Institute for
New Economic Thinking
AT THE OXFORD MARTIN SCHOOL


# IMPERFECT KNOWLEDGE, UNPREDICTABILITY AND THE FAILURES OF MODERN MACROECONOMICS

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Research jointly with Jennifer Castle, Jurgen Doornik, Søren Johansen and Felix Pretis

Institute for New Economic Thinking at the Oxford Martin School

(1) *Five theorems about conditional expectations*

(2) *Uncertainty, unpredictability and unanticipated shifts*

(3) *Empirical location shifts*

(4) *Imperfect knowledge and conditional expectations*

(5) *Modelling tools to detect shifts*

(6) *Conclusions*

**[1]** The conditional expectation is the **minimum mean square error** (MMSE) **unbiased** predictor.

**[2]** The expectation of the conditional expectation is the unconditional expectation, also called the **law of iterated expectations**.

These are well known: see Goldberger (1991, p. 46–51) for proofs.

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These are well known: see Goldberger (1991, p. 46–51) for proofs.

**[3]** **Incomplete knowledge** of the conditioning information need **not lead to biased expectations** (see e.g., Clements and Hendry, 2005).

**[4]** Conditional expectations can provide **unbiased forecasts** even in **mis-specified, mis-estimated models** (Hendry and Trivedi, 1972).

**[5]** Replacing unknown expectations by realized future outcomes, as in **New-Keynesian Phillips curve** (NKPC) models, is legitimate as such expectations can be shown to be unbiased (Galí and Gertler, 1999).

So why should we worry about **Imperfect Knowledge**?

"It would be an understatement to say that economic forecasts are a constant disappointment to investors. The trouble arises because the **forecasters' models are fundamentally flawed**.
.... so-called New Keynesian models .... rarely pick up big economic shifts .... **(which) are inherently unpredictable.**"
**John Plender,** *Financial Times*, **April 22 2017**

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During a visit to LSE in 2009, **Queen Elizabeth II asked Luis Garicano "why did no one see the the credit crisis coming?"**

Even earlier, **Prakash Loungani (2001) claimed "The record of failure to predict recessions is virtually unblemished."**

**How could this dismal record happen given theorems [1]–[5]??**

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Because **Imperfect Knowledge** has profound consequences—far beyond forecast failure.

# Route map

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You are **certain** you are sitting here (pace Descartes).

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**Uncertainty abounds**, both in the world and in our knowledge thereof.
But increased knowledge may help reduce our uncertainty.

**Unpredictability** is irreducible uncertainty.

There are **three levels of unpredictability**, dependent on the state of nature and our knowledge thereof.

Some aspects of unpredictability are measurable and quantifiable in reasonable ways: **probabilites** can be assigned to represent that unpredictability, as in rolling fair dice.

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**Some events are so unpredictable that reasonable probabilities cannot be assigned.**

A random variable $X$ is unpredictable **with respect to some information** $\mathcal{I}$, if knowing $\mathcal{I}$ does not change knowledge about $X$.

The distribution $D_X(X)$ of $X$ is unaffected by knowing $\mathcal{I}$ when $D_{X|\mathcal{I}}(X \mid \mathcal{I}) = D_X(X)$.

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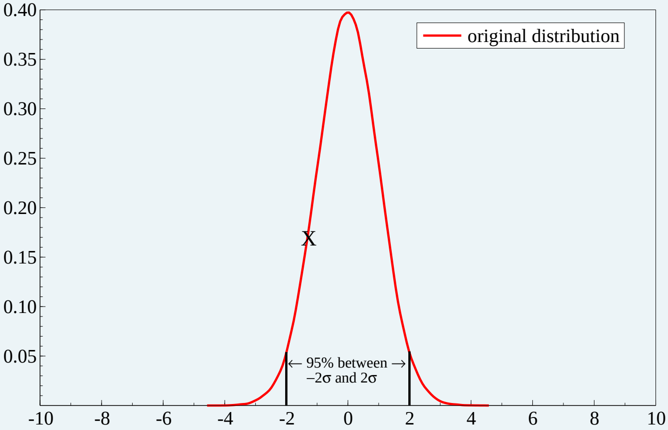
**(a) Intrinsic unpredictability occurs in a known distribution:**

**unknown knowns** from **chance distribution sampling**;
'independent errors' in statistical theory;
random numbers in a simulation...
But which draw matters: bet on Red but get Black at Roulette.

