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
(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*
Five (possibly misleading) theorems about conditional expectations

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

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

Because **Imperfect Knowledge** has profound consequences—far beyond forecast failure.
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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: probabilities can be assigned to represent that unpredictability, as in rolling fair dice.
Uncertainty and unpredictability

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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 $I$, if knowing $I$ does not change knowledge about $X$. The distribution $D_X(X)$ of $X$ is unaffected by knowing $I$ when $D_{X|I}(X | I) = D_X(X)$. 
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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

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.
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occurs from unanticipated **shifts of distributions**. Unknown numbers, signs, magnitudes & timings of such shifts. **Cannot usually attach probabilities to their occurrence.**
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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.

-10 -8 -6 -4 -2 0 2 4 6 8 10

0.40
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00

fat-tailed distribution
shift in distribution
Normal distribution

Fat-tailed distribution shift in distribution Normal distribution

[Image of graph with distributions and shifts]

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Extrinsic unpredictability wrecks economic agents' ability to plan inter-temporally: and leads to forecast failure.

Irrational to hold 'rational expectations' when shifts occur.

David F. Hendry (INET at Oxford Martin School)
Imperfect Knowledge
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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;

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.
Many shifts in post-war UK real GDP growth

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
Anthropogenic: UK CO₂ emissions per capita over 1860–2016

UK CO₂ 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

ONS data in black and Inflation Report forecasts in red.

Autoregressive forecasts of US GDP also go wrong over Great Recession.

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Deconstructing conditional expectations

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 $180^0$.

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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.**

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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 accidentally 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).
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
References I


