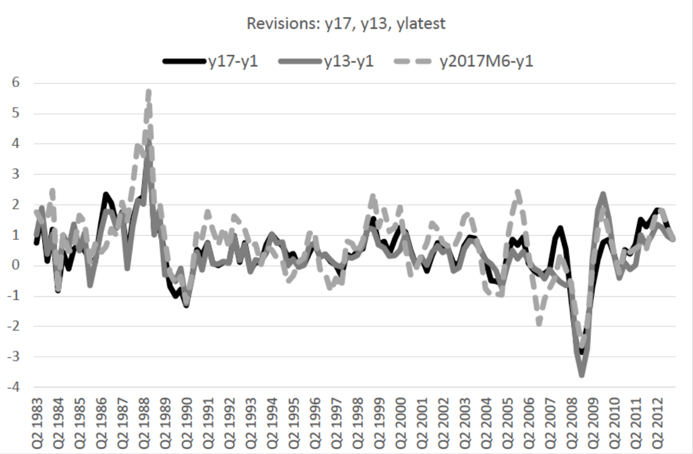
	$y^{17}-y^{1}$		$y^{17}-y^{13}$		$y^{latest}-y^{17}$	
Obs Period:	H0: news	H0: noise	H0: news	H0: noise	H0: news	H0: noise
1983Q2-2013Q1	0.59	**3.52**	0.45	**1.67**	**-1.84**	0.55
1993Q2-2013Q1	0.63	**2.41**	0.48	1.30	**-2.81**	-0.22
2007Q3-2013Q1	1.66	**2.90**	1.09	**1.78**	**-3.05**	**2.58**

UK Y-on-Y Growth Data Revisions

Display of y_t^{t+1} and y_t^{t+17}.



UK Y-on-Y Growth Data Revisions



A Time-varying model for data revisions I

- The model describes "mature" data, y_t^{t+l} with respect to an earlier estimate y_t^{t+b} as:

$$y_t^{t+l} = y_t^{t+b} + \beta_t + u_t,$$

  where β_t is a time-varying bias. The disturbance, u_t, characterises the measurement error assumed mean zero, so that $Var(u_t)$ measures the degree of measurement error in the initial release.
- The time-varying bias, β_t, follows a random walk process implying that the bias move slowly over time:

$$\begin{aligned} \beta_t &= \beta_{t-1} + e^{.5(h_0 + w_h \tilde{h}_t)} \zeta_{b,t} \\ \tilde{h}_t &= \tilde{h}_{t-1} + \zeta_{h,t}; \\ & \quad \zeta_{b,t}, \zeta_{h,t} \text{ are both } iidN(0,1). \end{aligned}$$

A Time-varying model for data revisions II

- And the measurement error also has a time-varying volatility:

$$(y_t^{t+l} - y_t^{t+b}) = rev_t^{(l-b)} = \beta_t + e^{.5(g_0 + w_g \tilde{g}_t)} \zeta_{u,t}$$

- We use a Bayes factor approach to check whether we need both stochastic volatility process. The results support the model above for $l = 17$ and $b = 1, 4, 8, 12$.

A Time-varying model for data revisions III

- The model implies a local mean:

$$rev_t^{(l-b)} = \overline{rev}_{t-1}^{(l-b)} + \omega_t$$

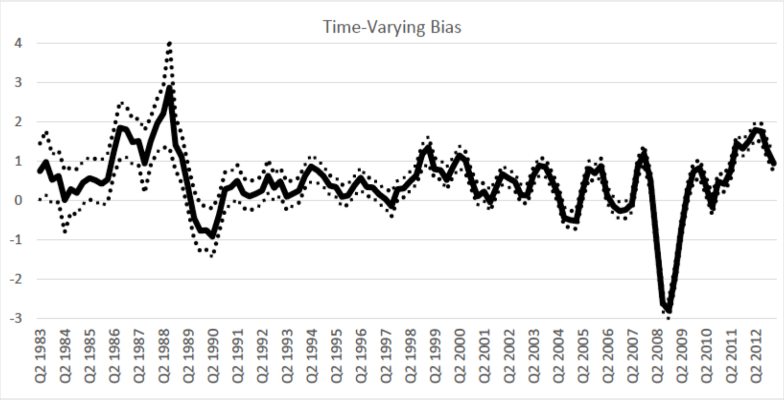
  where ω_t is a MA(1) process with a time-varying parameter θ_t.
- When computing the local mean, more weight is given to the most recent data if $\alpha_t = 1 - \theta_t$ is near to 1:

$$\overline{rev}_t^{(l-b)} = \overline{rev}_{t-1}^{(l-b)} + \alpha_t(rev_t^{(l-b)} - \overline{rev}_{t-1}^{(l-b)}).$$

  Weights are near to 1 if the bias variance is large in comparison to the variance of the measurement error, implying that historical revisions have little information to predict data revisions.

