Potential Output in a Commodity-Exporting Economy

Online Appendix

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1 Normalised Model Equations

The variables are normalised as follows:

Households

1. $c_t = \frac{C_t}{Z_t}$
2. $c_{N,t} = \frac{C_{N,t}}{Z_t(1+z_N)^t}$
3. $c_{T,t} = \frac{C_t}{Z_t(1+z_T)^t}$
4. $c_{H,t} = \frac{C_{H,t}}{Z_t(1+z_H)^t}$
5. $c_{F,t} = \frac{C_{F,t}}{Z_t(1+z_F)^t}$
6. $\lambda_t = \Lambda_t Z_t$
7. $k_t = \frac{K_t}{Z_t}$
8. $ngdp_t = \frac{NGDP_t}{P_t Z_t}$
9. $b^*_t = \frac{S_t B_t}{P_t NGDP_t}$
10. $nx_t = \frac{NX_t}{P_t NGDP_t}$
11. $\pi_t = \frac{P_t}{P_{t-1}}$
12. $\pi_{N,t} = \frac{P_{N,t}}{P_{N,t-1}}$
13. $\pi_{T,t} = \frac{P_{T,t}}{P_{T,t-1}}$
14. $\pi_{H,t} = \frac{P_{H,t}}{P_{H,t-1}}$
15. $\pi_{F,t} = \frac{P_{F,t}}{P_{F,t-1}}$
16. $\pi_{I,t} = \frac{P_{I,t}}{P_{I,t-1}}$
17. $\pi^I_{T,t} = \frac{P^I_{T,t}}{P^I_{T,t-1}}$
18. $i_t = \frac{I_t}{Z_t(1+z_I)^t}$
19. $v_t = V_t(1+z_I)^t$

Non-tradeable Firms

20. $y_{N,t} = \frac{Y_{N,t}}{Z_t(1+z_N)^t}$
21. $i_{N,t} = \frac{I_{N,t}}{Z_t(1+z_N)^t}$
22. $k_{N,t} = \frac{K_{N,t}}{Z_t}$
23. $r^K_{N,t} = \frac{R^K_{N,t}}{P_t}$
24. $w_{N,t} = \frac{W_{N,t}}{P_t Z_t}$
25. $mc_{N,t} = MC_{N,t}$
26. $j_{N,t} = \frac{J_{N,t}}{(1+z_I)^t Z_t}$
27. $q_{N,t} = Q_{N,t}$

Home-tradeable Firms

28. $y_{H,t} = \frac{Y_{H,t}}{Z_t(1+z_H)^t}$
29. $c^*_{H,t} = \frac{C^*_{H,t}}{Z_t(1+z_H)^t}$
30. $i_{H,t} = \frac{I_{H,t}}{Z_t(1+z_H)^t}$
31. $k_{H,t} = \frac{K_{H,t}}{Z_t}$
32. $r^K_{H,t} = \frac{R^K_{H,t}}{P_t}$
33. $w_{H,t} = \frac{W_{H,t}}{P_t Z_t}$
34. $mc_{H,t} = MC_{H,t}$
35. $\pi_{H,t} = \frac{P_{H,t}}{P_{H,t-1}}$
36. $j_{H,t} = \frac{J_{H,t}}{(1+z_I)^t Z_t}$
37. $q_{H,t} = Q_{H,t}$

Commodity Firms

38. $y_{X,t} = \frac{Y_{X,t}}{Z_t(1+z_X)^t}$
39. $k_{X,t} = \frac{K_{X,t}}{Z_t}$
40. $r^K_{X,t} = \frac{R^K_{X,t}}{P_t}$
41. $w_{X,t} = \frac{W_{X,t}}{P_t Z_t}$
42. $j_{X,t} = \frac{J_{X,t}}{(1+z_I)^t Z_t}$
43. $q_{X,t} = Q_{X,t}$

Relative Prices

44. $\tau_{I,t} = T_{I,t}(1+z_I)^t$
45. $\tau_{N,t} = T_{N,t}(1+z_N)^t$
46. $\tau_{T,t} = T_{T,t}(1+z_T)^t$
47. $\tau_{H,t} = T_{H,t}(1+z_H)^t$
48. $\tau_{F,t} = T_{F,t}(1+z^*)^t$
49. $\tau_{F^*,t} = T_{F^*,t}(1+z^*)^t$
50. $\tau^I_{T,t} = T^I_{T,t}(1+z^I_T)^t$
51. $\tau_{G,t} = T_{G,t}$
52. $\tau^G_{T,t} = T^G_{T,t}(1+z^G_T)^t$

Foreign Economy

53. $\pi^*_t = \frac{P^*_t}{P^*_{t-1}}$

Miscellaneous

54. $\Delta s_t = \frac{S_t}{S_{t-1}}$

The following presents the normalised model equations:

Household optimisation:

$$0 = \frac{\zeta_t z_t}{c_t z_t - h c_{t-1}} - h E_t \left\{ \beta \frac{\zeta_{t+1}}{c_{t+1} z_{t+1} - h c_t} \right\} - \lambda_t \tag{1}$$

$$0 = -\lambda_t + E_t \left\{ \beta \frac{\lambda_{t+1} \left(1 + r_t\right)}{z_{t+1} \pi_{t+1}} \right\} \tag{2}$$

$$0 = -\lambda_t + E_t \left\{ \beta \frac{\lambda_{t+1} \left(1 + r_t^F\right) s_{t+1}}{z_{t+1} \pi_{t+1}} \right\} \tag{3}$$

$$0 = -q_{H,t} + E_t \left\{ \beta \frac{\lambda_{t+1}}{\lambda_t z_{t+1}} \left[r_{H,t+1}^K + (1-\delta) q_{H,t+1} \right] \right\} \tag{4}$$

$$0 = -q_{N,t} + E_t \left\{ \beta \frac{\lambda_{t+1}}{\lambda_t z_{t+1}} \left[r_{N,t+1}^K + (1-\delta) q_{N,t+1} \right] \right\} \tag{5}$$

$$0 = -q_{X,t} + E_t \left\{ \beta \frac{\lambda_{t+1}}{\lambda_t z_{t+1}} \left[r_{X,t+1}^K + (1-\delta) q_{X,t+1} \right] \right\} \tag{6}$$

$$\begin{aligned} 0 = {} & -\tau_{I,t} + q_{H,t} v_t \left[1 - \Upsilon \left(\frac{j_{H,t} z_t (1+z_I)}{j_{H,t-1}} \right) - \Upsilon' \left(\frac{j_{H,t} z_t (1+z_I)}{j_{H,t-1}} \right) \frac{j_{H,t} z_t (1+z_I)}{j_{H,t-1}} \right] \\ & + E_t \left\{ \beta \frac{\lambda_{t+1} q_{H,t+1} v_{t+1}}{\lambda_t z_{t+1} (1+z_I)} \Upsilon' \left(\frac{j_{H,t+1} z_{t+1} (1+z_I)}{j_{H,t}} \right) \left(\frac{j_{H,t+1} z_{t+1} (1+z_I)}{j_{H,t}} \right)^2 \right\} \end{aligned} \tag{7}$$

$$\begin{aligned} 0 = {} & -\tau_{I,t} + q_{N,t} v_t \left[1 - \Upsilon \left(\frac{j_{N,t} z_t (1+z_I)}{j_{N,t-1}} \right) - \Upsilon' \left(\frac{j_{N,t} z_t (1+z_I)}{j_{N,t-1}} \right) \frac{j_{N,t} z_t (1+z_I)}{j_{N,t-1}} \right] \\ & + E_t \left\{ \beta \frac{\lambda_{t+1} q_{N,t+1} v_{t+1}}{\lambda_t z_{t+1} (1+z_I)} \Upsilon' \left(\frac{j_{N,t+1} z_{t+1} (1+z_I)}{j_{N,t}} \right) \left(\frac{j_{N,t+1} z_{t+1} (1+z_I)}{j_{N,t}} \right)^2 \right\} \end{aligned} \tag{8}$$

$$\begin{aligned} 0 = {} & -\tau_{I,t} + q_{X,t} v_t \left[1 - \Upsilon \left(\frac{j_{X,t} z_t (1+z_I)}{j_{X,t-1}} \right) - \Upsilon' \left(\frac{j_{X,t} z_t (1+z_I)}{j_{X,t-1}} \right) \frac{j_{X,t} z_t (1+z_I)}{j_{X,t-1}} \right] \\ & + E_t \left\{ \beta \frac{\lambda_{t+1} q_{X,t+1} v_{t+1}}{\lambda_t z_{t+1} (1+z_I)} \Upsilon' \left(\frac{j_{X,t+1} z_{t+1} (1+z_I)}{j_{X,t}} \right) \left(\frac{j_{X,t+1} z_{t+1} (1+z_I)}{j_{X,t}} \right)^2 \right\} \end{aligned} \tag{9}$$

and

$$0 = -\zeta_t \xi \epsilon_t^L \left(l_t\right)^{\nu-\omega} l_{H,t}^{\omega} + \lambda_t w_{H,t} \tag{10}$$

$$0 = -\zeta_t \xi \epsilon_t^L \left(l_t\right)^{\nu-\omega} l_{N,t}^{\omega} + \lambda_t w_{N,t} \tag{11}$$

$$0 = -\zeta_t \xi \epsilon_t^L \left(l_t\right)^{\nu-\omega} l_{X,t}^{\omega} + \lambda_t w_{X,t} \tag{12}$$

