Challenges of Climate Change: The challenge of uncertainty

David Mond

Warwick, November 7th, 2019

Challenges of Climate Change: The challenge of uncertainty

David Mond

Warwick, November 7th, 2019

- Uncertainty about the future

Challenges of Climate Change: The challenge of uncertainty

David Mond

Warwick, November 7th, 2019

- Uncertainty about the future
- Uncertainty about the present and past

Challenges of Climate Change: The challenge of uncertainty

David Mond

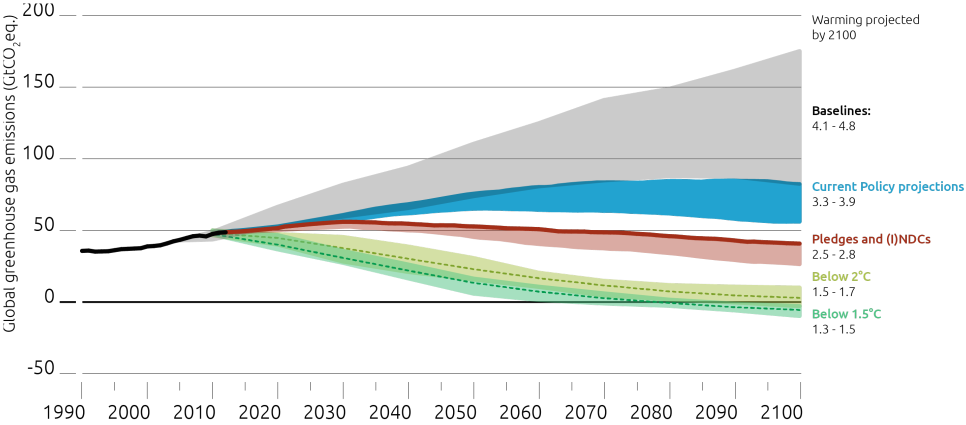
Warwick, November 7th, 2019

- Uncertainty about the future
- Uncertainty about the present and past
- The manufacture of doubt

I. Uncertainty about what will occur

All predictions of climate, like weather forecasts, are uncertain. In order to act sensibly in response to a prediction, one needs a measure of the uncertainty. How does one measure and express uncertainty? Using the language of *probability theory*. Consider the following graph, shown in Lecture 1.

Temperature predictions by Climate Action Tracker



It contains a lot of information, and an *acknowledgement* of uncertainty (the width of the range of predicted temperature increase in each scenario), but almost no *quantification* of uncertainty. On the RHS, it says that under BAU, the temperature increase by 2100 will be in the range 4.1 – 4.8°C , but gives no indication of how likely any of the possible increases are.

A very quick primer on probability

Probability Theory expresses probabilities by a number in the range 0 to 1. “1” means “certain”; “0” means ”impossible”. More generally: if the probability of a certain outcome in a trial is, say, 0.3, then in 10 trials, the given outcome will occur about 3 times, and in 100 tests, about 30 times. Indeed, at first, it is precisely by counting the *frequency* of an event in a sequence of trials that we arrive at an estimate of its probability. Later, *theories* can predict differing probabilities, without the need for many trials.

- The probability that a fair coin toss will show heads is 0.5 (i.e. $\frac{1}{2}$) $P(H) = 0.5$
- The probability of two independent events *both* happening is multiplicative, e.g. $P(HH) = \frac{1}{2} \times \frac{1}{2} = \frac{1}{4} = 0.25$
- The probability of at leat one of two disjoint events happening is additive e.g. $1 = P(H \text{ or } T) = P(H) + P(T)$; $\quad P(TH \text{ or } HH) = \frac{1}{4} + \frac{1}{4} = \frac{1}{2}$. Similarly,

  $$P(\text{rain on Monday or Tuesday}) = P(\text{rain on Monday}) + P(\text{rain on Tuesday})$$

  and in two coin tosses

  $$1 = P(HH) + P(HT) + P(TT) + P(TH)$$

This is probability theory at its most simple. In the same way the statement

$$P(\text{Hurricane in Puerto Rico in September}) = 0.17$$

can be justified by looking at frequency data i.e. historical records, *assuming the climate is not changing*.