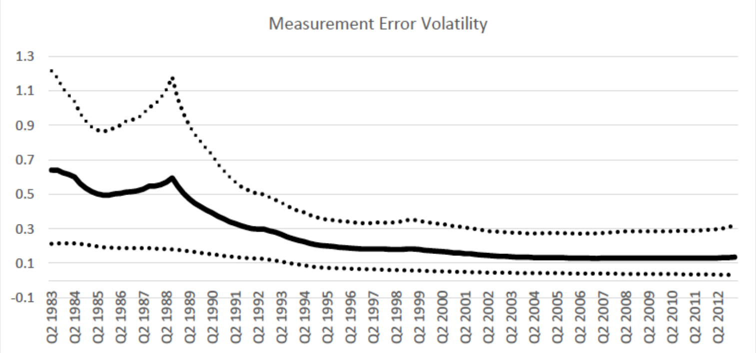
Time-Varying Bias.

Estimates for $y_t^{t+17} - y_t^{t+1}$.



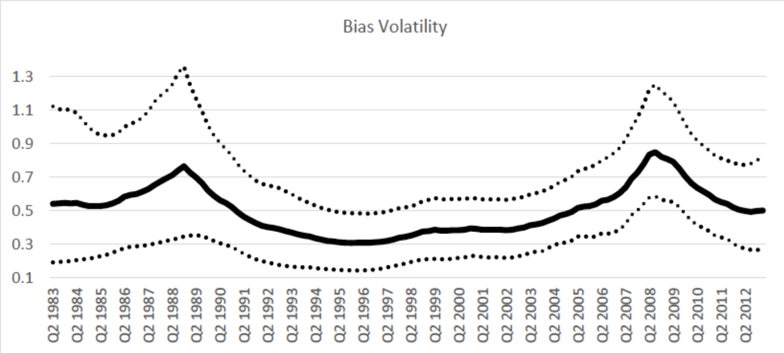
Measurement Error Volatility

Estimates for $y_t^{t+17} - y_t^{t+1}$.



