RES Easter School 2012
The Economics and Econometrics of Forecasting

Jennifer L. Castle
Birmingham University
April 2012

Lecture 4: Nowcasting
Why nowcast?

24 July 2009 ONS official GDP growth data:

**0.8% decline in GDP for 09Q2**

Much worse than anticipated – severe forecast failure.


‘the ONS said that its estimates were even less reliable than normal because the economy’s unpredictability meant its models had “broken down”.’

National Institute (Mitchell, 2009):

*Performance of statistical nowcasting models deteriorated with onset of recession.*

**Current nowcasting methods break down when structural breaks/turning points.**

Consider reasons for nowcasting and implications for how to produce robust nowcasts.
Problems

- **Missing data** – not all disaggregated contemporaneous data available to construct aggregate. Statistical agencies views differ on optimal trade-off between timeliness and accuracy.

- **Measurement error** – ‘flash’ estimates subject to potentially substantial revisions. Not reliable and accurate guide to current conditions.

- **Changing database** – different components unavailable in different periods and missing on non-systematic basis.

- **Breaks** – Nowcasts act as ‘early warning signals’ when they differ radically from the measured series. Rapid action to update/account for breaks, or warn of measurement error.
GDP outturns: initial and latest estimates

Percentage changes on a year earlier

Latest estimates

Initial estimates

Why nowcasting differs from forecasting:

**Contemporaneous Observations**

**Sources of contemporaneous data:**

- Disaggregates available closer to nowcast origin (e.g. retail sales);
- Covariates available at higher frequencies/more timely (e.g. new passenger car registrations, construction output, industrial new orders, road traffic, air passenger numbers, energy consumption);
- Surveys (business/consumer plans and expectations);
- *Google Trends* data (Choi and Varian, 2009);
- Prediction markets (Croxson and Reade, 2008).
**Objective:** nowcast of aggregate $y_T$.  

where:

$$y_t = \sum_{i=1}^{N} w_i y_{i,t},$$

- $y_{i,t}$ disaggregates;
- $w_i$ weights.

Data released with varying time delays: at $T$ some components observed, some unavailable until $T + \delta$.

At $T$:

- $J$ known components;
- $N - J$ unknown components.

$J$ not fixed, sets not uniquely defined.
• Forecast aggregate using aggregate information:

\[ \hat{y}_{T|T-\delta^*} = f \left( Y_{T-1}^0, Z_{T-\delta^*}^0 \right), \]

• Forecast disaggregates unknown at \( T \):

\[ \tilde{y}_{i,T|T-\delta^*} = f \left( y_{i,T-\delta}, Z_{T-\delta^*}^0 \right), \quad i = J + 1, \ldots, N, \]

and aggregate with the known data:

\[ \tilde{y}_{T|T} = \sum_{i=1}^{J} w_i y_{i,T} + \sum_{i=J+1}^{N} w_i \tilde{y}_{i,T|T-\delta^*} \]
Forecast aggregate, conditioning on aggregate and disaggregate information.

- Balanced panel:

\[
\bar{y}_{T|T-\delta} = f \left( Y_{T-\delta}^0, y_{i,T-\delta}^0, Z_{T-\delta}^0 \right), \quad \forall i \in N,
\]

- Unbalanced panel:

\[
\bar{y}_{T|T} = f \left( Y_{T-1}^0; Y_{1,T}; \ldots; Y_{J,T}; Y_{J+1,T-\delta}; \ldots; Y_{N,T-\delta}; Z_{T-\delta}^0 \right),
\]

- results in ‘ragged edge’ problem.
Can be shown that when predicting the aggregate, nothing is lost by directly predicting from disaggregate information, without predicting disaggregates.

\[ y_T = w_1 y_{1,T} + (1 - w_1) y_{2,T} \]  

(2)

Assume \( J = 0 \). DGP for the disaggregates is:

\[ y_{i,t} = \gamma_i' x_{t-1} + \eta_{i,t} \]  

(3)

where \( x_{t-1} = (y_{1,t-1}, \ldots, y_{N,t-1}; z_{t-1})' \) so:

\[ E_{T-1} [y_{i,T} | x_{T-1}] = \gamma_i' x_{T-1} \quad \text{for} \quad i = 1, 2 \]  

(4)
Aggregates versus disaggregates

Aggregating delivers:

\[
E_{T-1}[y_T \mid x_{T-1}] = \left( \sum_{i=1}^{2} w_i \gamma_i' \right) x_{T-1} = \psi' x_{T-1} \tag{5}
\]

Predicting \( y_T \) directly from \( x_{T-1} \) yields:

\[
E_{T-1}[y_T \mid x_{T-1}] = \pi' x_{T-1} \tag{6}
\]

Since the left-hand sides of (5) and (6) are equal:

\[
\pi' x_{T-1} = \psi' x_{T-1} \tag{7}
\]

so nothing is lost by predicting \( y_T \) directly, instead of aggregating component predictions once the same information set \( x_{T-1} \) is used for both.
Hendry and Hubrich (2009) generalize to non-constant weights, changing parameters. Does not mitigate breaks.

