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Climate Hysteresis and Monetary Policy

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Abstract

Since the birth of the natural rate hypothesis, the conventional notion that short-term output simply fluctuates around a relatively stable long-term trend became the norm in modern macroeconomics, including in the standard New Keynesian DSGE model. However, the global financial crisis (GFC) led to a serious rethinking of this norm, giving rise to the re-emergence of the Blanchard-Summers' hysteresis debate and a new business cycle paradigm in which the short-term output effects of financial crises permanently feed into long-term growth trends. Using a Bayesian-estimated structural multivariate filtering model calibrated to data for Australia and the United States, the innovation of this paper is the incorporation of climate hysteresis into the estimation of potential output and the output and unemployment gaps. The results suggest non-trivia implications for monetary policy in a carbon-constrained world. Not only are the model-based estimates of potential output and NAIRU more volatile with climate shock persistence, the climate-neutral output and unemployment gap estimates are much smaller than conventional estimates, with different implications for inflation signals during the upturn or downturn of the business cycle. For economies that are more susceptible to disruptive climate shocks, especially in the developing world, an environment in which both demand conditions and the underlying supply potential are rapidly changing will severely complicate the conduct of forward-looking macroeconomic policy.

Keywords

Potential output, output gaps, NAIRU, physical climate risks

JEL Classification

C51, C52, E32, E52, Q51

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Climate Hysteresis and Monetary Policy

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Since the birth of the natural rate hypothesis, the conventional notion that short-term output simply fluctuates around a relatively stable long-term trend became the norm in modern macroeconomics, including in the standard New Keynesian DSGE model. However, the global financial crisis (GFC) led to a serious rethinking of this norm, giving rise to the re-emergence of the Blanchard-Summers' hysteresis debate and a new business cycle paradigm in which the short-term output effects of financial crises permanently feed into long-term growth trends. Using a Bayesian-estimated structural multivariate filtering model calibrated to data for Australia and the United States, the innovation of this paper is the incorporation of *climate hysteresis* into the estimation of potential output and the output and unemployment gaps. The results suggest non-trivia implications for monetary policy in a carbon-constrained world. Not only are the model-based estimates of potential output and NAIRU more volatile with climate shock persistence, the climate-neutral output and unemployment gap estimates are much smaller than conventional estimates, with different implications for inflation signals during the upturn or downturn of the business cycle. For economies that are more susceptible to disruptive climate shocks, especially in the developing world, an environment in which both demand conditions and the underlying supply potential are rapidly changing will severely complicate the conduct of forward-looking macroeconomic policy.

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I. Introduction

Climate risks—whether physical in the form of increased frequency and severity of climate-induced weather anomalies or transitional in the form of the macroeconomic impacts from putting a price on carbon—create negative supply shocks to the macroeconomy. Evidence suggest that the effects of physical climate risks affect not only current macroeconomic conditions, but such negative effects also feed into long-term macroeconomic trends (Hsiang & Jina, 2014). Similarly, even a well calibrated carbon tax policy may create long-lasting stagflationary effects on the macroeconomy, although the magnitude of such effects is contingent upon the nature of the monetary regime (McKibbin, Morris, Panton, & Wilcoxen, 2017; McKibbin, Morris, Wilcoxen, & Panton, forthcoming). Simply put, in a structurally disrupted world that is continuously buffeted by climate shocks, conditioning macroeconomic stabilization policy on underlying trends that are constantly changing is extremely complicated, particularly in terms of the real-time calibration of forward-looking monetary policy.

Under the conventional inflation targeting regime, the optimal policy stance is typically conditioned on forecasts of the output gap (the deviation of current output from potential) or the unemployment gap (the deviation of current unemployment rate from the natural level or the non-accelerating inflation rate of unemployment—NAIRU[1]). With the forecasts of these unobservable variables already notoriously subject to errors under normal conditions (Orphanides & Norden, 2002), the task of distinguishing actual policy signals from noise is even more complicated in a climatically disrupted world. Apart from the measurement problem, the conventional inflation targeting framework is better suited at macroeconomic stabilization in a world characterized by demand shocks, not supply shocks.

In a *coincidentally divine* world where the welfare-relevant employment conditions remain invariant to adverse supply shocks, maintaining price stability is mechanically equivalent to maintaining stable output and employment conditions (Blanchard & Gali, 2007). Absent such divine coincidence, however, monetary policy faces a stark trade-off, especially in an environment with ongoing adverse supply shocks. The classic problem of inflation-output stability trade-off under adverse supply shocks is illustrated in the second quadrant of Figure 1.

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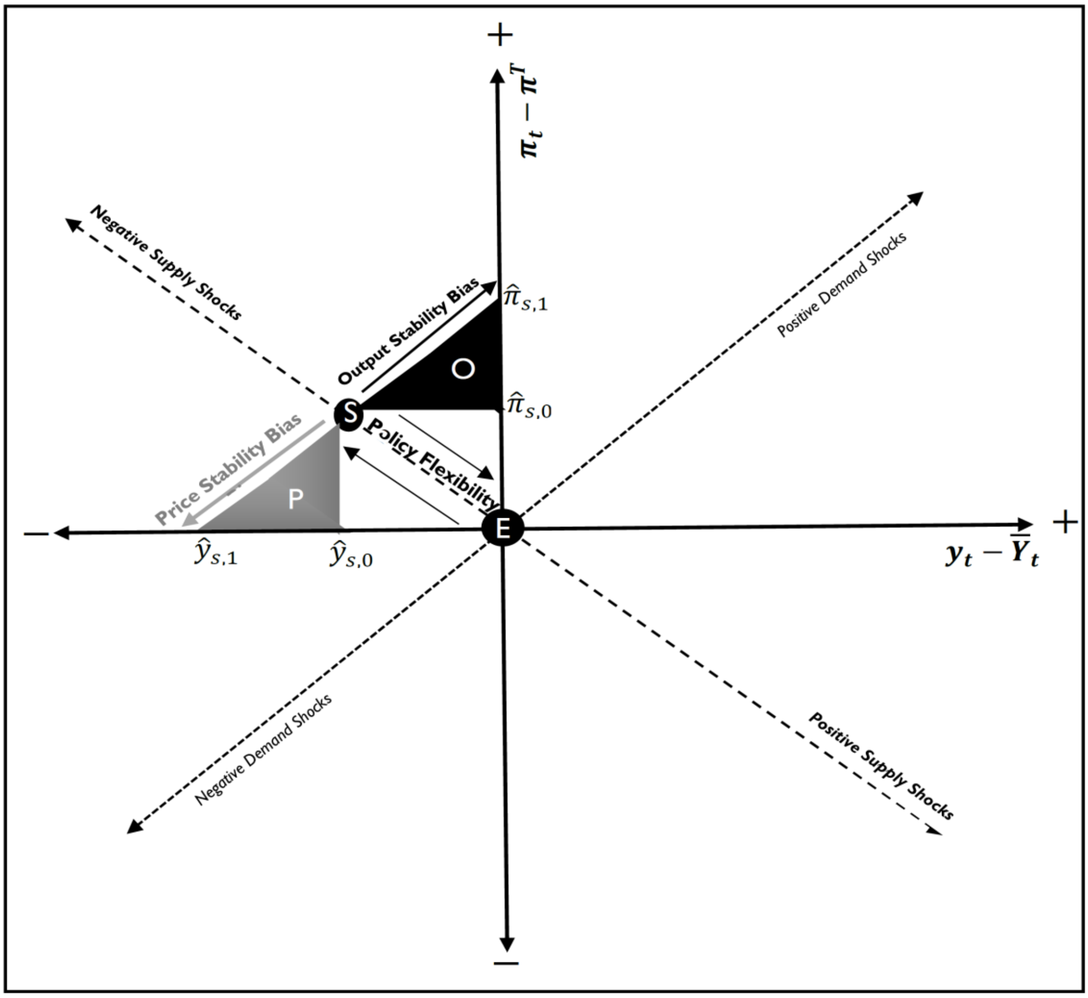
[1] Although interchangeably used in practice, NAIRU differs from the related concept of the natural rate of unemployment. As originally defined by Modigliani and Papademos (1978), NAIRU refers to the level of unemployment consistent with stable inflation in the short to medium term. The natural rate on the other hand is the rate at which inflation would gravitate to its long run expected steady state value, after all transitory shocks have fully worked through labour and product markets (Friedman, 1968).

Imagine an economy initially in equilibrium (at E) before being hit by an adverse supply shock, resulting into stagflation (negative output gap at $\hat{y}_{s,0}$ and an above-target inflation at $\hat{\pi}_{s,0}$). A flexible inflation targeting central bank that seeks to biasedly '*look through*' the output effect as only temporary and only reacts to tame inflationary pressure may further weaken output (as indicated by the move from $\hat{y}_{s,0}$ to $\hat{y}_{s,1}$).

Figure 1. Price-Output Stability Trade-off Under Adverse Supply Shocks



Despite the significant hit to industrial production and overall U.S. output from the 2005 Hurricane Katrina disaster, the U.S. Federal Reserve responded by tightening the policy stance by up to 25 basis points[2], working under the assumption that the growth effects of the disaster were only temporary, but near-term inflationary pressure must be tamed. Conversely, attempts at stimulating output via a loose policy stance may create further upward pressure on inflation (from $\pi_{s,0}$ to $\pi_{s,1}$).

[2] *See minutes of the September 20, 2005 Federal Open Market Committee (FOMC)*

As indicated by the *policy flexibility zone* in the diagram, the price-output stability trade-off is addressed in practice by *"flexibly"* conditioning policy reactions on shocks that are judged to be *non-transitory* and to the extent that they affect underlying macroeconomic conditions (Bernanke and Gertler, 1999). However, in an economy characterised by a sequence of ongoing climate-induced disruptions, making any accurate distinctions between transitory and permanent shocks is a faulty exercise (Brainard, 2019), rendering the flexible inflation targeting regime sub-optimal in a carbon-constrained world (McKibbin et al., 2017; McKibbin & Panton, 2018; McKibbin et al., forthcoming). The effects of the adverse supply shock illustrated in Figure 1 would be more complex, if instead of only affecting current output, the shock also affects the long-term growth trend. For example, a typical natural disaster that weakens households' balance sheets and depresses private consumption today may also negatively affect firms' current investment decisions (Batten, Sowerbutts, & Tanaka, 2016), potentially lowering future capital stock and weakening advancement in technical progress (Fankhauser & Tol, 2005).