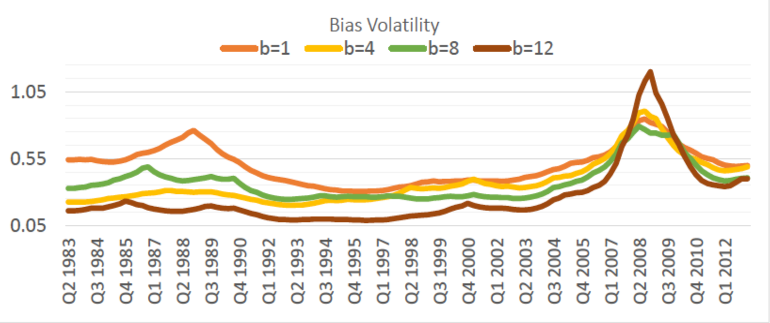
Bias Volatility

Estimates for $y_t^{t+17} - y_t^{t+1}$



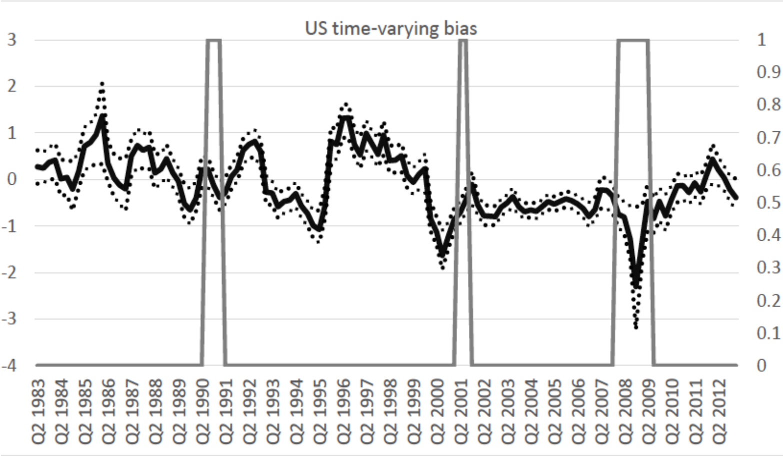
Bias Volatility for later releases

Estimates for:
$(y_t^{t+17} - y_t^{t+1}), (y_t^{t+17} - y_t^{t+4}), (y_t^{t+17} - y_t^{t+8}), (y_t^{t+17} - y_t^{t+12})$



US Data Revisions Time-varying bias.

As for UK data, $l = 17$ and $b = 1$.



Evaluating the Bank of England's Probabilistic Backcasts

- Let $\hat{y}^t_{t-B}, ..., \hat{y}^t_{t-2}, \hat{y}^t_{t-1}$ denote the MPC's point estimate of growth ending in quarter $t-1, ..., t-B$, as announced by the MPC in quarter t; and let $\hat{\sigma}^t_{t-b}, ..., \hat{\sigma}^t_{t-2}, \hat{\sigma}^t_{t-1}$ denote the corresponding set of standard deviation estimates.

Evaluating the Bank of England's Probabilistic Backcasts

- Let $\hat{y}^t_{t-B}, ..., \hat{y}^t_{t-2}, \hat{y}^t_{t-1}$ denote the MPC's point estimate of growth ending in quarter $t-1, ..., t-B$, as announced by the MPC in quarter t; and let $\hat{\sigma}^t_{t-b}, ..., \hat{\sigma}^t_{t-2}, \hat{\sigma}^t_{t-1}$ denote the corresponding set of standard deviation estimates.
- Because estimates are computed after ONS first release, the predicted bias is $\hat{y}^t_{t-1} - y^t_{t-1}$.

Evaluating the Bank of England's Probabilistic Backcasts

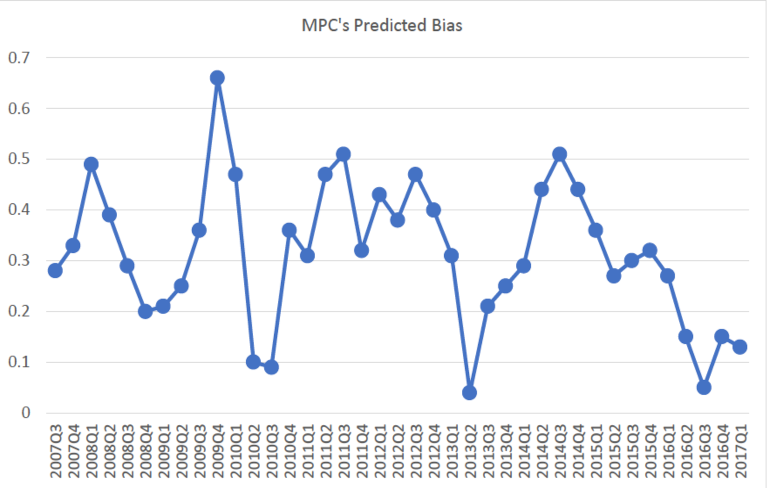
- Let $\hat{y}^t_{t-B}, ..., \hat{y}^t_{t-2}, \hat{y}^t_{t-1}$ denote the MPC's point estimate of growth ending in quarter $t-1, ..., t-B$, as announced by the MPC in quarter t; and let $\hat{\sigma}^t_{t-b}, ..., \hat{\sigma}^t_{t-2}, \hat{\sigma}^t_{t-1}$ denote the corresponding set of standard deviation estimates.
- Because estimates are computed after ONS first release, the predicted bias is $\hat{y}^t_{t-1} - y^t_{t-1}$.
- In general the predicted bias is $\hat{y}^{t+b}_t - y^{t+b}_t$, where y^{t+b}_t is ONS earlier b^{th} estimate and $\hat{y}^{t+b}_t$ is a MPC's prediction for mature GDP values that uses information up to $t+b$.