Capital accumulation:

$$0 = k_{H,t+1} E_t \left\{ z_{t+1} \right\} - (1-\delta) k_{H,t} - v_t \left[1 - \Upsilon \left(\frac{j_{H,t}}{j_{H,t-1}} z_t (1+z_I) \right) \right] j_{H,t} \tag{13}$$

$$0 = k_{N,t+1} E_t \left\{ z_{t+1} \right\} - (1-\delta) k_{N,t} - v_t \left[1 - \Upsilon \left(\frac{j_{N,t}}{j_{N,t-1}} z_t (1+z_I) \right) \right] j_{N,t} \tag{14}$$

$$0 = k_{X,t+1} E_t \left\{ z_{t+1} \right\} - (1-\delta) k_{X,t} - v_t \left[1 - \Upsilon \left(\frac{j_{X,t}}{j_{X,t-1}} z_t (1+z_I) \right) \right] j_{X,t} \tag{15}$$

Price and inflation indices:

$$\pi_t = \left[\gamma_N \left(\pi_{N,t} \tau_{N,t-1} (1+z_N) \right)^{1-\eta} + \gamma_T \left(\pi_{T,t} \tau_{T,t-1} (1+z_T) \right)^{1-\eta} \right]^{\frac{1}{1-\eta}} \tag{16}$$

$$\pi_{T,t} = \pi_{H,t}^{\gamma_H} \pi_{F,t}^{\gamma_F} \tag{17}$$

$$\pi_t^I = \pi_{T,t}^{I\ \gamma_T^I} \pi_{N,t}^{\gamma_N^I} \tag{18}$$

$$\pi_{T,t}^I = \pi_{H,t}^{\gamma_H^I} \pi_{F,t}^{\gamma_F^I} \tag{19}$$

$$\tag{20}$$

Consumer demand:

$$c_{N,t} = \gamma_N \left(\tau_{N,t} \right)^{-\eta} c_t \tag{21}$$

$$c_{T,t} = \gamma_T \left(\tau_{T,t} \right)^{-\eta} c_t \tag{22}$$

$$c_{H,t} = \gamma_H \gamma_T \left(\tau_{H,t} \right)^{-1} \left(\tau_{T,t} \right)^{1-\eta} c_t \tag{23}$$

$$c_{F,t} = \gamma_F \gamma_T \left(\tau_{F,t} \right)^{-1} \left(\tau_{T,t} \right)^{1-\eta} c_t \tag{24}$$

Investment demand:

$$i_{N,t} = \gamma_N^I \left(\frac{\tau_{N,t}}{\tau_{I,t}} \right)^{-1} i_t \tag{25}$$

$$i_{T,t} = \gamma_T^I \left(\frac{\tau_{T,t}^I}{\tau_{I,t}} \right)^{-1} i_t \tag{26}$$

$$i_{H,t} = \gamma_H^I \gamma_T^I \left(\frac{\tau_{H,t}}{\tau_{T,t}^I} \right)^{-1} \left(\frac{\tau_{T,t}^I}{\tau_{I,t}} \right)^{-1} i_t \tag{27}$$

$$i_{F,t} = \gamma_F^I \gamma_T^I \left(\frac{\tau_{F,t}}{\tau_{T,t}^I} \right)^{-1} \left(\frac{\tau_{T,t}^I}{\tau_{I,t}} \right)^{-1} i_t \tag{28}$$

Production:

$$y_{X,t} = a_t \tilde{Z}_{X,t} k_{X,t}^{\alpha_X} l_{X,t}^{\mu_X} \mathcal{L}^{1-\alpha_X-\mu_X} \tag{29}$$
$$y_{H,t} = a_t \tilde{Z}_{H,t} k_{H,t}^{\alpha_H} l_{H,t}^{1-\alpha_H} \tag{30}$$
$$y_{N,t} = a_t \tilde{Z}_{N,t} k_{N,t}^{\alpha_N} l_{N,t}^{1-\alpha_N} \tag{31}$$

Tradeable firms:

$$0 = k_{H,t} - \frac{\alpha_H}{1-\alpha_H} \frac{w_{H,t} l_{H,t}}{r_{H,t}^K} \tag{32}$$
$$0 = mc_{H,t} - \left(\frac{1}{1-\alpha_H}\right)^{1-\alpha_H} \left(\frac{1}{\alpha_H}\right)^{\alpha_H} \frac{\varepsilon_{\pi_{H,t}} w_{H,t}^{1-\alpha_H} r_{H,t}^{K\ \alpha_H}}{\tau_{H,t} \tilde{Z}_{H,t}} \tag{33}$$
$$\begin{aligned} 0 &= \frac{\pi_{H,t}}{\pi_H}\left(\frac{\pi_{H,t}}{\pi_H} - 1\right) + \frac{\theta_H - 1}{\psi_H} - \frac{\theta_H}{\psi_H} mc_{H,t} \\ &\quad - E_t\left\{\beta \frac{\lambda_{t+1}}{\lambda_t} \frac{y_{H,t+1}}{y_{H,t}} \frac{\tau_{H,t+1}}{\tau_{H,t}} \frac{\pi_{H,t+1}}{\pi_H}\left[\frac{\pi_{H,t+1}}{\pi_H} - 1\right]\right\} \end{aligned} \tag{34}$$

Non-tradeable firms:

$$0 = k_{N,t} - \frac{\alpha_N}{1-\alpha_N} \frac{w_{N,t} l_{N,t}}{r_{N,t}^K} \tag{35}$$
$$0 = mc_{N,t} - \left(\frac{1}{1-\alpha_N}\right)^{1-\alpha_N} \left(\frac{1}{\alpha_N}\right)^{\alpha_N} \frac{\varepsilon_{\pi_{N,t}} w_{N,t}^{1-\alpha_N} r_{N,t}^{K\ \alpha_N}}{\tau_{N,t} \tilde{Z}_{N,t}} \tag{36}$$
$$\begin{aligned} 0 &= \frac{\pi_{N,t}}{\pi_N}\left(\frac{\pi_{N,t}}{\pi_N} - 1\right) + \frac{\theta_N - 1}{\psi_N} - \frac{\theta_N}{\psi_N} mc_{N,t} \\ &\quad - E_t\left\{\beta \frac{\lambda_{t+1}}{\lambda_t} \frac{y_{N,t+1}}{y_{N,t}} \frac{\tau_{N,t+1}}{\tau_{N,t}} \frac{\pi_{N,t+1}}{\pi_N}\left[\frac{\pi_{N,t+1}}{\pi_N} - 1\right]\right\} \end{aligned} \tag{37}$$

Commodity firms:

$$0 = \alpha_X \frac{\tau_{X,t} y_{X,t}}{k_{X,t}} - r_{X,t}^K \tag{38}$$
$$0 = \mu_X \frac{\tau_{X,t} y_{X,t}}{l_{X,t}} - w_{X,t} \tag{39}$$

Importing firms:

$$0 = \frac{\pi_{F,t}}{\pi_F}\left(\frac{\pi_{F,t}}{\pi_F} - 1\right) + \frac{\theta_F - 1}{\psi_F} - \frac{\theta_F}{\psi_F} mc_{F,t}$$
$$- E_t\left\{\beta\frac{\lambda_{t+1}}{\lambda_t}\frac{y_{F,t+1}}{y_{F,t}}\frac{\tau_{F,t+1}}{\tau_{F,t}}\frac{\pi_{F,t+1}}{\pi_F}\left[\frac{\pi_{F,t+1}}{\pi_F} - 1\right]\right\} \tag{40}$$

$$mc_{F,t} = \varsigma\varepsilon_{\pi_{F,t}}\left(\frac{\tau_{F^*,t}}{\tau_{F,t}}\right) \tag{41}$$

Law of one price:

$$0 = \tau_{X,t} - \kappa_t\tau_{F^*,t} \tag{42}$$

Relative Prices:

$$0 = \frac{\tau_{N,t}}{\tau_{N,t-1}} - \frac{\pi_{N,t}(1+z_N)}{\pi_t} \tag{43}$$

$$0 = \frac{\tau_{T,t}}{\tau_{T,t-1}} - \frac{\pi_{T,t}(1+z_T)}{\pi_t} \tag{44}$$

$$0 = \frac{\tau^I_{T,t}}{\tau^I_{T,t-1}} - \frac{\pi^I_{T,t}(1+z^I_T)}{\pi_t} \tag{45}$$

$$0 = \frac{\tau_{H,t}}{\tau_{H,t-1}} - \frac{\pi_{H,t}(1+z_H)}{\pi_t} \tag{46}$$

$$0 = \frac{\tau_{F,t}}{\tau_{F,t-1}} - \frac{\pi_{F,t}(1+z^*)}{\pi_t} \tag{47}$$

$$0 = \frac{\tau_{F^*,t}}{\tau_{F^*,t-1}} - \frac{\Delta s_t\pi^*_t(1+z^*)}{\pi_t} \tag{48}$$

$$0 = \frac{\tau_{I,t}}{\tau_{I,t-1}} - \frac{\pi_{I,t}(1+z_I)}{\pi_t} \tag{49}$$

$$\tag{50}$$

Foreign sector:

$$c^*_{H,t} = \gamma^*_H\left(\frac{\tau_{H,t}}{\tau_{F^*,t}}\right)^{-\eta^*}\tilde{Y}^*_t \tag{51}$$