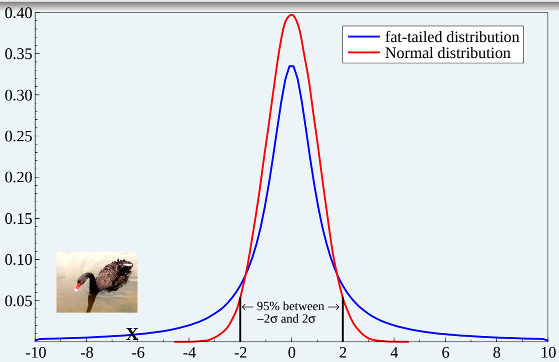
Called *intrinsic unpredictability* because it is a property of the random variable.




**Normal distribution often the basis for probability calculations; 'random sampling' from a known distribution underpins much statistical inference: X is example of intrinsic unpredictability.**

## (b) Instance unpredictability, or known unknowns:

outliers **from a known 'fat-tailed' distributions** can occur at unanticipated times, signs, and magnitudes–see **Taleb (2007)**




**Sometimes observe what are called 'black swan events': X shows instance unpredictability–unknown magnitude, sign and timing, but can attach probabilities to such events.**

**(c) Extrinsic unpredictability or unknown unknowns:**

**occurs from unanticipated shifts of distributions**.

Unknown numbers, signs, magnitudes & timings of such shifts.

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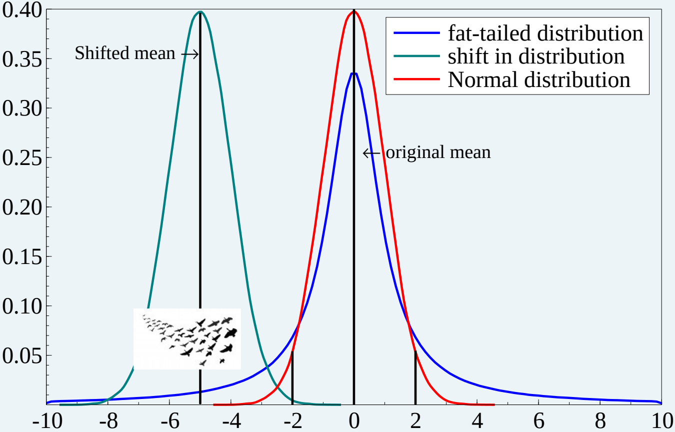
Most pernicious form of **extrinsic unpredictability** is a **location shift**: mean of the distribution of $X$ changes from previous 'level' by unknown magnitude and sign at unanticipated time—as in **Soros (2008)**.

**Can now get what seem initially to be 'flocks of black swans'.**

# Illustrating extrinsic unpredictability and location shifts




**Location shifts** **make new ordinary seem unusual relative to past.**

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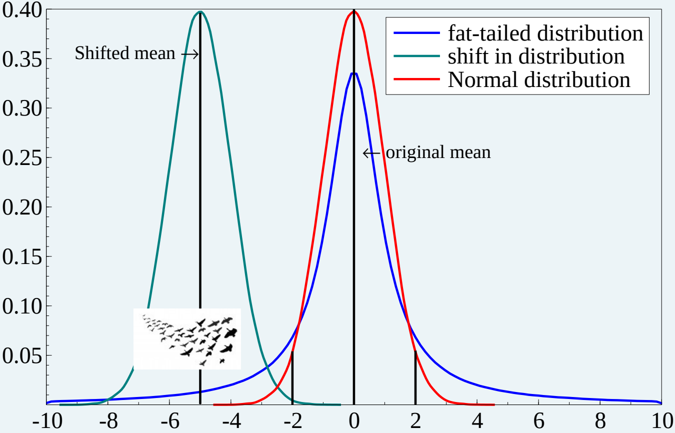


**Location shifts** **make new ordinary seem unusual relative to past.**
**Extrinsic unpredictability** **wrecks economic agents' ability to plan inter-temporally: and leads to forecast failure.**

**Irrational to hold 'rational expectations' when shifts occur.**

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**Dramatic shifts include**:
World War I; 1920–21 flu' epidemic; 1926 general strike;
1930's great depression; World War II; 1970's oil crises;
2008–2012 financial crisis and world-wide recession.