Unlike relatively rare financial crises whose onset might be foreseen (Kamisky & Reinhart, 1999; Rajan, 2005; Reinhart & Rogoff, 2009), the climate crisis creates series of ongoing shocks that structurally disrupts the macroeconomy in an unpredictable fashion (Fomby, Ikeda, & Loayza, 2013; Hsiang & Jina, 2014). Although a large literature is emerging on the monetary policy effects of climate risks, research effort has been largely focused on the financial stability implications of physical and transition risks (Bolton et al., 2020; England, 2015; NGFS, 2019) with scant findings on how these risks affect the overall nature of the monetary regime, with few notable exceptions (McKibbin et al., 2017; McKibbin et al., forthcoming).

Consistent with recent evidence on the long-term output effects of short-term shocks (L. M. Ball, 2009; Blanchard, 2018; Bluedorn & Leigh, 2018; Borio, Disyatat, & Juselius, 2013, 2016; Cerra & Saxena, 2008, 2017), the type of structural disruptions posed by climate-induced persistent weather anomalies may feed into both transitory and long-term growth dynamics, through what may be termed as *climate hysteresis*. Usual seasonal adjustments techniques that simply remove "normal" seasonal weather variations from macroeconomic data seriously falls short of capturing the "abnormal" climate-induced weather patterns (Boldin & Wright 2018), least to mention their long-term hysteresis effects. Although there is a strong literature on the effects of climate shocks on the macroeconomy (Buckle, Kim, Kirkham, McLellan, & Sharma, 2007; van de Ven & Fouquet, 2017), the current paper is the first attempt at incorporating climate hysteresis into the estimation of potential output and the output and unemployment gaps, to the best of my knowledge.

Apart from carefully creating a nexus between the literature on the macroeconomic effects of climate change and the monetary policy literature, this paper contributes to the literature by incorporating climate hysteresis effects into the estimation of potential output and the output and unemployment gaps, key unobservable variables that are crucial in the conduct of forward-looking macroeconomic stabilization policy, especially monetary policy. The rest of the paper is organized as follow: the next section provides a summary of the relevant literature on climate change and economic growth. The third section outlines the model. The results are analyzed in section four. The final section contains policy implications and the conclusion.

II. Related Literature

The unpredictable onset and frequency of physical climate risks have devastating effects on the environment and the macroeconomy (Cavallo & Noy, 2010; Dell, Jones, & Olken, 2014), with competing hypotheses on how such risks affect long-term output growth trends. Some findings suggest that while output may be negatively affected in the immediate aftermath of disasters, the introduction of new technologies following disasters may have positive effects on long-run growth (Crespo Cuaresma, Hlouskova, & Obersteiner, 2008; Hallegatte & Dumas, 2009; Skidmore & Toya, 2002). Related research findings, including Stromberg (2007), Yang (2008) and Strobl (2011), show that economies are likely to simply return to their pre-disaster growth trends provided the increased marginal product of capital in the post-disaster environment triggers increased capital inflows that stimulate economic activity.

Recent findings largely argue against the creative destruction or 'return-to-trend' arguments pushed in the earlier literature, with increased macroeconomic risks in the post-disaster environment identified as the main factor undermining growth. For example, for regions exposed to frequent episodes of severe physical climate shocks, uncertainty from high insurance claims (Bank of England, 2015), falling housing prices (Boustan, Kahn, Rhode, & Yanguas, 2020), increased permanent risk-aversion tendencies following exposures to natural disasters (Cameron and Shah 2013), and outmigration from affected regions (Strobl, 2011; Boustan et al., 2020) are some of the increased risks factor that may affect current and future macroeconomic outcomes for such regions. Hsiang and Jina (2014) provide evidence that for economies that are frequently exposed to cyclones, the short-term growth effects may be small, but those negative effects strongly persist over time, gradually lowering the long-term growth and development trajectories of the affected economies. Earlier findings by Fomby et al. (2013) also suggest that the growth effects in the aftermath of climate-induced disasters may persist for longer, especially in the case of drought.

Apart from the measured effects of large and severe natural disasters that may be relatively infrequent, the short-term impact of climate change is felt in the form of ongoing abnormal variations in weather patterns. Although a summer of extreme heatwaves or an incident of flooding may be small in and of itself, scientific evidence (IPCC, 2018) suggests that such events will become more severe and frequent over time with changing climatic conditions, subjecting the economy to an ongoing cycle of adverse supply shocks and structural disruptions. As temperature rises, the associated elevated level of heat stress negatively affects labor supply and productivity (Dell, Jones, & Olken, 2012; Heal & Park, 2015; Kjellstrom, Maître, Saget, Otto, & Karimova, 2019; Zander, Botzen, Oppermann, Kjellstrom, & Garnett, 2015) and accelerates the depreciation of capital (Stern, 2013) resulting in costly capital adjustment and reallocation (Zhang, Deschenes, Meng, & Zhang, 2017). Therefore, whether in the form of large natural disasters or gradual worsening of weather anomalies, physical climate risks pose a serious challenge to macroeconomic stabilization.

On the macroeconomics front, the current paper is closely related to Alichi et al. (2019) who introduce partial labor market hysteresis in a multivariate model applied to the United States. They show that when short-term shock persistence is embedded in the model via hysteresis, the estimated output gaps are much smaller and NAIRU more volatile than conventional estimates that consider output cyclicality to fluctuate around a rather relatively smooth potential growth path. Closely related earlier findings include Bluedorn and Leigh (2018) who document empirical evidence on output shocks persistence and Cerra and Saxena (2008, 2017) who argue that the output gap can be poorly measured and inconsistent with macroeconomic fundamentals when the frequency and depth of economic crises are the key drivers of the path of potential growth. These findings are consistent with earlier modelling by Pagan (1997) and Harding and Pagan (2002) who provide evidence on the persistence of short-term output shocks.

III. Model

From the literature, climate-induced weather anomalies affect the macroeconomy from many angles, including weakening labour productivity, fast depreciation of capital and increased macroeconomic risks and uncertainty. In order to incorporate the persistence of these climate-induced shocks into the estimation of potential output and the output and unemployment gaps, it is useful to start with a simple simulation experiment, with New Keynesian micro-foundations in the spirit of Alichi et al. (2019).

Assume standard Cobb-Douglas production function with constant returns to scale:

(1)
$$\overline{Y}_t = A_t K_t^{\alpha} L_t^{1-\alpha}$$

where potential output, capital and potential employment are represented by $\overline{Y}_t$, K_t and L_t respectively, and α the share of capital in production, with firms minimizing their labor costs ($W_t L_t$), the rental costs of capital ($r_t^k K_t$) and the capital adjustment costs (c)—the cost associated changing investment and capital stock to match existing labor supply and productivity. Consistent with the literature (Benes, Kumhof, & Laxton, 2014; Hayashi, 1982; Sargent, 1978), the adjustment costs follow a quadratic process:

(2)
$$r_t^k K_t \frac{1}{2} c \left(\frac{K_t}{K_{t-1}} - 1\right)^2$$

Assuming perfectly competitive labor and capital markets, with firms taking wages and rental costs as given, the cost minimization problem takes the form:

(3)
$$\min_{L_{t+i}, K_{t+i}} E_t \sum_{i=0}^{\infty} \beta^i \left(W_{t+i} L_{t+i} + r_{t+i}^k K_{t+i} \left[1 + \frac{1}{2} c \left(\frac{K_{t+i}}{K_{t+i-1}} - 1\right)^2\right] + \lambda_{t+i}\left(\overline{Y}_{t+i} - A_{t+i} K_{t+i}^{\alpha} L_{t+i}^{1-\alpha}\right) \right)$$

where β is the discount factor and λ_t and E_t are the Lagrange multiplier and expectation operator respectively. For the above optimization problem, the first order conditions (FOCs) become:

(4)
$$Labor: \qquad W_t - \lambda_t (1-\alpha) \frac{\overline{Y}_t}{L_t} = 0$$

(5)
$$\begin{aligned} Capital: \ r_t^k \left[1 + \frac{1}{2} c \left(\frac{K_t}{K_{t-1}} - 1\right)^2\right] + r_t^k K_t C \left(\frac{K_t}{K_{t-1}} - 1\right) \frac{1}{K_{t-1}} \\ + \beta c E_t \left[r_{t+1}^k K_{t+1} \left(\frac{K_{t+1}}{K_t} - 1\right)\left(-\frac{K_{t+1}}{K_t^2}\right)\right] - \lambda_t \alpha \frac{\overline{Y}_t}{K_t} = 0 \end{aligned}$$

When compactly expressed as in (6), the FOCs show that the evolution of capital is contingent upon labor supply and the costs associated with adjusting capital investment to match labor supply or productivity.