**BUT contemporaneous information is available at** $T$ – **unbalanced panel**

- helps distinguish between breaks and measurement error
- especially when breaks occur simultaneously across the disaggregates (or a subset)

Need a combination of forecasting unknown disaggregates, augmented with structural break detection

Current methods – dynamic factor models/MIDAS.
Selecting nowcasting models

Nowcasts required of $N - J$ unknown disaggregates.

GUM:

$$y_{i,t} = \beta' x_{t-1} + \alpha' f_{t-1} + \sum_{j=1}^{T-1} \varsigma_j 1_{t_j=t} + \nu_t, \quad i = J + 1, \ldots, N$$  \hspace{1cm} (8)

- $x_{t-1}$: all available information (lagged disaggregates, survey data, leading indicators)
- $f_{t-1}$: set of $q$ latent common factors ($f_t = \Lambda'y_{d,t}$);
- $1_{t_j=t}$: set of $T - 1$ impulse-indicators.

Selection using Autometrics (Doornik, 2009a, Doornik, 2009b) for more variables than observations (and $\therefore$ perfect collinearity)

Forecasts:

$$\tilde{y}_{i,T|T-1} = \gamma' x^{*}_{T-1} + \theta' f^{*}_{T-1} + \varsigma' d_{T-1}$$  \hspace{1cm} (9)
Nowcasting strategy

If break occurs in \( J \) observed disaggregate series, use information to improve forecast \( \tilde{y}_{i,T|T-1}, \ i = J + 1, \ldots, N. \)

1. Detect whether break occurred at \( T \)

\[
y_{i,T} = \beta' x_{t-1} + \rho' f_{t-1} + \sum_{j=1}^{T} \varsigma_j 1_{t_j = t} + v_t, \quad i = 1, \ldots, J; t = 1, \ldots, T.
\]

(10)

Test whether \( \hat{\varsigma}_T \) significant
Conservative significance level: \( 0.5\% \leq \alpha \leq 0.1\% \)
(Conventional tests low or no power at end-point)
Forecast error:

\[
e_{i,T} = y_{i,T} - \tilde{y}_{i,T|T-1}, \quad i = 1, \ldots, J,
\]
2. If evidence of break at $T$, adjust $N - J$ unknown disaggregates (role of judgment).

Is break thought to be:

- permanent or transitory?
  - measurement error or location shift;
- idiosyncratic or common?
  - correlated with unknown disaggregates at $T$.

Forecasting rule:

$$\hat{y}_{i,T|T} = (1 - I_k) \tilde{y}_{i,T|T-1} + I_k \tilde{y}^*_{i,T|T}, \quad i = J + 1, \ldots, N, \quad (11)$$

where $I_k = 1$ when $k\alpha J \geq p$ for $p = \sum_{i=1}^{J} 1_T$ and $\tilde{y}^*_{i,T|T}$ intercept corrected forecast.
IC forecast:

\[
\tilde{y}_{i,T}^* = \tilde{y}_{i,T|T-1} + \frac{1}{p} \sum_{j=1}^{p} \hat{\varsigma}_{p,T} \tag{12}
\]

Or weighted average based on correlations between the disaggregates.

IC analogous to setting forecast back on track but across disaggregate series as opposed to through time.

Error variance equal to uncorrected error variance.

Contrast to standard intercept correction that sets forecast back on track and doubles the error variance.

Alternative: differencing – doesn’t impose break magnitude but doubles error variance.
Let:

\[ y_{i,T} = \psi_i y_{i,T-1} + v_{i,T} \]  

(13)

- when \( l_k = 0 \): \( \tilde{y}_{i,T|T-1} = \hat{\psi}_i y_{i,T-1} \);
- when \( l_k = 1 \): \( \tilde{y}^*_{i,T|T} = \tilde{y}_{i,T|T-1} + \mu_{p,T} \);

where

\[ \mu_{p,T} = \sum_{j=1}^{p} \hat{\varsigma}_{p,T} \]

Forecast error:

\[
\tilde{v}^*_{i,T} = y_{i,T} - \tilde{y}^*_{i,T|T} = \tilde{v}_{i,T} - \mu_{p,T}
\]  

(14)

\( \tilde{v}_{i,T} \) = forecast error from uncorrected forecast  
\( \mathbb{V} \left[ \tilde{v}^*_{i,T} \right] \approx \mathbb{V} \left[ \tilde{v}_{i,T} \right] \) as \( \mu_{p,T} \) nearly a fixed constant for each \( i \) when \( J \) is large.
Split disaggregates into blocks corresponding to groups of variables (e.g. industrial production, prices, financial variables, interest rates, labour variables, housing market variables, etc.)