Evaluating the Bank of England's Probabilistic Backcasts

- Let $\hat{y}^t_{t-B}, ..., \hat{y}^t_{t-2}, \hat{y}^t_{t-1}$ denote the MPC's point estimate of growth ending in quarter $t-1, ..., t-B$, as announced by the MPC in quarter t; and let $\hat{\sigma}^t_{t-b}, ..., \hat{\sigma}^t_{t-2}, \hat{\sigma}^t_{t-1}$ denote the corresponding set of standard deviation estimates.
- Because estimates are computed after ONS first release, the predicted bias is $\hat{y}^t_{t-1} - y^t_{t-1}$.
- In general the predicted bias is $\hat{y}^{t+b}_t - y^{t+b}_t$, where y^{t+b}_t is ONS earlier b^{th} estimate and $\hat{y}^{t+b}_t$ is a MPC's prediction for mature GDP values that uses information up to $t+b$.
- "Mature" values are observed (released by the ONS) at $t+l$: the ONS GDP estimation error is $y^{t+l}_t - y^{t-b}_t$ and the MPC's backcast error is $y^{t+l}_t - \hat{y}^{t+b}_t$.

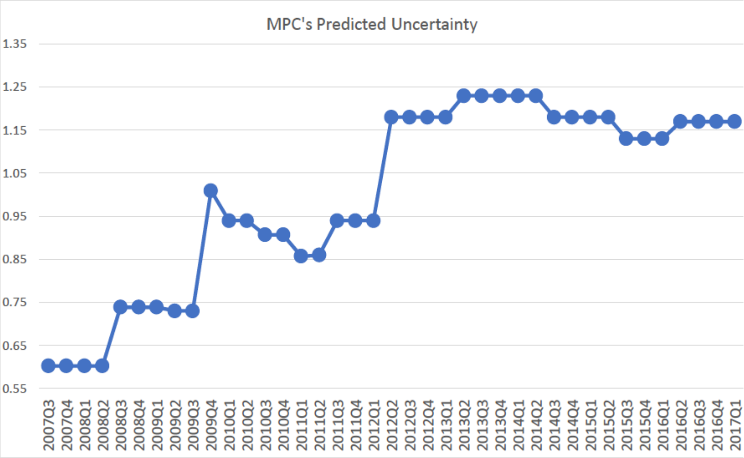
MPC's Predicted bias with b=1

Computed as $\hat{y}_t^{t+1} - y_t^{t+1}$

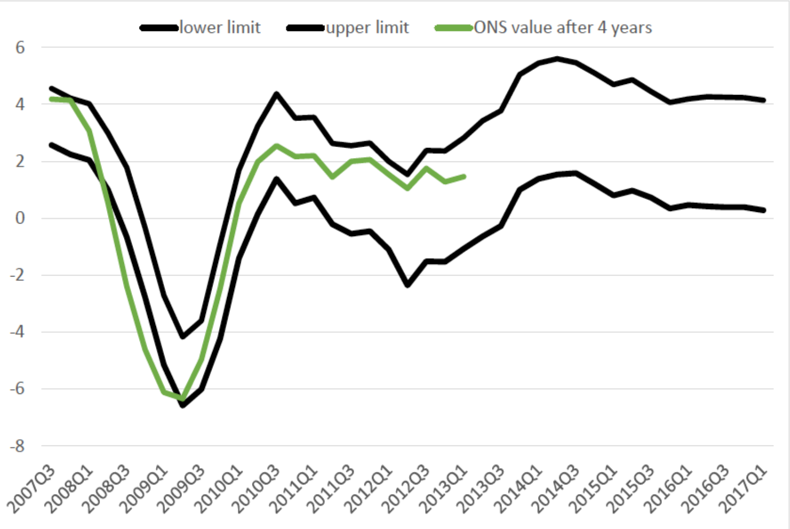


MPC's Predicted Standard Error (Uncertainty) with b=1

$$se(y_t^{t+l} - \hat{y}_t^{t+1})$$



MPC's Backcasts 90% Predicted Interval with b=1



Benchmark Backcasting Model I

- Because time-series models of stationary data converge to the unconditional mean and variance at long horizons, we compute predictions using the recursively updated (in real-time) unconditional mean and standard deviation of the revisions.
- The probabilistic backcasts for the observation t, using information up to $t+b$, which includes a time series of ONS revisions between the l^{th} data release and the b^{th} release for observations up to $t-l+1$ is

