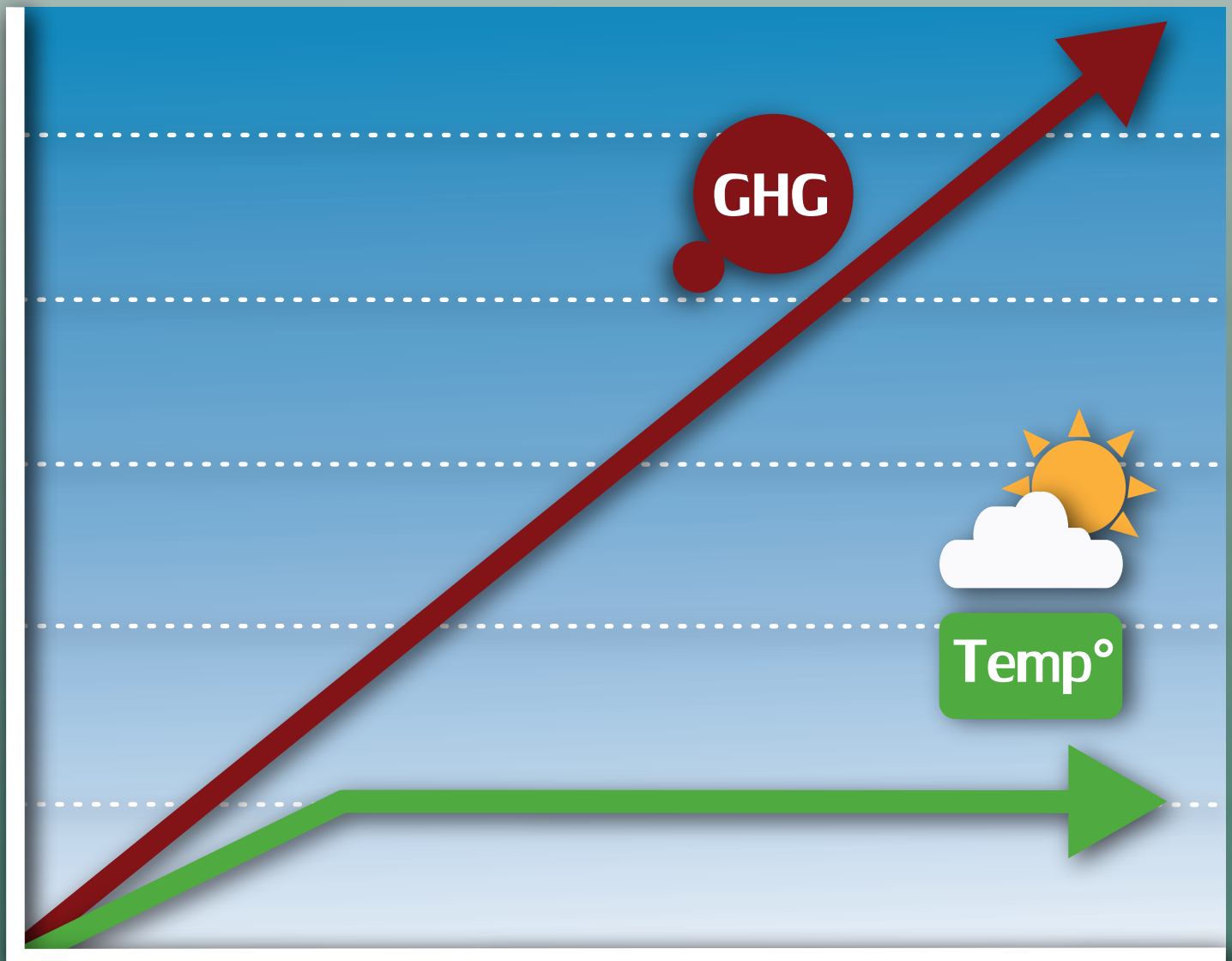


# *Climate Policy Implications of the Hiatus in Global Warming*

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October 2014





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## Executive summary

The fact that CO<sub>2</sub> emissions lead to changes in the atmospheric carbon concentration is not controversial. Nor is the fact that CO<sub>2</sub> and other greenhouse gases (GHGs) absorb infrared energy in the atmosphere and contribute to the overall greenhouse effect. Increases in CO<sub>2</sub> levels are therefore expected to lead to atmospheric warming, and this is the basis for the current push to enact policies to reduce GHG emissions.

For more than 25 years, climate models have reported a wide span of estimates of the sensitivity of the climate to CO<sub>2</sub> emissions, ranging from relatively benign to potentially catastrophic, reflecting a wide range of assumptions about how the climate system may or may not amplify the effects of GHG emissions. These continuing uncertainties have direct policy implications. Economic models for analysing climate policy are calibrated using climate models, not climate data. In a low-sensitivity model, GHG emissions lead only to minor changes in temperature, so the socioeconomic costs associated with the emissions are minimal. In a high-sensitivity model, large temperature changes would occur, so marginal economic damages of CO<sub>2</sub> emissions are larger.

While it is common these days for politicians, journalists, and other observers to say the climate is warming “faster than expected,” the data show that, over the past two decades, warming has actually slowed down to a pace well below most model projections. Depending on the data set used, there has been no statistically significant temperature change for the past 15 to 20 years. Yet atmospheric GHG levels have increased rapidly over this interval, and there is now a widening discrepancy between most climate model projections and observed temperatures. While a pause in warming is not itself inconsistent with a continuing long term trend, there is no precedent for such a large and continuing gap between models and observations. Some climatologists have argued that within another few years at most, if the pause continues, it will lead inescapably to the conclusion that climate models are oversensitive to GHGs.

Since economic models are trained to match climate models, if climate models overstate the effect of CO<sub>2</sub> emissions, economic models will overstate the social damages associated with them. In fact, economic models of climate

policy allow for even more exaggerated effects of carbon dioxide emissions than do climate models. Consequently, there is good reason to suppose that economic models too may be subject to revision over the next few years.

One implication of these points is that, since climate policies operate over such a long time frame, during which it is virtually certain that important new information will emerge, it is essential to build into the policy framework clear feedback mechanisms that connect new data about climate sensitivity to the stringency of the emissions control policy. A second implication is that, since important new information about climate sensitivity is expected within a few years, there is value to waiting for this information before making any irreversible climate policy commitments, in order to avoid making costly decisions that are revealed a short time later to have been unnecessary.

# 1. The hiatus

## 1.1 The issue and the policy connection

Carbon dioxide (CO<sub>2</sub>) emissions from fossil fuel use lead to changes in the atmospheric carbon concentration. Since CO<sub>2</sub> absorbs infrared energy in the atmosphere it is called a greenhouse gas (GHG) and it contributes to the overall greenhouse effect. Increases in CO<sub>2</sub> levels are therefore expected to lead to atmospheric warming, and this is the basis for the current push to enact policies to reduce GHG emissions. The control options for CO<sub>2</sub>, such as carbon capture and storage, tend to be very costly, so governments have been reluctant to impose deep CO<sub>2</sub> reduction targets.

Another factor that has held back action on CO<sub>2</sub> is the uncertainty over its actual harm. It is a natural component of the atmosphere and a benign component of both human and plant respiration. Its potential for environmental harm arises indirectly, through its effect on average temperatures around the world. The rate at which changes in GHG concentrations cause changes to the global average temperature, which is called “climate sensitivity,” has proven very difficult to pin down. Since the late 1970s, climate models have reported estimates of long term sensitivity from doubling atmospheric CO<sub>2</sub> levels ranging from 1.5 °C to 4.5 °C, thus covering a span from relatively benign to potentially catastrophic.<sup>1</sup> The size and persistence of the span, despite the many billions of dollars spent on research, reflect the difficulty of determining how the complex dynamics of the climate may or may not amplify the effects of GHG emissions. These continuing uncertainties have direct policy implications, since economic models for analysing climate policy are calibrated using climate models, not climate data. In a low-sensitivity model, GHG emissions lead only to minor changes in temperature, so the socioeconomic costs associated with the emissions must also be minimal. In a high-sensitivity model, large temperature changes would occur, so marginal economic damages of CO<sub>2</sub> emissions must be larger.

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1. See table of past sensitivity estimates in Lewis and Crok (2014).

Politicians, journalists, and other observers have lately taken to saying that the climate is now warming “faster than expected.”<sup>2</sup> But the data show the exact opposite: over the past two decades the pace of warming has actually slowed to a pace well below almost all model projections. The most recent report of the Intergovernmental Panel on Climate Change (IPCC, 2013: Chapter 9, Box 9.2) referred to a “hiatus” or pause in warming, dating the onset at about 1998.<sup>3</sup> This report explains the evidence for the warming hiatus and then explores what it implies for climate policy. I begin by reviewing the evidence for changing temperature trends, and then, drawing on the IPCC Report as well as other recent climatological studies, I look at what they imply both for climate models and the economic models used for analysing climate policy.