But if the climate is changing, probability estimates such as

$$P(\text{Hurricane in Puerto Rico in September 2019}) \simeq 0.23$$

require *theory* as well as frequency data to make and to interpret. There aren't enough hurricanes to justify this purely by frequency data. And the prediction

$$P(\text{Hurricane in Puerto Rico in September 2025}) \simeq 0.32$$

becomes even harder to justify and to interpret – though climate science does just this. This science is what insurance companies rely onto calculate their premiums. Their business works: they provide insurance cover which people are willing to pay for, and, in general, they do not go bankrupt.

But if the climate is changing, probability estimates such as

$$P(\text{Hurricane in Puerto Rico in September 2019}) \simeq 0.23$$

require *theory* as well as frequency data to make and to interpret. There aren't enough hurricanes to justify this purely by frequency data. And the prediction

$$P(\text{Hurricane in Puerto Rico in September 2025}) \simeq 0.32$$

becomes even harder to justify and to interpret – though climate science does just this. This science is what insurance companies rely onto calculate their premiums. Their business works: they provide insurance cover which people are willing to pay for, and, in general, they do not go bankrupt.

A brief aside:

But if the climate is changing, probability estimates such as

$$P(\text{Hurricane in Puerto Rico in September 2019}) \simeq 0.23$$

require *theory* as well as frequency data to make and to interpret. There aren't enough hurricanes to justify this purely by frequency data. And the prediction

$$P(\text{Hurricane in Puerto Rico in September 2025}) \simeq 0.32$$

becomes even harder to justify and to interpret – though climate science does just this. This science is what insurance companies rely onto calculate their premiums. Their business works: they provide insurance cover which people are willing to pay for, and, in general, they do not go bankrupt.

A brief aside: In a survey carried out by the Royal Statistical Society in 2012

> *a total of 97 UK MPs were asked this probability problem: if you toss a fair coin twice, what is the probability of getting two heads?*

But if the climate is changing, probability estimates such as

$$P(\text{Hurricane in Puerto Rico in September 2019}) \simeq 0.23$$

require *theory* as well as frequency data to make and to interpret. There aren't enough hurricanes to justify this purely by frequency data. And the prediction

$$P(\text{Hurricane in Puerto Rico in September 2025}) \simeq 0.32$$

becomes even harder to justify and to interpret – though climate science does just this. This science is what insurance companies rely onto calculate their premiums. Their business works: they provide insurance cover which people are willing to pay for, and, in general, they do not go bankrupt.

A brief aside: In a survey carried out by the Royal Statistical Society in 2012

> *a total of 97 UK MPs were asked this probability problem: if you toss a fair coin twice, what is the probability of getting two heads?*
>
> *Only 38 of the 97 replied correctly, although 72 said they felt confident when dealing with numbers.*

But if the climate is changing, probability estimates such as

$$P(\text{Hurricane in Puerto Rico in September 2019}) \simeq 0.23$$

require *theory* as well as frequency data to make and to interpret. There aren't enough hurricanes to justify this purely by frequency data. And the prediction

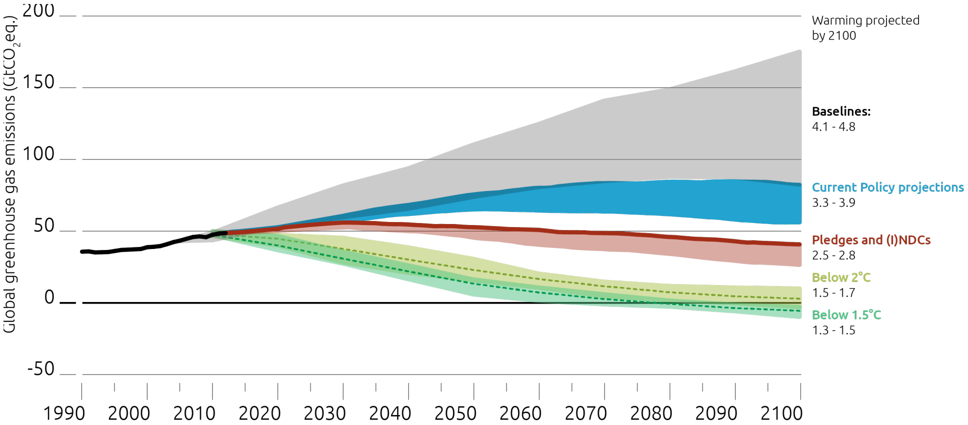
$$P(\text{Hurricane in Puerto Rico in September 2025}) \simeq 0.32$$

becomes even harder to justify and to interpret – though climate science does just this. This science is what insurance companies rely onto calculate their premiums. Their business works: they provide insurance cover which people are willing to pay for, and, in general, they do not go bankrupt.