Market clearing:

$$0 = y_{N,t} - c_{N,t} - i_{N,t} - \frac{\psi_N}{2}\left(\frac{\pi_{N,t}}{\bar{\pi}^N} - 1\right)^2 y_{N,t} \tag{52}$$

$$0 = y_{H,t} - c_{H,t} - c^*_{H,t} - i_{H,t} - \frac{\psi_H}{2}\left(\frac{\pi_{H,t}}{\bar{\pi}^H} - 1\right)^2 y_{H,t} \tag{53}$$

$$0 = y_{F,t} - c_{F,t} - i_{F,t} - \frac{\psi_F}{2}\left(\frac{\pi_{F,t}}{\pi^F} - 1\right)^2 y_{F,t} \tag{54}$$

$$0 = i_t - j_{H,t} - j_{N,t} - j_{X,t} \tag{55}$$

$$0 = l_t - \left[l_{H,t}^{1+\omega} + l_{N,t}^{1+\omega} + l_{X,t}^{1+\omega}\right]^{\frac{1}{1+\omega}} \tag{56}$$

$$0 = ngdp_t - \tau_{H,t}y_{H,t} - \tau_{N,t}y_{N,t} - \tau_{X,t}y_{X,t} \tag{57}$$

$$0 = nx_t - \tau_{H,t}\frac{c^*_{H,t}}{ngdp_t} + \tau_{F^*,t}\left(\frac{c_{F,t} + i_{F,t}}{ngdp_t}\right) + \tau_{X,t}\frac{y_{X,t}}{ngdp_t} \tag{58}$$

$$0 = b^*_t - \frac{b^*_{t-1}(1 + r^*_{t-1})\Delta s_t ngdp_{t-1}}{\pi_t ngdp_t z_t} - nx_t \tag{59}$$

Interest rates and monetary policy:

$$1 + r^F_t = (1 + r^*_t)\exp(-\psi_b\left(b^*_t - b^*\right) + \tilde{\psi}_{b,t}) \tag{60}$$

$$\frac{1 + r_t}{1 + r} = \left(\frac{1 + r_{t-1}}{1 + r}\right)^{\rho_R}\left[\left(\frac{\pi_t}{\Pi}\right)^{\phi_\pi}\left(\frac{y_t z_t}{y_{t-1}\bar{z}}\right)^{\phi_y}\right]^{(1-\rho_R)} \exp(u_{R,t}) \tag{61}$$

2 Data and Estimation

2.1 Data Sources

This section describes the data used to estimate the model.

Population: Quarterly gross domestic product in chain volume measure (ABS Catalogue 5206.0) divided by quarterly gross domestic product per capita also in chain volume measure (ABS Catalogue 5206.0).

Real GDP per capita: Quarterly gross domestic product per capita in chain volume measure (ABS Catalogue 5206.0).

Investment per Capita: Quarterly gross fixed capital formation in chain volume measure (ABS Catalogue 5206.0) divided by population.

Consumption per capita: Quarterly all sectors final consumption expenditures (including public sector) in chain volume measure (ABS Catalogue 5206.0) divided by population.

Net exports-to-GDP: Net exports-to-GDP is computed as exports-to-GDP less imports-to-GDP. Exports-to-GDP is quarterly exports in current price measure divided by quarterly gross domestic product in current price measure. Imports-to-GDP is quarterly imports in current price measure divided by quarterly gross domestic product in current price measure (ABS Catalogue 5206.0).

Nominal interest rate: Cash rate (RBA Bulletin Table F1). The monthly series is converted into quarterly frequency by arithmetic averaging.

Nominal exchange rate: Australian Trade-Weighted Index (RBA Bulletin Table F11).

CPI Inflation: Percentage change in the Consumer Price Index excluding interest and tax (ABS Catalogue 6401.0).

Non-tradeable inflation: Percentage change in the Non-tradeables Price Index excluding interest and tax (ABS Catalogue 6401.0).

Commodity prices: Quarterly Commodity Price Index (RBA Bulletin Table I2).

Hours worked: Quarterly Hours Worked Index (ABS Catalogue 5206.0).

Foreign output: Quarterly index of Australia's major trading partners' GDP, calculated at purchasing power parity exchange rates (RBA).

Foreign inflation: Foreign inflation is computed implicitly as Australian Trade-Weighted Index (RBA Bulletin Table F11) divided by Australian real Trade-Weighted Index (RBA Bulletin Table F15) and multiplied by trimmed-mean inflation (ABS Catalogue 6401.0).

Foreign interest rate: Foreign interest rate is computed as the average policy rate in the Euro area, the United States, and Japan (RBA Bulletin Table F13). The monthly series are converted into quarterly frequency by arithmetic averaging. German interest rate is used before the introduction of the Euro (FRED Database series INTDSRDEM193N).

2.2 Estimation Procedure

The model is estimated and solved using the technique developed in Kulish & Pagan (2017) for models with structural changes. Following Kulish & Rees (2017), I allow for the structural break in steady-state commodity prices, κ, and in the variance of commodity price shock, σ_k, to happen at possibly different dates in the sample, T_κ and T_σ. Hence, for the data sample $t = 1, 2, \cdots, T$, and assuming that $T_\kappa < T_\sigma$, three different regimes occur:

1. First regime: For $t = 1, 2, \cdots, T_\kappa - 1$, steady-state commodity prices are normalised to 1. In the initial regime, the first-order approximation to the equilibrium conditions around the steady state is a linear rational expectations system of equations that is given by:
$$A_0 y_t = C_0 + A_1 y_{t-1} + \mathbb{E}_t B_0 y_{t+1} + D_0 \varepsilon_t \tag{62}$$
where the structural matrices A_0, C_0, A_1, B_0 and D_0 correspond to the initial steady state, y_t is vector of state and jump variables and ε_t is a vector of exogenous *iid* shocks. The solution, if it exists and is unique, will be a Vector Autoregression (VAR) that takes the form:
$$y_t = C + Q y_{t-1} + G \varepsilon_t \tag{63}$$

2. Second regime: For $t = T_\kappa, \cdots, T_\sigma - 1$, steady-state commodity prices may take on a different value, say κ^*. The structural form of the model then becomes:
$$A_0^* y_t = C_0^* + A_1^* y_{t-1} + \mathbb{E}_t B_0^* y_{t+1} + D_0 \varepsilon_t \tag{64}$$
where the superscript $*$ is associated with the matrices that correspond to the new steady-state commodity price level. Note that the matrix D_0 is unchanged as the break in the variance of commodity prices hasn't occurred yet. The solution, if it

exists and is unique, will be a VAR that takes the form:

$$y_t = C^* + Q^* y_{t-1} + G^* \varepsilon_t \tag{65}$$

3. Third regime: For $t = T_\sigma, \cdots, T$, the variance of the commodity price shock σ_κ changes. The structural form of the model then becomes:

$$A_0^* y_t = C_0^* + A_1^* y_{t-1} + \mathbb{E}_t B_0^* y_{t+1} + D_0^{**} \varepsilon_t \tag{66}$$

   where the matrix D_0^{**} denotes the matrix corresponding to the new variance of shock to commodity prices while other structural matrices are maintained as in the second regime. The solution, if it exists and is unique, will be a VAR that takes the form:

$$y_t = C^* + Q^* y_{t-1} + G^{**} \varepsilon_t \tag{67}$$

Based on the three regimes, the time-varying reduced form is given by:

$$y_t = C_t + Q_t y_{t-1} + G_t \varepsilon_t \tag{68}$$

Given a data sample, one can form an observable variables vector, y_t^{obs}, that relates to the variables in the model by:

$$y_t^{obs} = H y_t + v_t \tag{69}$$

where v_t is a vector of iid measurement errors with zero mean and covariance matrix V. Together, the state equation, Equation (68), and the observation equation, Equation (69), form a state-space model. Hence, the data sample's likelihood function can be constructed by using the Kalman filter as outlined in Kulish & Pagan (2017).