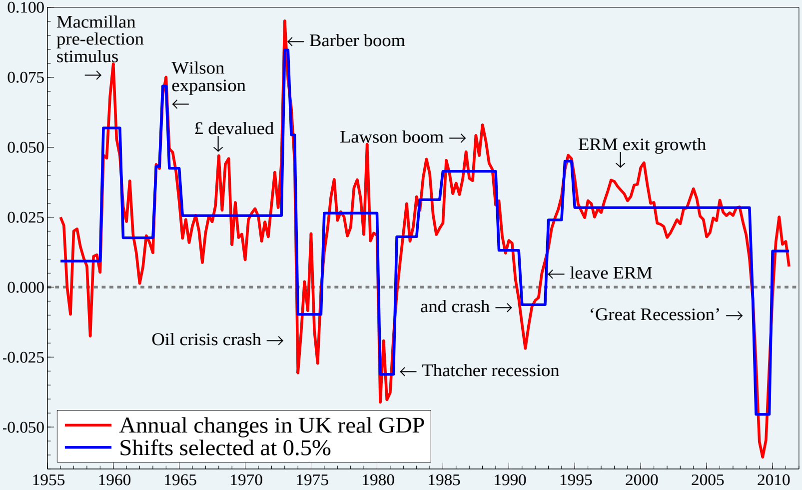
**Key financial innovations** & changes in credit rationing:
personal cheques (1810s), telegraph (1850s), credit cards (1950s), ATMs (1960s); deregulating banks and building societies (1980s) etc.

**Many policy regime shifts**:
on-off gold standard till Bretton Woods (1945), floating exchange rates (1973); ERM; Keynesian, Monetarism, inflation targeting policies; creation of EU and Euro zone; Brexit, etc.

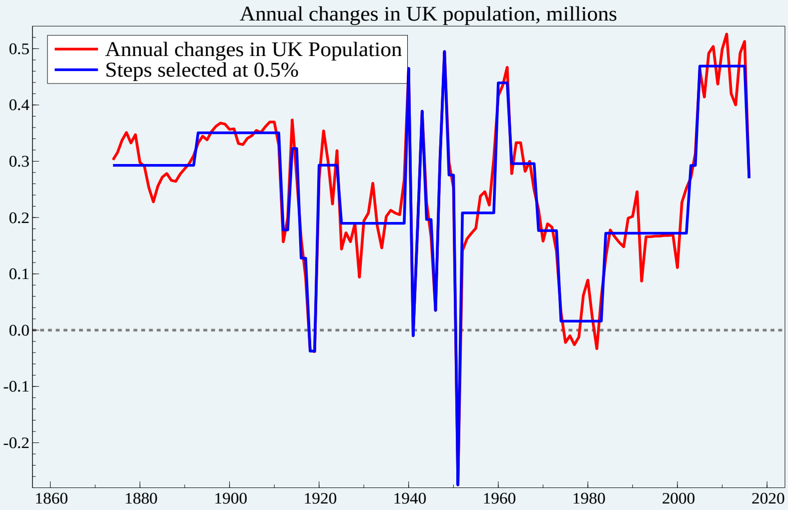
**Huge changes in technology**: electricity, refrigeration, telephones, TV, cars, flight, nuclear, medicine, computers, communications.

**Important evolving changes**: globalization & development.

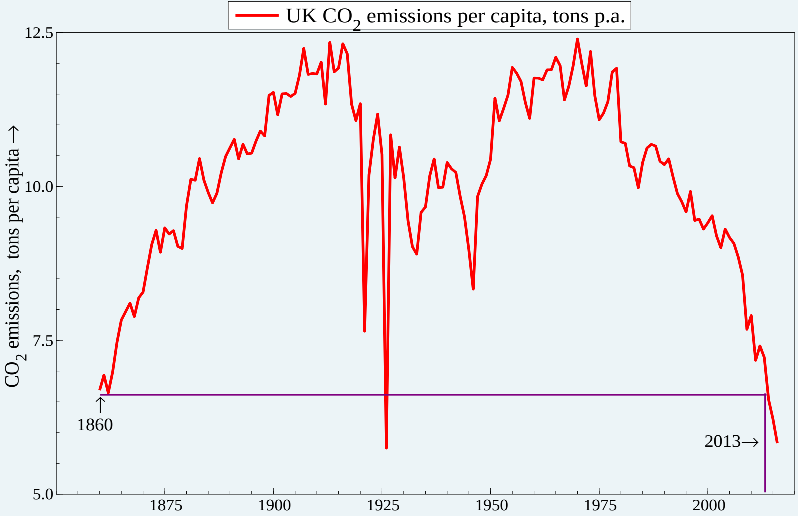
**But implications rarely foreseen before shifts occur.**