One distinct possibility raised by the hiatus is that climate models may exhibit too much sensitivity to rising greenhouse gas (GHG) levels. That is, they may be projecting too much warming in response to expected future CO<sub>2</sub> emissions. This would imply that economic estimates of the marginal social costs of carbon dioxide emissions are biased high. The climate literature suggests that this possibility will either be confirmed or refuted in the next couple of years. From this I draw two policy implications. First, since climate policies tend to involve long term commitments, I argue that GHG policy measures should build in a clear feedback mechanism that automatically adjusts the stringency of the policy to new information about the actual severity of the climate change problem. Second, I argue that since critically important information can be expected to emerge in the next few years, and in light of the slow-moving nature of the climate issue, it would be worth awaiting the resolution of the major questions raised by the hiatus before making long-term policy commitments based on models that we have reason to believe are soon going to undergo a major rethink.

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2. For example, President Obama claimed that “[w]hat we do know is the temperature around the globe is increasing faster than was predicted even ten years ago” (press conference, November 14 2012, reported in *Washington Post*, 2012); See also “Climate Change Worse Than Expected, Argues Lord Stern” (*Scientific American*, April 3, 2013); “Climate Changing Faster Than Expected” (*Discovery News*, February 11, 2013); “Global Warming is Accelerating” (National Wildlife Federation, undated); “Earth Warming Faster Than Expected” (*Science News*, March 25, 2012); etc.

3. In this report, all references to the IPCC report are to the contribution of Working Group I.



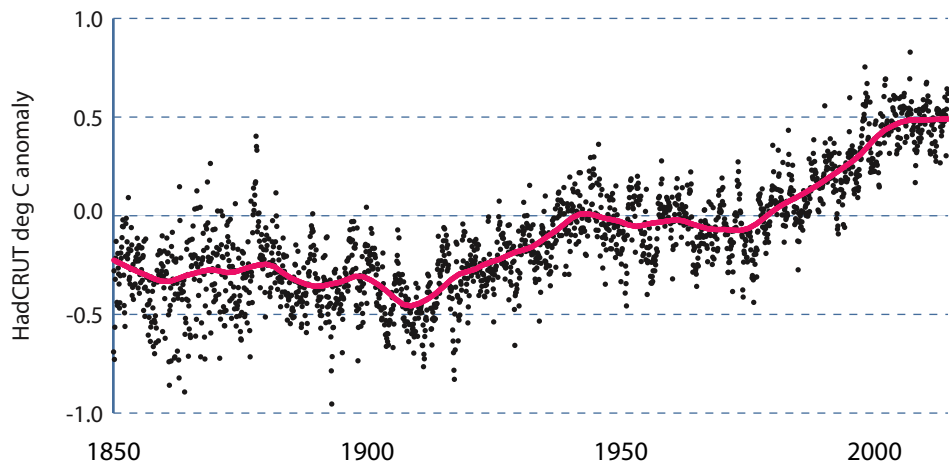
## 1.2 The duration of the pause

While the IPCC still uses the iconic word “unequivocal” to describe warming of the climate system over the past century in its most recent reports (IPCC SPM, 2013), a new word entered its lexicon that has the potential to become equally iconic: “hiatus.” For instance:

Despite the robust multidecadal timescale warming, there exists substantial multi-annual variability in the rate of warming with several periods exhibiting almost no linear trend (including the warming **hiatus** since 1998). (IPCC, 2013: Chapter 2, page 39; emphasis added)

The slowdown is visible in global surface temperature data sets. **Figure 1** shows the well-known monthly Hadley Centre “HadCRUT4” temperature record, which combines land and ocean data from 1850 to the present (Morice et al., 2012), along with a smoothed line showing the variations in the trend along the way.<sup>4</sup>

**Figure 1: Global surface average temperature anomaly**



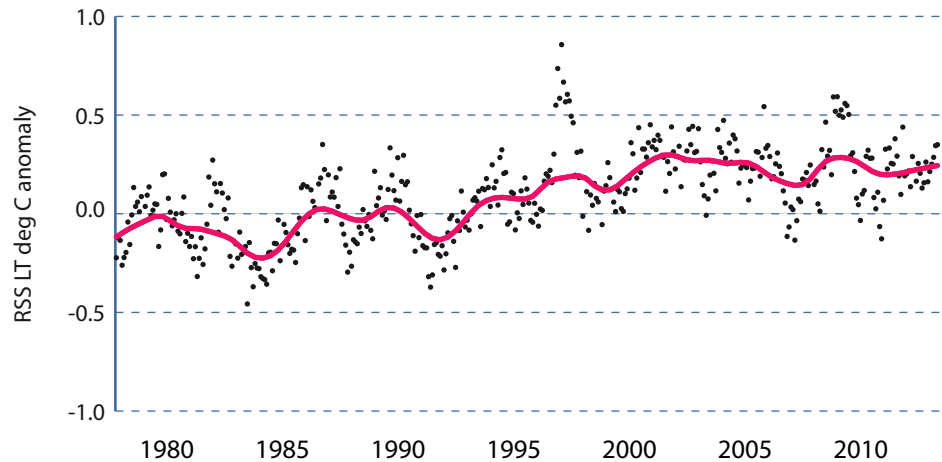
Source: UK Hadley Centre.

While the leveling off is visible at the end, there are several earlier periods that also exhibit flat or declining trends, including a lengthy hiatus from about 1940 to about 1980. So our initial impression is that the current hiatus is visible, and clearly contradicts rhetorical claims that the warming trend is accelerating, but that it is not necessarily indicative of future trends.

<sup>4</sup> The graph shows averaged “anomalies” or departures from local means. The smoothed line is constructed using a lowess filter with bandwidth parameter equal to 0.09.

Over the last 30 years, atmospheric temperature data have also been available from weather satellites. **Figure 2** shows the Remote Sensing Systems (RSS) monthly global lower troposphere (LT) record (Mears and Wentz, 2005) covering 1979 to the present. A smoothed line is superimposed to show the variations in trend.<sup>5</sup>

**Figure 2: RSS lower troposphere record along with smoothed series**



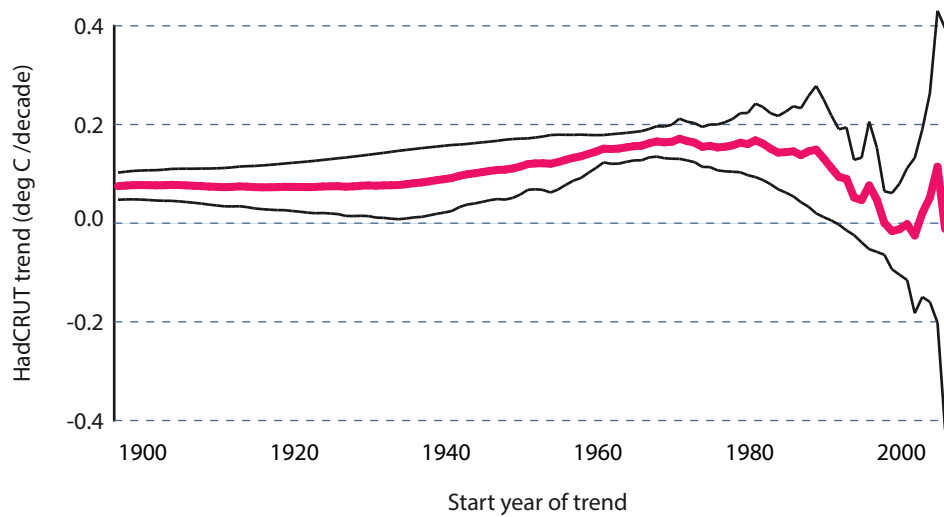
Source: Mears and Wentz, 2005.

It is clear from both figures 1 and 2 that sometime around 2000 the data ceased its upward path and has leveled off. The question of whether warming has “stopped” cannot be answered without imposing an arbitrary assumption about the time period in question. If one looks at the past 100 years, for instance, there is a statistically significant upward trend of about 0.07 degrees C/decade in the data. If one looks only at the past 15 years, there is no trend. **Figure 3** illustrates the role of the sample length. It shows the magnitude of the trend (in degrees C/decade) through the Hadley global surface record, and the accompanying 95% confidence interval bounds as the sample start date moves forward from 1900 to 2009.<sup>6</sup> An increase in figure 3 implies acceleration in warming and a decrease implies deceleration.

5. Computed using a lowess filter with bandwidth parameter of 0.11.

6. The confidence intervals are derived using the method of Vogelsang and Franses (2005), which is applicable to any trend-stationary time series and is robust to autocorrelation of any length.