Requirements:
- close linkages: breaks likely to spread within block;
- different release timings;
- common trends or cycles for subsets of disaggregates

Apply intercept correction to each block separately.

Strategy is computationally feasible, allows for breaks in-sample and at nowcast origin, employs full information set but relies on some proportion of known disaggregates containing signal about unknown disaggregates
Signal extraction problem at $T$.

If $\tilde{y}_{i,T|T-\delta}$ differs significantly from $y_{i,T}$:
- outlier due to measurement error?
- more permanent location shift?
- combination of both?

**observationally equivalent with one data point**

Measurement errors $\Rightarrow$ autocorrelated residuals **but** only few observations to detect.

**Residual analysis needed at end of sample**
No measurement error: \( t = 1, \ldots, T^e \)

Data measured with error: \( s = T^e, \ldots, T \)

DGP for disaggregates:

\[
y_{i,t} = \psi_i y_{i,t-1} + v_{i,t} \quad \text{for } t = 1, \ldots, T; \ i = 1, \ldots, J
\]  

(15)

\[v_{i,t} \sim \text{IN} \left[0, \sigma^2_{v_i}\right]; \ |\psi_i| < 1.\]

For \( 1, \ldots, T^e \): model coincides with (15)

For \( s = T^e, \ldots, T \) we observe \( y_{i,s} = y_{i,s}^* + \eta_{i,s}. \)

Assume \( \eta_{i,s} \sim \text{IN} \left[0, \sigma^2_{\eta_i}\right]; \ E \left[y_{i,s}^* \eta_{i,t}\right] = 0 \) for all \( s, t. \)

(Systematic measurement error: e.g. \( E[\eta_{i,s}] = \mu \eta_i \neq 0 \))
Residual analysis under measurement error

For \( T^e, \ldots, T \):

\[
y_{i,s} = \psi_i y_{i,s-1} + (v_{i,s} + \eta_{i,s} - \psi_i \eta_{i,s-1}) = \psi_i y_{i,s-1} + e_{i,s}
\]

When \( \psi_i = 1 \), residuals over \( s \):

\[
E[e_{i,s}] \approx 0
\]

\[
V[e_{i,s}] \approx \sigma^2_{v_i} + (1 + \psi_i^2) \sigma^2_{\eta_i}
\]

\[
E[e_{i,s} e_{i,s-1}] = \rho_i \approx \frac{-\psi_i \sigma^2_{\eta_i}}{\sigma^2_{v_i} + (1 + \psi_i^2) \sigma^2_{\eta_i}}
\]

\( \rho_i \) denotes late-onset error autocorrelation (assuming \( \sigma^2_{\eta_i} \) constant as \( s \to T \))

If last few residuals exhibit increase in variance and autocorrelation, more weight placed on measurement error hypothesis

Castle (Oxford)  Forecasting  April 2012  20 / 50
Residual analysis under location shifts

Alternatively, indicator-impulse saturation used to detect late onset shifts
Some cases can be justified *ex ante* (e.g. VAT changes).

**Problem:**
Measurement error and location shifts at $T$ require different forecasting models.

- Measurement error $\Rightarrow$ EWMA schemes optimal
- Location shift $\Rightarrow$ intercept correction and differencing
  
  *But exacerbates impact of measurement errors*

Location shift requires $+$ IC for nowcast period
Measurement error requires $-$ one-off IC to offset error

**Resolving conflict between opposite responses is central to accurate nowcasting**
Can we distinguish between location shifts and measurement errors?

- measurement error at $T$ does not ‘carry forward’, although effects will in dynamic process;
- data at $T$ usually revised: revisions to errors at $T + 1$ informative about source of error from $T$ to $T + 1$;
- next nowcast error (from $T + 1$ to $T + 2$) large if source is location shift, $\therefore$ repeated mis-forecasting indicative of location shift;
- extraneous contemporaneous data help to discriminate: discrepancy from existing models persist or disappear;
- variance of measurement errors usually changes as the forecast origin approaches.
Simplest model:

\[ y_t = y^* + \epsilon_t \]  \hspace{1cm} (16)

where \( \epsilon_t \sim \text{IN} \left[ 0, \sigma^2_\epsilon \right] \).