(6) $$\frac{r_t^k K_t \left[1 + \frac{1}{2} c \left(\frac{K_t}{K_{t-1}} - 1\right)^2\right] + r_t^k K_t c \left(\frac{K_t}{K_{t-1}} - 1\right) \frac{K_t}{K_{t-1}} - \beta c E_t \left[r_{t+1}^k K_{t+1} \left(\frac{K_{t+1}}{K_t} - 1\right) \frac{K_{t+1}}{K_t}\right.}{\alpha} - \frac{W_t L_t}{1 - \alpha} = 0$$

Absent capital-adjustment costs, the capital-labor ratio can simply be expressed as:

(7) $$\frac{r_k^k K_t}{w_{L_t}} = \frac{\alpha}{1 - \alpha}$$

Under more realistic assumptions where firms make costly (rather than costless) capital adjustments, the constant capital-labor ratio in (7) can only be achieved over a relatively longer time horizon. That is, in the short term, the optimal amount of capital that firms hold, relative to available labor supply or productivity, may be largely a function of the level of uncertainty in their operating environment (Bernanke, 1983; Bloom, 2009). For example, Bernanke (1983) argues that apart from the potentially high costs require to revise or adjust current investments in the face of macroeconomic uncertainties, optimizing behaviour requires that long-term investment decisions are informed by an understanding of uncertainties over the longer-term horizon. For firms with investments in regions or sectors that are highly susceptible to unpredictable and extreme aggregate shocks (like those due to rapidly changing climatic conditions), the assumption of high adjustment costs is a reasonable one. To evaluate how capital adjusts to a change in potential employment, say due to weakening labor productivity because of rising temperature and heat stress (Chavaillaz et al., 2019; Kjellstrom et al., 2019), the linearized version of equation (6) becomes:

(8) $$\hat{k}_t = \frac{c}{c + \beta c + 1} \hat{k}_{t-1} + \frac{\beta c}{c + \beta c + 1} E_t \hat{k}_{t+1} + \frac{1}{c + \beta c + 1} \hat{l}_t$$

where $\hat{k}_t$ and $\hat{l}_t$ represent the deviations of labour and capital from their initial steady states. By applying the method of undetermined coefficients à la Campbell (1998) and Christiano (2002), equation (8) collapses to much straightforward solution regarding the law of motion for capital when potential employment deviates from steady state:

(9) $$\hat{k}_t = \rho \hat{k}_{t-1} + \eta \hat{l}_t$$

where $\eta = 1 - \rho$ represents labor share of output.

By substituting (9) into (8) (and restricting the coefficients in front of $\hat{k}_{t-1}$ to zero) and omitting explosive solutions, equation (10) reveals that the higher the adjustment costs, the slower firms will take to adjust their investments, further amplifying the potential losses for firms in sectors exposed to persistent macroeconomic risks affecting employment, including physical and transition climate risks.

$$\rho = \frac{c + \beta c + 1 \pm \sqrt{(c + \beta c + 1)^2 - 4\beta c^2}}{2\beta c} \tag{10}$$

More importantly, in the face of persistent shocks to the economy that drive potential employment away from its steady state level (e.g. say persistent decline in labor productivity due to heat stress with rising temperature), the effect on potential output will be in the form of direct and contemporaneous fall due to falling labor supply or productivity, and indirect (gradual) decline due to costly capital adjustments to match available level of employment or productivity. To measure output elasticity with respect to these two effects, equation (9) is rewritten as:

$$K_t = \rho K_{t-1} + (1-\rho)\frac{K}{L}L_t = \sum_{i=0}^{\infty} \rho^i (1-\rho)\frac{K}{L}L_{t-i} \tag{11}$$

with the production function in (1) rewritten as

$$\overline{Y}_t = A_t[K(L_t, L_{t-1}, \dots)]^{\alpha} L_t^{1-\alpha} \tag{12}$$

By differentiating (12) with respect to L_t and compactly rearranging, the elasticity of output with respect to labor are presented below, with the contemporaneous (direct) effect captured in (13) and the gradual (indirect) capital adjustment effect represented by (14).

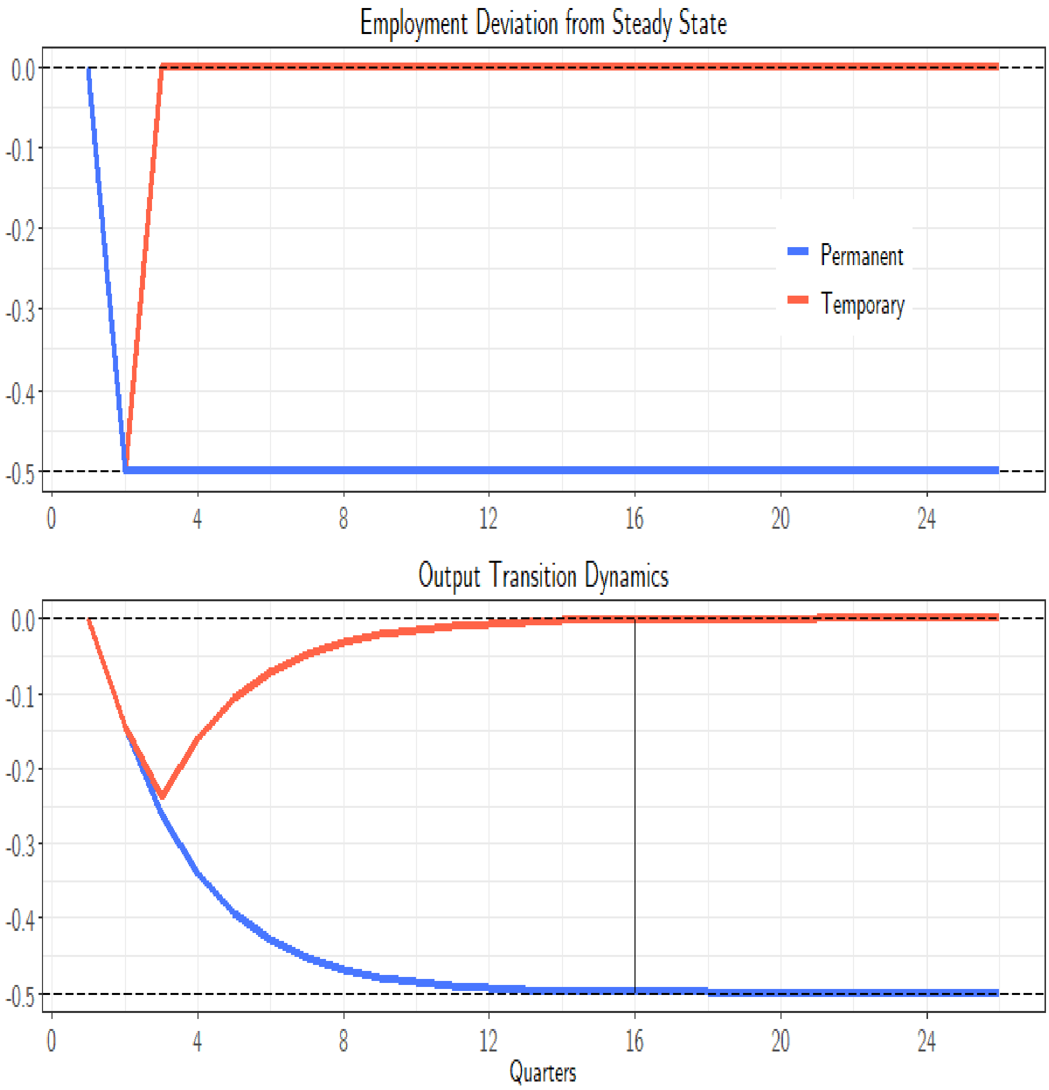
$$\frac{\frac{\partial \overline{Y}_t}{\overline{Y}_t}}{\frac{\partial L_t}{L_t}} = (1-\alpha) + \alpha(1-\rho) \tag{13}$$

$$\frac{\frac{\partial \overline{Y}_{t+i}}{\overline{Y}_{t+i}}}{\frac{\partial L_t}{L_t}} = \alpha\rho^i(1-\rho) \quad \text{for } i = 1,2,\dots \tag{14}$$

Based on (13) and (14), it can be seen that in the long run, persistent changes in NAIRU will translate one-for-one into potential output, with the labor productivity effects of climate shocks (Zander et al., 2017; Strobl, 2011; Boustan et al., 2020) serving as one of the several channels through which climate change might affect potential output. The labor market effects of climate change may also result from climate-related emigration (Cattaneo & Peri, 2015). For regions with harsher and persistent weather anomalies, out-migration of the labor force may weaken long-term potential employment (Strobl, 2011; Boustan et al., 2020). As people emigrate to regions with relatively better climate conditions within or across countries, there may be more unemployment or underemployment, with the associated reduction in income, savings and or investment translating into lower potential output (Fankhauser &Tol, 2005). To assess these arguments, a simulation experiment based on equations (13) and (14) is performed. Consider a 0.5 percentage point decline in potential labour supply or labor productivity, say due to extreme and persistent heatwaves and other harsh climate-induced weather conditions, to examine the effects on output and capital. Consistent with the New Keynesian DSGE literature (Smets & Wouter, 2003), the calibrated values for β, α and the adjustment costs parameter, c, are set at 0.99, 2/3 and 20 respectively. Figure 2 presents the effect on output and the transition path back to steady state following the shock.

In the first scenario, the decline is assumed to be permanent while in the second scenario, a one-time temporary decline (say due to once-in-a decade heatwave or bushfire) is assumed. In either scenario, the fall in output is deeper in the first year of the shock, followed by a gradual decline towards the initial steady state (temporary shock) or a lower, permanent steady state (permanent shock). Beyond the year of impact of the shock, the gradual output transition dynamics can be explained by the pace of capital adjustments by firms. Whether permanent or temporary, the simulation results suggest that output returns to steady state within four years. This is consistent with recent arguments that although the natural rate hypothesis may have passed its time (Farmer, 2013), a more plausible working null hypothesis would be that there exists labor market hysteresis, with the magnitude of the effects on long-term growth less than unity (Blanchard, 2018) and gradually fading over time (up to 4 years as per Figure 2). That is, while the effects of climate-induced weather shocks may not be permanent, the disruptions caused by these shocks may have relatively longer stagflationary effects (i.e. rising inflation combined with falling output), distinguishing them from typical demand shocks.

Figure 2. Simulated Output Effects from Steady-state Deviation of Potential Employment



Source: Author's calculations

Using data on real GDP, inflation, the unemployment rate, capacity utilization and a measure of climate-induced weather shocks for Australia and the United States, the goal in this paper is to derive estimates of potential output and the output and unemployment gaps that embody the persistence of short-term climate shocks. Based on the simulation results above, some anecdotal inference can be made that for climate shocks that affect labor productivity, their output effects may persist for up to at least four years. In the spirit of Borio, Disyatat, & Juselius (2016) and Alichi et al. (2019), the modelling approach follows two steps. First, climate-induced weather shocks are embedded into the estimation of *climate-neutral* output gaps. Second, the climate-neutral output gaps are then incorporated in the estimation of NAIRU, with climate shocks and their hysteresis effects allow to persist for up to four years. The full procedure is demonstrated below.

