Producing forecasts with DSGE models:

Issues and solutions

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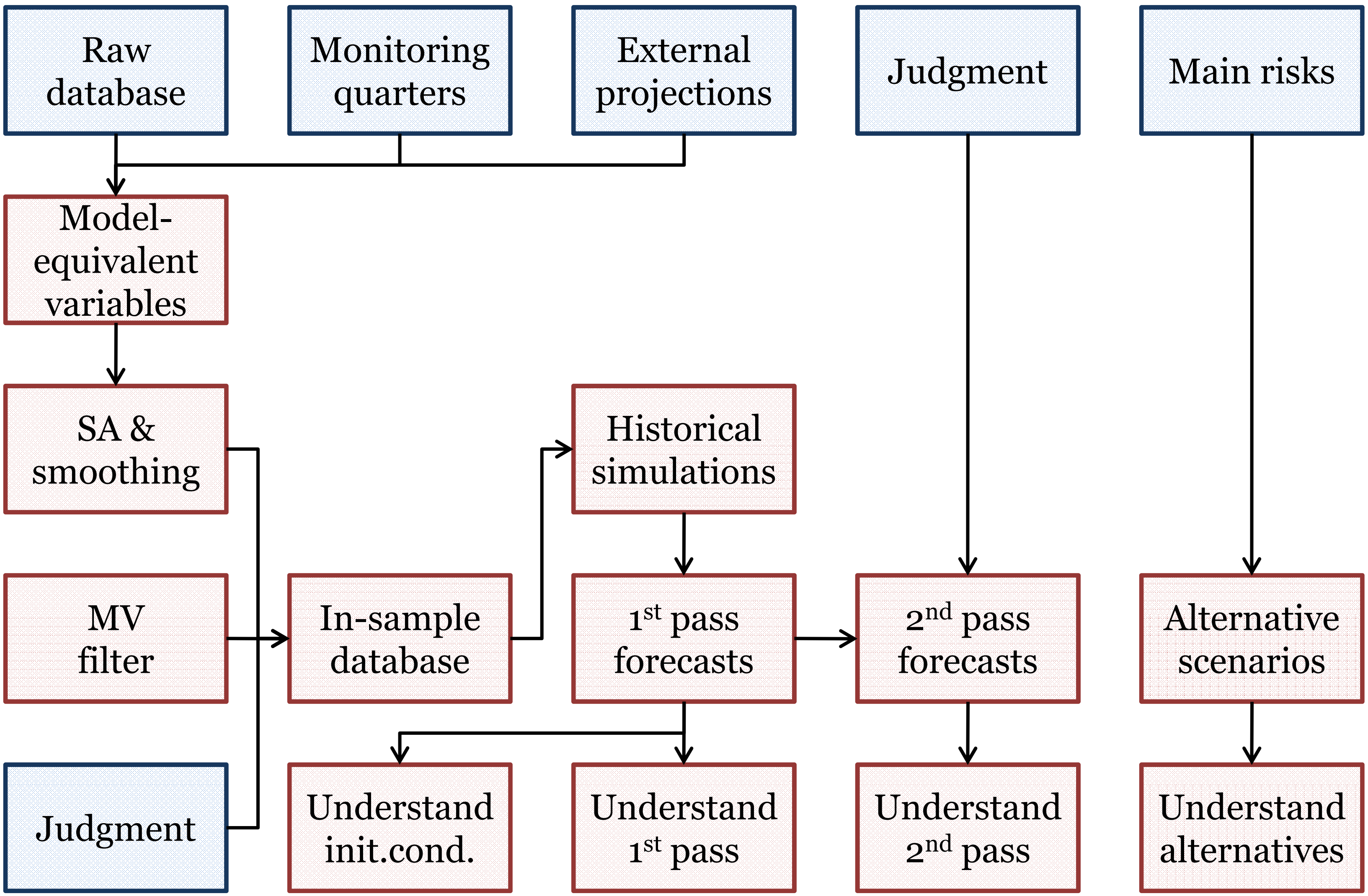
DSGE forecast production at RBNZ