Most of the literature on DSGE models' estimation employ Bayesian estimation techniques which take into account prior probability distributions on the estimated parameters. I adopt Bayesian methods to estimate the parameters (ϑ) as well as the dates of structural changes ($\mathbf{T}$). In this framework, the information in the data sample's likelihood function, $\mathcal{L}(Y|\vartheta, \mathbf{T})$, updates the prior distribution on non-calibrated parameters and dates of structural changes, $p(\vartheta, \mathbf{T})$, to generate a posterior distribution:

$$p(\vartheta, \mathbf{T}|Y) = \mathcal{L}(Y|\vartheta, \mathbf{T}) p(\vartheta, \mathbf{T}) \tag{70}$$

The nonlinear mapping from the DSGE model to the likelihood function implies that the analytical construction of the posterior distribution for the parameters is a complex task. As such, the Metropolis Hastings algorithm is used to simulate from the joint posterior distribution of the parameters and the dates of the breaks. I sample 400,000 posterior draws, discarding the first 100,000 draws as burn-in.

3 Alternative Output Gap Estimation Methods

3.1 Quadratic Detrending

One of the simplest methods to calculate potential output and the output gap is by employing a quadratic trend which decomposes output into two uncorrelated components: trend and cycle. This method assumes that potential output is well approximated by a deterministic quadratic trend in relation to time and the output gap is a residual from the trend line. Hence, potential output and output gap are obtained by estimating a linear regression of the log of real GDP on a constant, time trend, and time trend squared:

$$y_t = \beta_0 + \beta_1 t + \beta_2 t^2 + \epsilon_t \tag{71}$$

where y_t is the log of real GDP, t is the time trend, and ϵ_t is the error term of the regression. Potential output would then be given as:

$$y_t^* = \hat{\beta}_0 + \hat{\beta}_1 t + \hat{\beta}_2 t^2 \tag{72}$$

where $\hat{\beta}_0$, $\hat{\beta}_1$ and $\hat{\beta}_2$ are the estimated coefficients of the linear regression. To estimate the output gap, potential output is subtracted from the log of actual output:

$$x_t = y_t - y_t^* = \hat{\epsilon}_t \tag{73}$$

which shows that the output gap is simply the residual of the estimated linear regression equation. It is noteworthy that the output gap measure obtained using quadratic detrending has a zero mean over the sample period, as linear regression assumes that the mean of estimated residual is zero. To estimate the output gap for Australia using the quadratic detrending method, I use the logarithm of the seasonally adjusted quarterly real GDP series over the period 1993:Q1-2017:Q1.

3.2 Hodrick-Prescott Filter

Developed by Hodrick & Prescott (1997), the Hodrick-Prescott (HP) filter is a simple and widely used statistical method for estimating potential output and the output gap. In the HP filter method, real GDP is represented as a sum of a trend component that varies smoothly over time and a cyclical component, which captures short-run fluctuations:

$$y_t = y_t^* + x_t \tag{74}$$

where y_t is the log of real GDP, y_t^* is potential output, and x_t is the output gap. The HP filter then finds the value of potential output that minimises the deviation of potential output from actual output while imposing a restriction on the degree of variation in potential output growth. This leads to the following dynamic optimisation problem:

$$\min_{\{y_t^*\}_{t=1}^{T}} \left\{ \sum_{t=1}^{T} (y_t - y_t^*)^2 + \lambda \sum_{t=2}^{T-1} \left[(y_{t+1}^* - y_t^*) - (y_t^* - y_{t-1}^*) \right]^2 \right\}$$

The first term in the above expression is the square of potential output's deviation from actual output and the second term is the square of the one-period variation in the growth of potential output. The exogenous parameter λ is a positive number that penalises the variability of potential output and thus determines the extent of admissible changes in potential output growth. In that sense, the higher(lower) the value of the parameter λ is, the more(less) smoothed the potential output and more(less) volatile the output gap. To estimate the output gap for Australia using the HP filter method, I use the logarithm of the seasonally adjusted quarterly real GDP series over the period 1993:Q1-2017:Q1, with the parameter λ set at 1600, which is standard in the literature for quarterly time series.

3.3 Beveridge-Nelson Decomposition

The Beveridge-Nelson (BN) decomposition, developed by Beveridge & Nelson (1981) assumes that a nonstationary real GDP series can be decomposed into two components, a permanent component and a transitory component:

$$y_t = y_t^* + x_t \tag{75}$$

where y_t is the log of real GDP, y_t^* is the permanent component (i.e. potential output), and x_t is the transitory component (i.e. output gap). The Beveridge-Nelson technique assumes that real output is integrable of order 1 and its first difference, Δy_t, is integrable of order 0. Hence, the permanent component follows a random walk with a drift:

$$y_t^* = \beta + y_{t-1}^* + \alpha \epsilon_t \tag{76}$$

where y_t^* is a random walk, β is the drift, and $\alpha\epsilon_t$ is an error term. Meanwhile, the cyclical component is stationary:

$$x_t = \varphi_p^*(L) x_t - \psi_q^*(L) \epsilon_t + (1 - \alpha) \epsilon_t \tag{77}$$

where L is the lag operator, $\varphi_p^*(L) = \varphi_1 L + \varphi_2 L^2 + \cdots + \varphi_p L^p$ and $\psi_q^*(L) = \psi_1 L + \psi_2 L^2 + \cdots + \psi_q L^q$. This implies that y_t is an ARIMA(p,1,q) process and Δy_t is an ARMA(p,q) process.

To implement the BN decomposition for Australia, I adopt the methodology developed in Kamber et al. (2018) which allows for the imposition of a low signal-to-noise ratio. Kamber et al. (2018) show that their proposed methodology for output gap estimation results in a more intuitive output gap measure and is better at predicting inflation and output growth than other methodologies of trend-cycle decomposition like detrending and the HP filter. Hence, estimating the output gap for Australia using this methodology would allow for a better comparison with the DSGE model-based output gap. I compute the output gap by estimating an AR(12) forecasting model for the first difference of log real GDP using the seasonally adjusted quarterly real GDP series over the period 1992:Q4-2017:Q1[1].

3.4 Production Function Approach

The production function approach assumes that output is a Cobb-Douglas aggregate of the available technology and the input factors capital and labour:

$$Y_t = A_t K_t^{\alpha} L_t^{1-\alpha} \tag{78}$$

where Y_t is real GDP, A_t is total factor productivity, K_t is capital stock, and L_t is total labour hours. The parameter α is capital's share in output, calibrated at 0.4 to match the share of capital from total income in Australia over the period 1993:Q1-2017:Q1.

The capital stock series is constructed from total investment using the perpetual inventories method:

$$K_t = (1-\delta)K_{t-1} + I_t \tag{79}$$

where, in each period, the capital stock is measured by augmenting the previous period's capital (net of depreciation) with the current period's investment flow. In line with the calibration of the DSGE model, the rate of capital depreciation δ is set at 0.005, while an initial benchmark is computed as $K_{1993:Q1} = I_{1993:Q1}/(\delta + g_i)$ with g_i being the average investment growth rate over the period 1993:Q1-2017:Q1. Total labour hours are defined as the product of the number of hours available in the labour force and the employment rate:

$$L_t = LF_t H_t (1 - U_t) \tag{80}$$

[1]The BN decomposition is computed by modifying the MATLAB code made available by Kamber et al. (2018).

where LF_t is the total labour force, H_t is the number of hours worked per person, and U_t is the unemployment rate. Finally, the available technology is measured as the Solow residual from the Cobb-Douglas production function:

$$A_t = \frac{Y_t}{K_t^{\alpha} L_t^{1-\alpha}} \tag{81}$$

Measures of potential capital, potential labour, and potential total factor productivity are needed in order to compute an estimate of potential output using the following production function:

$$Y_t^* = A_t^* K_t^{\alpha} L_t^{*1-\alpha} \tag{82}$$

Hence, before computing potential output it is important to clearly define the potential capital and labour as well as trend level of total factor productivity:

- Capital stock: The contribution of capital to potential output is measured as the total usage of the economy's existing capital stock. Thus, consistent with previous literature, the capital stock series is not smoothed in the production function approach as the capital stock itself is a measure of the economy's overall capacity.

- Labour hours: The contribution of labour hours to potential output is defined as

  $$L_t^* = LF_t^* H_t^* (1 - NAIRU_t) \tag{83}$$

  where LF_t^* is trend labour force and H_t^* is the trend hours worked per person, both obtained by mechanically detrending, using the HP filter, the labour force and hours worked series, respectively. I calculate trend unemployment rate as the non-accelerating inflation rate of unemployment, $NAIRU_t$ using the model developed in Cusbert (2017).

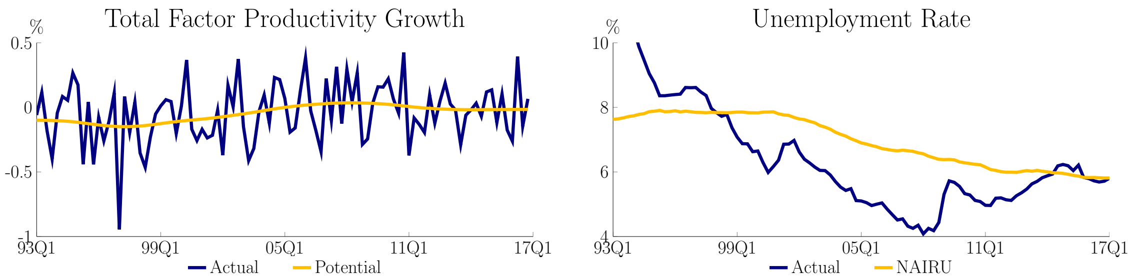
- Total factor productivity: The potential level of total factor productivity, A_t^*, is computed by detrending the Solow residual using the HP filter.