$$N(\hat{y}_t^{t+b,unc}, \hat{\sigma}_t^{2,t+b,unc})$$

Benchmark Backcasting Model II

where

$$
\begin{aligned}
\hat{y}_t^{t+b,unc} &= y_t^{t+b} + \hat{\beta}_t^{t+b,unc} \text{ for } t = T-(b-1)+1, ..., T+P \\
\hat{\beta}_t^{t+b,unc} &= \frac{1}{t-l+1} \sum_{\tau=1}^{\tau=t-l+1} rev_\tau^{(l-b)} \\
\hat{\sigma}_t^{t+b,unc} &= \sqrt{\frac{1}{t-l+1} \sum_{\tau=1}^{\tau=t-l+1} \left(rev_\tau^{(l-b)} - \hat{\beta}_t^{t+b} \right)^2} \\
rev_\tau^{(l-b)} &= y_\tau^{\tau+l} - y_\tau^{\tau+b}.
\end{aligned}
$$

Accuracy of GDP Estimates (or Backcasts)

Note that ONS bias with $b = 1$ is 0.33 over the period.

	Bias	RMSE	RMSE Ratio to ONS est.
MPC, b=1	-0.046	1.243	0.931
Uncond., b=1	-0.223	1.335	1.000
MPC, b=4	-0.024	1.138	0.951
Uncond., b=4	-0.034	1.173	0.980
MPC, b=8	-0.070	0.953	0.973
Uncond., b=8	-0.067	0.971	0.991
MPC, b=12	0.092	0.770	0.948
Uncond, b=12	0.139	0.806	0.992
MPC, b=16	-0.025	0.283	0.997
Uncond, b=16	-0.005	0.283	0.997

Accuracy of Revisions Predictive (or Backcasts) Densities

	Logscore	CRPS	90%Cov. p-value	75%Cov. p-value	50%Cov. p-value
MPC, b=1	2.070	0.702	0.279	0.296	0.531
Uncond., b=1	2.118	0.735	0.028	0.136	0.531
MPC, b=4	1.898	0.655	0.798	0.054	0.114
Uncond., b=4	2.631	0.687	0.000	0.000	0.005
MPC, b=8	1.513	0.559	0.103	0.535	0.147
Uncond., b=8	2.055	0.595	0.001	0.000	0.001
MPC, b=12	1.215	0.520	0.175	0.842	0.732
Uncond, b=12	2.533	0.483	0.000	0.000	0.015
MPC, b=16	0.571	0.196	0.289	0.006	0.000
Uncond, b=16	1.166	0.110	0.915	0.024	0.000

Properties of well-calibrated predicted densities I

- Clements (2014) suggests that in a predictive density, that matches the true but unobserved data density, the (*ex ante*) predicted variance is equal to the (*ex post*) average squared prediction error. This implies:

$$E[(y_t^{t+l} - \hat{y}_t^{t+b})^2 | \text{calibration}] = \hat{\sigma}_t^{2,t+b}$$

  for $b = 1, ..., B$ where we set $l = 17$, so that the "prediction horizons" decline with b.

- We extend Clements (2014) and show that

$$E[CRPS_t^b | calibration] = \left(\hat{\sigma}_t^{t+b} / \sqrt{\pi}\right)$$

  where $CRPS_t^b = \hat{\sigma}_t^{t+b} \left[z_t(2\Phi(z_t) - 1) + 2\phi(z_t) - (1/\sqrt{\pi})\right]$ and $z_t = (y_t^{t+l} - \hat{y}_t^{t+b}) / \hat{\sigma}_t^{t+b}$.

Properties of well-calibrated predicted densities II

- And that

$$E\left[\log S_t^b | \text{calibration}\right] = 0.5(1 + \log 2\pi) + \log\left(\hat{\sigma}_t^{t+b}\right),$$

where $\log S_t^b = \frac{(y_t^{t+l} - \hat{y}_t^{t+b})^2}{2\hat{\sigma}_t^{2,t+b}} + \ln(\hat{\sigma}_t^{t+b}) + 0.5\ln(2\pi)$.