Some of the issues (and solutions)

1. Treating stochastic trends

2. Adding judgment to DSGE forecasts

3. Communicating DSGE forecasts

1. Stochastic trends

- Data typically suggest many more than one common real trend
- How we treat stochastic trends determines how we set up initial conditions for forecasts
- Some of them important for monetary policy, e.g. relative price of tradables / non-tradables

1. Stochastict trends: Two types of solutions

Outside	**Inside**
build a stationary model pre-filter data accordingly choose univariate or multivariate methods	introduce a number of unit roots in the model use sector-specific productivities et c. Kalman filter with diffuse initial condition

1. Stochastic trends: Inside solution

- BGP models with multiple stochastic trends
- No need to stationarise model: first- order accurate solution valid with unit roots retained
- Taylor (log-)expansion around a snapshot of BGP at an arbitrary date; Taylor coefficients independent of that date
- Preferable form

$$\begin{bmatrix} a_t \\ x_t^f \end{bmatrix} = \begin{bmatrix} T & 0 \\ F & 0 \end{bmatrix} \begin{bmatrix} a_{t-1} \\ x_{t-1}^f \end{bmatrix} + R\,e_t \qquad T := \begin{bmatrix} I & T_1 \\ 0 & T_2 \end{bmatrix}$$

$$x_t^b = U\,a_t$$

1. Stochastic trends: Preferences & technology

- Stochastic trends in relative prices and real quantities
  - sector-specific productivities
  - sector-specific iceberg costs, etc.
- Nominal expenditure ratios must stable in the long run (for the approximate solution to hold)
- Implications for elasticities of substitution:
  - unitary in long run
  - reduced in short run by deep habit, adjustment costs, etc.

1. Stochastic trends: Example of utility function

- Tradables and non-tradables driven by distinct unit-root productivity processes (not cointegrated)
- Utility with consumption of tradables and non-tradables

$$\max \mathrm{E}_0 \sum \beta^t \left(\log \Gamma_t + \cdots\right)$$

$$\Gamma_t := \left(C_t^\tau - \chi C_{t-1}^\tau\right)^\omega \left(C_t^n - \chi C_{t-1}^n\right)^{1-\omega}$$