**Figure 3: Magnitude of linear trend through HadCRUT data, allowing start year of sample to vary from 1900 to 2009**

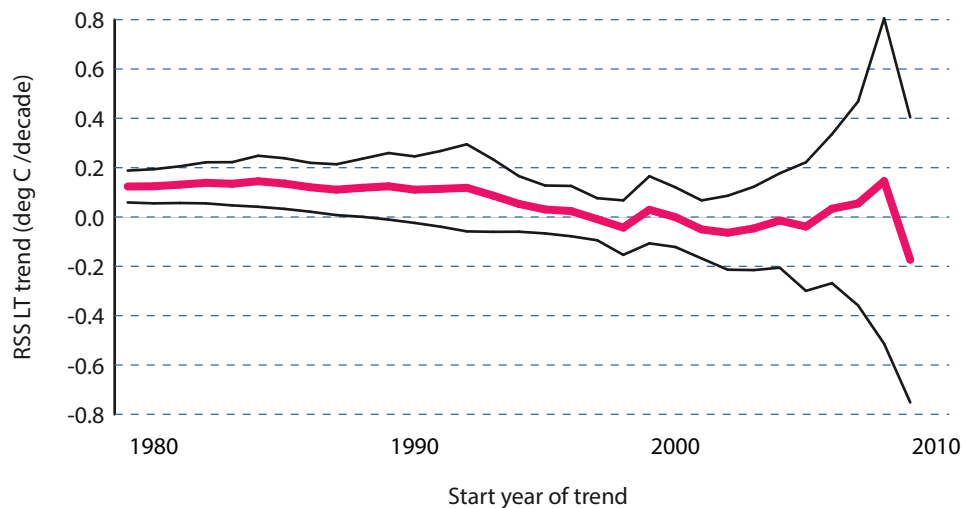


Note: Upper and lower 95% confidence intervals are shown (thin black lines).

Source: McKittrick, 2014.

**Figure 4** shows the same calculations for the RSS data post-1979.

**Figure 4: Magnitude of linear trend through RSS lower troposphere data, allowing start year of sample to vary from 1979 to 2009**



Note: Upper and lower 95% confidence intervals are shown (thin black lines).

Source: McKittrick, 2014.

These data support several observations.

- ◆ Over the whole of the post-1900 interval, the warming trend is just under 0.075 °C/decade, or about 0.75 °C per century. At this rate it would take about 267 years to get to the 2 °C target level of warming that many world leaders say needs to be avoided.
- ◆ The surface trend rate peaks if the sample start date is in the mid-1970s, and thereafter as the sample start date moves forward, the subsequent trend declines. As of the start of the current century, the trend is generally negative.
- ◆ The lower bound of the confidence interval meets the zero axis in 1995 in the HadCRUT series and 1988 in the RSS series. This means that there is no statistically significant warming trend in the Hadley surface data in a sample confined to the past 19 years, and no statistically significant warming trend in the RSS lower tropospheric data in a sample confined to the past 26 years. Lower troposphere data are also available from the University of Alabama-Huntsville using the method of Spencer and Christy (1990). A similar analysis suggests a hiatus of 16 years (McKittrick, 2014).

Taking all these points together, the data confirm the general point raised in the 2013 IPCC report that we are currently experiencing a hiatus in global warming that has lasted for just under 20 years.

### 1.3 Why it matters

Referring back to figure 1, a leveling-off period is not, on its own, the least bit remarkable, since similar intervals have been observed before. In the current case, though, it coincides with 20 years of rapidly increasing atmospheric greenhouse gas levels. Since 1990, atmospheric CO<sub>2</sub> levels have risen from 354 parts per million (ppm) to just under 400 ppm, a 13 percent increase.<sup>7</sup> According to the IPCC, taking into account changes both in GHG and aerosol levels, estimated Radiative Forcing increased by 43 percent after 2005 (IPCC SPM-9).<sup>8</sup> Climate models all projected that this should have led to a pronounced warming of the lower troposphere and surface. Instead, as noted, temperatures have flatlined and even started declining.

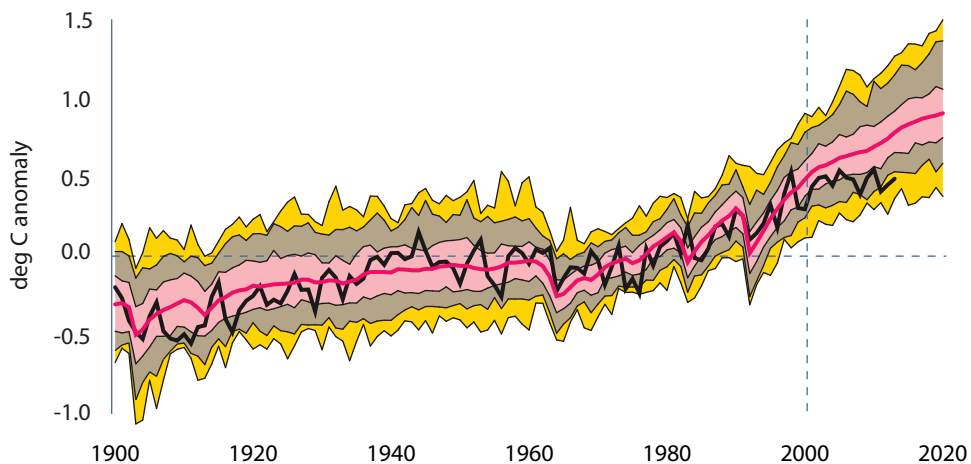
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7. Data from [ftp://ftp.cmdl.noaa.gov/products/trends/co2/co2\\_mm\\_mlo.txt](ftp://ftp.cmdl.noaa.gov/products/trends/co2/co2_mm_mlo.txt).

8. “Radiative Forcing” is the term used in climate analysis to describe the overall warming effect of greenhouse gases on the climate, based on the changes in absorption of infrared radiation in the atmosphere.

A small discrepancy between models and observations is not unusual. However the current hiatus is rather long in duration, and it has opened up a widening gap between observations and projections from most climate models.

**Figure 5: Reproduction of post-1900 portion of Figure 9.8 from IPCC 2013 Working Group I Report**



**Figure 5** is based on Figure 9.8 from the IPCC (2013) Fifth Assessment Report (which is denoted AR5), and illustrates the comparison between observations and models over the 1900–2020 interval. The model simulations used for the AR5 are collectively called “CMIP5”—referring to the 5th Coupled Model Intercomparison Project. The graph is constructed as follows.<sup>9</sup>

- ◆ The black line shows the surface temperature record (HadCRUT4). The data are positioned to average zero over the interval 1961–1990.
- ◆ The red line shows the CMIP5 mean, in other words the average temperature from 108 climate model simulations. The data are positioned to average zero over the interval 1961–1990.
- ◆ The yellow shading shows the outer envelope of all 108 climate model simulations year by year. The maximum in any one year is not necessarily from the same model as that for the next year, and likewise for the minimum.

<sup>9</sup> The model runs follow the RCP4.5 emissions scenario. All emission scenarios are identical for the historical interval (prior to 2000) and the climate model projections from all scenarios remain similar at least through 2030, so the scenario choice is not influential in figure 5.

- ◆ The inner tan shading shows the range of model estimates year-by-year excluding the lowest and highest 2.5%, thus showing the central 95% of the distribution of model projections.
- ◆ The inner pink shading shows the range of model estimates year-by-year excluding the lowest and highest 16.5%, thus showing the central two-thirds (66%) of the distribution of model projections. In other words, two-thirds of the model runs remain within the pink band around the overall model mean.

Climate models were used to backcast, or reproduce, temperatures for the past centuries. The 1900–2000 portion of the red line is not a “prediction,” instead it is the outcome of a matching process that goes back and forth between measurements of the climate and development of the climate simulation models.<sup>10</sup> In other words, it is not the case that the models were initialized with data as of 1900 and then run forwards. Instead, 20th century input data (GHG levels, volcanic activity, solar changes, etc.) and observed temperatures were used to guide model behaviour over the historical interval. The close match between observations and models over the 20th century is not, on its own, evidence of forecasting ability, and indeed cannot be invoked as such to the extent that the models are tuned to achieve it, a point the IPCC itself emphasizes in a number of places (e.g., Chapter 9, Box 9.1).

As noted, the red line in figure 5 is the mean of climate model runs, and the pink band shows the range within which two-thirds of model runs fall. Since the design of climate models embodies the mainstream thinking on how the various components of the climate system work, this region provides a visual summary of the central tendency of mainstream climatology, or at least what climate modelers expect to be the result of the rising GHG levels. There are variations in how specific processes are represented in different models, which leads to the different realizations as shown. However, the fact that most runs remain within a fairly narrow neighbourhood of the mean indicates that expectations are not all that widely dispersed. This implies that the models share an overall central tendency, as is to be expected since they are based on common underlying assumptions about the physics of climate processes.

If we are interested in testing the ability of the theory behind climate models to provide accurate forecasts of the future climate, we need to look at the post-2000 interval in figure 5. It is over that segment that, at some point, modelers could no longer compare the output of their models to actual temperatures and they therefore had to rely on the model structure to get the output right. Over that interval the CMIP5 mean and central two-thirds range move up steadily in response to the ongoing run-up in atmospheric GHG levels and sharply-rising radiative forcing, but the observed temperatures instead flatten

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10. See the description of the model tuning process in the AR5, Chapter 9, Box 9.1.

out, eventually falling below 95% of model runs. There was one previous interval in the mid-1970s in which observations briefly fell outside the 95% range, but that is partly a visual artifact of the normalization step that constrains all series to a zero mean over the 1961–1990 range, thus “pinching together” the distribution. And in that case the observations quickly reverted to the model mean.