A brief aside: In a survey carried out by the Royal Statistical Society in 2012

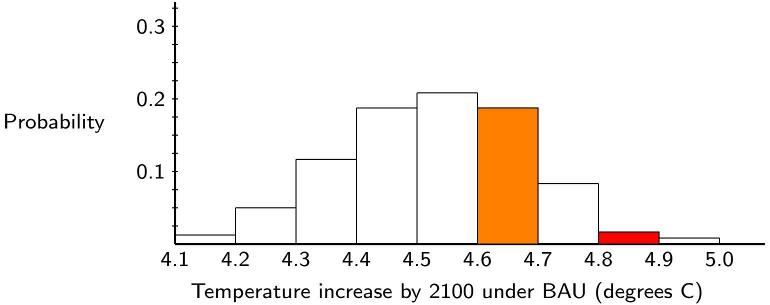
> *a total of 97 UK MPs were asked this probability problem: if you toss a fair coin twice, what is the probability of getting two heads?*
>
> *Only 38 of the 97 replied correctly, although 72 said they felt confident when dealing with numbers.*

Returning to the graph of expected temperature rises:



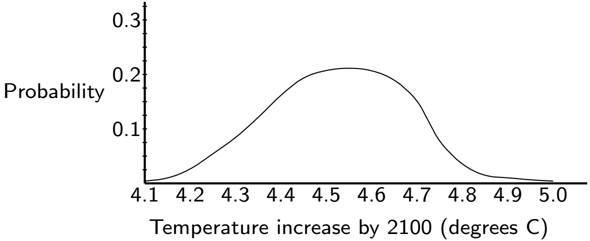
This says that the predicted range under BAU ("Baselines") is between 4.1 and 4.8$^\circ\mathrm{C}$. The uncertainty is better quantified by a graph or chart showing a "probability distribution".

For example, the following bar chart (made up for the purpose of the lecture!).

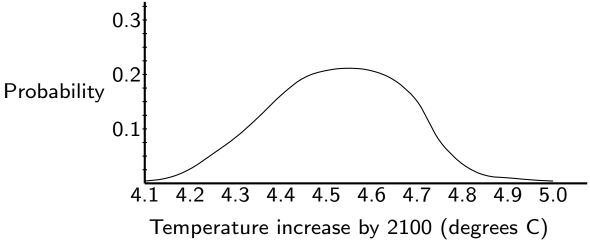


This says, for example, that the probability that the temperature rise will be between 4.6°C and 4.7°C is just under 0.2 (orange rectangle), whereas the probability that it will be between 4.8°C and 4.9°C is about 0.025 (red rectangle). The more precise is the estimate, the more concentrated is the distribution. Typically, climate predictions cannot be precise – they depend on too many factors, including a lack of knowledge about how the earth's atmosphere will react to higher temperatures, and about the complex feedbacks that may be triggered as temperatures rise.

A probability distributions of this kind is often shown as a smooth curve –

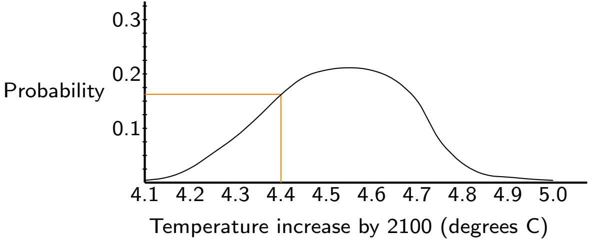


A probability distributions of this kind is often shown as a smooth curve –



The interpretation is is not e.g.