Figure 1 plots the actual and potential input variables derived using the production function approach.

3.5 Structural Vector Autoregression

Structural vector autoregressive (SVAR) models provide an approach to estimate potential output based on macroeconomic modelling while allowing for endogenous variables to interact and imposing feedback effects among them (Sims 1980). In SVAR models, the

Figure 1: Actual and Potential Input Variables



dynamics guiding the endogenous variables are determined by an identical number of shocks. This allows shocks, such as supply and demand shocks, to be explicitly identified. Based on the work of Blanchard & Quah (1989), the imposition of a suitable set of long-run restrictions on the variance-covariance matrix in the estimation of a reduced-form VAR would identify the permanent and transitory shocks that affect the variables. Potential output within the SVAR model is then computed by adding up the deterministic component to the permanent component of shocks.

I specify a trivariate vector autoregression system that includes the change in the unemployment rate Δu_t, the log of real GDP y_t, and the inflation rate π_t over the period 1991:Q1-2017:Q1. The moving average representation of the system is given as:

$$\begin{bmatrix} \Delta u_t \\ y_t \\ \pi_t \end{bmatrix} = \begin{bmatrix} B_{11}(L) & B_{12}(L) & B_{13}(L) \\ B_{21}(L) & B_{22}(L) & B_{23}(L) \\ B_{31}(L) & B_{32}(L) & B_{33}(L) \end{bmatrix} \begin{bmatrix} \varepsilon_{\Delta u,t} \\ \varepsilon_{y,t} \\ \varepsilon_{\pi,t} \end{bmatrix} + \begin{bmatrix} \psi_{\Delta u,t} \\ \psi_{y,t} \\ \psi_{\pi,t} \end{bmatrix} \tag{84}$$

where $\begin{bmatrix} \psi_{\Delta u,t} & \psi_{y,t} & \psi_{\pi,t} \end{bmatrix}'$ is the deterministic trend vector, $\varepsilon_{\Delta u,t}$ is the unemployment shock, $\varepsilon_{y,t}$ is the output shock, and $\varepsilon_{\pi,t}$ is the inflation shock.

To retrieve the structural shocks, I impose a set of identifying restrictions on the trivariate VAR system resulting in the following long-run representation:

$$\begin{bmatrix} \Delta u_t \\ y_t \\ \pi_t \end{bmatrix} = \begin{bmatrix} B_{11}(1) & B_{12}(1) & B_{13}(1) \\ 0 & B_{22}(1) & B_{23}(1) \\ 0 & 0 & B_{33}(1) \end{bmatrix} \begin{bmatrix} \varepsilon_{\Delta u,t} \\ \varepsilon_{y,t} \\ \varepsilon_{\pi,t} \end{bmatrix} + \begin{bmatrix} \psi_{\Delta u,t} \\ \psi_{y,t} \\ \psi_{\pi,t} \end{bmatrix} \tag{85}$$

These restrictions imply that the unemployment shock affects long-run unemployment only. Further, the output shock – which according to Blanchard & Quah (1989) represents a productivity shock – affects long-run unemployment and long-run output. Meanwhile, the inflation shock affects long-run unemployment, output, and inflation. After the identification of the three shocks, I compute potential output from the deterministic component and the non-transitory component of shocks.

4 Estimated Output Gap as Indicator of Inflation

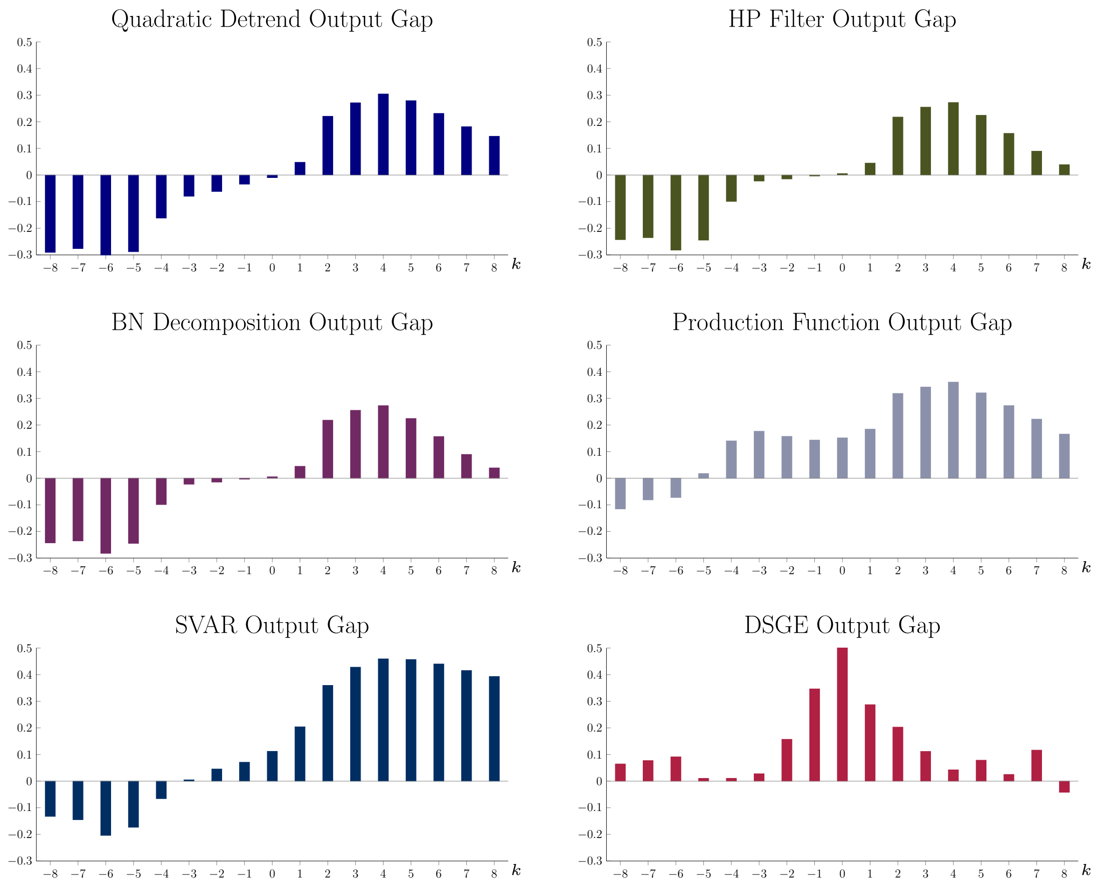
The reduced-form relationship between real economic activity and inflation, known as the Phillips curve (Phillips 1958), has been frequently used for forecasting inflation. As such, the search for a proper specification of the Phillips curve is ongoing and the output gap remains one of the key indicators of inflation considered by policy-making institutions (Coenen et al. 2008). Here, I examine whether the alternative univariate and multivariate output gap measures are useful predictors of inflation. I particularly focus on comparing the predictive content for inflation of the output gap derived from the DSGE model to that of alternative estimates.

4.1 Cross-Correlations

In order to examine the performance of the alternative output gap estimates in explaining inflation, I compute the cross-correlation coefficients between the output gap and leads and lags of inflation. The measure of inflation I use is the quarterly percentage change in the trimmed mean measure of the consumer price index (CPI). As argued by Norman & Richards (2010), the trimmed mean measure of CPI is a better measure than headline CPI for Australia as it reduces the noise in price data. Figure 2 presents the cross-correlation between leads and lags of inflation and the alternative measures of the output gap. The output gap measures from the quadratic detrend, the HP filter, and the BN decomposition are all negatively correlated with lagged inflation at all lags considered. The output gap measures computed using the SVAR approach and the production function approach reveal a negative correlation with lagged inflation at lags $k = \{-8, -7, \cdots, -5\}$ and a weak positive correlation with lagged inflation at lags $k = \{-2, -1\}$. Meanwhile, only the DSGE model-based flexible-price output gap displays a positive correlation with lagged inflation, with the correlation becoming stronger as the lags decrease. Hence, the correlation pattern between inflation and the DSGE model-based output gap is different from the correlation pattern between inflation and other measures of the output gaps.

The contemporaneous cross-correlation between inflation and output gap estimates is negligible for most measures of the output gap except the SVAR measure where the correlation is 0.11 and the DSGE model-based measure where the correlation peaks at 0.50. This suggests that the DSGE model-based output gap could provide a better guide to the degree of spare capacity in the economy today than other measures of the output gap. Finally, all output gap measures display positive correlation with lead inflation. The positive correlation is the strongest for the DSGE mode-based output gap for the first lead and for the SVAR output gap for all other leads $k = \{2, 3, \cdots, 8\}$. As such, while the DSGE model-based output gap could provide guidance on the economy's current performance relative to full capacity, alternative output gap measures may predict inflation better.