Three cases:

- \( y^* \) is constant – measurement error;
- \( \epsilon_t = 0 \ \forall t \) but \( y^* \) alters – location shift;
- both \( y^* \) shifts and \( \epsilon_t \neq 0 \)

Nowcast at time \( T \) from estimation sample \( 1, \ldots, T - \delta \) for small \( \delta \)

Sequence of nowcasts as if in real time, at \( T + 1, T + 2 \) etc.
Despite measurement error, 1-step minimum MSE forecasting device:

\[
\hat{y}_{T+1|T} = \bar{y}(T) = \frac{1}{T} \sum_{t=1}^{T} y_t.
\]

Thus:

\[
E_{T+1} \left[ \hat{y}_{T+1|T} \mid \mathcal{I}_{T+1} \right] = y^*
\]

\[
\text{Var}_{T+1} \left[ \hat{y}_{T+1|T} \right] = \sigma^2 \epsilon \left( 1 + \frac{1}{T} \right)
\]

Full-sample estimate \( \bar{y}(T) \) of \( y^\star \) is unbiased predictor, with smallest variance of any sample size choice, which is just \( \frac{1}{T} \) larger than nowcast from the known location \( y^\star \).
2. Location shifts only

Best predictor of $y_{T+1}$ is $\tilde{y}_{T+1}|T = y_T$.

When no location shifts, $\tilde{y}_{T+1}|T = y_T = y^*$ is exact;
When shift at $T$ ($\nabla(T)y^*$) a one-period mistake is made:

$$y_{T+1} - \tilde{y}_{T+1}|T = y_{T+1} - y_T = \nabla(T)y^*$$

nowcast at $T + 2$ unbiased if process remains constant:

$$y_{T+2} - \tilde{y}_{T+2}|T+1 = y_{T+2} - y_{T+1} = 0.$$ 

Best 1-step predictor is lagged value, uses smallest possible sample size – final observation – ignoring all earlier observations.
3. Cross solutions

1. Use $\tilde{y}_{T+1|T} = y_T$ but only measurement error:

$$
E_{T+1} [\tilde{y}_{T+1|T}] = E_{T+1} [y_T] = y^*
$$

$$
\text{Var}_{T+1} [\tilde{y}_{T+1|T}] = 2\sigma^2
$$

Predictor unbiased but variance increases by $(T - 1)/T$.

2. Use $\hat{y}_{T+1|T}$ when $\epsilon_t = 0 \ \forall t$ but location shift $(\nabla_{(\tau)}y^*)$:

$$
E_{T+1} [y_{T+1} - \hat{y}_{T+1|T}] = \frac{\tau^* \nabla_{(\tau^*)}y^*}{T}
$$

$\bar{y}(T)$ is biased predictor – impact of in-sample break under-estimated when not modelled. Either model break or use rolling sample spanning post-break period.
DGP: \( \hat{y}_{T+1} = y_a^* + \hat{\epsilon}_{T+1} \) and \( \hat{y}_{T+2} = y_a^* + \hat{\epsilon}_{T+2} \) where no unmodelled in-sample shifts, but:

\[
y_a^* = y^* + \nabla_{(T+1)} y^*
\]

and after data revision at \( T + 2 \):

\[
y_{T+1} = y_a^* + \epsilon_{T+1}
\]

- \( \bar{y}(T) \) minimum MSE estimator of \( y^* \), with variance \( \sigma_{\epsilon}^2 T^{-1} \) on average;
- \( y_{T+1} - \hat{y}_{T+1} \) estimates revision error;
- \( \hat{y}_{T+1} - y_T \) and \( y_{T+1} - y_T \) estimate \( \nabla_{(T+1)} y^* \) imprecisely;
- \( V_{T+1} [\hat{\epsilon}_{T+1}] \) and \( V_{T+2} [\hat{\epsilon}_{T+2}] \) larger than \( \sigma_{\epsilon}^2 \)
\((y_{T+1} + \ddot{y}_{T+2})/2\) estimates \(y^*_a\) with variance of \(\frac{1}{4} (\sigma^2_\epsilon + V_{T+2}[\ddot{\epsilon}_{T+2}])\), combining with \(\bar{y}\) estimated up to \(T\), and the estimate of \(\nabla(T+1)y^*\) gained from \(y_{T+1} - y_T\) yields:

\[
\tilde{y}^*_a = \frac{1}{2} \left( \bar{y}(T) + (y_{T+1} - y_T) + \frac{1}{2} (y_{T+1} + \ddot{y}_{T+2}) \right) 
\]

with:

\[
V_{T+2}[\tilde{y}^*_a] = \frac{1}{4} \left( \sigma^2_\epsilon \left( 2 + \frac{1}{T} \right) + \frac{1}{4} \left( \sigma^2_\epsilon + V_{T+2}[\ddot{\epsilon}_{T+2}] \right) \right) 
\]

Weighted estimator (18) has lower variance under certain conditions, see Castle and Hendry (2010).
Signal extraction suggests using both latest \(y_{T+1}\) and \(y_T\), where weights vary with measurement error variance.
Empirical application from Castle, Fawcett, and Hendry (2009). Compute nowcasts of Euro-area quarterly GDP growth. Quarterly observations indexed by $t$; $\tau$ denotes the monthly index, with $t = 3\tau$.