A. The Stochastic Process for Output

Although variously defined in the literature (Kiley, 2013), in this paper, the output gap ($\hat{y}_t$) is defined consistent with Okun's Law as the deviation of real output y_t from potential ($\overline{y}_t$) in log terms:

$$\hat{y}_t = \ln y_t - \ln \overline{y}_t \tag{15}$$

The law of motion underpinning output stochasticity consists of three equations, beginning with the structural micro-foundations derived above (equations 13 and 14) and as anecdotally evidenced by the simulation experiment (Figure 2) that changes in NAIRU affect potential output, with the output effects lasting for up to four years (16).

$$\overline{y}_t = \overline{y}_{t-1} + G_t^{\overline{y}} - \eta(\overline{U}_t - \overline{U}_{t-1}) - \rho\frac{(\overline{U}_{t-1} - \overline{U}_{t-5})}{4} + \varepsilon_t^{\overline{y}} \tag{16}$$

$$G_t^{\overline{y}} = \theta G_t^{ss\overline{y}} + (1-\theta)G_{t-1}^{\overline{y}} + \varepsilon_t^{G\overline{y}} \tag{17}$$

Changes in NAIRU ($\Delta\overline{U}_t$) are modelled to have direct impact on potential output through hysteresis, with the direct contemporaneous effect from persistent deviation of employment from steady state captured by the term $\eta(\overline{U}_t - \overline{U}_{t-1})$—the share of labor in a Cobb-Douglas production function (equation 9). When potential employment falls from its steady state due to climate-induced shocks, this will result in higher NAIRU, causing capital to gradually adjust to match available employment or labor productivity. This is captured by the last term in (16) $\left(\rho\frac{(\overline{U}_{t-1}-\overline{U}_{t-5})}{4}\right)$. Potential output also evolves according to a level shock ($\varepsilon_t^{\overline{y}}$) and a non-constant trend growth ($G_t^{\overline{y}}$) that is a function of steady state trend growth (G_t^{ssy}) as in (17).

$$\hat{y}_t = \phi_1\hat{y}_{t-1} + \phi_2 CI_t + \phi_3\varepsilon_t^{G\overline{y}} - \phi_4\varepsilon_t^{\overline{y}} + \varepsilon_t^{\hat{y}} \tag{18}$$

A climate index (CI), capturing persistent weather anomalies, is directly embedded in the output gap equation (18), similar to the treatment of financial imbalances in the estimation of finance-neutral output gaps in Borio et al. (2016).

Note that since climate shocks can affect both actual and potential output, the sign of the effect on the output gap is endogenously determined in the model by way of diffuse initialization[3] (Commandeur & Koopman, 2007). Apart from shocks that may temporarily create excess demand relative to potential ($\varepsilon_t^{\hat{y}}$), the output gap equation also accounts for plausible forward-looking behavior by consumers regarding future productivity and income that may bring forward excess consumption. This is captured by including the shock to trend output growth ($\varepsilon_t^{G\overline{y}}$), while level shocks to potential growth that may create excess supply relative to demand are captured by $\varepsilon_t^{\overline{y}}$.

B. Phillips Curve

(19)
$$\pi_t = \lambda_1 E_t \pi_{t+1} + (1-\lambda_1)\gamma_{t-1} + \lambda_2 \hat{y}_t + \varepsilon_t^{\pi} + \lambda_3 \varepsilon_t^{\overline{y}}$$
$$\text{where } \gamma_{t-1} = (\pi_{t-1} \times \hat{y}_{t-1})$$

A Phillips curve is added to the model to aid in identifying shocks to output and provide additional information in the estimation of potential output and the output gap. A special feature of the Phillips curve specified here is the inclusion of a lagged rescaled output gap $\pi_{t-1} \times y_{t-1}$ to capture full underlying inflation pressure in the economy. This is consistent with macroeconomic theory that facing higher adjustment costs, firms are more prone to upward nominal price adjustments during period of high inflation, causing the Phillips curve to be steeper during such periods compared with periods of lower inflation dynamics (Laurence Ball, Mankiw, & Romer, 1988; Lawrence Ball & Mazumder, 2011). Therefore, an interaction variable constructed as the product of inflation and the output gap is a good way to capture the full nature of underlying pressure in the economy (Lansing, 2019).

Also note the inclusion of the term ($\varepsilon_t^{\overline{y}}$) to capture shocks to productivity that may reduce marginal costs and inflation, consistent with the DSGE literature (see Woodford, 2003). However, in a climatically disrupted environment where constant weather shocks create price volatility with plausible negative effects on productivity, such shocks may result in higher inflation. To account for this possibility, the parameter λ_3 is estimated via diffuse initialization[4].

[4]In state space modelling, when nothing is known about the initial value of a state variable, diffuse initialization is the approach through which that initial value is endogenously estimated within the state-space context (Hamilton, 1994)

C. NAIRU Estimation with Climate Hysteresis Embedded

Equations (20) to (23) describe the evolution of unemployment, with u_t denoting the unemployment gap–the deviation of the unemployment rate (U_t) from NAIRU ($\overline{U}_t$).

(20) $$\hat{u}_t = \overline{U}_t - U_t$$

(21) $$\overline{U}_t = \tau_4 \overline{U}_t^{\ ss} + (1-\tau_4)\overline{U}_{t-1} + G_t^{\overline{U}} - \frac{1}{2}\varpi(\hat{y}_t + \hat{y}_{t-1}) + \varepsilon_t^{\overline{U}}$$

(22) $$G_t^{\overline{U}} = \tau_3 G_{t-1}^{\overline{U}} + \varepsilon_t^{G^{\overline{U}}}$$

(23) $$\hat{u}_t = \tau_2 \hat{u}_{t-1} + \tau_1 \hat{y}_t + \varepsilon_t^{\hat{u}}$$

Based on Benes et al. (2014) and in the spirit of Alichi et al. (2019) who incorporate labor market hysteresis in the estimation of potential output and output gap for the United States, climate hysteresis is embedded in the NAIRU equation (21) through the inclusion of the 2-year moving average of the climate-neutral output gap in (18). As it is unclear how expectations are affected by projected climatic variations, climate-induced changes embedded in the NAIRU are modelled to be adaptive—depending on abnormal weather variations in the previous and current periods as captured by the inclusion of the two-year moving average of the climate-neutral output gap $\left(\frac{1}{2}\varpi \times \ y_t + y_{t-1}\ \right)$. Under conditions of climate-induced weather anomalies that persistently distort both demand and supply conditions in the economy, the output gap may never close, implying a persistently changing NAIRU. This time-varying specification also includes non-climate shocks to NAIRU ($\varepsilon_t^{\overline{U}}$) and variation in the trend ($\varepsilon_t^{G^{\overline{U}}}$). Note also the dependence of the unemployment gap on the output gap in (23), consistent with Okun's law.

D. Capacity Utilization Gap

Measures of capacity utilization are incorporated into the model to provide more information on the overall level of slack in the economy.

(24) $$\hat{c}_t = C_t - \overline{C}_t$$

(25) $$\overline{C}_t = \delta_2 \bar{C}^{ss} + (1-\delta_2)\overline{C}_{t-1} + G_t^{\overline{C}} + \varepsilon_t^{\bar{C}}$$

(26) $$G_t^{\overline{C}} = (1-\delta_1)G_{t-1}^{\overline{C}} + \varepsilon_t^{G\bar{C}}$$

(27) $$\hat{c}_t = \kappa \hat{y}_t + \varepsilon_t^{\hat{c}}$$

The equilibrium capacity utilization rate $(\overline{C}_t)$ is time-varying, with a growth rate of $G_t^{\overline{C}}$ and subject to shocks $(\varepsilon_t^{\bar{C}})$ whose effects gradually fade over time, contingent on the value of the parameter δ_2. Ranging from unstable and costly energy supply (van de Ven & Fouquet, 2017) and weakened labor productivity (Kjellstrom et al., 2019; Chavaillaz et al., 2019) to costly adaptation to rapidly changing working conditions (Chambwera et al., 2014), the effects of changing climatic conditions on industrial capacity and production cannot be overemphasized. To keep things simple in this paper, the capacity utilization effects of climate change are captured in equation (27) via the inclusion of the climate-neutral output gap in the estimation of the capacity utilization gap—the deviation of current capacity (C_t) utilization rate from the equilibrium rate $(\overline{C}_t)$.

IV. Data and Estimation

A. Data

Measuring climate hysteresis effects requires the crucial task of identifying climate-induced weather shocks whose effects are not merely transitory, but relatively permanent and persistently feed into long-term macroeconomic trends. To this end, the Standardized Precipitation Evapotranspiration Index (SPEI) by Vicente-Serrano et al. (2010) is employed as a proxy for climate-induced persistent weather anomalies. The SPEI captures current weather conditions (represented by current temperature and precipitation patterns[5]) relative to cumulative patterns from previous periods, statistically standardized to enable uniform comparisons across space, time, and different climate regimes, within and across countries. Therefore, unless a distinctive pattern of climate-induced weather anomalies is taking place over time, the SPEI measured at a time scale of 12 months or longer would gravitate towards zero due to averaging over shorter time periods. This feature is important in the current paper as it allows only climate-induced persistent weather shocks to be incorporated in examining *climate hysteresis* effects. A summary of the computation methodology of the SPEI is provided in Appendix A.3 (see detailed technical treatment in Vicente-Serrano et al., 2010). In addition to weather shocks, the macroeconomic dataset used in estimating the model include real GDP, inflation, unemployment rate and measure of capacity utilization for Australia and the United States (see Table A.2 in the Appendix).

[5] the SPEI can be computed using only temperature and precipitation data with a simple method (Thornthwaite, 1948), although the results are more accurate based on modern approaches that include data on wind speed, surface humidity and solar radiation.

B. Bayesian Estimation

The model is estimated using Bayesian techniques, specifically the regularized maximum likelihood approach in the spirit of Ljung (1999), with the Kalman filter employed in estimating the latent variables in the model (Hamilton, 1994). Consistent with the literature, tight priors are utilized as in Alichi et al. (2019), except for selected climate variables for which diffuse initialization is followed, as indicated in the text. For the United States, the priors for the steady state output growth and NAIRU are calibrated as 1.8 percent and 4.3 percent respectively as per the projections in the CBO's *Budget and Economic Outlook: 2020 to 2030*. For Australia, the steady state potential output growth rate of 2.7 percent is calibrated, consistent with the average from the OECD's long-term projections over the four decades ending in 2060, while NAIRU is calibrated at 4.6 based on the OECD's historical average over the two decades ending in 2021. The Bayesian priors and posterior estimates for both Australia and the United States are summarized in Appendix Table A.1.