Figure 2: Dynamic Cross-Correlations between Output Gaps (t) and Inflation ($t+k$)



4.2 Out-of-Sample Inflation Forecast

As an indicator of demand and supply activities, the output gap is often considered a measure of inflationary pressures in the economy. As such, the information contained in the output gap could improve the precision of inflation forecasts. In this section, I quantify the extent to which the alternative output gap measures provide a means of improving inflation forecasts, using a simulated out-of-sample methodology. The procedure employed for forecast evaluation is similar to the one used by Stock & Watson (1999) for the U.S., Billmeier (2004) for European countries, and Coenen et al. (2008) for the Euro area. The forecast evaluation depends on several factors that include, among others, the measure of inflation considered, the model employed to construct the inflation forecasts, the benchmark model used for comparison, and the loss function used in forecast evaluation. In this paper, I restrict my attention to Australian trimmed mean CPI measure and consider the mean-squared forecast error (MSFE) for forecast evaluation.

The out-of-sample inflation forecast is obtained using bivariate models of inflation and the output gap that are estimated using rolling sub-samples of 40 quarters each. More formally, the general specification of the bivariate models is:

$$\pi_{t+h}^{h} = a + b(L)\pi_t + c(L)x_t + \varepsilon_{t+h}^{h} \tag{86}$$

where L is the lag operator, $b(L)$ and $c(L)$ are finite polynomials of orders p and q respectively, x_t is the measure of the output gap, π_t is the annualised quarterly inflation, and π_{t+h}^{h} is the annualised h-quarter percentage change in the trimmed mean CPI defined as:

$$\pi_{t+h}^{h} = 100\left(\left(\frac{P_{t+h}}{P_t}\right)^{\frac{4}{h}} - 1\right) \tag{87}$$

To provide a benchmark for comparison, I consider three alternative specifications. The first specification assumes inflation follows a smooth random walk model as in Coenen et al. (2008), where the forecast is computed as the average inflation rate during the previous four quarters[2]:

$$\pi_{t+h}^{RW} = 100\left(\frac{P_t}{P_{t-4}} - 1\right) \tag{88}$$

The second specification I consider is a univariate autoregressive inflation forecasting model based on the specification in equation (86) but omits the output gap:

$$\pi_{t+h}^{h} = a' + b'(L)\pi_t + \varepsilon_{t+h}^{h} \tag{89}$$

Given that it is always possible to improve on the univariate specification by adding more regressors, I consider a third specification where the output gap in the bivariate model is replaced by real output growth:

$$\pi_{t+h}^{h} = a'' + b''(L)\pi_t + c''(L)gy_t + \varepsilon_{t+h}^{h} \tag{90}$$

where gy_t is the quarterly annualised growth rate of real output. van Norden (1995)

[2]In the random walk specification, the inflation forecast is independent of the forecast horizon and hence doesn't change as the forecast horizon varies.

explains that this specification uses a larger information set than an autoregressive specification as it contains information on both inflation and output growth. Hence, such a specification provides a stronger test for the usefulness of output gap in inflation forecasting.

Using Ordinary Least Squares procedure, the forecasting models are estimated on rolling sub-samples starting from the subsample 1993:Q1-2002:Q4, at forecast horizons $h = \{1, 2, \cdots, 8\}$. The number of lags are selected in a way to minimise the Akaike Information Criterion applied on the full sample with a maximum of four lags specified for each regressor. For each sub-sample, a forecast of inflation is obtained and the forecast error is computed as:

$$\varepsilon_{t+h}^{h,f} = \pi_{t+1}^{h,f} - \pi_{t+h}^{h} \tag{91}$$

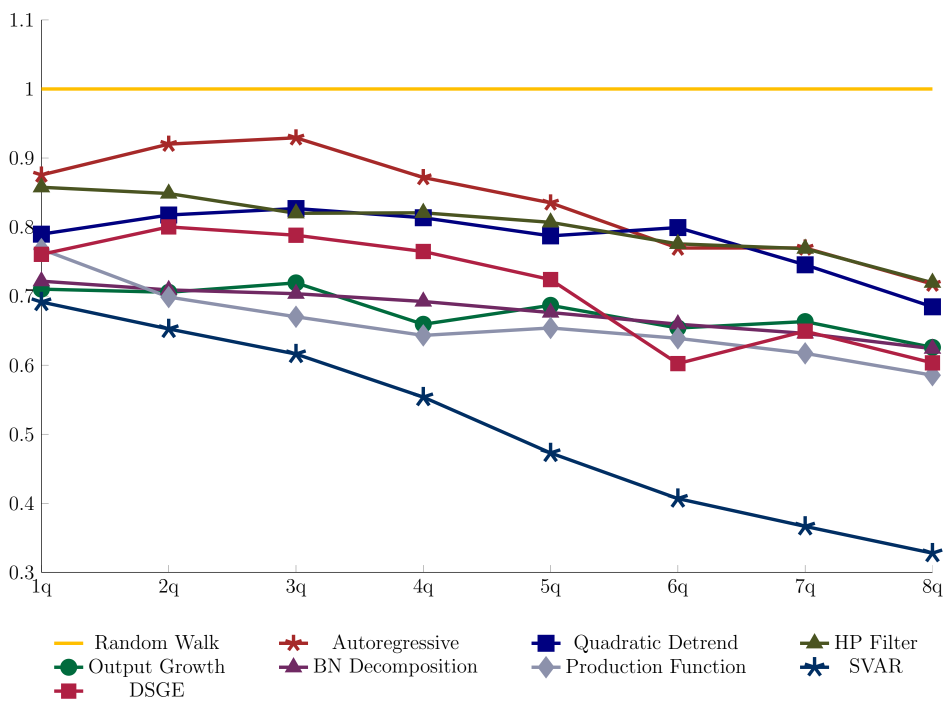
where π_{t+h}^{h} is the realised inflation rate and $\pi_{t+1}^{h,f}$ is the model forecast of inflation. Then, for F number of forecasts, the mean-squared forecast error is computed as:

$$MSFE = \frac{1}{F}\left(\sum_{f=1}^{F} \varepsilon_{t+h}^{h,f}\right)^2 \tag{92}$$

Overall, I compare nine models of inflation: the random walk model (RW), the autoregressive model (AR), the output growth model (Growth), and six bivariate models. The first, second and third bivariate models include univariate output gap estimates: the quadratic detrended output gap, the HP filtered output gap, and the output gap from the BN decomposition. The fourth and fifth bivariate models are specified in terms of the output gaps estimated by the production function approach and the SVAR methodology. Finally, the sixth bivariate model includes the Kalman-filtered DSGE model-based estimate of the flexible-price output gap. The use of the one-sided Kalman-filtered rather than the two-sided Kalman-smoothed estimate of the output gap ensures that the DSGE model-based estimate is not at an informational advantage in the forecasting exercise compared to other measures of the output gap.

Figure 3 summarises the forecast accuracy of each of the different models considered relative to the random walk model. The results reveal that the bivariate models of the output gap significantly improve the inflation forecast accuracy when compared to the random walk model over all forecast horizons. In particular, the bivariate models specified in terms of the SVAR, BN decomposition, production function approach, and the DSGE model-based output gap estimates possess significantly more forecasting power for inflation when compared with the random walk model. This result matches the findings in Coenen et al. (2008) for the Euro area. When compared with the autoregressive model, the bivariate models specified in terms of the quadratic detrended output gap and the HP filtered output gap reveal the lowest improvement in forecasting accuracy, with some of these measures even performing worse than the autoregressive model in the long-term forecast horizons. On the other hand, each of the bivariate models specified in terms of the BN decomposition output gap, the production function approach, the SVAR output gap, and the DSGE model-based output gap do improve over the autoregressive model of inflation over all the forecast horizons. When considering the bivariate model specified in terms of output growth, it is revealed that the output gap estimates from the univariate models underperform in forecasting inflation relative to the output growth model over all the forecast horizons. The bivariate model specified in terms of the DSGE model-based output gap measure slightly improves over the output growth model only for the sixth, seventh and eighth quarter horizons, but is outperformed by the output growth model for all other horizons. The bivariate model which includes the SVAR measure of the output gap improves over the output growth model over all the forecast horizons, with the improvement becoming more significant for the long-term forecast horizons.