It is also noteworthy that prior to 2000 the red and black lines continually touch and cross, diverging and converging as the average model tracks observations over time. From 1900 to 1998, there isn’t an interval longer than 12 years during which the red and black lines do not cross. But the post-1998 gap is something new. It is now into its 16th year, it has reached a large magnitude (about  $+0.3^{\circ}\text{C}$ ) and it is still widening. Even if temperatures were to start rising again over the next few years, it is difficult to foresee the black line in figure 5 catching up to and re-crossing the red line any time in the foreseeable future. Instead, the gap is now so large that the observations are in the bottom 2.5% of model runs.

The IPCC AR5 discusses the model-observation divergence in Chapter 9, Box 9.2 of the Working Group I Report. They report that over the 1998–2012 interval, 111 out of 114 climate model runs they examined overpredicted the HadCRUT4 observational series. The IPCC informally proposes several candidate explanations for this discrepancy, including the possibility that models are simply too sensitive to greenhouse gases, but at this point they do not favour any one solution to the problem. One possible explanation of the hiatus that has received a lot of attention is the proposal that the ocean is absorbing heat at a faster rate than before. But the IPCC notes that three of five empirical studies have found the trend in ocean heat absorption actually decreased over the past decade.<sup>11</sup>

While observed warming has been much lower than most model runs over the post-1998 interval, the IPCC balances that observation with the fact that warming outpaced most model projections over the period 1983 to 1998. But that comparison may involve a subtle bit of cherry-picking. There was a strong volcanic eruption in 1982 (leading to cooling through 1985) and a strong El Nino in 1998, so the endpoints yield an unusually high observed trend. And over that interval, the observations still remained within the central two-thirds of the model spread (figure 5). The current hiatus could be an artifact of the comparison against the warm 1998 El Nino, but as figures 3 and 4 show, the trend values began decelerating prior to 1998, and there is no unusual volcanic activity to explain low 2013 temperatures, so the modern discrepancy is not so easily explained away.

11. The five studies are Domingues et al. (2008), Ishii et al. (2009), Levitus et al. (2012), Palmer et al. (2007) and Smith and Murphy (2007). The IPCC Report does not specify which three imply a slowdown in OHC rise, but from visual inspection of IPCC Figure 3.2a they are likely Ishii et al., Levitus et al., and Smith et al.



## 1.4 The question mark

Fyfe et al. (2013) compared the distribution of trends in CMIP5 models to that in the HadCRUT4 temperatures over the 1993 to 2012 interval, and found the model trends far exceed observations. They report that the average CMIP5 trend from 1998 to 2012 was 0.21 °C/decade while the corresponding trend in HadCRUT4 was only 0.04 °C/decade, or one-fifth the predicted rate. The absence of warming over the past 15 to 20 years amidst rapidly rising GHG levels raises a nontrivial question about mainstream climate modeling. In an interview with the newspaper *Der Spiegel*, the well-known German climatologist Hans von Storch said:

We're facing a puzzle. Recent CO<sub>2</sub> emissions have actually risen even more steeply than we feared. As a result, according to most climate models, we should have seen temperatures rise by around 0.25 degrees Celsius (0.45 degrees Fahrenheit) over the past 10 years. That hasn't happened. In fact, the increase over the last 15 years was just 0.06 degrees Celsius (0.11 degrees Fahrenheit) -- a value very close to zero. This is a serious scientific problem that the Intergovernmental Panel on Climate Change (IPCC) will have to confront ... At my institute, we analyzed how often such a 15-year stagnation in global warming occurred in the simulations. The answer was: in under 2 percent of all the times we ran the simulation. In other words, over 98 percent of forecasts show CO<sub>2</sub> emissions as high as we have had in recent years leading to more of a temperature increase ... **If things continue as they have been, in five years, at the latest, we will need to acknowledge that something is fundamentally wrong with our climate models.** A 20-year pause in global warming does not occur in a single modeled scenario. But even today, we are finding it very difficult to reconcile actual temperature trends with our expectations." (*Der Spiegel*, 2013; emphasis added)

Climatologist Judith Curry of Georgia Tech recently observed:

Depending on when you start counting, this hiatus has lasted 16 years. Climate model simulations find that the probability of a hiatus as long as 20 years is vanishingly small. **If the 20 year threshold is reached for the pause, this will lead inescapably to the conclusion that the climate model sensitivity to CO<sub>2</sub> is too large.** (Curry, 2014; emphasis added)



Both of these experts point to 20 years as the point at which a hiatus forces a decisive break between models and observations. The pause in the RSS data already exceeds this. Absent a strong burst of warming, the HadCRUT4 pause (in the sense of statistical insignificance) will reach 20 years at the end of this year, and the UAH pause will do so at the end of 2017. What is likely to be required for a major professional reappraisal of mainstream models is a 20-year span with a trend numerically near or below zero. That will require a few more years of the hiatus for RSS and HadCRUT4, but only a few. If we set the trend threshold consistent with a hiatus to be a rate of warming below  $0.05^{\circ}\text{C}/\text{decade}$ , then we will reach the 20 year mark in the RSS data at the end of 2015, and in the HadCRUT data at the end of 2017. The UAH trends tend to be larger but such a trend magnitude would likely be observed by the end of 2018. With GHG levels continuing to rise over that time, and no historical precedent for such a large discrepancy, it will at that point be all but impossible to reconcile current climate models with observations.

## 2. Climate sensitivity: the connection to policy models

### 2.1 IAMS and the climate sensitivity parameter

Climate policy is analyzed using what are called Integrated Assessment Models (IAMs). These consist of highly simplified dynamic models of the economy coupled with even more highly simplified models of the climate. The economic modeling elements will be discussed in more detail in the next section. Economic activity within the model yields a certain quantity of CO<sub>2</sub> emissions each period. These are added to the stock of CO<sub>2</sub> in the atmosphere that evolves slowly over time as new emissions occur and old emissions are slowly sequestered out. The stock (or atmospheric concentration) then feeds into a model that determines the average temperature of the climate. Changes in temperature affect people, which in turn give rise to economic benefits and costs. Rising temperature may hurt people by reducing the productivity of capital, or it may be that people just have a strong preference for yesterday's temperature, or both. These so-called "Damage Functions" will be discussed in the next section.

The rate at which CO<sub>2</sub> emissions lead to changes in the atmospheric carbon concentration is not typically controversial. But the sensitivity of the climate to changes in the stock of CO<sub>2</sub> is, as noted in the Introduction. The *prima facie* meaning of the warming hiatus and the growing divergence between models and observations is that models may be more sensitive than is realistic. If we suppose for a moment that this is the case, it also implies a problem for IAMs since they are constrained to reflect the sensitivity of climate models. If IAMs were empirically based, the recent economics literature would have reflected the changing evidence on declining climate sensitivity, but this has not happened. Nor has it happened in climate modeling, but there have emerged in recent years a number of empirical sensitivity estimates that are pointing to the low end of the distribution. The next section briefly explains this literature.

## 2.2 Empirical estimates of climate sensitivity

Climate models contain many numerical parameters. While there isn't one specifically called "sensitivity" the way there is in an IAM, there are others that indirectly determine the model's overall behaviour, including sensitivity, such as through the strength of key feedback processes. Model-based estimates of sensitivity are derived by examining how models behave. The IPCC characterizes GCMs by two such measures, the Equilibrium Climate Sensitivity (ECS) and the Transient Climate Response (TCR). The first measures the temperature change after CO<sub>2</sub> levels double in the atmosphere, allowing for the climate to fully achieve its new state with all feedbacks having played out. Transient Climate Response (TCR) is an operational concept related to ECS. It is the estimated rate of warming after 70 years with CO<sub>2</sub> increasing at 1 percent per annum, thus doubling. Since it corresponds to real time observations it can be estimated empirically, allowing for a comparison of model structures against the data (Lewis and Crok, 2014).