Three releases:
Flash estimate $\approx 43$ days after reference quarter;
Two revised releases in following consecutive months.

Denote releases as vintages:
- $y^v_1$ released at $\tau + 2$
- $y^v_2$ released at $\tau + 3$
- $y^v_3$ released at $\tau + 4$

Survey data – 0 publication lag
Other data (e.g. industrial production, financial variables) released with intermediate lag of between 1 and 3 months.
<table>
<thead>
<tr>
<th>Label</th>
<th>Description</th>
<th>Lag release</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Y_t$</td>
<td>real GDP, million, constant prices</td>
<td>2,3,4</td>
</tr>
<tr>
<td>$IP_t$</td>
<td>industrial production index (NSA)</td>
<td>3</td>
</tr>
<tr>
<td>$IPC_t$</td>
<td>industrial production index for construction (NSA)</td>
<td>3</td>
</tr>
<tr>
<td>$SCI_t$</td>
<td>service sector confidence indicator (survey)</td>
<td>0</td>
</tr>
<tr>
<td>$RS_t$</td>
<td>retail trade index, except motor vehicles, constant prices</td>
<td>2</td>
</tr>
<tr>
<td>$CARS_t$</td>
<td>new passenger car registrations, total</td>
<td>2</td>
</tr>
<tr>
<td>$MCI_t$</td>
<td>industry confidence indicator (survey)</td>
<td>0</td>
</tr>
<tr>
<td>$ESI_t$</td>
<td>economic sentiment indicator (base=100)</td>
<td>0</td>
</tr>
<tr>
<td>$CCI_t$</td>
<td>consumer confidence indicator (survey)</td>
<td>0</td>
</tr>
<tr>
<td>$RCI_t$</td>
<td>retail trade confidence indicator (survey)</td>
<td>0</td>
</tr>
<tr>
<td>$EER_t$</td>
<td>real effective exchange rate, CPI deflated, core group</td>
<td>1</td>
</tr>
<tr>
<td>$EUROX_t$</td>
<td>Dow Jones Euro Stoxx Broad stock exchange index</td>
<td>1</td>
</tr>
<tr>
<td>$OECDLI_t$</td>
<td>OECD composite leading indicator, Euro area, trend restored</td>
<td>0</td>
</tr>
<tr>
<td>$EUROCOIN_t$</td>
<td>Eurocoin indicator</td>
<td>0</td>
</tr>
<tr>
<td>$UR_t$</td>
<td>unemployment rate, total</td>
<td>2</td>
</tr>
<tr>
<td>$M1_t$</td>
<td>Index of notional stock, money M1</td>
<td>2</td>
</tr>
<tr>
<td>$SPREAD_t$</td>
<td>$=(3MTB-10YB)/100$</td>
<td>1</td>
</tr>
</tbody>
</table>
Calculate nowcasts for period 2003Q2–2008Q1, (20 observations).

For each quarter, compute 3 nowcasts of quarterly GDP growth;

- \( H_1 \) for month at end of reference quarter;
- \( H_2 \) for month after end of reference quarter;
- \( H_3 \) for second month after end of reference quarter.
## Timing of nowcasts and data releases

<table>
<thead>
<tr>
<th></th>
<th>M1</th>
<th>M2</th>
<th>M3</th>
<th>M4</th>
<th>M5</th>
<th>M6</th>
<th>M7</th>
<th>M8</th>
<th>M9</th>
<th>M10</th>
<th>M11</th>
<th>M12</th>
</tr>
</thead>
<tbody>
<tr>
<td>Q1</td>
<td>$H_1$</td>
<td>$H_2$</td>
<td>$H_3$</td>
<td>$y_t^{v_1}$</td>
<td>$y_t^{v_2}$</td>
<td>$y_t^{v_3}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Q2</td>
<td>$H_1$</td>
<td>$H_2$</td>
<td>$H_3$</td>
<td>$y_t^{v_1}$</td>
<td>$y_t^{v_2}$</td>
<td>$y_t^{v_3}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Q3</td>
<td>$y_t^{v_3}$</td>
<td>$H_1$</td>
<td>$H_2$</td>
<td>$H_3$</td>
<td>$y_t^{v_1}$</td>
<td>$y_t^{v_2}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Q4</td>
<td>$H_2$</td>
<td>$H_3$</td>
<td>$y_t^{v_1}$</td>
<td>$y_t^{v_2}$</td>
<td>$y_t^{v_3}$</td>
<td>$H_1$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Empirical Specifications