A probability distributions of this kind is often shown as a smooth curve –

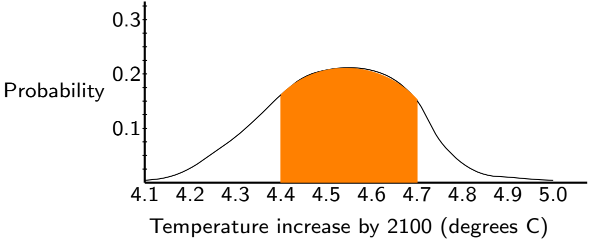


The interpretation is is not e.g.

$$P(\text{temperature rise of } 4.4^{\circ}\mathrm{C}\ ) = 0.16$$

but

A probability distributions of this kind is often shown as a smooth curve –



The interpretation is not e.g.

$$P(\text{temperature rise of } 4.4^\circ\mathrm{C}\ ) = 0.16$$

but

$$P(\text{temperature rise is between } 4.4^\circ\mathrm{C} \text{ and } 4.7^\circ\mathrm{C}\ ) = \frac{\text{area under graph between 4.4 and 4.7}}{\text{total area under graph}}$$

Fat tails and risk

Definition of *risk*:

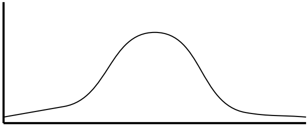
Risk of event E$=$ (Probability of E occuring) $\times$ (Damage due to E)

Fat tails and risk

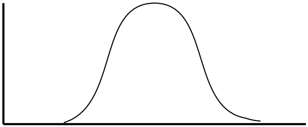
Definition of *risk*:

Risk of event E= (Probability of E occuring) $\times$ (Damage due to E)

A probability distribution like



as opposed to



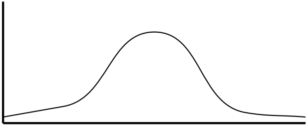
is called a "fat-tailed distribution".

Fat tails and risk

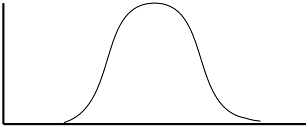
Definition of *risk*:

Risk of event E$=$ (Probability of E occuring) $\times$ (Damage due to E)

A probability distribution like

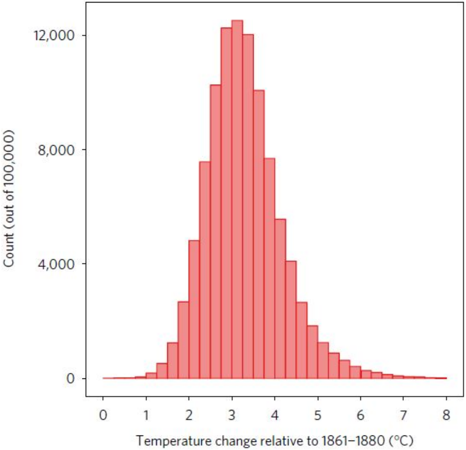


as opposed to



is called a "fat-tailed distribution". In the context of climate change, the sting is in the tail. If there is significant probability of a very high temperature rise, which would entail catastrophic consequences, then the *risk* is very much higher in the first than in the second, even though both suggest the same "most likely" temperature rise.

A real life bell-curve distribution

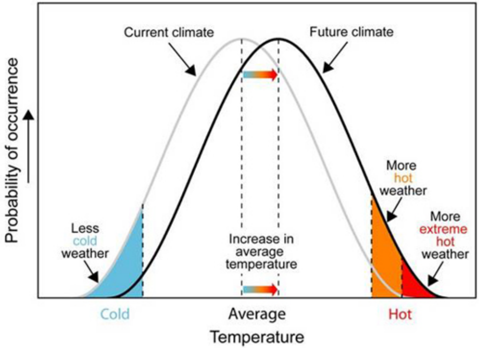


This was arrived at by running 100,000 computer simulations in which the parameters for population growth, GDP growth and carbon intensity (amount of carbon per unit of GDP) were varied according to their own estimated probability distributions.