The formula for TCR used by the IPCC (AR5, Chapter 10.8.1) is:

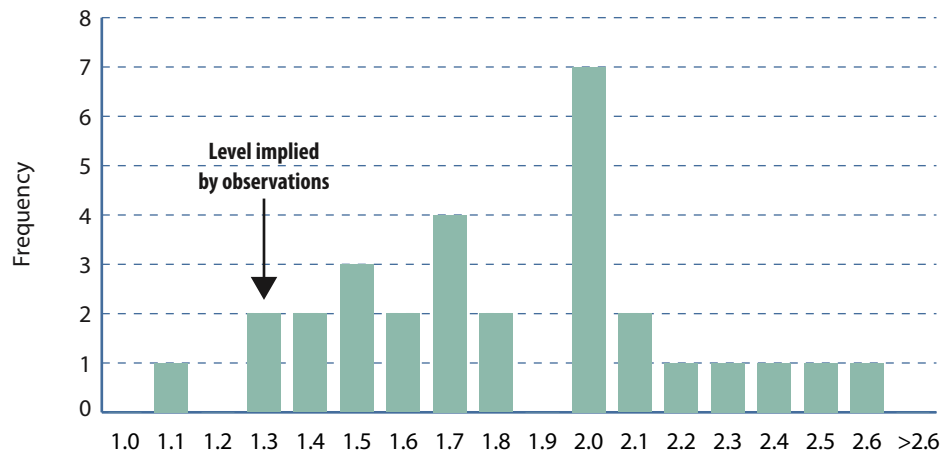
$$\text{TCR} = \Delta T / \Delta F \times \Delta F_{2x}$$

The fraction term to the right of the equals sign is the estimated change in temperature ( $\Delta T$ ) over 1750–2011, divided by the estimated change in radiative forcing ( $\Delta F$ ) for the same interval. The last term ( $\Delta F_{2x}$ ) is the equilibrium forcing rate measured in W/m<sup>2</sup> associated with doubling the CO<sub>2</sub> concentration in the atmosphere.

In its 2005 report, the IPCC stated TCR is *very likely* between 1.0 and 3.5 °C. Table 9.5 in the AR5 lists the TCRs of 30 CMIP5 models. They range from 1.1 to 2.6, with a median of 1.8, a mode of 2.0 and an average of 1.8 (**figure 6**).<sup>12</sup>

12. The figure shows the data tabulated in Table 9.5 in the AR5, and is shown online at <http://climateaudit.org/2013/12/09/does-the-observational-evidence-in-ar5-support-its-the-cmip5-models-tcr-ranges/>.

**Figure 6: Distribution of Transient Climate Response magnitudes in CMIP5 models, compared to TCR derived from observations**



Data source: IPCC, 2013: Table 9.5.

The data reported in the AR5 yield an empirical estimate of TCR of only 1.3 °C, down at the low end. The calculations are shown in [Box 1](#). Only one CMIP5 model has a TCR below the empirical level, two have the same value and 27 have values above it. In other words, most models are programmed to yield more warming in response to greenhouse gases than is presently consistent with long term observations.

**Box 1**

The value of  $\Delta F_{2x}$  used in the AR5 is 3.71 W/m<sup>2</sup>. Although it is not stated explicitly, it can be inferred from Section 8.3.2.1. That section cites calculations in Myhre et al. (1998), which proposed the following formula:

$$\Delta F_{2x} = \alpha \ln ( C/C_0 )$$

where  $\alpha = 5.35$  and  $C/C_0$  is the ratio of the current atmospheric CO<sub>2</sub> concentration to the preindustrial level ( $C_0 = 278$  ppm). Myhre et al. (1998) used it to estimate a forcing value for CO<sub>2</sub> doubling of

$$\Delta F_{2x} = 5.35 \times \ln(2) = 3.71$$

That this value is still used can be confirmed by the fact that  $\ln(2)$  is a constant, so as long as  $\alpha$  hasn't changed,  $\Delta F_{2x}$  must also be the same. AR5 Section 8.3.2.1 states that atmospheric CO<sub>2</sub> has risen from 278 ppm to 390.5 ppm and this resulted in forcing of 1.82 W/m<sup>2</sup>. Note that:

$$\Delta F = 5.35 \times \ln(390.5/278) = 1.82$$

which confirms that the current estimate of  $\alpha$  remains 5.35. The numbers and formulae given in AR5 therefore yield the following empirical estimate for TCR:

- ◆ Warming from 1850 to 2011 ( $\Delta T$ ) = about 0.8 °C (p. SPM-3).  
Assuming stable temperatures from 1750 to 1850 (global observations are not available back this far), that makes the temperature change 1750 to 2011 about 0.8 °C.
- ◆ The change in radiative forcing ( $\Delta F$ ) from 1750 to 2011 was estimated as 2.29 W/m<sup>2</sup> (p. SPM-9).
- ◆ The current  $\Delta F_{2x}$  value is 3.71 W/m<sup>2</sup>.

Using the IPCC's formula this implies:

$$\text{TCR} = \Delta T / \Delta F \times \Delta F_{2x} = 0.8 / 2.29 \times 3.71 = 1.3 \text{ °C}$$

As for ECS, the AR4 reported a likely range of 2.0–4.5 °C, with a best estimate of around 3 °C. In the AR5 the IPCC changed the range to 1.5–4.5 °C but did not offer a best estimate. Five recent papers in peer-reviewed journals have used diverse empirical methods that incorporate up-to-date temperature data (including Ocean Heat Content) in order to constrain the estimate of equilibrium sensitivity to values consistent with observations. They all yielded ECS estimates below 2.0 °C. These papers are:<sup>13</sup>

- ◆ Aldrin et al. (2012): ECS best estimate **1.76** °C, likely range 1.3–2.5 °C
- ◆ Lewis (2013): ECS best estimate **1.64** °C, likely range 1.3–2.2 °C
- ◆ Masters (2013): ECS best estimate **1.98** °C, likely range 1.2–5.2 °C
- ◆ Ring et al. (2012): ECS best estimate **1.80** °C, likely range 1.4–2.0 °C. (Note ECS falls to 1.6 °C if HadCRUT3 is replaced by HadCRUT4.)
- ◆ Otto et al. (2013): ECS best estimate **1.91** °C, likely range 1.3–3.0 °C

Lewis (2014) shows that an influential early study of climate sensitivity that yielded a long upper tail of possible temperature changes (over 10 °C) and a median ECS of 3.5 °C contained computational errors that substantially biased the estimates upward. Correcting the methods and using the same data yielded a much lower median ECS estimate (2.4 °C) and likely range of 1.2–5.2 °C, down from 1.6–15.1 °C. Using updated, post-2000 data further reduces this to about 1.65 °C with a likely range of 1.2–2.9 °C (Lewis, personal communication).

## Summary

The discussion up to this point can be summarized as follows. There has been no statistically significant warming for about 18 years despite a rapid rise in GHG levels and a corresponding increase in radiative forcing. Climate models overpredicted warming since 1998. There is no historical analogue for a discrepancy between models and observations lasting this long and growing this wide. The global average temperature anomaly is now below 97.5% of the climate model projections used in the IPCC report of 2013, and within a few years may be below 100% of them. A string of recent studies in the peer-reviewed literature over the past few years have yielded empirical climate

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<sup>13</sup>. There is a discussion of some of these studies in IPCC, 2013: Sct. 10.8.2.1.

sensitivity levels one-third to one-half lower than the median estimate used in IPCC reports since 1990.

But none of this information has been absorbed into the economic analysis of climate policy, since IAMs are calibrated using climate models rather than climate data. To the extent models overstate the effects of CO<sub>2</sub> emissions, so do IAMs, thereby yielding biased estimates of the social cost of carbon and overly stringent policy prescriptions. Consequently, the need to re-examine climate models also implies a need to re-examine economic models.

The Appendix discusses some further recent evidence of model-observational discrepancies. The next section begins the analysis of policy implications.

## 3. Implications for IAMs

### 3.1 Economic dynamics in an IAM

The economic model in an IAM is based on conventional growth theory. Every year the agents in the economy allocate capital and labour (effort) to convert energy and inputs into consumable outputs. The value of the output equates to real income, which agents then divide up between paying for current consumption and saving for future consumption. Savings takes the form of additions to the capital stock. The motivation for saving is that extra capital in the future can support higher levels of consumption. But savings behaviour is constrained by two forces, which combine to create a discount factor against future consumption. First, one must wait to realize the extra consumption, so it is intrinsically less valued than the equivalent amount of consumption today. Second, if one is wealthier when the extra consumption becomes available, the law of diminishing marginal utility implies it will be worth less than when one was less well off. The allocation between savings and consumption is determined by the marginal productivity of capital (which determines the benefit of saving) and the discount factor on future consumption. The value to the agents of each period's consumption is called *utility*, and the sum of all future utility levels, downweighted each period by the discount factor, represents the current wealth of the economy. Thus total wealth is determined not only by the current endowment of labour, capital, and other inputs, but also by the savings/consumption plans for the future. The main assumption behind growth models is that the savings path is chosen so as to maximize current well-being, or in other words the discounted path of current and future utility, subject to the constraints implied by the availability of labour, capital, and resources.

IAMs build out this basic structure so as to include some features relevant to the climate problem. Each period, energy use, capital levels, and consumption yield a certain quantity of CO<sub>2</sub> emissions. Depending on the sophistication of the model, agents can, if they wish, choose different combinations of energy, capital, and goods to yield different levels of CO<sub>2</sub> emissions. If the model includes different agents in different regions, they can trade with each other, and they will also have different production functions,



which determine the levels of output given their stocks of capital, labour and resources. Each region will also have a government and, presumably, a tax system, and the government can choose to put taxes on CO<sub>2</sub> emissions as a means of inducing agents to choose combinations of energy, capital, and goods that reduce those emissions.