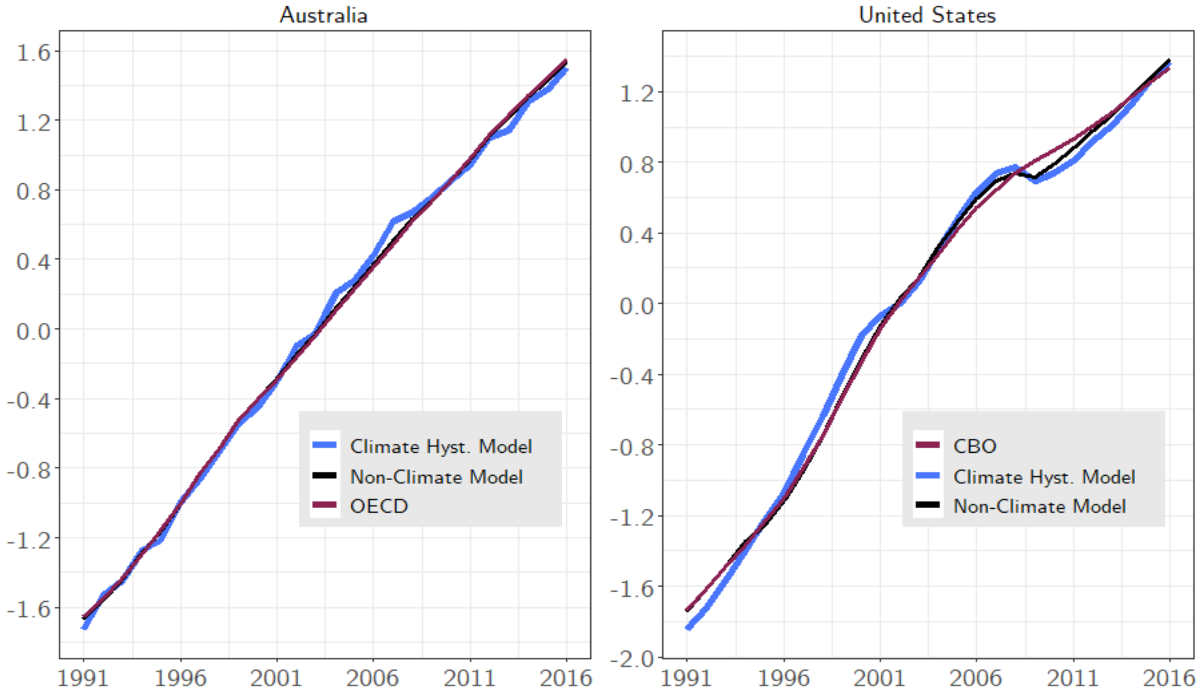
V. Results

A. Potential Growth, Output Gaps and NAIRU

To examine potential hysteresis effects, two models are estimated: the model as described by equations (15)-(27), with a climate index included in the output gap equation (18) which is termed as the '*climate hysteresis model*', and a version of the model that omits the climate index from (18), termed as the '*non-climate model*'. In this section, model-based estimates of potential growth trends, output gaps and NAIRU are analyzed and compared with official estimates—OECD estimates for Australia and CBO estimates for the United States.

Figure 3 presents potential output trends (in log deviations from 1990) for Australia and the United States. When the standard assumption of smooth trend growth in developed economies is removed by incorporating climate hysteresis into the model, potential growth follows a more cyclical pattern, with climate shocks seem to generate more volatility in the trends in both countries. Volatilities in trend growth imply serious complication for generating any accurate signals for real-time macroeconomic policymaking, particularly in a structurally disrupted environment where short-term output is even more volatile.

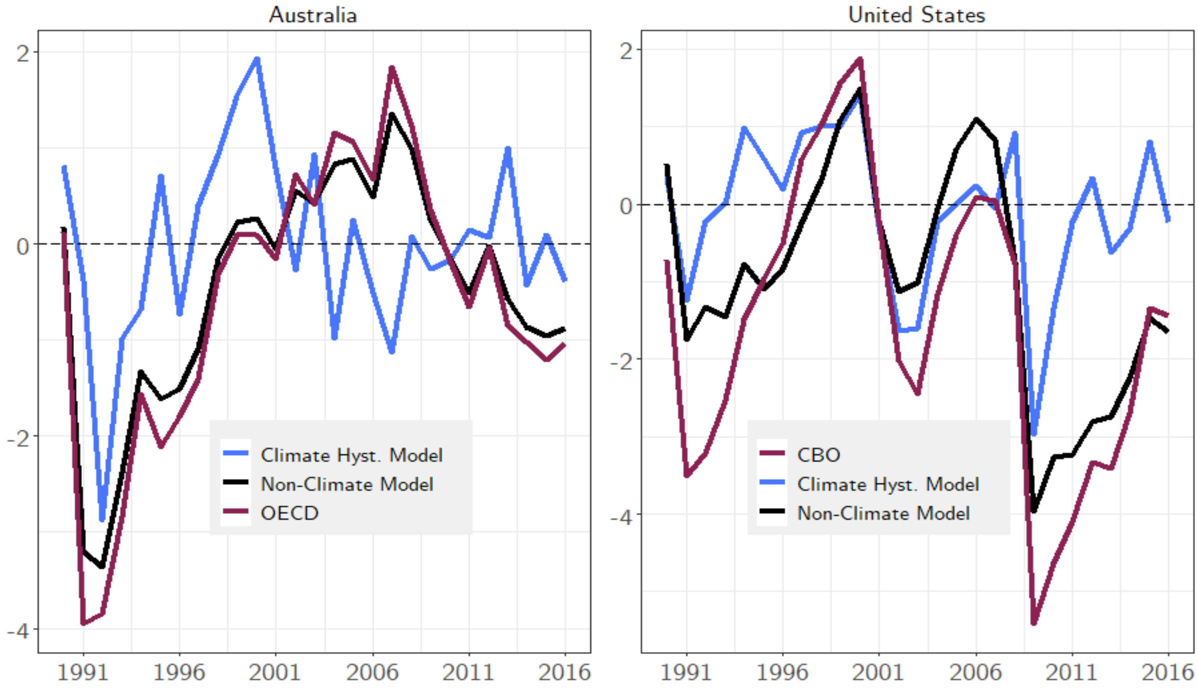
Figure 3. Model-based versus Official estimates of Potential Growth Trends
(Log Deviations from 1990)



Source: Author's estimates; OECD and CBO data.
Note: The log deviations of potential growth from 1990 series are normalized with zero mean and variance one

These complications can be better examined by analyzing the trends in the model-based output gap estimates against the official estimates as presented in Figure 4. Throughout the 1990s for example, the model with climate hysteresis suggested less potential supply capacity relative to demand, indicative of a much slower or weaker potential growth compared with conventional measures of potential output. That is, given the same current demand condition but less potential growth, the output gap is much smaller compared with estimates that assume more (stable) excess supply capacity. In the years following the global financial crisis (GFC), model-based estimates of the output gap in both Australia and the United States suggested less potential supply capacity (although more pronounced for the climate-based model estimates). As economies become more subjected to frequent disruptions, both actual and potential output will be constantly changing as key drivers of potential output become more volatile (Debelle, 2019). Therefore, measures of potential output and the output gap that do not account for these structural disruptions will create two problems for maintaining macroeconomic stability.

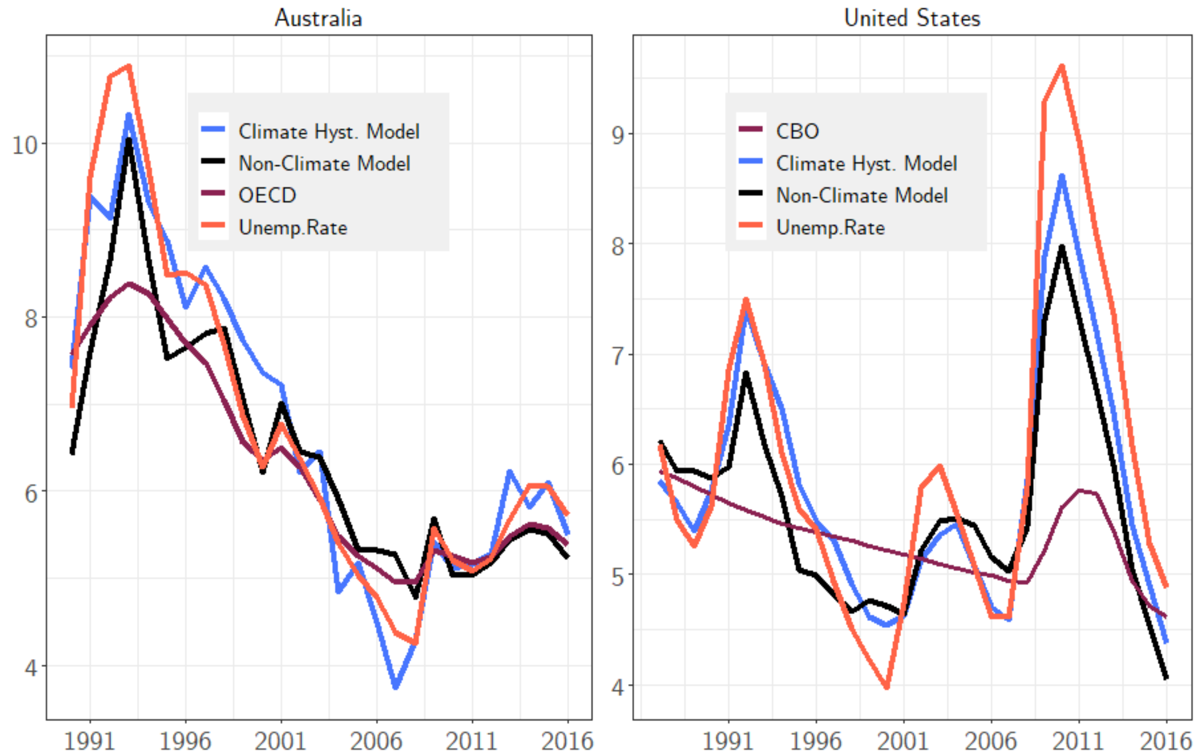
Figure 4. Model-based versus Official Output Gaps Estimates



Source: Author's estimates; OECD and CBO data.