[A] Benchmark quarterly univariate models:

\[ H_1 : \Delta \hat{y}_t = f(\Delta y_{v1}^{t-1}, \ldots, \Delta y_{v1}^{t-4}; \Delta y_{v2}^{t-1}, \ldots, \Delta y_{v2}^{t-4}; \Delta y_{v3}^{t-2}, \ldots, \Delta y_{v3}^{t-4}) \]
\[ H_2 : \Delta \hat{y}_t = f(\Delta y_{v1}^{t-1}, \ldots, \Delta y_{v1}^{t-4}; \Delta y_{v2}^{t-1}, \ldots, \Delta y_{v2}^{t-4}; \Delta y_{v3}^{t-1}, \ldots, \Delta y_{v3}^{t-4}) \]
\[ H_3 : \Delta \hat{y}_t = f(\Delta y_{v1}^{t}, \ldots, \Delta y_{v1}^{t-4}; \Delta y_{v2}^{t-1}, \ldots, \Delta y_{v2}^{t-4}; \Delta y_{v3}^{t-1}, \ldots, \Delta y_{v3}^{t-4}) \]

[B] Benchmark quarterly models with covariates:
Conditioning variables \( x_t = (\Delta ip_t, \Delta ipc_t, \Delta SCI_t, \Delta rs_t, \Delta CARS_t, \Delta MCI_t, \Delta ESI_t, \Delta CCI_t, \Delta RCI_t, \Delta eer_t, \Delta eurox_t, \Delta oecdli_t, \Delta EUROCOIN_t, \Delta ur_t, \Delta m1_t, \text{SPREAD}_t) \), and \( (x_t^{r1}, x_t^{r2}, x_t^{r3}) \).

[C] Disaggregate nowcasts

1-step ahead forecasts from recursively-selected models for each horizon.
1. Obtain forecasts for monthly variables released with lag
   Automatic Gets with IIS at $\alpha = 1\%$
   Direct forecasts, depending on publication lag
   Models selected and estimated recursively
   Record retained final observation impulses
   Also test for final observation impulses in contemporaneous data (surveys)

2. Compute nowcasts of GDP growth
   Create quarterly time series for monthly variables:

   $$\mathbf{x}_{t}^{r1} = x_{\tau-2}, x_{\tau-5}, x_{\tau-8}, \ldots$$

   $$\mathbf{x}_{t}^{r2} = x_{\tau-1}, x_{\tau-4}, x_{\tau-7}, \ldots$$

   $$\mathbf{x}_{t}^{r3} = x_{\tau}, x_{\tau-3}, x_{\tau-6}, \ldots$$
Methodology

Form GUM with all three quarterly series – avoids aggregation issue and allows all monthly data to be included in quarterly model

GUM includes all in-sample data for the conditioning variables and latest available vintage of GDP growth.

Models selected recursively with IIS for each nowcast origin and each nowcast horizon

Nowcasts computed by plugging in forecasts for variables selected but unknown at nowcast horizon.

Nowcasts compared to actuals given by final available vintage of data, (December 2008).