Already it is clear that for this type of model to be implemented as a numerical simulation, it is necessary to have a lot of equations and parameter values at one's fingertips. Even with the simple economy described so far, for any set of starting values there are infinitely many combinations of functions and parameters that would fit, so arbitrary choices must be made. Economists have certain preferred functional forms that they use for such models, and certain preferred parameter values, based on a combination of intuition, a smattering of empirical evidence, familiarity, and mathematical convenience. These selections yield the equations of the economic component of the IAM.

### 3.2 Damage functions

GHG emissions feed into the climate component of an IAM through what is called the “damage function.” There are several relevant aspects to this. First, as noted previously, emissions affect temperatures (slowly) and changes in temperature affect utility. The changes are often assumed to be harmful, whether they are positive or negative. Any number of stories can be told to justify this assumption, but they are not typically amenable to formal proof.

Since the changes happen slowly over time, the costs to society of a unit of emissions today consist not only of the damages today, but also the damages spreading out over time as the stock of carbon in the air goes up, then (eventually) down. In order to put a value on the damages of today's emissions, for the purpose of deciding how much the emitter should pay in carbon taxes, it is necessary to run the model forward in time, compute the incremental effects of today's emissions into the long future, then add up all the changes in real income or consumption, discount future changes appropriately, and arrive at a single discounted present value. This is called the “Social Cost of Carbon” or SCC.

The rate at which emissions lead to changes in the atmospheric stock of CO<sub>2</sub> is not typically controversial. The key uncertainties around the parameterizations that determine the SCC of a model are:

- ◆ The discount rate by which future damages are weighed less against current income.
- ◆ The sensitivity function that translates changes in CO<sub>2</sub> to changes in temperature.

- ◆ The damages function that translates changes in temperature into changes in utility via effects on consumption and productivity.

Marten (2011) provides a useful summary of some of the main features of a handful of well-known IAMs, namely DICE (Nordhaus and Boyer, 2000), PAGE (Hope, 2006), and FUND (Tol, 1997). He also discusses a newly-proposed damage function by Weitzman (2010). In his Table 1 (p. 26) he lists the SCC computed by varying the discount rate over the range 2.5 to 5 percent, which is smaller than the usual range of sensitivity analysis for public policy experiments, and by swapping only the sensitivity and damage functions among the three leading models. The resulting SCC estimates range from \$0 to \$206 per tonne: in other words, for all their equations and complexity, the IAMs do not actually provide any policy guidance. In effect they just dress up guesswork in a garb of pseudo-precision.<sup>14</sup> The range can only be narrowed by arbitrary opinions (such as insisting on a low discount rate, though that only limits the range to between \$11 and \$206).

The damage functions are especially illustrative of the arbitrariness of such models. Marten translates the DICE model damage function into the following:

$$D_t / Y_t = [ 1 - 1 / ( 1 - m(\Delta T_t) ) ] \quad (1)$$

where  $D_t$  is current (year  $t$ ) damages expressed as a fraction of current real consumption,  $Y_t$ ,  $\Delta T_t$  is the amount by which current temperature differs from preindustrial temperature, and  $m$  is the function

$$m(\Delta T_t) = 0.0023888\Delta T_t^2 \quad (2)$$

Because  $m$  is a simple parabola, any change in temperature up or down compared to the apparently optimal age before industrialization is a bad thing—and the badness is known with precision to 7 decimal places. The Weitzman modification replaces equation (2) with

$$m(\Delta T_t) = 0.0023888\Delta T_t^2 + 0.0000051\Delta T_t^{6.754}$$

adding even more numerical pseudo-precision to our knowledge of the badness of the change in temperature. The FUND model of Richard Tol, to its credit, does not reduce to such simplicity, instead it embeds an attempt to have different, empirically based measures of damages across 16 different

<sup>14</sup> I endorse Robert Pindyck's (2013) view on IAMs: "[The] models are so deeply flawed as to be close to useless as tools for policy analysis. Worse yet, their use suggests a level of knowledge and precision that is simply illusory, and can be highly misleading."

regions of the world, with varying effects in agriculture, forestry, etc.; and allowing for the possibility that an increase in emissions may have beneficial side-effects through aerial CO<sub>2</sub> fertilization of plants.

The sensitivity functions play a big role in driving the variation in results. The most basic formula would just have a doubling of CO<sub>2</sub> levels yield an increase in radiative forcing (denoted  $\Delta F_{2x}$ ) which then raises temperature according to an adjustment factor  $\lambda$ :

$$\Delta T_{2x} = \lambda \Delta F_{2x} \quad (3)$$

Using conventional parameter choices, this would yield a prediction that doubling atmospheric CO<sub>2</sub> would raise temperatures by about 1.2 °C, and in all IAMs (even applying the Weitzman damage function) the global economic costs of that change would be effectively zero. But based on the typical sensitivity levels in climate models, equation (3) is usually modified so that temperature increases themselves cause additional temperature increases, according to a feedback term  $f$ :

$$\Delta T_{2x} = \lambda \Delta F_{2x} + f \Delta T_{2x}$$

Solving the above for  $\Delta T_{2x}$  yields an equilibrium climate sensitivity of

$$\Delta T_{2x} = \lambda \Delta F_{2x} / (1 - f) \quad (4)$$

The feedback parameter  $f$  in equation (4) has an enormous effect on the climate sensitivity estimate. The closer it gets to a value of 1, the greater the temperature response from additional carbon emissions.<sup>15</sup>

Rather than simply using empirical estimates of  $\Delta T_{2x}$  itself, the practice is to use the conventional value of  $\Delta F_{2x}$  (3.71 W/m<sup>2</sup>), and a value of  $\lambda$  (0.32) that yields 1.2 °C non-feedback warming from CO<sub>2</sub> doubling, and then to give  $f$  an innocuous-looking distribution that implies a range of values for  $\Delta T_{2x}$ , which can be used to create distributions of  $\Delta T_{2x}$  encompassing a range, a mean, a median, and so forth.

As Marten (2011) notes, in order to match the median and range of climate model sensitivity estimates, the conventional assumption is that  $f$  is normally distributed with a mean of 0.61 and a standard deviation of 0.17. This implies a central  $\Delta T_{2x}$  value of 3.0 °C, well above the recent empirical estimates mentioned above, all of which are below 2.0 °C. Letting  $f$  go down by two standard deviations implies a likely (95%) lower bound in the models

<sup>15</sup> More recent IAMs add in things like ocean heat transfer, to try and build in more realism, but a reciprocal term like the one in equation (4) always appears. See Marten (2011: 10–12).

of 1.6 °C, which is higher than the likely lower bound in all recent empirical estimates. In other words, the mean and lower end of sensitivity in IAMs are calibrated to match conventional climate models, but this results in values skewed well above those based on empirical evidence.

A further problem with equation (4) is revealed by allowing  $f$  to move up two standard deviations. This yields  $\Delta T_{2\sigma} = 1 / (1 - 0.95) \times 3.71 = 23.7$  °C. In other words, despite the fact that the long term trend in the HadCRUT4 series is only about 0.75 °C per *century*, should atmospheric CO<sub>2</sub> levels double by 2100, IAMs deem it equally likely that the world's temperature will increase by 1.6 °C or 23.7 °C. Even GCMs, for all their faults, do not embed such bizarre behaviour. Moreover, given the assumption about the distribution of  $f$  and the functional form of the sensitivity equation, IAMs could yield an outcome where  $(1 - \lambda) = 0$ , which would imply that a single tonne of CO<sub>2</sub> emissions would heat the Earth up to the temperature of the interior of the sun.

While these are low-probability “tail events,” they figure into the cost calculations because the models are run many times allowing  $f$  to vary according to its distribution, then the resulting damages are observed and the SCC computed. This creates a heavy skew in the upper tail of SCC costs, dragging up the mean and median. Indeed the presence of “tail events” in IAMs, rather than being dismissed as mathematical aberrations, are now sometimes treated as actual forms of risk. For instance, an entire section of a recent report from the White House was devoted to exploring the potential costs of so-called Tail Risks (White House, 2014). Clearly the recent empirical evidence on lower climate sensitivity has not been assimilated at all into economic models.

For all their faults, IAMs are useful for assessing the role of the discount rate, since that at least follows objective formulae. And the growth theory basis is familiar enough that it allows economists to think through the issues of long term climate policy in a well-understood dynamic framework. But the use of a climate component calibrated to GCMs and endowed with a grossly exaggerated upper tail means that the resulting estimated social costs of carbon are almost certainly skewed too high.

## 4. Policy implications of the hiatus

To re-cap:

- 1 A nearly 20-year-long pause in the rise of global average temperatures in the face of rising greenhouse gas concentrations makes it likely that climate models have been overestimating anthropogenic warming.
- 2 To the extent that these inflated estimates of climate sensitivity are input into economic models as a basis for decision-making, we risk enacting overly-stringent and overly-costly policies.
- 3 A few more years of temperature data will likely allow a more definitive understanding about the nature of the climate change threat and will enable better policy development with less uncertainty and wider agreement.