Source: "Less than $2^{\circ}\mathrm{C}$ warming by 2100 unlikely" Adrian E. Raftery, Alec Zimmer, Dargan M. W. Frierson, Richard Startz & Peiran Liu, Nature Climate Change volume 7, pages 637 - 641 (2017)

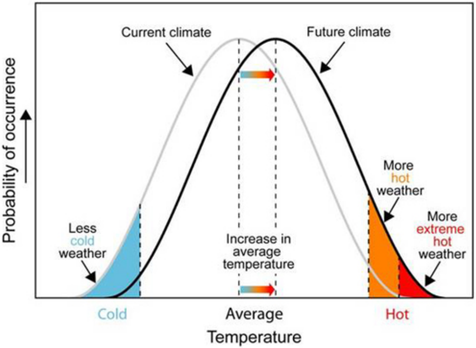
One more remark about bell curves

Similar-looking bell-curves appear in many contexts. For example, (another made up curve)



One more remark about bell curves

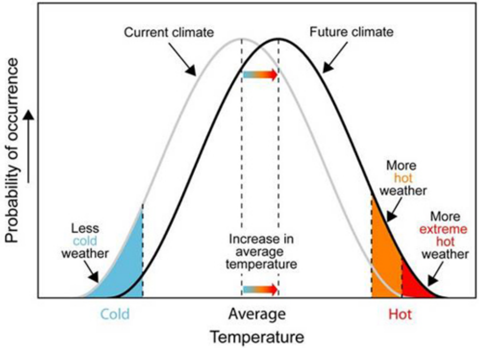
Similar-looking bell-curves appear in many contexts. For example, (another made up curve)



The small displacement to the right means that the orange area below the curve for "Future climate" is very much greater than the orange area below the "Current climate" curve.

One more remark about bell curves

Similar-looking bell-curves appear in many contexts. For example, (another made up curve)



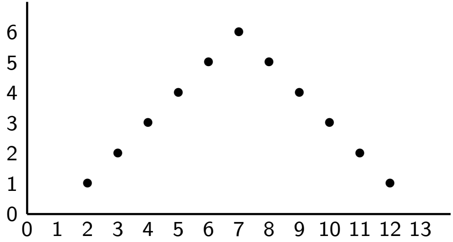
The small displacement to the right means that the orange area below the curve for "Future climate" is very much greater than the orange area below the "Current climate" curve.

A small increase in average temperature yields a large increase in frequency of extreme events.

Where do bell-curves come from?

1. If you throw a fair dice, the chance of getting each number $n = 1, 2, 3, 4, 5$ or 6 is the same, $1/6$.
2. If you throw two dice, then for each m and n between 1 and 6, the chance that (first dice, second dice)$= (m, n)$ is the same: $1/36$. But if you are interested in the *total*, things change:
   - there is just one way of getting a total of 2, namely $(1, 1)$.
   - there are two ways of getting a total of 3: (1,2) and $(2, 1)$
   - there are three ways of getting 4: $(1, 3)$, $(2, 2)$ and $(3, 1)$
   - there are 4 of getting 5: (1,4), (2,3), (3,2) and (4,1), etc.

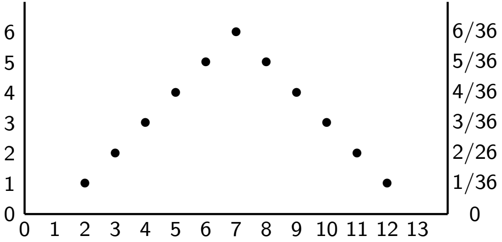
   For the possible totals, the numbers of ways are shown here:



Where do bell-curves come from?

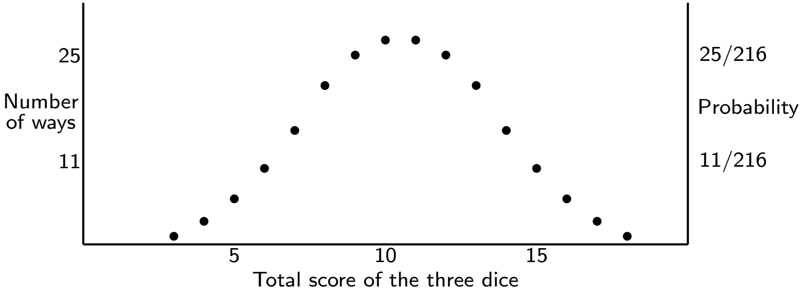
1. If you throw a fair dice, the chance of getting each number $n = 1, 2, 3, 4, 5$ or 6 is the same, $1/6$.
2. If you throw two dice, then for each m and n between 1 and 6, the chance that (first dice, second dice)$= (m, n)$ is the same: $1/36$. But if you are interested in the *total*, things change:
   - there is just one way of getting a total of 2, namely $(1, 1)$.
   - there are two ways of getting a total of 3: (1,2) and $(2, 1)$
   - there are three ways of getting 4: $(1, 3)$, $(2, 2)$ and $(3, 1)$
   - there are 4 of getting 5: (1,4), (2,3), (3,2) and (4,1), etc.