1. Stochastic trends: Curse of dimensionality

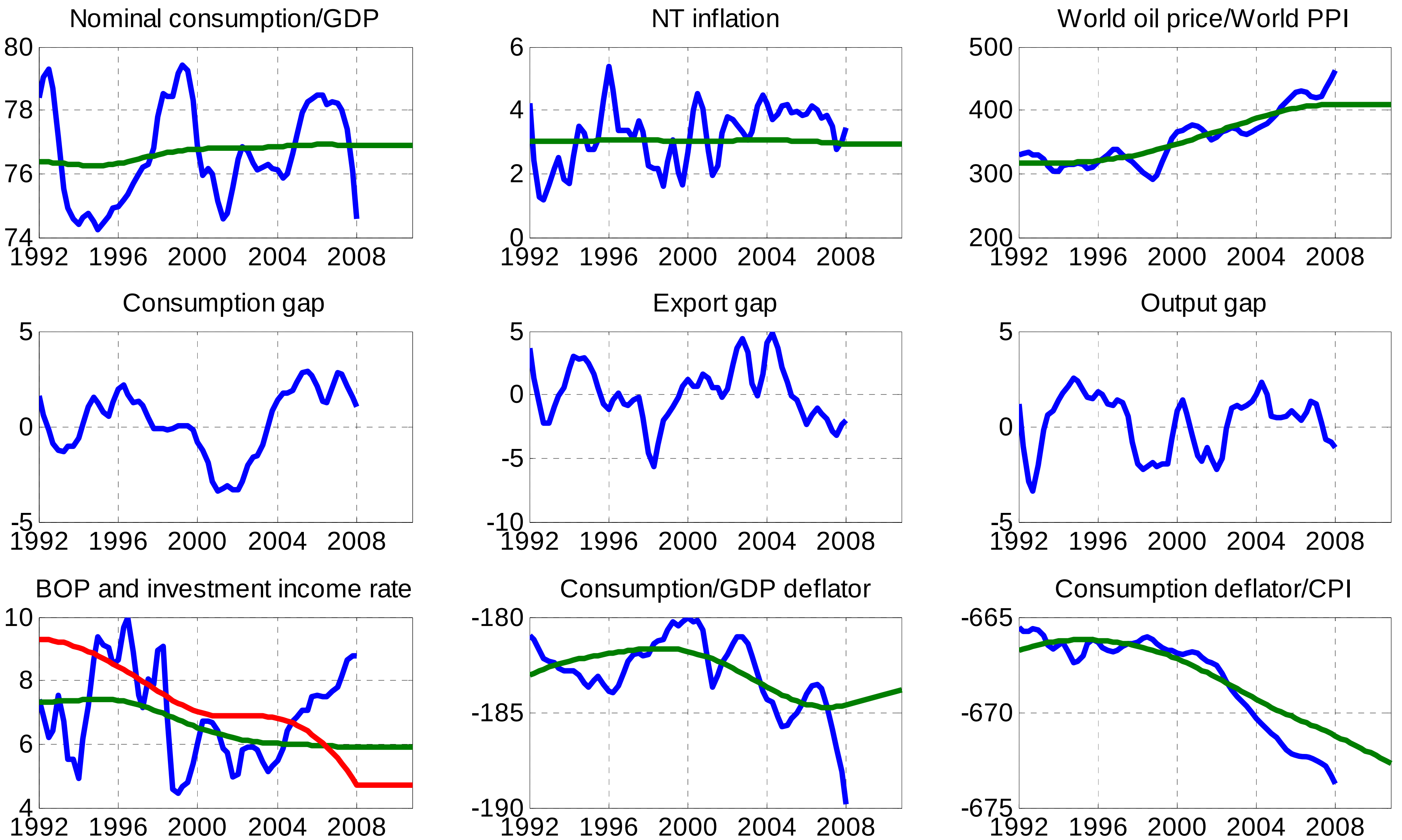
- KITT has more than 20 observables, very few combinations pass co-integration tests
- Demand for pre-filtering (MPC & governor): previous model's legacy
- No unique/universal trend-cycle decomposition within DSGEs
- Pragmatic solution?
  - include only some (=policy important) trends
  - pre-filter remaining trends
  - use MV filters with some consistency imposed

1. Stochastic trends: Designing MV filters

- MV filter with I(2) (HP-like) trends
- NIPA identities and other definitions
  - e.g. long-run sustainability of current account
- Would be identical to univariate filters…
- …unless we start imposing tunes/judgment:

Automatic	**Forecast-specific**
stabilising trends in e.g. • nominal ratios • growth and interest rates in pre-sample and post-sample	tuning e.g. • gaps in GDP components • growth rates in relative prices

1. Stochastic trends: Example of MV filter



2. Adding judgment: Why?

- Core (DSGE) projection models must have good forecasting properties to inform policy decisions
- …but staff & policymakers
  - process information in many other different ways
  - have access to off-model information
- Baseline needs to be *staff projection* combining many pieces of information rather than *model simulation*
- Governor signs the baseline and the forecasts need to reflect his beliefs

2. Adding judgment: What kind?

Structural judgment Conditional on distribution of particular structural shocks	**Reduced-form judgment** Conditional on distributions of particular endogenous variables

Unanticipated mode Future judgment not foreseen	**Anticipated mode** Future judgment foreseen

Hard conditions Judgment imposed as a single point	**Density conditions** Judgment imposed as a distribution

Reduced-form judgment:

Exactly determined Number of judgment conditions = number of shocks backed out	**Underdetermined** Number of judgment conditions = number of shocks backed out