1 Adjustments made if significant impulses at $T$. 
### Stage 1: GUM specification

<table>
<thead>
<tr>
<th>Forecast</th>
<th>GUM Variables</th>
<th>ESE</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta \hat{ip}_\tau$</td>
<td>$\Delta ip_{\tau-3}, \ldots, \tau-12; \Delta ipc_{\tau-3}, \ldots, \tau-12; SCI_{\tau}, \ldots, \tau-12; C; S; l$</td>
<td>1.02%</td>
<td>1.32%</td>
</tr>
<tr>
<td>$\Delta \hat{ipc}_\tau$</td>
<td>$\Delta ip_{\tau-3}, \ldots, \tau-12; \Delta ipc_{\tau-3}, \ldots, \tau-12; SCI_{\tau}, \ldots, \tau-12; C; S; l$</td>
<td>2.04%</td>
<td>3.83%</td>
</tr>
<tr>
<td>$\Delta rs_\tau$</td>
<td>$\Delta rs_{\tau-2}, \ldots, \tau-12; \Delta CARS_{\tau-2}, \ldots, \tau-12; \Delta ip_{\tau-3}, \ldots, \tau-12; \Delta ipc_{\tau-3}, \ldots, \tau-12; C; l$</td>
<td>0.59%</td>
<td>0.63%</td>
</tr>
<tr>
<td>$\Delta \hat{CARS}_\tau$</td>
<td>$\Delta rs_{\tau-2}, \ldots, \tau-12; \Delta CARS_{\tau-2}, \ldots, \tau-12; \Delta ip_{\tau-3}, \ldots, \tau-12; \Delta ipc_{\tau-3}, \ldots, \tau-12; C; l$</td>
<td>2.81%</td>
<td>3.41%</td>
</tr>
<tr>
<td>$\Delta eer_\tau$</td>
<td>$\Delta eer_{\tau-1}, \ldots, \tau-12; \Delta eurox_{\tau-1}, \ldots, \tau-12; SPREAD_{\tau-1}, \ldots, \tau-12; C; l$</td>
<td>1.30%</td>
<td>1.08%</td>
</tr>
<tr>
<td>$\Delta eurox_\tau$</td>
<td>$\Delta eer_{\tau-1}, \ldots, \tau-12; \Delta eurox_{\tau-1}, \ldots, \tau-12; SPREAD_{\tau-1}, \ldots, \tau-12; C; l$</td>
<td>2.22%</td>
<td>3.33%</td>
</tr>
<tr>
<td>$\Delta spread_\tau$</td>
<td>$\Delta eer_{\tau-1}, \ldots, \tau-12; \Delta eurox_{\tau-1}, \ldots, \tau-12; SPREAD_{\tau-1}, \ldots, \tau-12; C; l$</td>
<td>0.14%</td>
<td>0.16%</td>
</tr>
<tr>
<td>$\Delta ur_\tau$</td>
<td>$\Delta ur_{\tau-2}, \ldots, \tau-12; \Delta rs_{\tau-2}, \ldots, \tau-12; \Delta ip_{\tau-3}, \ldots, \tau-12; \Delta ipc_{\tau-3}, \ldots, \tau-12; ESI_{\tau}, \ldots, \tau-12; C; l$</td>
<td>0.35%</td>
<td>0.56%</td>
</tr>
<tr>
<td>$\Delta m1_\tau$</td>
<td>$\Delta m1_{\tau-2}, \ldots, \tau-12; SPREAD_{\tau-1}, \ldots, \tau-12; \Delta ip_{\tau-3}, \ldots, \tau-12; \Delta ipc_{\tau-3}, \ldots, \tau-12; C; l$</td>
<td>0.47%</td>
<td>0.89%</td>
</tr>
</tbody>
</table>
Stage 1: GUM specification

GUM includes: $SCI_{t-i}^r$, $MCI_{t-i}^r$, $ESI_{t-i}^r$, $CCI_{t-i}^r$, $RCI_{t-i}^r$, $SPREAD_{t-i}^r$, $\Delta ip_{t-i}^r$, $\Delta ipc_{t-i}^r$, $\Delta rs_{t-i}^r$, $\Delta CARS_{t-i}^r$, $\Delta eer_{t-i}^r$, $\Delta eurox_{t-i}^r$, $\Delta oecdli_{t-i}^r$, $\Delta ur_{t-i}^r$, $\Delta EUROCOIN_{t-i}^r$, $\Delta m1_{t-i}^r$, for $i = 0, \ldots, 2$ and $j = 1, 2, 3$, an intercept and impulse indicator dummies.

Also LDVs:

$$H_1 : \Delta y_{v1}^{t-1}, \Delta y_{v1}^{t-2}; \Delta y_{v2}^{t-1}, \Delta y_{v2}^{t-2}; \Delta y_{v3}^{t-1}, \Delta y_{v3}^{t-2}$$

$$H_2 : \Delta y_{v1}^{t-1}, \Delta y_{v1}^{t-2}; \Delta y_{v2}^{t-1}, \Delta y_{v2}^{t-2}; \Delta y_{v3}^{t-1}, \Delta y_{v3}^{t-2}$$

$$H_3 : \Delta y_{v1}^{t-1}, \Delta y_{v1}^{t-2}; \Delta y_{v2}^{t-1}, \Delta y_{v2}^{t-2}; \Delta y_{v3}^{t-1}, \Delta y_{v3}^{t-2}$$

150–152 variables + $T$ indicator dummies.

Models selected recursively at $\alpha = 1\%$
Stage 2: computing nowcasts

Nowcasts computed as:

\[ \Delta \hat{y}_{t}^{H_k} = \hat{\beta}' \bar{x}_t + \hat{\gamma}' \tilde{x}_t + \hat{\delta}' \iota_t \]  

(19)

- \( \bar{x}_t \) – retained variables known at \( t \) for horizon \( k \);
- \( \tilde{x}_t \) – forecasts for retained variables unknown at \( t \) for horizon \( k \);
- \( \iota_t \) – retained impulse indicators.