   For the possible totals, the numbers of ways are shown here:

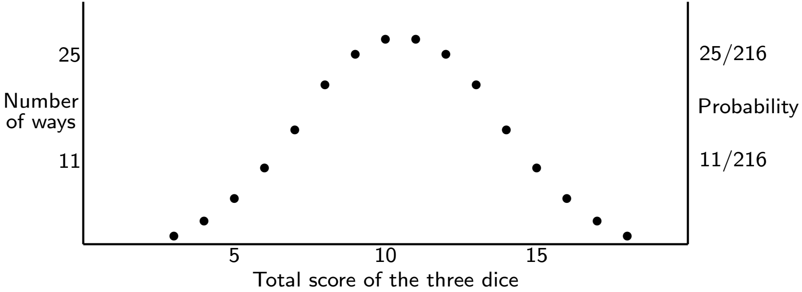


The probability of getting these totals is shown on the right hand axis.

If we throw three dice we get the following picture:

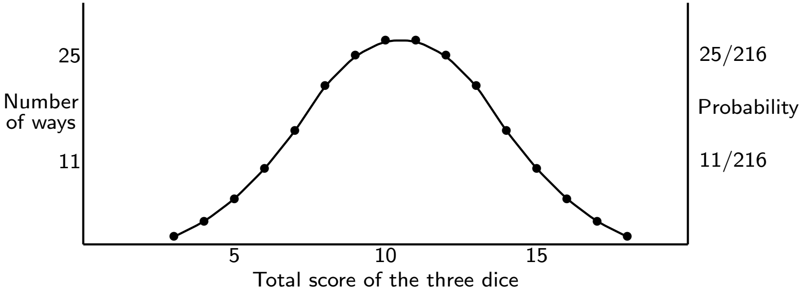


If we throw three dice we get the following picture:



Already, a bell shape is beginning to appear. With more dice, this becomes clearer and clearer.

If we throw three dice we get the following picture:



Already, a bell shape is beginning to appear. With more dice, this becomes clearer and clearer.

A *Galton Board* demonstrates the same phenomenon in a different way: see the demonstration at https://www.youtube.com/watch?v=kDkmSI39sWQ

How does this explain the appearance of a bell curve in, say, the distribution of heights of individuals in a large population, or the distribution of temperatures on May days? One can think of it like this: the temperature on May 7th is determined by an enormous number of different factors, beginning with the temperature on May 6th, the windspeed and direction, the clouds, the temperature of the air in the places the wind is blowing through on its way to us, etc etc etc. Each can "point" in different directions. The chance that all these factors will align to make the day hot is low: most likely some will have a cooling effect, and some a warming effect. There are many different ways of getting a moderate temperature: wind from the south, slightly cloudy, warm air in France where the wind comes from, or wind from the west, less cloud, calm at sea, etc etc etc. The large number of different ways of arriving at a moderate temperature contrasts with the small number of ways of arriving at a very high or very low temperature. So just as with the throw of many dice, the middling, moderate outcome is most common.

Similar reasoning applies in many many different fields where we see the same bell curve.

II. Uncertainty about what has occurred

As you heard in the Economics lecture, one way of pressuring people and organisations to reduce emissions is to make them pay for the damage their emissions cause. But how to estimate this damage?

Fictitious Example: By 2030, the $2^\circ\mathrm{C}$ temperature rise has wiped out the European winter sports industry, causing an economic loss of around $15 billion per year. How much should Exxon Mobil pay? That question seems easy to answer: Exxon Mobil is responsible for 17% of the carbon emitted since 1980, a year by which they knew the effects of fossil fuel emissions on the climate. The carbon emitted between 1980 and 2030 is 63% of the total in the atmosphere. So Europe's bill to Exxon could be based on a figure of

$$\$15 \text{ billion} \times \frac{17}{100} \times \frac{63}{100} = \$1.6 \text{ billion}$$

Less Fictitious Example: The cost to Puerto Rico of Hurricane María in 2017 was between $40 billion and $85 billion. How much should Exxon Mobil pay for that? Hurricanes have always occurred, but this hurricane was unusually big. How much did climate change contribute to the damage?