This leads to two implications for policy.

### 4.1 Wait for new information

On the typical time scales of climate policy, a delay of two or three years has no long run implications. But where important new information is expected in that time frame, the benefits in terms of better economic policy formation may be substantial. Thus the hiatus and the model-observational discrepancy indicate that policymakers will be in a much better position to know what is the optimal climate policy stance in about two years. Consequently, this is a poor time to make irreversible commitments to a particular climate policy strategy. While there would be very little downside to waiting for the information that will emerge in the next couple of years, there is considerable upside, since it would avoid the problem of making plans based on information that turns out to be obsolete.

A recent report from the White House, mentioned above, insists that delaying action on CO<sub>2</sub> mitigation is far more costly than acting now. However,

the key premise of that argument is that we know with certainty what action must be taken and when it must be taken by, so the optimal sequence involves making as early a start as possible. The flaw in that analysis was alluded to in the last section: the models used to compute the optimal policy and timetable embed a range of climate sensitivities already known to be too high, and there is no provision in the analysis for the near-term emergence of information that could substantially reduce the sensitivity estimates further. A better strategy would be to hold off until the data is in on the sensitivity issue. However if policymakers believe action must be taken, it is essential that any action is flexible and responsive to new information that emerges, as proposed in the next section.

## 4.2 Policy must embed an empirical feedback mechanism

Should a policymaker feel that some kind of decision or policy plan must be implemented before the hiatus issue is resolved, it will be important to build into it a structure that connects real-world information about the severity of the problem to the stringency of the policy. Otherwise, there is a very real possibility of making a long term commitment to a policy path chosen on the basis of an assumption that we are in a high-sensitivity world, only to learn that we are in a low-sensitivity world and the policy is much more costly than it ought to have been.

In previous works (e.g., McKittrick, 2010, 2012, 2013) I have outlined how one such dynamic pricing mechanism for CO<sub>2</sub> emissions could be implemented, that yields the optimal dynamic price path for emissions regardless of how the scientific questions get settled in the years ahead, while providing full policy certainty for economic decision-makers.

The mechanism would consist of two components:

- ◆ A revenue-neutral carbon tax which starts at a modest level and is thereafter tied to atmospheric temperatures.<sup>16</sup> If temperatures go up, so does the tax, and if they go down, so does the tax. Presumably, a lower bound of zero would be established.

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<sup>16</sup>. Specifically I have recommended that the tax track the mean temperature of the tropical troposphere. Climate models identify this region as exhibiting a rapid adjustment to change in forcing, and relatively large, amplified response to warming at the surface. This region is also subject to careful measurement by both weather balloon and weather satellite systems and is not biased by urbanization and other contaminating influences on the surface temperature record.

- ◆ A futures market in which the government sells a limited number of exemption certificates dated up to thirty years ahead, each of which exempts the owner from paying the tax on one tonne of emissions. The certificates would be tradable in a secondary market. As the year for which they are usable approaches, the certificate price would converge on the current carbon tax rate, since nobody would buy one for more than the tax rate, and nobody would sell one for less. Hence the market would tend to constrain the price of certificates in such a way as to reveal an objective forecast of future tax rates, which will, in turn, imply an objective forecast of future temperatures. The market for exemption certificates will thereby provide a natural mechanism to connect all available scientific information about current and future climate change to the pricing mechanism.

I provide here only a very minimal sketch: for a more detailed non-technical survey see McKittrick (2013). In McKittrick (2010) I showed how, under a set of basic assumptions, a temperature-indexed (or “state-contingent”) carbon tax yields a price path closely correlated with the unobservable solution of the dynamic optimization problem IAMs attempt to solve. The difference is that IAMs only get the solution right if they have all the right parameters, which is unlikely. The state-contingent approach gets it right without having to know the correct parameters in advance.

The policy is forward-looking since investment and purchase decisions are based on expectations, so firms and households would need to forecast temperature changes over time, and then use them to forecast the emissions tax path. If a firm expects that there will be a lot of warming, it will expect the carbon tax to go up and will opt for “low carbon” investment options. If a firm does not expect warming, it would likewise not expect the tax to rise. Either way, the firm would have an incentive to obtain the best possible forecasts, since errors in either direction would be costly. Firms would not have an incentive to take any view on the climate issue except the most objective one possible.

Key to the logic of the policy is that the tax is tied to a temperature measure selected so as to isolate, as much as possible, the anthropogenic component of climate change. It would make no sense to have a tax that primarily tracks natural cycles like El Nino, for instance. Thus, whatever measure is chosen, it would likely be subject to some averaging and smoothing out in order to dampen weather fluctuations out of the formula.

The futures market would play two roles. First, it would offer complete pricing certainty to any firm engaged in long-term planning. If a firm considering building, say, a pulp mill is worried about CO<sub>2</sub> emissions becoming expensive a decade ahead, it could buy permits today to cover all or part of the expected emissions down the road. Second, the futures market would become, in effect, the world’s best climate model. It would be the place where

the most accurate and objective information about future temperature changes would be put to use guiding present-day investments.

If such a policy mechanism were put in place, it would be very interesting to see how the market prices the post-hiatus interval. Market participants would have to decide between two basic options. Some might decide that the hiatus will continue and models will break down, leading to a downward revision in thinking about climate sensitivity and a flat or at most shallow rise in temperatures—and the carbon tax rate—over the coming decades. Others might decide that warming will come back with a vengeance shortly and the tax rate will soar along with it. The price of exemption certificates would indicate which view is predominant. Anyone who fundamentally disagrees with the price path could treat the basis of his disagreement as inside information and make profitable trades from it.



## Appendix

### Further evidence on the discrepancy

#### A1. Tropical troposphere

A careful read of IPCC (2013) Chapter 9, especially pages 29–42, shows that signs of model over-estimation go well beyond just the surface record. The troposphere over the tropics is a key region for assessing GCM performance. It makes up half the free atmosphere of the planet, it is where most of the incoming solar energy enters the climate system, and, due to the moist convection processes that govern energy transport throughout the region, it is where the strongest and most rapid warming is projected to take place in response to rising greenhouse gas levels (see discussion in, for example, IPCC, 2005: Chapter 10).

Tropical atmospheric temperatures have been monitored since 1958 by weather balloons and since 1979 by weather satellites. GCMs show a rate of warming too high to reconcile with either record. Climate model runs used for the AR4 (denoted CMIP3) yield post-1979 warming trends significantly higher than those in satellite or weather balloon observations (McKittrick et al., 2010). CMIP5 models predicted even higher trends in the tropical troposphere than did CMIP3 models, and the model-generated range no longer overlaps with the range of observed trends in either the Lower Troposphere (LT) or Mid-Troposphere (MT). Observed trends are, at a maximum, 0.13 °C/decade (LT) and 0.12 °C/decade (MT), whereas the model trends at each layer range from 0.15 – 0.41 °C/decade.

**Table A1**

**Tropical troposphere trend ranges reported in IPCC (2013), Chapter 9**

|    | Models      |             | Observed<br>(uncertainty range) |
|----|-------------|-------------|---------------------------------|
|    | CMIP3       | CMIP5       |                                 |
| LT | 0.10 – 0.41 | 0.15 – 0.41 | 0.06 – 0.13                     |
| MT | 0.10 – 0.41 | 0.15 – 0.41 | 0.02 – 0.12                     |

Note: All numbers in °C/decade.

McKittrick and Vogelsang (2014) examined the 1958–2012 temperature record collected by weather balloons and found that, controlling for a mean-shift in the late 1970s associated with internal variation in the climate, the trend terms in three weather balloon series are near zero and statistically insignificant. It is a remarkable feature of the tropical troposphere record that there is no warming trend over the post-1958 interval, despite the large buildup of GHGs. Climate models uniformly predicted considerable warming over this interval, and the discrepancy with observations is statistically significant.

Model-predicted tropical Sea Surface Temperature (SST) trends are also high compared to observations. The mean tropical SST trend in models is 0.19 °C/decade whereas the maximum observed trend is 0.14 °C/decade. One reason for this discrepancy may be that models project a 0.7–3.2% per decade increase in precipitable water (humidity) whereas observations only show a 0.0–1.4% per decade increase.

CMIP3 models that did not include representation of volcanic eruptions substantially overestimated Ocean Heat Content (OHC) uptake in the latter part of the 20th century. Most CMIP5 models include an adjustment after 1992 for volcanic effects that temporarily drops OHC without changing the overall trend. This leads to a visually better fit between models and observations (as shown in IPCC Figure 9.17), but none of the observational series actually show a dip associated with the 1992 Pinatubo eruption.