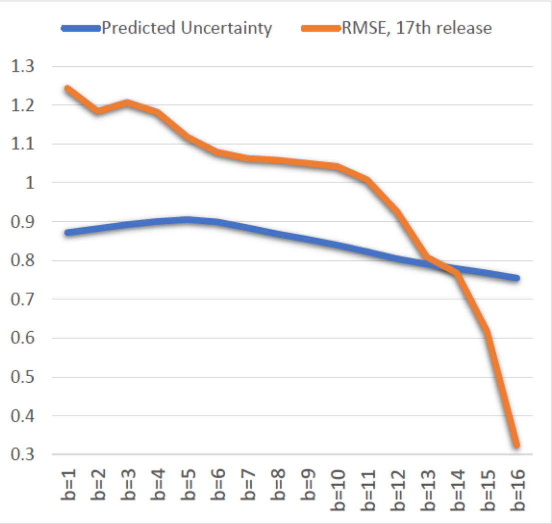
Properties of well-calibrated predicted densities III

- We test whether each null hypothesis holds for MPC's backcasts for $b = 1, ..., 16$ with $l = 17$.
- We use the observed differences for $t = 2007Q3 - 2013Q1$ between the computed measure and its expected values in a t-test strategy.
- The rejection of the null provides evidence that the MPC's backcast densities do not fit well the actual data

T-statistics for the test that the observed accuracy measure is equal to its expected value (MPC backcasts)

	MSE	CRPS	Logscore
b=1	1.34	1.38	1.61
b=2	1.22	1.36	1.47
b=3	1.29	1.45	1.53
b=4	1.19	1.31	1.40
b=5	0.92	0.98	1.20
b=6	0.75	0.82	1.11
b=7	0.86	1.12	1.36
b=8	1.19	1.57	**1.90**
b=9	1.20	1.57	**1.89**
b=10	1.23	1.60	**2.00**
b=11	1.08	1.38	**1.80**
b=12	0.74	1.04	1.43
b=13	0.03	0.41	0.95
b=14	-0.19	0.09	0.79
b=15	-1.20	-1.02	0.07
b=16	**-5.49**	**-4.82**	**-2.90**

Term Structure of Realised and Predicted MPC Backcast Uncertainty



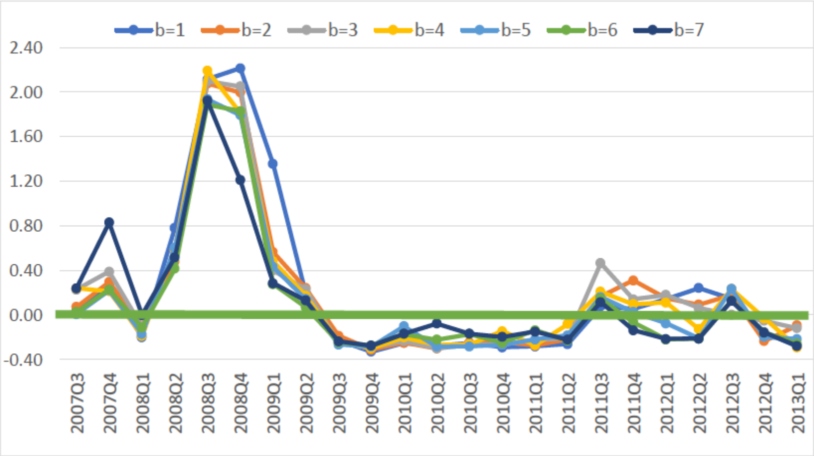
Data Uncertainty using CRPS deviations I

- We measure data uncertainty using:

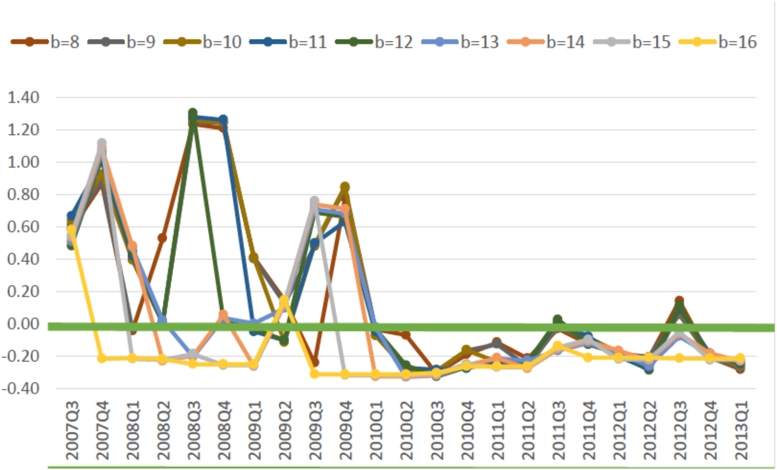
$$d_t^{CRPS^b} = \{\hat{\sigma}_t^{t+b}\left[z_t(2\Phi(z_t) - 1) + 2\phi(z_t) - (1/\sqrt{\pi})\right]\} - \{\hat{\sigma}_t^{t+b}/\sqrt{\pi}\}$$

  where $z_t = (y_t^{t+l} - \hat{y}_t^{t+b})/\hat{\sigma}_t^{t+b}$.
- Rossi et al (2016) suggest that these deviations are caused by differences between realised and predicted risk and are also due to Knightian uncertainty (i.e. the forecaster is unable to characterise completely the probability distribution).
- Jurado et al (2015) argue that proper measurement of uncertainty requires the removal of forecastable components of y_t^{t+l} based on y_t^{t+b}.
- Because $d_t^{CRPS^b}$ removes the effect of predictable data revisions, we propose to use $d_t^{CRPS^b}$ as a measure of data uncertainty.

CRPS deviations for b=1,...,7

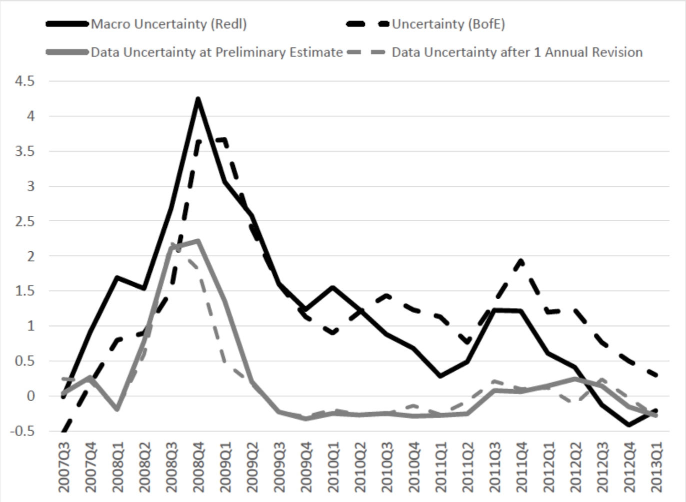


CRPS deviations for b=8,...,16



UK GDP Growth Data Uncertainty and other Macro Uncertainty Measures

Max correlation is at the time of first release and approx. 0.8.



Conclusions I

- We propose a measure of data uncertainty. The measure is calculated for UK GDP growth data; and is based on identifying the component of future data revisions that the Bank of England is unable to predict correctly after observing earlier ONS growth estimates.
- We find that UK data uncertainty rises at the onset of recessions; and is positively correlated with measures of UK macroeconomic uncertainty, such as the measures computed by Redl (2017) and Bank of England (2016).
- Data uncertainty might be interpreted as an additional souce and layer of uncertainty relative to the more traditional macroeconomic uncertainty measures discussed in Bloom (2014).

Conclusions II

- We find that the MPC's point estimates of historical GDP growth are more accurate measures of revised ONS data than the equivalently timed estimates from the ONS themselves.
- We find that the MPC's probabilistic backcasts for GDP growth are, on average, well-calibrated and perform well relative to a benchmark model; but the MPC do appear to have over-estimated (ex ante) data uncertainty for observations in the 2010-13 period. Data revisions to mature ONS data ($b > 8$) are harder to predict, because of the unknown impact of future benchmark revisions.

Conclusions III

- We commend the Bank of England for communicating the (*ex ante*) predictable component of data revisions in their published fan charts;
- and we recommend the ONS reconsiders if and how they communicate the uncertainty associated with their early GDP estimates.
- We do believe, however, that the Bank of England would improve communication further if they stated explicitly what data vintage they seek to forecast.