2. Adding judgment: How?

- Structural & unanticipated: Rather trivial…

$$x_t = T\, x_{t-1} + R\, e_t$$

- Structural & anticipated: Solution needs to be expanded forward

$$x_t = T\, x_{t-1} + R_0\, e_t + R_1\, \mathrm{E}_t\left[e_{t+1}\right] + \cdots + R_k\, \mathrm{E}_t\left[e_{t+k}\right]$$

- Reduced-form & unanticipated: Equivalent to Kalman filter

$$x_t = T\, x_{t-1} + R\, e_t$$

$$C_t\, x_t = y_t + \omega_t$$

2. Adding judgment: How?

- Reduced-form & anticipated, point forecast: Extension of Waggoner-Zha for RE and uncertainty in initial conditions

$$x_t = T\, x_{t-1} + R_0\, e_t + R_1\, \mathrm{E}_t\left[e_{t+1}\right] + \cdots + R_k\, \mathrm{E}_t\left[e_{t+k}\right]$$

$$C_t\, x_t = y_t + \omega_t$$

- Find likelihood-maximising paths for

$$z = \left[x'_{t-1} \quad e'_t \cdots e'_{t+k} \quad \omega'_t \cdots \omega'_{t+k}\right]'$$

- Solve

$$\min z'\,\Omega^{+} z \quad \text{s.t.} \quad C\,x = y + \omega \;\Rightarrow\; D\,z = d$$