**Here, most shifts correspond to major economic policy changes:**
**but even the growth rate is far from a stationary process.**

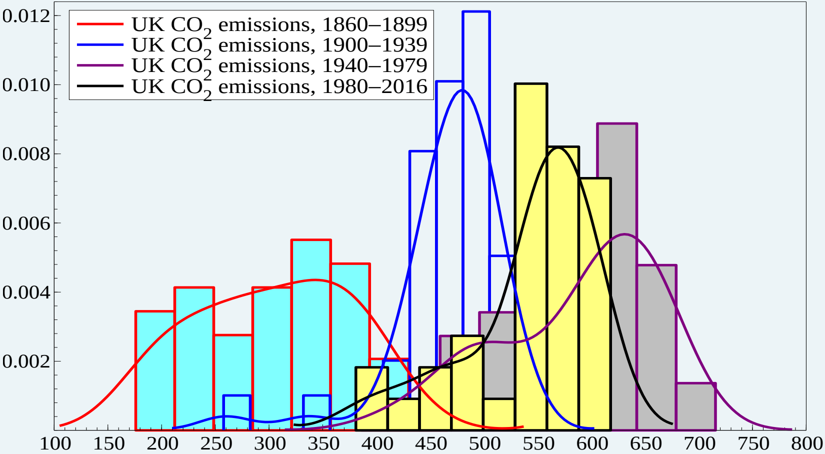



**Annual changes in the UK population over 1870–2016, in millions**



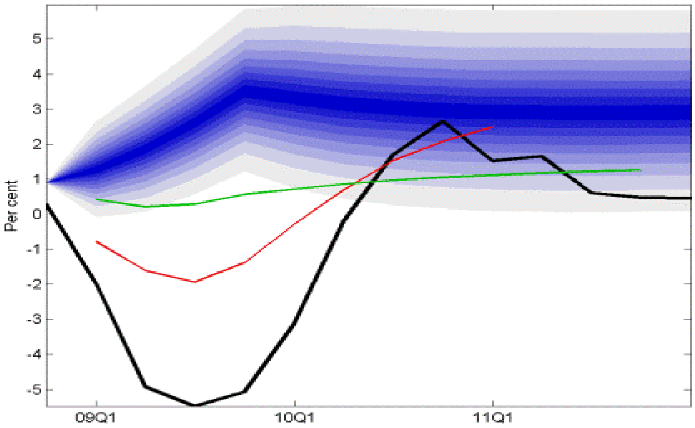

**UK $CO_2$ emissions per capita, in tons per annum over 1860–2016.**

# Distributional shifts of total UK $CO_2$ emissions per annum




**Sub-period distributions of UK $CO_2$ emissions in millions of tonnes (Mt) per annum.**

# Forecast failure: DSGE Compass pointing in the wrong direction

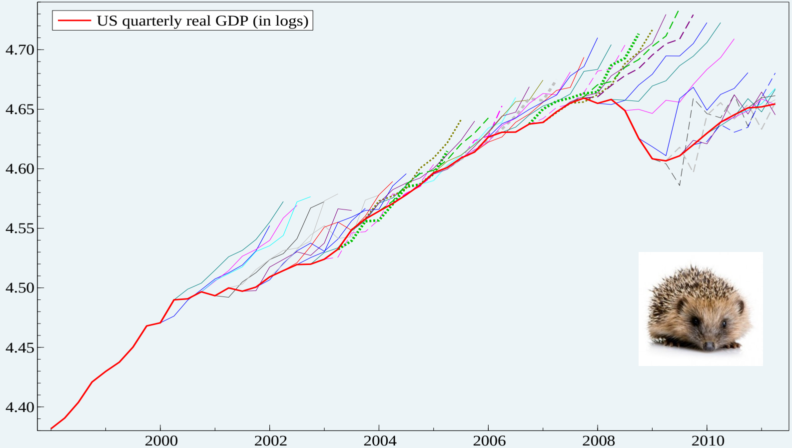



**Bank of England ex post COMPASS density GDP-growth 'forecasts' over Great Recession in blue and Statistical Suite forecasts in green.**