There is a whole new field of Attribution Science which attempts to answer questions like this, by combining sophisticated climate physics, statistics and computer simulations. In the analogous lawsuits against tobacco companies for causing lung cancer, the attribution science is easier: there is precise data comparing the incidence of lung cancer among smokers and among non-smokers. Will juries in future lawsuits have to be trained in attribution science?

III. The creation of uncertainty

They say governments hate uncertainty. US President Truman reputedly said "Can't someone bring me a one-handed economist?".

III. The creation of uncertainty

They say governments hate uncertainty. US President Truman reputedly said "Can't someone bring me a one-handed economist?".

Or perhaps not. In the context of climate change, it seems they really love it: it enables them not to take decisions which will impact their future electoral success or their major donors' share price.

III. The creation of uncertainty

They say governments hate uncertainty. US President Truman reputedly said "Can't someone bring me a one-handed economist?".

Or perhaps not. In the context of climate change, it seems they really love it: it enables them not to take decisions which will impact their future electoral success or their major donors' share price. In any case, "uncertainty" has played a major rôle in justifying (or perhaps only excusing) inaction, at least according to the governments concerned. The density of climate-change deniers at the upper echelons of government is far higher than in the general populace – witness the US, where one of the two political parties has all but given up on science altogether, as a means of hanging on to its denial of climate science. Recall also Margaret Thatcher's change of heart, referred to in the first lecture.

III. The creation of uncertainty

They say governments hate uncertainty. US President Truman reputedly said "Can't someone bring me a one-handed economist?".

Or perhaps not. In the context of climate change, it seems they really love it: it enables them not to take decisions which will impact their future electoral success or their major donors' share price. In any case, "uncertainty" has played a major rôle in justifying (or perhaps only excusing) inaction, at least according to the governments concerned. The density of climate-change deniers at the upper echelons of government is far higher than in the general populace – witness the US, where one of the two political parties has all but given up on science altogether, as a means of hanging on to its denial of climate science. Recall also Margaret Thatcher's change of heart, referred to in the first lecture.

Because doubt is so valuable, there is a market for it. Beginning in the 1950s, when the link between smoking and lung cancer began to appear, companies began an aggressive campaign to cast doubt on the research. In 1953 they hired the public relations firm of Hill and Knowlton.

From *Inventing Conflicts of Interest: A History of Tobacco Industry Tactics*, by Allan M. Brandt, American Journal of Public Health, 102 (1), 2012

> *Hill understood that simply denying emerging scientific facts would be a losing game. [...] companies should declare the positive value of scientific skepticism, of science itself. Knowledge, Hill understood, was hard won and uncertain, and there would always be skeptics. What better strategy than to identify, solicit, support, and amplify the views of skeptics of the causal relationship between smoking and disease? Moreover, the liberal disbursement of tobacco industry research funding to academic scientists could draw new skeptics into the fold. The goal, according to Hill, would be to build and broadcast a major scientific controversy. The public must get the message that the issue of the health effects of smoking remains an open question. Doubt, uncertainty, and the truism that there is more to know would become the industry's collective new mantra.*

From *Inventing Conflicts of Interest: A History of Tobacco Industry Tactics*, by Allan M. Brandt, American Journal of Public Health, 102 (1), 2012

> *Hill understood that simply denying emerging scientific facts would be a losing game. [. . .] companies should declare the positive value of scientific skepticism, of science itself. Knowledge, Hill understood, was hard won and uncertain, and there would always be skeptics. What better strategy than to identify, solicit, support, and amplify the views of skeptics of the causal relationship between smoking and disease? Moreover, the liberal disbursement of tobacco industry research funding to academic scientists could draw new skeptics into the fold. The goal, according to Hill, would be to build and broadcast a major scientific controversy. The public must get the message that the issue of the health effects of smoking remains an open question. Doubt, uncertainty, and the truism that there is more to know would become the industry's collective new mantra.*

Astonishingly, some of the very same scientists recruited to this role by the tobacco companies went on to serve as Merchants of Doubt in later controversies over acid rain and sulphur dioxide emissions, the destruction of the ozone layer by CFCs, the dangers of secondary smoking, and, now, on the human causes of climate change.