First, the size of the business cycle would be repeatedly overstated under the assumption that rapidly changing demand conditions fluctuate around a relatively stable trend growth. During a downturn for example, there would be much larger negative output gap than would otherwise be if potential growth is modelled with hysteresis from persistent structural disruptions embedded. Second, as a result of maintaining relatively stable goal posts regarding potential growth in a structurally disrupted environment, the mistaken signals from demand pressure may create policy-induced shocks to the economy. All else equal, a large negative output gap would imply a more accommodative monetary policy stance, a move that may create excess demand pressure and financial stability risks if the output gap was much smaller due to structural disruptions that are persistently weakening potential supply capacity but whose effects are not engendered into policymaking (Borio et al., 2016). This is consistent with arguments by Friedman and Schwartz (1965) that the U.S. Federal Reserve mistakenly pursued an overly tightened policy stance during the Great Depression, and arguments by Coibion et al. (2018) about the Fed's mistaken loose policy stance in the 1970s. In the wake of the GFC, similar policy mistakes were lamented (Bean et al., 2010).

Figure 5. Estimates of NAIRU (Percent)



Source: Author's estimates; OECD and CBO data.

Figure 5 presents a comparison of the trends for model-based estimates of NAIRU against the OECD estimates (for Australia) and the CBO estimates (for the United States). Like potential output estimates, the model-based estimates of NAIRU are more volatile than official estimates, with larger magnitude when climate shocks and related hysteresis effects are embedded into the modelling. Slacks in the labor market are also consistent with the trends in potential output and output gaps (Appendix Figure A), with the results largely supportive of the evidence that short-term (demand) shocks that drive the cyclicality in output also affect long-run unemployment dynamics—via hysteresis. While the modelling of the structural determinants of NAIRU are out of the scope of the current paper, the NAIRU trends are largely reflective of the relative levels of spare capacity estimated from each model. In the case of Australia, the climate model-based NAIRU estimates for the decade leading to 2000 are higher than the non-climate and official estimates, but consistently lower throughout the years leading to the GFC. This may be due to the fact that during the period 1990-2000, the climate-neutral estimates of potential output were relatively lower. The climate model estimates are similar to recent NAIRU estimates by Cusbert (2017) for Australia, although the magnitude and volatility of the estimates in the current paper are higher due to the inclusion of climate effects.

For the United States, the model-based NAIRU estimates are also volatile compared with CBO estimates, especially so in the aftermath of the GFC, consistent with evidence by Alichi et al. (2019). The output gaps along with the respective model-based estimates of unemployment gap are plotted in Appendix Figure A. While the unemployment gap, when estimated using the NAIRU concept without consideration of the Beveridge curve relationship, may be at odds with efficient labor market outcomes (Rogerson, 1997), the closed matching of the output and unemployment gaps shows a strong coherence regarding the signals on how far the current state of the economy is away from the model-based potential.

The different unemployment and output gap magnitudes suggest different underlying inflation dynamics. For example, given the same level of high unemployment during a recession, the climate hysteresis model with smaller output and unemployment gaps (due to lower potential output and higher NAIRU estimates) would be associated with less disinflationary pressure compared with conventional model estimates. These differences in measures of economic slack imply different forward-looking monetary policy decisions, particularly in terms of inflation forecasting. The next section explores relative inflation forecast performance.

B. Inflation Forecasts Evaluation Experiment

Based on the results above, climate shocks appear to contain useful content for understanding the nature of underlying trends in the economy. Whether or not climate shocks, or more precisely climate-neutral output gaps, have predictive power in improving the forecasts of macroeconomic activity and whether such predictive ability is robust over time is the question explored in this section through a simple forecasting experiment. The goal here is to compare the predictive contents of the three output gap measures discussed above in terms of forecasting *headline inflation*.

Following the literature (Orphanides & Norden, 2005; Pichette, Robitaille, Salameh, & St-Amant, 2019), consider a simple linear forecasting models of the form:

$$\pi_t^h = \delta + \sum_{i=1}^{m} \lambda_i \, \pi_{t-i}^1 + \sum_{i=1}^{n} \psi_i \, \hat{y}_{t-i} + \varepsilon_{t+h} \tag{28}$$

where δ is a constant, $\pi_t^h = \log P_t - \log P_{t-h}$ is inflation over *h* periods ending in t and P is the consumer price index[6].

6 The headline personal consumption expenditure (PCE) is used in the case of the United States and headline CPI (excluding the 1999-2000 interest and tax changes) for Australia.

Due to the very small sample size[7], the model is estimated with a single lag (m). An extended version of (28) that includes a rescaled output gap instead of the standard measure is also estimated. This is consistent with the Phillips curve in equation (18). The rescaled output gap constructed as the product of inflation and the output gap. To serve as a benchmark for comparison with the model-based output gaps, an autoregressive (AR1) model that omits the output gap or the rescaled output gap is estimated:

$$\pi_t^h = \delta + \sum_{i=1}^{m} \lambda_i \, \pi_{t-i}^1 + \varepsilon_{t+h} \tag{29}$$

Standard conventional forecast comparison tests, including the Diebold-Mariano test (Diebold & Mariano, 1995), are not appropriate here since the AR benchmark is nested within the output gap models. Also, considering that standard tests for nested models, including the Clark-McCracken's tests (Clark & McCracken, 2001, 2009), are based on global forecast performance over a given sample period without accounting for any possibility of change in the relative forecasting performance of two models over time as evidence suggests (Stock & Watson, 2003a), the Fluctuation Test by Giacomini and Rossi (2010) is employed in this paper. The Giacomini-Rossi's Fluctuation Test was designed to specifically account for time-varying instability in relative forecast performance (See Appendix A.4 for summary details of the Fluctuation Test). This is particularly useful for relative forecasts evaluations in the current paper since the competing output gap measures seem to follow divergent paths over some time period, before converging again over another time period. In this context, the relative underlying demand pressures and the associated inflation dynamics may differ across the competing output gap models over time. Hence, the need for forecast comparisons based on a test that account for such instability and fluctuations, for models that are nested or otherwise.

As a common practice in the literature, the Mean Squared Forecast Error (MSFE) is used as the loss function in comparing the predictive performance of the models for the Fluctuation Test. Using inflation and output gap data over the period 1985-2016, the models are estimated and used for one-year-ahead out-of-sample forecasting beginning in 1992, with a window size of six years. Note that considering the very small sample size, this exercise is largely illustrative, and these results must be interpreted with caution.

7 Statistical reference drawn from small samples can be improved with the use of Bootstrapped standard errors (Gonçalves and White, 2005). The standard errors were bootstrapped with 10,000 repetitions on the OLS estimation of equations (28) and (29).

Another shortcoming of the forecasting exercise is the fact that only final data is used without comparing the outcomes when real-time data is used to inform policy. The use of final data means that forecast errors due to data revisions are not evaluated here.

Figure 6 plots the 2-sided Fluctuation Test results comparing the relative forecast performance of the output gap model and the naïve AR benchmark (the left graph for each country) as well as relative forecast performance of the climate model against the non-climate output gaps (the right graph for each country). In the case of Australia, the null hypothesis of equal forecast performance is rejected against the alternative that the output gap models produce statistically significant and better inflation forecast than the AR benchmark since the values of the test statistic fall below the negative critical value lines. For the climate hysteresis output gap, this is especially so during the period 1996-95, and during 2001-2002 for the non-climate output gaps. Climate shocks seem to contain predictive contents for forecasting inflation in the case of Australia, largely indicative of the fact that compared with the non-climate output gaps, the climate hysteresis output gap also shows better and statistically significant forecast performance, especially during 1994-1996.

In the case of the United States, the forecast performances of the respective output gap estimates relative to the AR benchmark are mixed. While the non-climate output gap estimates prove to be more predictive and statistically outperform the naïve AR benchmark in terms of forecasting PCE inflation (especially during 2005-2013), the AR benchmark statistically outperforms the climate model, especially during 1995-1998. Similarly, the forecast performance of the climate hysteresis output gap compared with the other gap estimates is mixed. While the climate model shows better and statistically significant forecast performance during 2011-2012, the opposite is true during 1995-1999.

Figure 6. Evaluation: Output Gaps vs AR Benchmark Inflation Forecasts

Source: Author's calculations.
Note: The figure reports the 2-sided Giacomini-Rossi (2010) rolling-window fluctuation test statistic for the output gap models (28) against the AR benchmark at 5% level of significance. For each country, the first graph (Left) compares the output gap models with the AR benchmark while the second (Right) compares the Climate-hysteresis model output gap inflation forecast with forecasts based on the non-climate model and official estimates. When the estimated test statistic is below the negative critical value line, then the respective output gap measure forecasts significantly better than the benchmark. When it is above the positive critical value line, then the AR benchmark significantly outperforms the output gap model's forecast. The climate hysteresis model performs significantly better than the other output gap estimates when the test statistic falls below the negative critical value line for graphs on the right, and vice versa.

The introduction of the rescaled output gaps produces similar relative inflation forecast performance for with marked improvement in the climate model's inflation forecast performance in the case of the United States, especially during the GFC (see Appendix Figure B). The unstable and changing nature of the relative information forecast performances of the various output gap measures largely relate to the different unemployment and output gap magnitudes estimated under each model. For example, the climate hysteresis model with smaller output and unemployment gaps is associated with less disinflationary pressure during a downturn, since the gap between current demand conditions and the potential supply capacity is less.