## **A2. Models are becoming more like each other and less like the real world**

In a remarkable analysis, Swanson (2013) showed that the development phase between the 4th and 5th IPCC Assessment Reports lead to models becoming both more alike and more unrealistic. His study examined a number of climate metrics and compared how well CMIP3 models (used in the AR4) and CMIP5 models (used in the AR5) did at reproducing them. The CMIP3 models tended, in some respects, to overstate observed warming, but formed a dispersion that encompassed observations. The CMIP5 models are less dispersed overall, but instead of converging on reality, they converged on the model mean itself, and in the process moved farther away from reality.

He looked at two metrics: the observed warming of near surface air temperature by latitude, and the frequency of anomalously cold and warm events. This captures two important aspects of models: the overall warming trend and the pattern of extreme events. He measured warming by computing the difference between the 2002–2011 mean temperature and the 1979–2011 mean temperature, or in other words, the 2002–2011 anomaly against the post-1979 mean.

The observational data were the HadCRUT4 surface air temperature archive and the ERA-Interim reanalysis data from the European Centre for Medium Range Weather Forecasting. Over the South Pole, the ERA-Interim data set shows 0 °C warming whereas models project from -0.5 °C cooling to +1.2 °C warming. Moving northward in latitude, models converge to a range of about 0.0 to 0.5 °C warming in the tropics (-30 to +30) then disperse in the high northern latitudes, showing about -0.1 to +1.5 °C warming at the north pole. Observed temperatures show a region of warming in the far south, cooling around -60 degrees latitude, little or no warming through the tropics, and warming in the northern hemisphere to a maximum of about +1.9 °C at the North Pole.

While observations tend to be low compared to models everywhere except the Arctic region, the model spread is at least wide enough to contain the observed anomalies almost everywhere. The same comparison using the CMIP5 models reveals virtually no overlap between model simulations and observations. Instead the models cluster more tightly around the model mean even as it moves farther away from the observations everywhere except the Arctic. Swanson summarizes the change as follows:

Curiously, simulation analogues for the observed warming have largely disappeared in the CMIP5 project. The HadCRUT4 and reanalysis warming lie on the fringes of the model envelope, roughly 2 standard deviations (internally calculated from the inter-simulation spread) removed from the model simulation ensemble mean. Curiously, the CMIP5 simulations appear to be approaching a consensus, as the inter-simulation standard deviation is 25% smaller among the CMIP5 project simulations than among the CMIP3 project simulations (Table 1). **However, this consensus appears to explicitly exclude the observed warming.** (Swanson, 2013; emphasis added)

Next, Swanson examined model simulations of the probability of extreme warm and cold events. The analysis covered 33 years (1979–2011) and looked at each month individually. In the CMIP3 model runs, although the models tend to over-predict warm events and under-predict cold events, observations are still within the span of models. In the CMIP5 runs, the model spread tightens, with the standard deviation shrinking by 50%, indicating a higher degree of consensus for model behaviour. But in so doing it has now completely excluded the observations. The HadCRUT4 observations fall more than 2 standard deviations from the model mean and the ERA observations fall more than 4 standard deviations away, and there are no longer any models that simulate the observed pattern of cold and warm extreme weather frequency. As Swanson points out, “this consensus appears to explicitly exclude the observed behaviour.”

Swanson concludes by conjecturing that modelers have subtly tuned their GCMs to do a better job of replicating the sharp Arctic warming, but in so doing they have made them perform worse everywhere else. He notes:

While the observed Arctic warming is spectacular and important, it is unclear why it is more important from the perspective of the evolution of the overall climate system than the relatively modest warming in the tropics and southern hemisphere. It is unclear whether the CMIP5 simulations are even getting the reason for the actual Arctic warming correct, as they are inconsistent with the strong Arctic warming but only modest warming in the Northern Hemisphere midlatitudes and tropics that best describes the recent evolution of the actual climate system.

### **A3. Most models lack explanatory power for the spatial pattern of warming over land**

Though both the AR4 and AR5 devote a whole chapter to model evaluation, neither reviews evidence concerning the ability of models to reproduce the spatial pattern of trends over land. Prior to the AR4 there wasn't much work on the topic. Berk et al (2001) wrote an editorial in the journal *Climatic Change* lamenting that, on the few occasions people checked the spatial trend pattern, there was a tendency to use what they called "eyeball assessments": putting colour plots side-by-side and declaring that they look similar.

Koutsoyiannis et al. (2008) and Anagnostopoulos et al. (2010) compared long term (100-year) temperature and precipitation trends in a total of 55 locations around the world to model projections. The models performed quite poorly at the annual level, but they also did poorly even when averaged up to the 30-year scale, even though this is typically assumed to be the level they work best at. They also did no better over larger and larger regional scales. The authors concluded that there is no basis for the claim that climate models are well-suited for long term predictions over large regions.

Fildes et al. (2011) took the same data set and compared model predictions against a "random walk" alternative, consisting simply of using the last period's value in each location as the forecast for the next period's value in that location. The test measures the sum of errors relative to the random walk. A perfect model gets a score of zero, meaning it made no errors. A model that does no better than a random walk gets a score of 1. A model receiving a score above 1 did worse than uninformed guesses. Simple statistical forecast models that have no climatology or physics in them typically got scores between 0.8 and 1, indicating slight improvements on the random walk, though in some cases their scores went as high as 1.8. The CMIP3 climate models got scores ranging

from 2.4 to 3.7, indicating a complete failure to provide valid forecast information at the regional level, even on long time scales. The authors commented: “This implies that the current [climate] models are ill-suited to localised decadal predictions, even though they are used as inputs for policy making.”

McKittrick and Tole (2012) created several statistical models that tested the ability of CMIP3 models to explain the spatial pattern of temperature trends over land in comparison with observations of patterns of changes in socioeconomic variables, such as Gross Domestic Product and population. The IPCC explicitly claims socioeconomic do not affect surface temperature records as this would imply non-climatic contamination from processes like urban heat islands, which they claim have been removed from the raw data.

McKittrick and Tole used two types of methods (classical and Bayesian) to study the issue. In the classical testing framework, 10 of the 22 climate models predicted a spatial pattern of trends that was negatively correlated with observations and had to be removed from most of the analysis to avoid biasing the results. In 10 other cases they found the climate models predicted a pattern that was loosely correlated with observations, but not significantly so—in other words not significantly better than random numbers. In only 2 cases was there statistically significant evidence of explanatory power.

They then ran an “encompassing” test, which asks if each of the 22 GCMs does such a good job explaining the surface temperature data that the socioeconomic indicators can be ignored, or vice versa. In all 22 cases the probability that the socioeconomic data could be left out was zero, but only in 3 of 22 cases did the data call for retaining the GCM, and in one of those cases the fit was negative (opposite to the observed patterns) so it didn’t count. So, again, only 2 of 22 climate models demonstrated enough explanatory power to be worth retaining, but in all 22 cases the data gave primary support to the socioeconomic measures that imply residual contamination of the surface temperature record.

Bayesian methods were then used to check if the climate models might work better in an unknown linear combination, along with a linear combination of some or all of the socioeconomic variables. The optimal combination was identified as consisting of 3 of the 7 socioeconomic variables and 3 of the 22 GCMs. They concluded that a valid model of the pattern of temperature changes at the earth’s surface requires both measures of data contamination induced by regional socioeconomic variations and some climate model processes.

The three climate models consistently identified as having explanatory power were from China, Russia and NCAR. Climate models from Norway, Canada, Australia, Germany, France, Japan and the UK, as well as American models from Princeton and two US government labs (NASA and NOAA), failed to exhibit any explanatory power for the spatial pattern of surface temperature trends in any test, alone or in any combination.

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Ross McKittrick is a Professor of Economics at the University of Guelph and Senior Fellow of the Fraser Institute. He specializes in environmental economics. He has published many studies on the economic analysis of pollution policy, economic growth and air pollution trends, climate policy options, the measurement of global warming, and statistical methods in paleoclimatology. His latest book is *Economic Analysis of Environmental Policy*, published by University of Toronto Press (Fall 2010). He has also published numerous invited book chapters, newspaper and magazine essays, and think-tank reports.

In 2003, his (coauthored) book, *Taken by Storm: The Troubled Science, Policy and Politics of Global Warming*, won the \$10,000 Donner Prize for the best book on Canadian Public Policy.

Professor McKittrick has been cited in media around the world as an expert on the science and policy of global warming. He has made invited academic presentations in Canada, the United States, and Europe, and has testified before the US Congress and the Canadian Parliamentary Finance and Environment Committees. In 2006, he was one of 12 experts from around the world asked to brief a panel of the US National Academy of Sciences on paleoclimate reconstruction methodology.

## Acknowledgments

The author is indebted to the anonymous reviewers for their comments, suggestions, and insights. Any remaining errors or oversights are the sole responsibility of the author. As the researcher worked independently, the views and conclusions expressed in this paper do not necessarily reflect those of the Board of Trustees of the Fraser Institute, the staff, or supporters.

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### Date of issue

October 2014

### ISBN

978-0-88975-319-8

### Citation

McKittrick, Ross (2014). *Climate Policy Implications of the Hiatus in Global Warming*. Fraser Institute. <<http://www.fraserinstitute.org>>

### Cover design

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