From *Inventing Conflicts of Interest: A History of Tobacco Industry Tactics*, by Allan M. Brandt, American Journal of Public Health, 102 (1), 2012

> *Hill understood that simply denying emerging scientific facts would be a losing game. [. . .] companies should declare the positive value of scientific skepticism, of science itself. Knowledge, Hill understood, was hard won and uncertain, and there would always be skeptics. What better strategy than to identify, solicit, support, and amplify the views of skeptics of the causal relationship between smoking and disease? Moreover, the liberal disbursement of tobacco industry research funding to academic scientists could draw new skeptics into the fold. The goal, according to Hill, would be to build and broadcast a major scientific controversy. The public must get the message that the issue of the health effects of smoking remains an open question. Doubt, uncertainty, and the truism that there is more to know would become the industry's collective new mantra.*

Astonishingly, some of the very same scientists recruited to this role by the tobacco companies went on to serve as Merchants of Doubt in later controversies over acid rain and sulphur dioxide emissions, the destruction of the ozone layer by CFCs, the dangers of secondary smoking, and, now, on the human causes of climate change. By the 1980s, scientists at Exxon Mobil, BP, Shell and other big oil companies understood the consequences for the climate of the continuing burning of fossil fuels. But rather than changing their business model, the companies adopted the strategy they had learned from the tobacco companies, and hired the doubt merchants. They spend hundreds of millions of dollars subsidising Foundations like The American Enterprise Institute, the Heritage Foundation, the George C. Marshall Foundation, etc etc, all of which trumpeted a strongly pro-free market, anti-regulation message, ridiculed climate science, and attacked climate scientists, sometimes in ways which were obviously dishonest.

If you listen to the 2017 and 2018 lectures of Benny Peiser, from the Global Warming Policy Foundation, to GSD students here in Warwick, you will hear exactly the same script.

- The facts are not yet in, it's too soon to make a decision
- We can't explain the Medieval Warm Period / The Little Ice Age / the Warming Hiatus from 1998 to 2012; so other forces are at work, and human agency is not the key factor.
- A paper by Dr A and Professor B [a theologian and a retired professor of theatre studies, published privately, not peer reviewed] disputes the predictions of temperature rise.
- Climate is fundamentally chaotic, and therefore impossible to predict.
- Above all, don't *theorise*; "go on the facts alone".

The last is particularly obstructive, because it is an attempt to disable science altogether, while appearing to call for a level-headed, scientific attitude. As we see even when calculating the probability of different scores in dice throwing, almost all reasoning involved theories and their application.
The climate controversy is very far from being an honest scientific disagreement. On one side are scientists trying to warn humanity of an approaching catastrophe, and on the other there are vast and enormously powerful corporations whose behaviour is dictated by the single principle: *Maximise shareholder value*. Forty years ago, the oil companies learned from their own scientists of the threat that their business posed to the world. Following this principle, they chose to conceal and deny it.

Further reading

On Statistics:

1. Charles Wheelan, *Naked Statistics*, W.W. Norton and Co., 2013. This book is an easy read, aimed at non-scientists. It is enjoyable and illuminating.

On attribution science:

1. Myles Allen, *Liability for Climate Change*, Nature 421, pages 891–892 (2003). This article seems to be freely available at https://www.nature.com/articles/421891a
2. Friederike E. L. Otto, Ragnhild B. Skeie, Jan S. Fuglestvedt, Terje Berntsen & Myles R. Allen, *Assigning historic responsibility for extreme weather events*, Nature Climate Change volume 7, pages 757–759 (2017). Also freely available via Myles Allen's homepage (or I have a copy).

On the manufacture of doubt:

1. Naomi Oreskes and Erik Conway, *Merchants of Doubt*, Bloomsbury Press, 2010.
2. George Monbiot, *Heat*, Penguin Books, 2007.