VI. Conclusion

This paper has examined the effects of persistent climate-induced weather shocks on potential output and NAIRU as well as the associated output and unemployment gaps. To inform the incorporation of climate hysteresis effects into the model, the modelling began with a simulation experiment based on a standard Cobb-Douglas production function with firms facing quadratic adjustment costs in responding to deviation of potential labor supply from steady state. Consistent with the recent literature, the modelling approach followed two steps. First, climate-induced weather shocks were embedded into the estimation of *climate-neutral* output gaps. Second, the climate-neutral output gaps were then incorporated in the estimation of NAIRU, with climate shocks and their hysteresis effects modelled to persist for up to four years.

The results suggest that macroeconomic slacks are smaller when both actual conditions and potential supply capacity are modelled to change simultaneously, with recessions that may be less disinflationary, and booms that may be less inflationary. In a world characterized by persistent climatic disruptions, measures of potential output and the output gap that do not account for these structural disruptions would create problems for maintaining macroeconomic stability. First, the size of the business cycle would be repeatedly overstated under the assumption that rapidly changing demand conditions fluctuate around a relatively stable trend growth. Second, because of maintaining relatively stable goal posts regarding potential growth in a structurally disrupted environment, the mistaken signals from demand pressure may create policy-induced shocks to the economy. All else equal, a large negative output gap would imply a more accommodative monetary policy stance, a move that may create excess demand pressure and financial stability risks if the output gap was much smaller due to structural disruptions that are persistently weakening potential supply capacity but whose effects are not engendered into policymaking.

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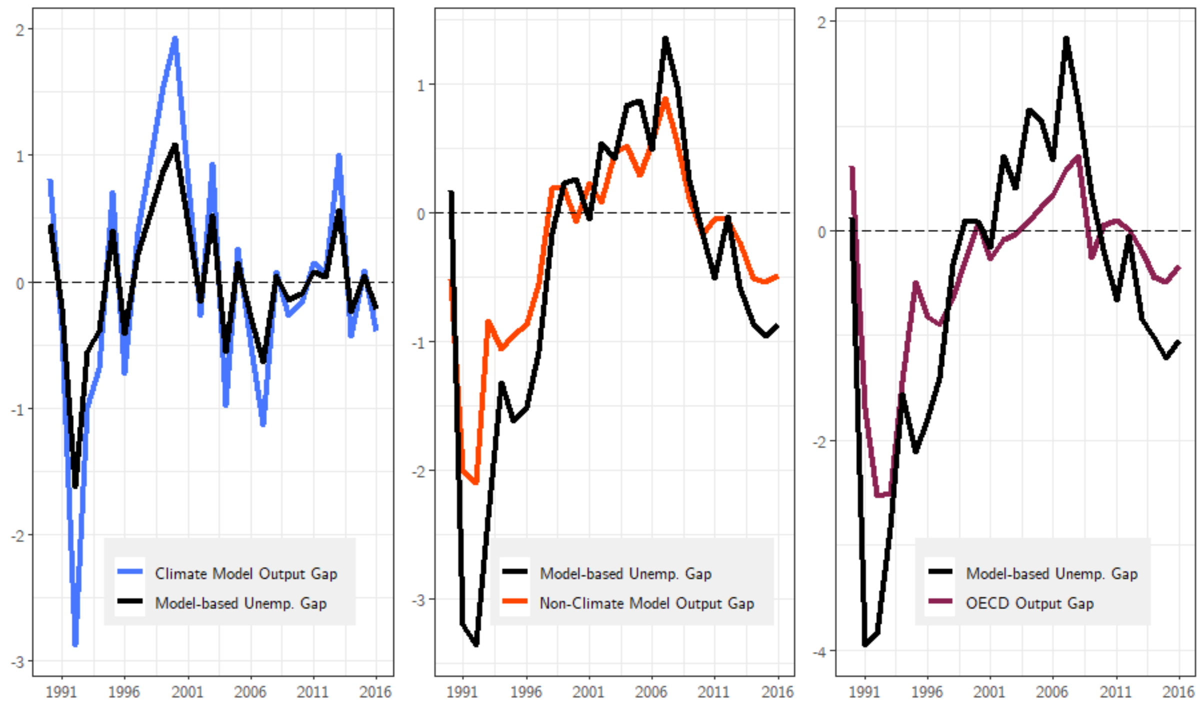
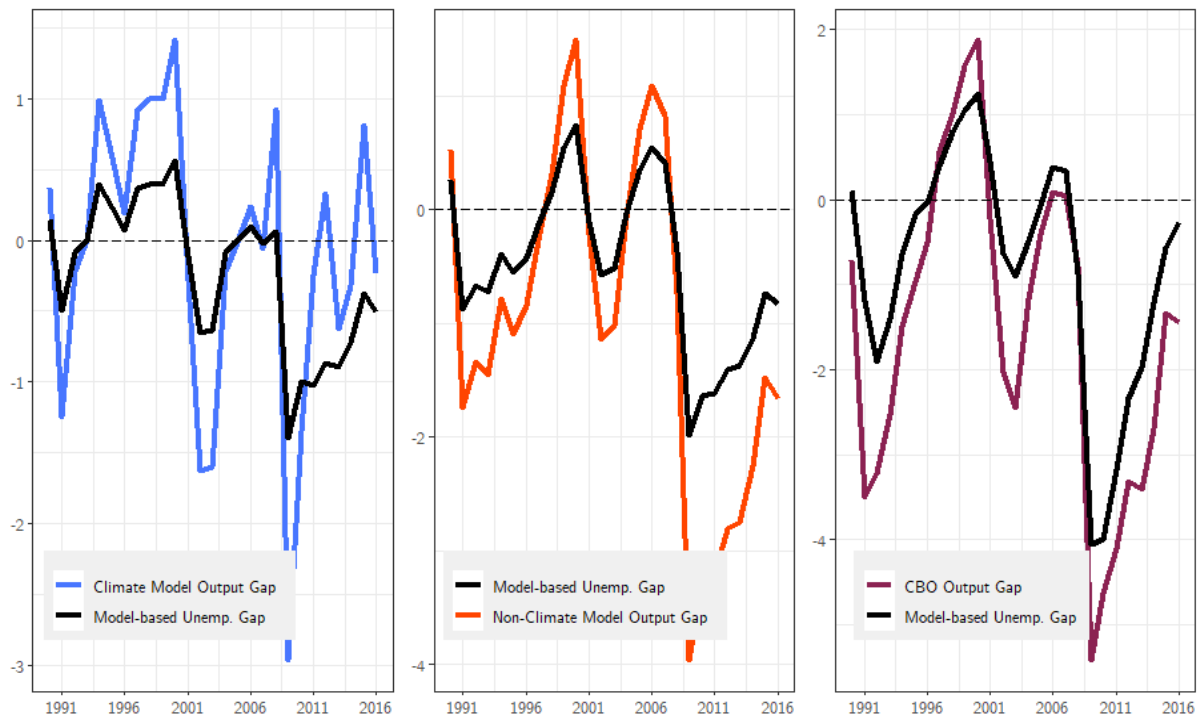
APPENDIX

Appendix Figure A. Model-based Output and Unemployment Gaps Estimates (Percent)

Australia

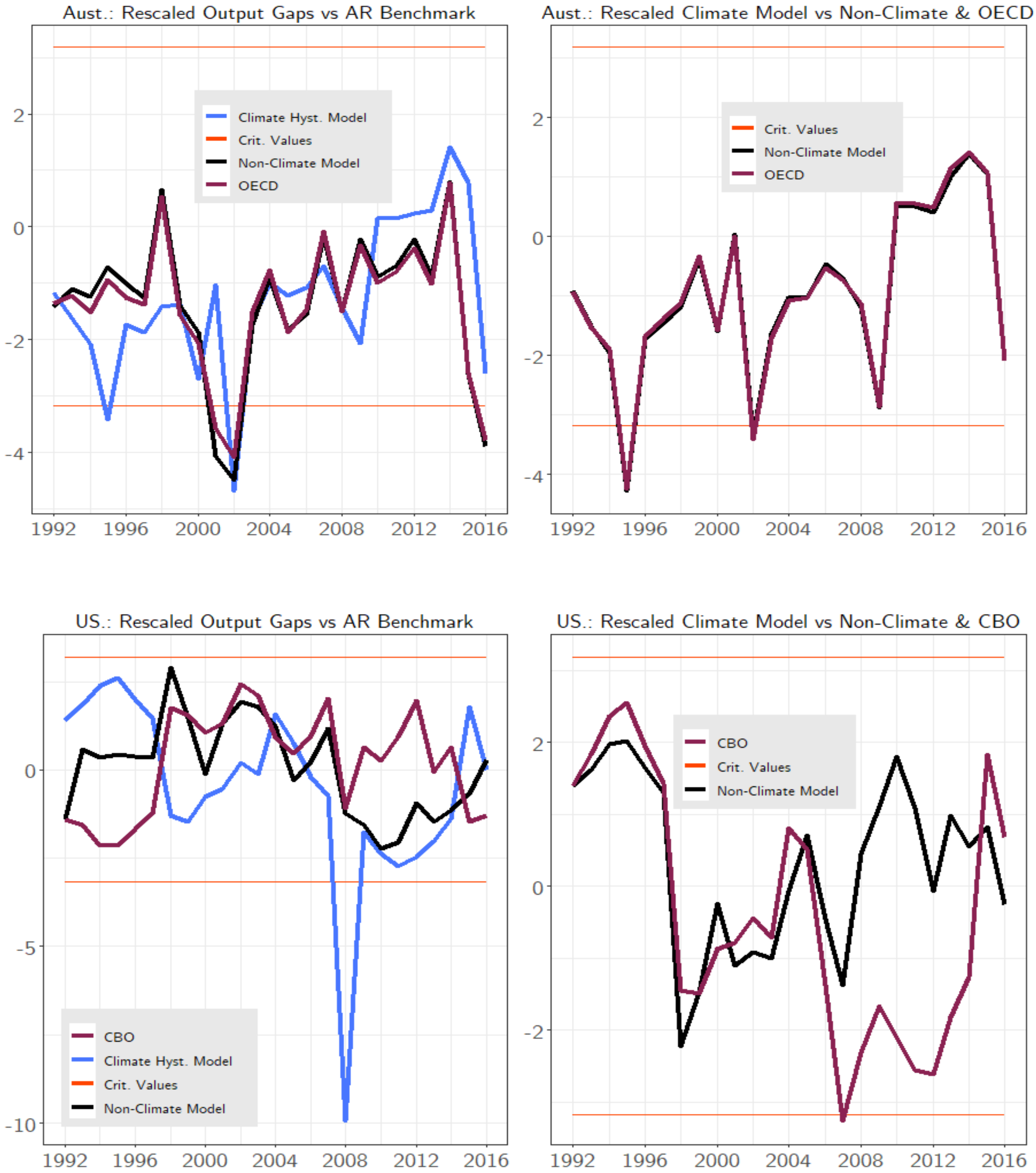


United States



Source: Author's calculations; OECD and CBO data.
Note: Each figure plots the model-based output gap and the unemployment gap computed based on that model's estimated NAIRU.