[C1]  *Ex post* nowcasts – all disaggregates known
[C2] Disaggregate nowcasts (19)
[C3] Double differenced device: \( \tilde{x}_\tau = x_{\tau-l} \)
### Results

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C1</th>
<th>C2</th>
<th>C3</th>
</tr>
</thead>
<tbody>
<tr>
<td>$H_1$</td>
<td>0.2951</td>
<td>0.9823</td>
<td>0.4340</td>
<td>0.7994</td>
<td>0.7531</td>
</tr>
<tr>
<td>$H_2$</td>
<td>0.3056</td>
<td>1.2245</td>
<td>0.4808</td>
<td>0.6372</td>
<td>0.6222</td>
</tr>
<tr>
<td>$H_3$</td>
<td>0.1486</td>
<td>1.0372</td>
<td>0.8320</td>
<td>0.8320</td>
<td>0.8320</td>
</tr>
</tbody>
</table>

**Table:** Actual RMSE for [A] and ratio of RMSE to the univariate benchmark model [A] for [B] and [C].
MAE and RMSE for nowcasting models

Mean Absolute Error (%)

RMSE (%)

H1  H2  H3

A  B  C1  C2  C3

A  B  C1  C2  C3

0.025  0.050  0.075

0.1  0.2  0.3

Castle (Oxford)
Higher-frequency monthly data yields smaller RMSE, particularly over short horizons

Main benefits come from:
- rapid incorporation of information available at the monthly frequency;
- accounting for outliers using IIS;
- use of recursive selection and estimation to update models rapidly.

Little benefit to well-specified econometric models to forecast the monthly indicators as opposed to robust forecasting device such as DDD.
Revisions

<table>
<thead>
<tr>
<th></th>
<th>$\Delta y_t^{v_1} - \Delta y_t^{v_2}$</th>
<th>$\Delta y_t^{v_1} - \Delta y_t^{v_3}$</th>
<th>$\Delta y_t^{v_1} - \Delta y_t^{o_f}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>ME (%)</td>
<td>0.0045</td>
<td>-0.0059</td>
<td>-0.0674</td>
</tr>
<tr>
<td>SD (%)</td>
<td>0.0214</td>
<td>0.0391</td>
<td>0.1583</td>
</tr>
</tbody>
</table>

**Table:** Magnitude of revisions over nowcast horizon

Substantial measurement errors in the first few vintages of data

Little information content in the revisions initially.

In nowcasting context, detecting measurement errors close to nowcast origin is difficult.
Revisions to GDP growth

\[
\Delta y^v_f (\Delta y^v_1 - \Delta y^v_2) (\Delta y^v_1 - \Delta y^v_3) (\Delta y^v_1 - \Delta y^v_f)
\]
Significant impulses at $\alpha = 1\%$:

\[
\begin{align*}
\Delta ipc_\tau &= 2005(12); 2006(1) \\
\Delta CARS_\tau &= 2005(5); 2005(6) \\
MCI_\tau &= 2003(12) \\
ESI_\tau &= 2003(12) \\
\Delta ur_\tau &= 2006(4); 2007(7); 2007(9); 2008(1) \\
\Delta m1_\tau &= 2005(1); 2005(6); 2006(12) \\
SPREAD_\tau &= 2007(8)
\end{align*}
\]

No impulses for $\Delta ip_\tau, SCI_\tau, \Delta rs_\tau, CCI_\tau, RCI_\tau, \Delta eer_\tau, \Delta eurox_\tau, \Delta oecdli_\tau$ and $\Delta EUROCOIN_\tau$. 
Monthly impulses at $\alpha = 1\%$
Recall rule:

\[ \Delta \hat{y}_t = (1 - I_k) \Delta \tilde{y}_t + I_k \Delta \tilde{y}_t^* \]  

- \( \Delta \tilde{y}_t \) nowcasts obtained from [C2];
- \( \Delta \tilde{y}_t^* \) DDD given by:

\[
\begin{align*}
\Delta \tilde{y}_t^* &= \begin{cases} 
\Delta y_{v2}^{t-1} & \text{for } H_1 \\
\Delta y_{v3}^{t-1} & \text{for } H_2 \\
\Delta y_{v1}^{t-1} & \text{for } H_3 
\end{cases}
\end{align*}
\]

<table>
<thead>
<tr>
<th></th>
<th>C2</th>
<th>C2-adjust</th>
</tr>
</thead>
<tbody>
<tr>
<td>( H_1 )</td>
<td>0.2359</td>
<td>0.2327</td>
</tr>
<tr>
<td>( H_2 )</td>
<td>0.1948</td>
<td>0.2146</td>
</tr>
<tr>
<td>( H_3 )</td>
<td>0.1236</td>
<td>0.1603</td>
</tr>
</tbody>
</table>
Nowcasting differs significantly from forecasting: problems of missing data, measurement errors, changing database, and breaks.

Location shifts induce nowcast failure, but interact with measurement errors to make discrimination difficult in the available time horizon.

Methodology includes Gets recursive selection for many covariates, higher frequency data, in-sample and end-point break detection, robust devices.

Application suggests substantial gains to flash estimates.

Apparent ‘break down’ of the ONS’s current models, reported by the Financial Times, shows the difficulty of nowcasting in times of economic uncertainty and structural change.