- Exactly determined solution independent of Ω

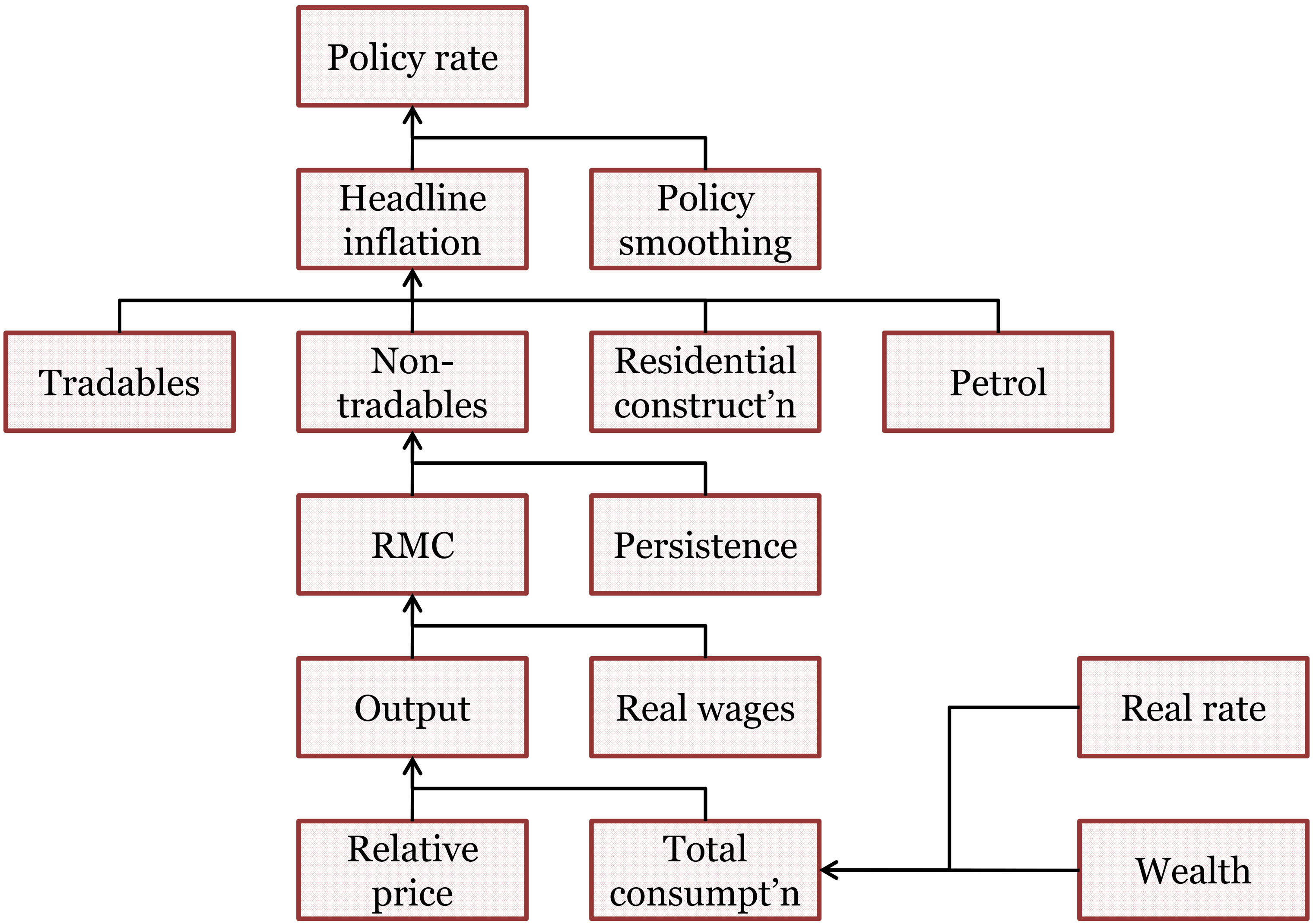
3. Communicating forecasts

- Unravel story for policymakers who are non-modellers but understand models
- Maximise structural interpretation
- Many possible perspectives, e.g.