Figure 3: The MSFE of Alternative Models Relative to Random Walk



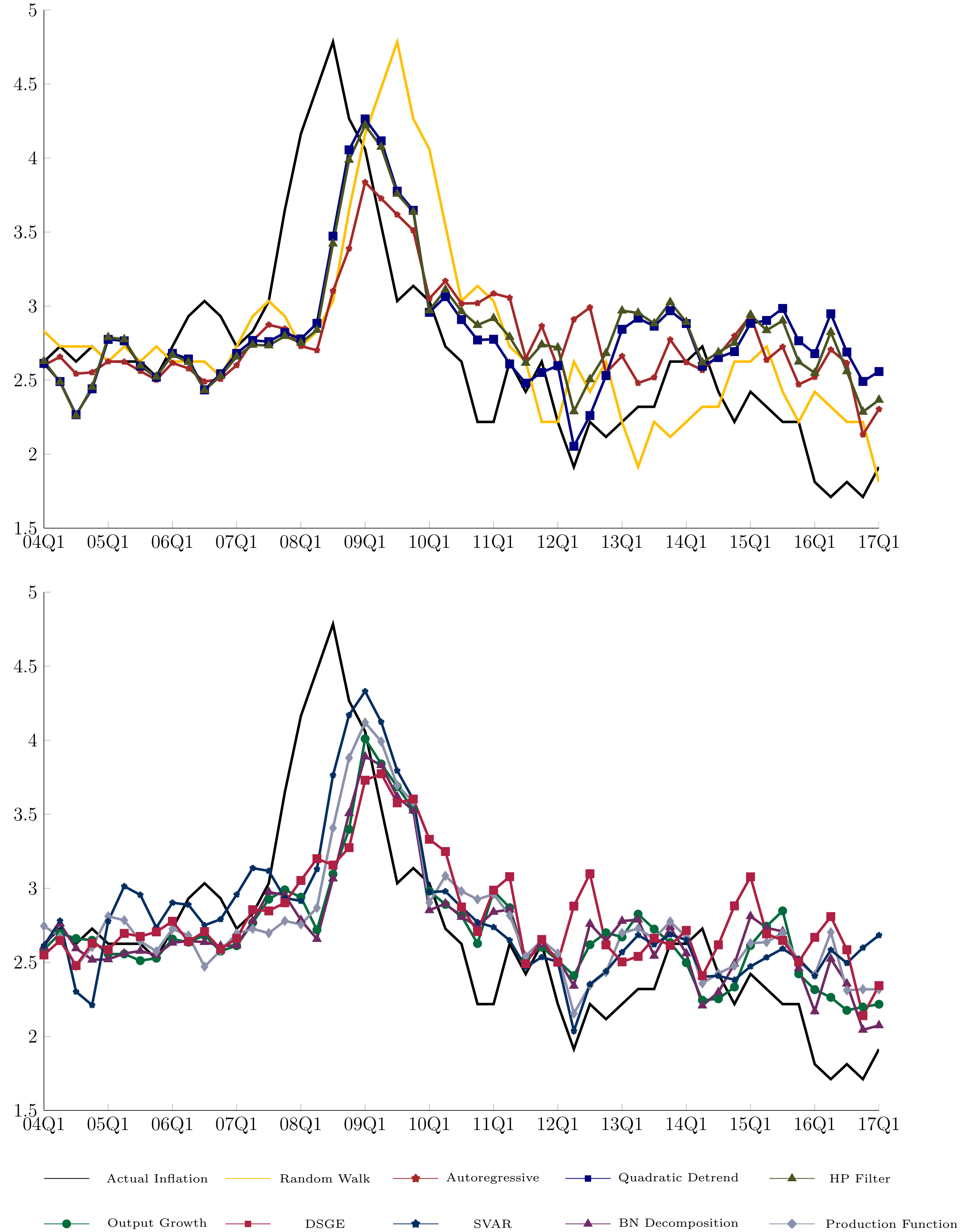
To sum up, the comparison of the predictability of inflation across the different output gap measures depends on the benchmark model chosen for comparison and the forecast horizon specified. In general, the results reveal that there exists favourable

Table 1: Analysis of Inflation Forecast Accuracy

	MSFE	MSFE/RW	MSFE/AR	MSFE/Growth
1 Quarter Horizon				
Quadratic Detrend Output Gap	0.410	0.790	0.902	1.112
HP Filter Output Gap	0.446	0.858	0.980	1.208
BN Decomposition Output Gap	0.375	0.722	0.824	1.016
Production Function Output Gap	0.399	0.768	0.877	1.081
SVAR Output Gap	0.359	0.691	0.790	0.974
DSGE Output Gap	0.395	0.761	0.868	1.071
Random Walk	0.520	1.000	1.142	1.408
Autoregressive Model	0.455	0.875	1.000	1.233
Real Output Growth	0.369	0.710	0.811	1.000
2 Quarter Horizon				
Quadratic Detrend Output Gap	0.324	0.817	0.888	1.159
HP Filter Output Gap	0.336	0.849	0.922	1.203
BN Decomposition Output Gap	0.281	0.709	0.771	1.005
Production Function Output Gap	0.253	0.639	0.694	0.905
SVAR Output Gap	0.258	0.652	0.709	0.925
DSGE Output Gap	0.317	0.800	0.870	1.134
Random Walk	0.396	1.000	1.087	1.417
Autoregressive Model	0.364	0.920	1.000	1.304
Real Output Growth	0.280	0.706	0.767	1.000
4 Quarter Horizon				
Quadratic Detrend Output Gap	0.320	0.814	0.933	1.234
HP Filter Output Gap	0.323	0.821	0.941	1.245
BN Decomposition Output Gap	0.273	0.692	0.794	1.050
Production Function Output Gap	0.274	0.696	0.798	1.055
SVAR Output Gap	0.218	0.554	0.635	0.840
DSGE Output Gap	0.301	0.765	0.877	1.160
Random Walk	0.394	1.000	1.147	1.517
Autoregressive Model	0.343	0.872	1.000	1.322
Real Output Growth	0.260	0.659	0.756	1.000
8 Quarter Horizon				
Quadratic Detrend Output Gap	0.321	0.685	0.954	1.094
HP Filter Output Gap	0.337	0.719	1.003	1.150
BN Decomposition Output Gap	0.292	0.624	0.870	0.997
Production Function Output Gap	0.335	0.714	0.996	1.142
SVAR Output Gap	0.154	0.328	0.457	0.524
DSGE Output Gap	0.283	0.603	0.841	0.964
Random Walk	0.468	1.000	1.394	1.598
Autoregressive Model	0.336	0.717	1.000	1.147
Real Output Growth	0.293	0.626	0.872	1.000

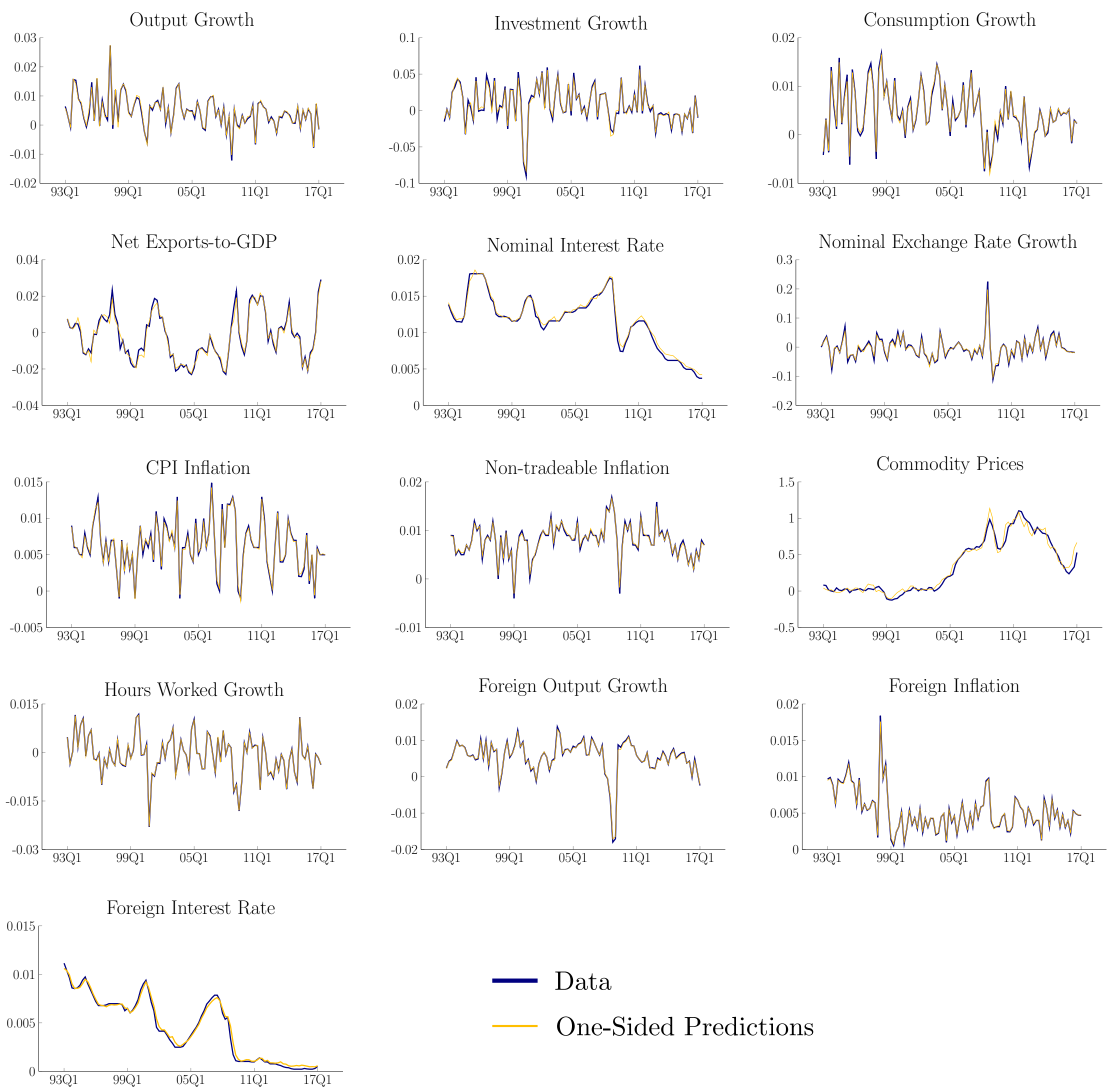
evidence regarding the inflation forecasting power of the DSGE model-based output gap, when compared to the random walk and the autoregressive models as well as to other conventional univariate output gap measures. However, the DSGE model-based output gap seems to be outperformed by the SVAR estimate of the output gap for all forecast horizons. Further, the output growth model and the production function model perform better than the DSGE model-based output gap for short-term horizons and share similar forecast performance over the longer forecast horizons.