**ONS data in black and *Inflation Report* forecasts in red.**

http://bankunderground.co.uk/2015/11/20/how-did-the-banks-forecasts-perform-before-during-and-after-the-crisis

# Autoregressive forecasts of US GDP




Autoregressive forecasts of US GDP also go wrong over Great Recession. Source: Real Gross Domestic Product, Billions of Chained 2009 Dollars, Quarterly, Seasonally Adjusted Annual Rate. GDPC1 from Federal Reserve Economic Data. http://research.stlouisfed.org/fred2

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In Euclidean Geometry, the angles of a triangle add to $180^0$–a famous theorem proved by generations of school children.

Draw a triangle on a globe and add the angles–not $180^0$.

**Theorems need assumptions**, and Euclid assumed a flat surface. But a globe is not flat: theorem is misleading outside its context.

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**Theorems need assumptions**, and Euclid assumed a flat surface. But a globe is not flat: theorem is misleading outside its context.

The five theorems about conditional expectations **assume the distributions are constant**: but just seen numerous 'real world' examples where that assumption is false.

**For inter-temporal calculations, all 5 fail when distributions shift.**
**Imperfect Knowledge about shifts has deleterious consequences.**

Critics include Frydman and Goldberg (2007), Hendry and Mizon (2014), Hendry (2017), Hendry and Muellbauer (2017).

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Having more candidate variables $N$ than observations $T$, so $N > T$, to search over when selecting a model was once believed impossible.
I **accidently** discovered a powerful way to solve this problem.

Most contributors to Magnus and Morgan (1999) found models of food demand that were non-constant over the sample 1929–1952, so **dropped that earlier data**. To investigate why, yet replicate others' models, in Hendry (1999) I added **impulse indicators** for all observations pre-1952.

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This revealed **three very large 'outliers'** due to a 'US Great Depression food program' and post-war de-rationing.

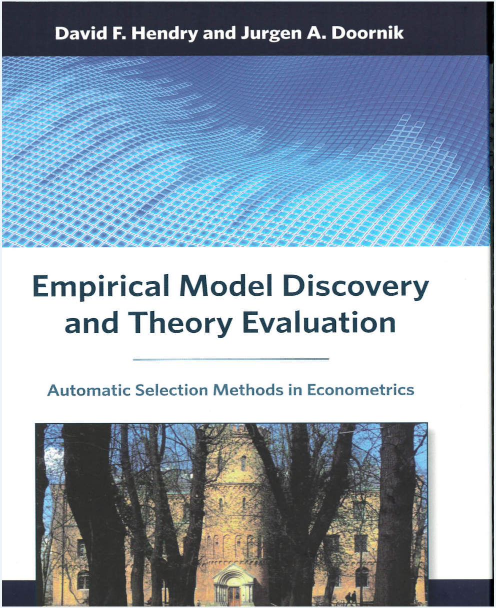
To check that my model was constant over the period from 1953 on, I included impulse indicators for this later period.
Lo! I had included more variables plus indicators than observations.

**Formalised as impulse-indicator saturation, IIS has led to a statistical theory for modelling multiple location shifts.**

*Autometrics*, **our latest computational tool includes indicator saturation methods for shifts and outliers of any magnitude and sign, at any number of time points.**

**Approach extends to the discovery of causal models hidden in a welter of information, while retaining theory insights, even when more candidate variables than observations:** see Hendry and Doornik (2014) and Hendry and Johansen (2015).

# Key source



David F. Hendry and Jurgen A. Doornik
Empirical Model Discovery and Theory Evaluation
Automatic Selection Methods in Econometrics

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**Imperfect knowledge is ubiquitous–but some aspects of ignorance are more troublesome than others:**
**lack of knowledge about shifts of distributions can lead to invalid theory, model break down, forecast failure  incorrect policy responses.**

**My talk had five main aims:**

**1] relate unpredictability to imperfect knowledge about shifts;**

**2] illustrate the empirical prevalence of location shifts;**

**3] derive implications for failures of rational expectations,**

**4] and the invalidity of inter-temporal mathematics of DSGEs;**

**5] yet note how to successfully model ever-changing worlds.**

**I hope you are now certain the talk was worth hearing.**

# Thank you

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