  - contributions of individual historical shocks from Kalman filter
  - effects of individual data outturns on differences between this and last forecast rounds
- Here: focus on reconciliation trees

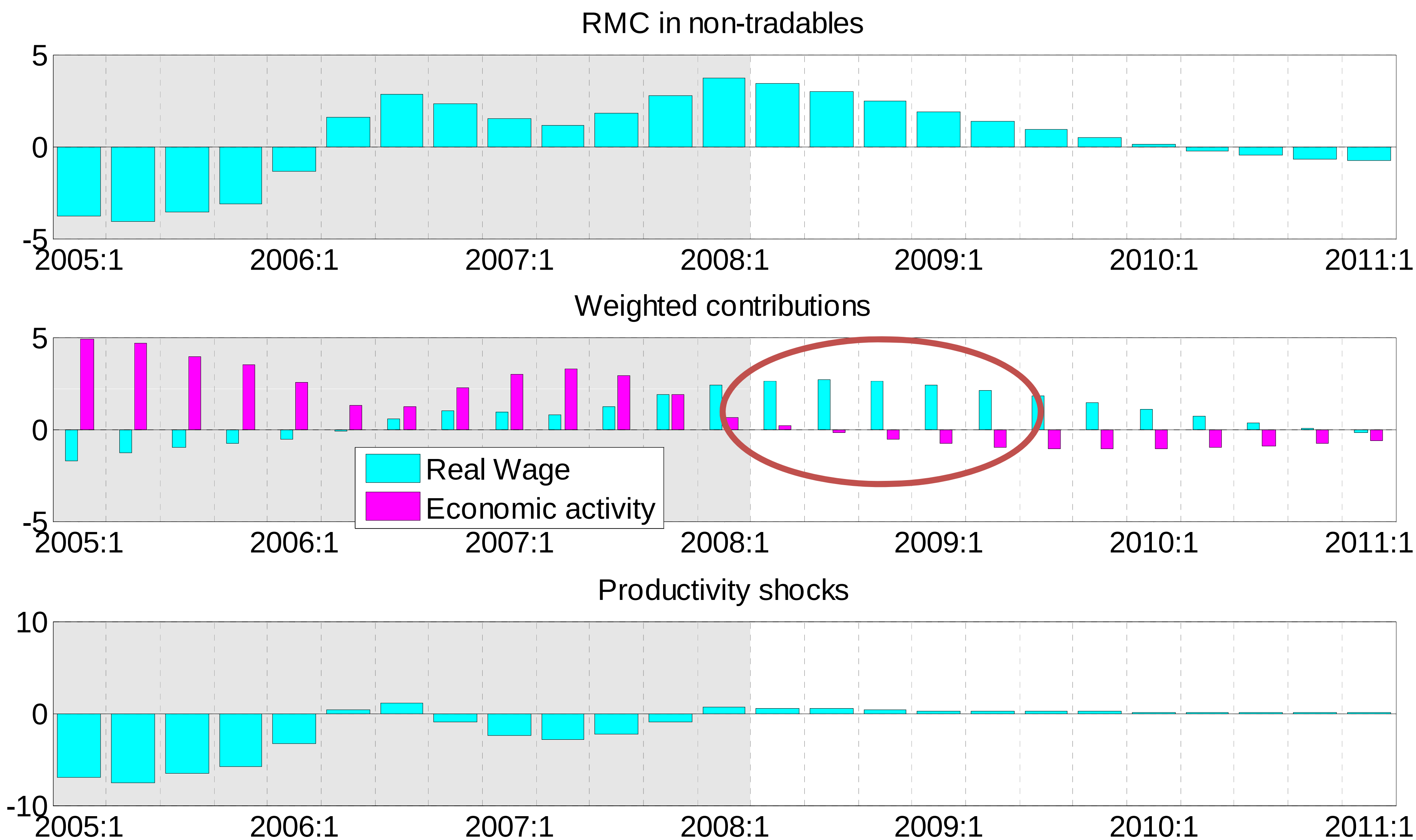
3. Communicating forecasts: Reconciliation trees