Figure 4: The Four-Quarter Inflation Forecast of Alternative Models



5 Additional Results

Figure 5: Data and One-Sided Predictions



Sources: ABS; Author's calculations; FRED; RBA

Figure 6: Posterior and Prior Distributions

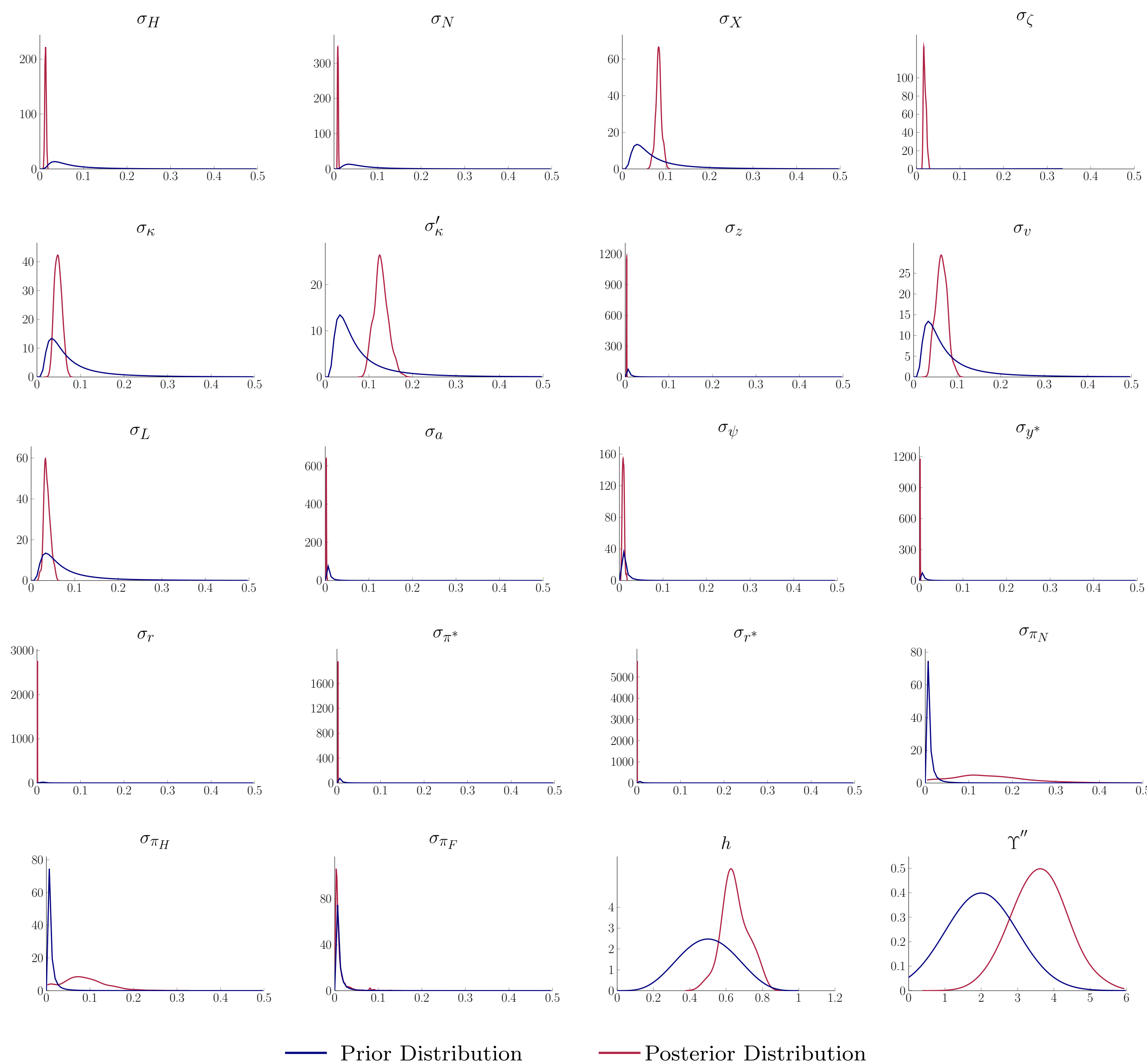
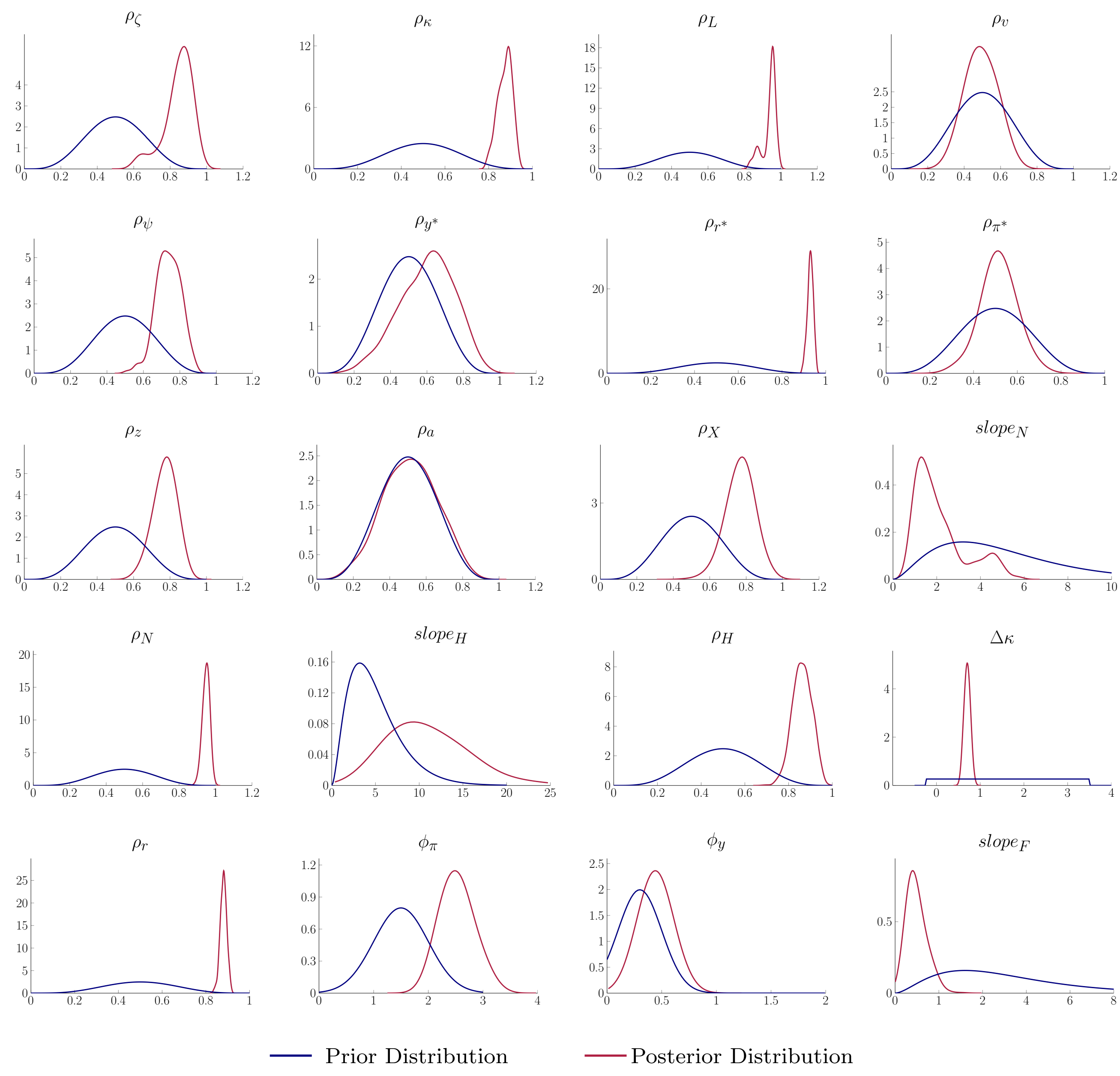


Figure 6 (Continued): Posterior and Prior Distributions



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