Appendix Figure B. Evaluation: Rescaled Output Gaps vs AR Benchmark Inflation Forecasts



Source: Author's calculations.
Note: The figure reports the 2-sided Giacomini-Rossi's rolling-window fluctuation test statistic for the rescaled output gap models against the AR(1) benchmark at 5% level of significance. For each country, the first graph (Left) compares the rescaled output gap models with the AR benchmark while the second (Right) compares the rescaled Climate-hysteresis model output gap inflation forecast with forecasts based on the other rescaled output gap estimates. When the estimated test statistic is below the negative critical value line, then the respective output gap measure forecasts significantly better than the benchmark. When it is above the positive critical value line, then the AR(1) benchmark significantly outperforms that output gap model's forecast. The climate hysteresis model performs significantly better than the other output gap estimates when the test statistic falls below the negative critical value line for graphs on the right, and vice versa.

Table A.1: Bayesian Priors

	Australia				United States			
	Mode		Standard Error		Mode		Standard Error	
	Prior	Posterior	Prior	Posterior	Prior	Posterior	Prior	Posterior
η	0.700	0.712	0.210	0.027	0.700	0.651	0.210	0.018
θ	0.153	0.141	0.007	0.058	0.290	0.311	0.007	0.067
ϕ_1	0.600	0.570	0.020	0.017	0.671	0.635	0.020	0.016
ϕ_3	0.300	0.323	0.091	0.027	0.300	0.319	0.091	0.022
ϕ_4	0.800	0.822	0.241	0.025	0.800	0.812	0.240	0.021
ϖ	--	0.463	--	0.033	--	0.455	--	0.030
λ_1	0.250	0.377	0.003	0.003	0.410	0.409	0.001	0.001
λ_2	0.082	0.093	0.002	0.001	0.082	0.088	0.002	0.001
τ_4	0.100	0.131	0.030	0.017	0.120	0.126	0.036	0.016
τ_3	0.880	0.890	0.004	0.003	0.880	0.875	0.004	0.004
τ_2	0.400	0.435	0.120	0.03	0.407	0.418	0.122	0.025
τ_1	0.350	0.451	0.150	0.03	0.521	0.507	0.156	0.028
δ_1	0.100	0.109	0.025	0.017	0.100	0.105	0.104	0.017
δ_2	0.200	0.210	0.060	0.018	0.200	0.199	0.060	0.016
κ_1	2.167	2.153	0.585	0.053	2.167	2.147	0.585	0.048

Source: Author's estimates

Note: The use of (--) for parameters that were diffusedly initialized within the Kalman filter.

Table A.2. Data Sources

Indicator	Sources
SPEI	Global SPEI database (based on monthly climate data from the Climatic Research Unit of the University of East Anglia)
Inflation Rate	CPI: Reserve Bank of Australia. PCE: US Bureau of Economic Analysis
Unemployment Rate	Australian Bureau of Statistics U.S Bureau of Labor Statistics
Capacity Utilization *Australia: Manuf. Production Index* *US: Manuf. Cap. Utilization Index*	OECD (for Australia) U.S. Federal Reserve
Real Gross Domestic Product	Australian Bureau of Statistics US Bureau of Economic Analysis
Official Output Gap Statistics	OECD; CBO

A.3: Climate Index

The Standardized Precipitation Evapotranspiration Index (SPEI)

Despite its multitemporal nature, the lack of temperature and changes in evapotranspiration in determining drought conditions is a key weakness of the widely used standardized precipitation index (SPI). Developed by Vicente-Serrano et al (2010), the SPEI improves on the SPI with the inclusion of evapotranspiration. For a given month i, the SPEI is computed, based on the Thornthwaite method (Thornthwaite, 1948) as the difference precipitation (P_i) and potential evapotranspiration (PET_i)

$$D_i = P_i - PET_i \tag{30}$$

where the difference, D_i, captures the water balance (deficit or surplus) for month i. At a given time scale k (3, 6 or 12 months), the aggregated water balance, D_n^k is the sum of D_i before the current month, n^{th}

$$D_n^k = \sum_{i=0}^{k-1} (P_{n-i} - PET_{n-i}), \quad n \geq k \tag{31}$$

To ensure comparability across space and time according to the heterogeneity in climatic conditions between and within countries, the D_n^k series at different time scales are fitted to a probability distribution. Extremity in weather conditions is accounted for by adjusting the distribution of the D_n^k using a density function of log-logistic probability:

$$f\ x\ = \frac{\omega}{\theta}\left(\frac{x-\mu}{\theta}\right)^{\omega-1}\left(1+\left(\frac{x-\mu}{\theta}\right)^{\omega}\right)^{-2} \tag{32}$$

where the parameters θ, ω and μ represent the scale, shape, and origin for the D_n^k series in the range $(\mu > D < \infty)$. With $f(x)$ transformed into a normalized random variable, the value of the SPEI is bounded between -3 and 3. Annual SPEI values are obtained by averaging the 12-monthly series of each year over the period 1980-2016. To capture climatic conditions specific to a particular country (Australia and United States in this paper), the 12-month SPI and SPEI averaging is done across grid cells that overlap a country's cropland areas, following the literature (see Couharde et al, 2019). Note that since the 12-month SPEI values are obtained by averaging values over shorter time periods, non-zero SPEI values at the 12-month scale (or longer) will indicate persistent underlying weather anomalies over time.

Table B.1. SPEI Drought Classification

SPEI > 2	Exceptionally moist
1.60 < SPEI < 1.99	Extremely moist
1.30 < SPEI < 1.59	Very moist
0.80 < SPEI < 1.29	Moderately moist
0.51 < SPEI < 0.79	Slightly moist
0.50 < SPEI < 0.50	Near normal conditions
0.79 < SPEI < 0.51	Slightly dry
1.29 < SPEI < 0.80	Moderately dry
1.59 < SPEI < 1.30	Very dry
1.99 < SPEI < 1.60	Extremely dry
SPEI < 2	Exceptionally dry

Source: NOAA's National Centres for Environmental Information

Note that while the SPEI is primarily a drought classification index, the two key components—temperature and precipitation—and the multi-scalar nature of the SPEI values make the index ideal for examining the broader effects of global warming beyond the effects of drought. For example, an extreme drought may be due to a combination of persistent rise in temperature and acutely low precipitation (rainfall) over a prolong period, two phenomena that are found in the climate-economy literature to have devastating effects on economic growth. Apart from the temperature effects of labour productivity and capital depreciation, droughts are found to have more persistent growth effects than other climate-induced natural disasters (Fomby et al., 2013).

Appendix A.4. Giacomini-Rossi Fluctuation Test

Based on a chosen general loss function, $L(.)$, (like the standard Mean Square Forecast Error—MSFE), the Giacomini-Rossi's (Giacomini and Rossi, 2010) Fluctuation Test compares the relative forecasting performance of two competing models over time for sequences of R in-sample and P out-of-sample loss differences computed over the rolling windows of size *m* as:

$$m^{-1}\sum_{j=t-\frac{m}{2}}^{t+\frac{m}{2}-1}\Delta L_j\left(\theta_{j-h,R},\gamma_{j-h,R}\right), t = R+h+\frac{m}{2},\dots,T-\frac{m}{2}+1$$

Provided the following assumptions hold,

i. $\left\{P^{-\frac{1}{2}}\sum_{t=R+h}^{R+h+[\tau P]}\Delta L_t\left(\theta_{t-h,R},\gamma_{t-h,R}\right)\right\}$ follows the Central Limit Theorem

ii. $\sigma^2 = \underset{P\to\infty}{lim} E\left(P^{-\frac{1}{2}}\sum_{t=R+h}^{T}\Delta L_t\left(\theta_{t-h,R},\gamma_{t-h,R}\right)\right)^2 > 0$

iii. $\frac{m}{P}\to\mu\in\ 0,\infty$ as $m\to\infty$, $P\to\infty$, whereas $R<\infty, h<\infty$

then the null hypothesis of equal predictive forecast performance at each point in time (not over the global sample period as in conventional tests) becomes:

$$H_0\colon E\left[\Delta L_t\left(\theta_{j-h,R}, \gamma_{j-h,R}\right)\right] = 0$$

where the two-sided alternative is

$$E\left[\Delta L_t\left(\theta_{j-h,R}, \gamma_{j-h,R}\right)\right] \neq 0$$

Under the two-sided alternative, the Fluctuation Test Statistic is the largest value over the sequence of the relative forecast error losses is

$$F_{t,m}^{\mathrm{OOS}} = \sigma^{-1} m^{-\frac{1}{2}} \sum_{j=t-\frac{m}{2}}^{t+\frac{m}{2}-1} \Delta L_j\left(\theta_{j-h,R}, \gamma_{j-h,R}\right)$$

where $\hat{\sigma}$ is a heteroskedasticity- and autocorrelation-consistent (HAC) estimator (Newey and West, 1987) of the long-run variance of the loss differences. The null hypothesis is rejected against the two-sided alternative,

$$E\left[\Delta L_t\left(\theta_{j-h,R}, \gamma_{j-h,R}\right)\right] \neq 0,$$

when

$$\max\left|F_{t,m}^{\mathrm{OOS}}\right| > k_\alpha$$

where the critical value, k_α is contingent upon the choice of the size of the rolling window relative to the number of out-of-sample loss differences *P,* or formally, *m = [μP].*