- Create a tree of equations following a certain logic, choose LHS variables
- Quantify first-order effects of RHS variables
- Do not use t+1 terms; expand expectations forward instead
- Forward expansions lead to Beveridge-Nelson decomposition

3. Communicating forecasts: Example of reconciliation tree



3. Communicating forecasts: Example of one reconciliation node



3. Communicating forecasts: Beveridge-Nelson

- Asymptotic forecast of any (unit-root) variable adjusted for deterministic drift

$$\tilde{x}_t = \mathrm{E}_t\left[x_{t+\infty}\right] - \left(d_{t+\infty} - d_t\right)$$

- Extremely easy to evaluate for triangular forms

$$\begin{bmatrix} a_t^1 \\ a_t^2 \end{bmatrix} = \begin{bmatrix} I & T_1 \\ 0 & T_2 \end{bmatrix} \begin{bmatrix} a_{t-1}^1 \\ a_{t-1}^2 \end{bmatrix} + \cdots \qquad \begin{aligned} \tilde{a}_t^1 &= a_t^1 + T_1\left(I - T_2\right)^{-1} a_t^2 \\ \tilde{x}_t^b &= U_1\,\tilde{a}_t^1 \end{aligned}$$

- Easy to evaluate contributions of individual shocks and judgment

3. Communicating forecasts: Example of Beveridge-Nelson

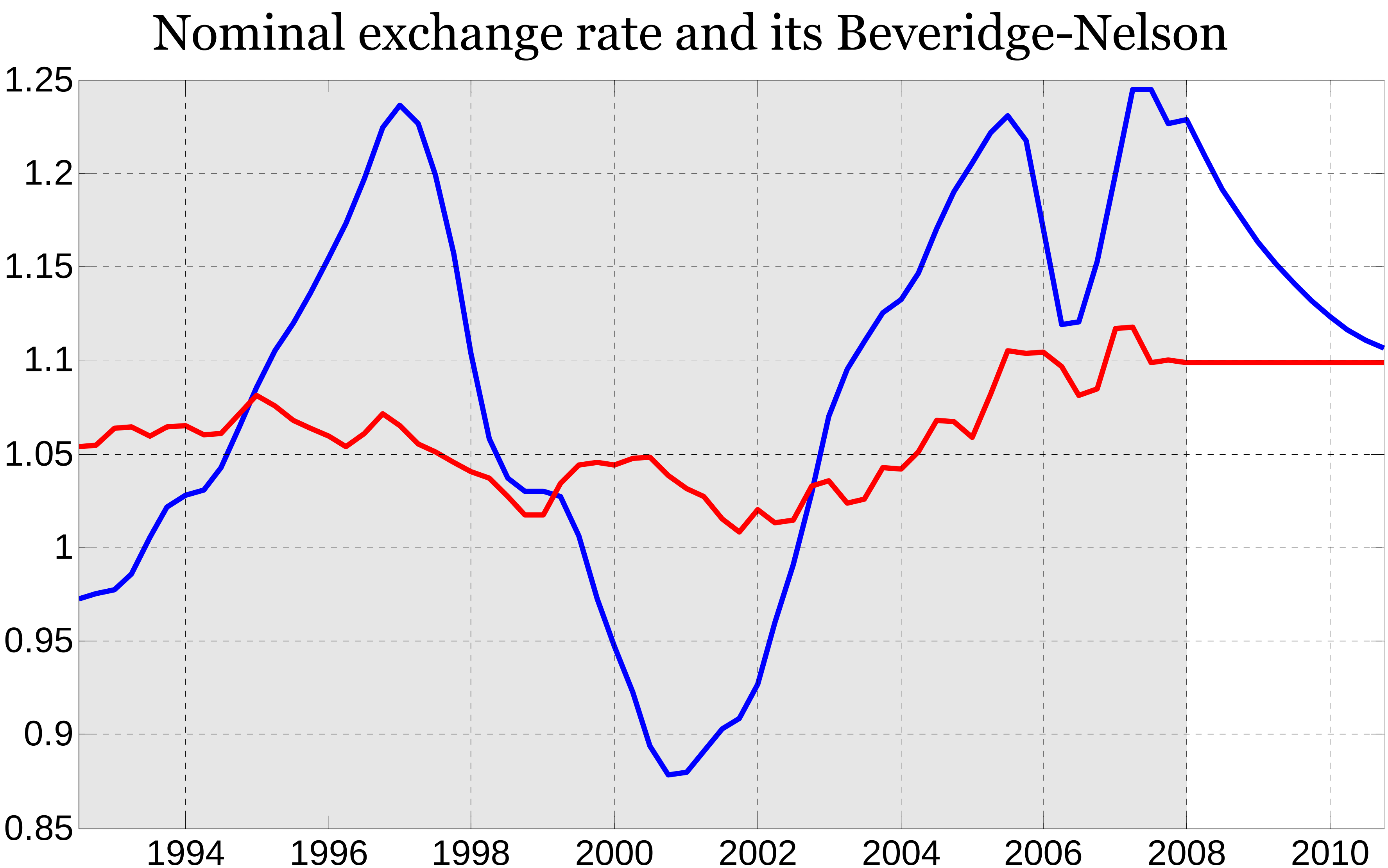
- Iterate UIP forward

$$s_t = \mathrm{E}_t\left[s_{t+\infty} - \sum\left(i_{t+k} - i^*_{t+k}\right) + \cdots\right]$$

- Explain BN trends

$$\mathrm{E}_t\left[s_{t+\infty}\right] = \mathrm{E}_t\left[p_{t+\infty} - p^*_{t+\infty} - \left(a_{t+\infty} - a^*_{t+\infty}\right)\right]$$

3. Communicating forecasts: Example of Beveridge-Nelson



Lessons learned from NZ experience

- Projection models need to be exposed to a large variety of (simple) techniques for modellers to:
  - understand DSGE-based forecasts
  - communicate the forecasts with non-modellers
  - maximise the structural DSGE interpretation
- Devices to translate model outcomes into language understandable to other staff and end-users
- Everything needs to be applied effectively and seamlessly (that's what you get when using IRIS...)