ECONOMIC MODELLING & MACHINE LEARNING

A PROOF OF CONCEPT

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OECD
BETTER POLICIES FOR BETTER LIVES

Economic forecasting with Adaptive Trees

I. MOTIVATION

Linear models are constrained by economic complexity

Economic complexity

Non-linearities

Multiple interactions

Multiple discontinuities

Structural change

Relationships between variables may change over time, suddenly or incrementally

Context-specific impact of policies

Depending on countries

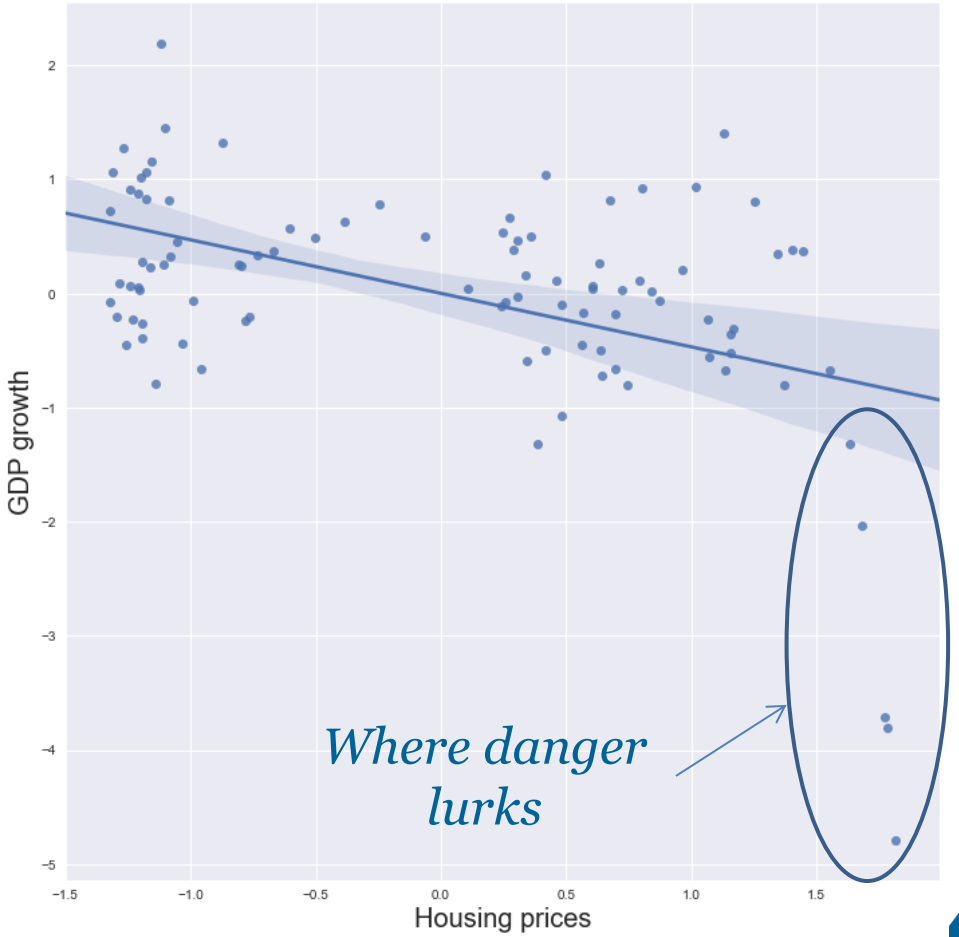
Depending on people's place in income, skills, or age distribution

Especially around
turning points

Non-linearities

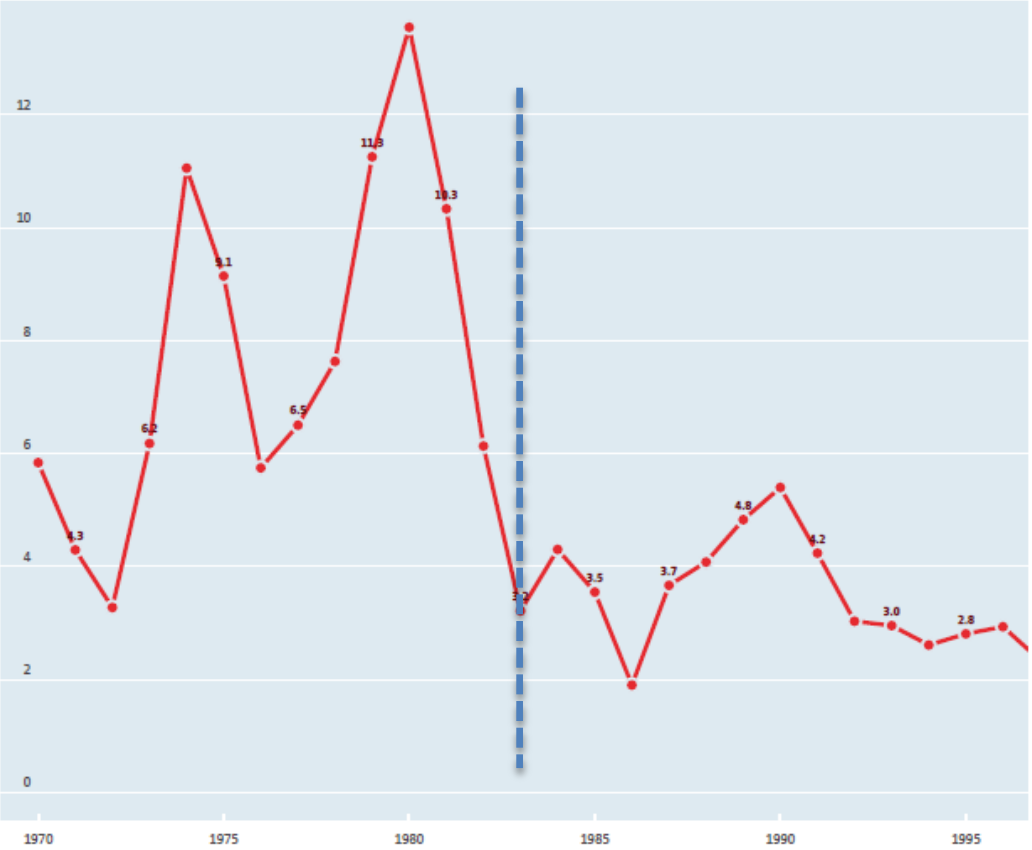
Housing prices against GDP growth, UK

Non-linear behaviour past a given threshold, at a tipping point



Structural change

Inflation in the US, 1970-2017



Monetary policy helped tame inflation and changed the nature of the Philipps Curve, by stabilising inflation expectations.

Machine learning provides tools to tackle these challenges

What is machine learning ?

- Powerful methods designed to extract information from data

How is different from econometrics ?

- Modelling without a model: no prior knowledge is required
- Relies on cross-validation to prevent overfitting and underfitting

How can it be useful ?

- Uncover complex patterns in data, even from a vast array of variables
- Data comes first, theory comes next

II. ADAPTIVE TREES

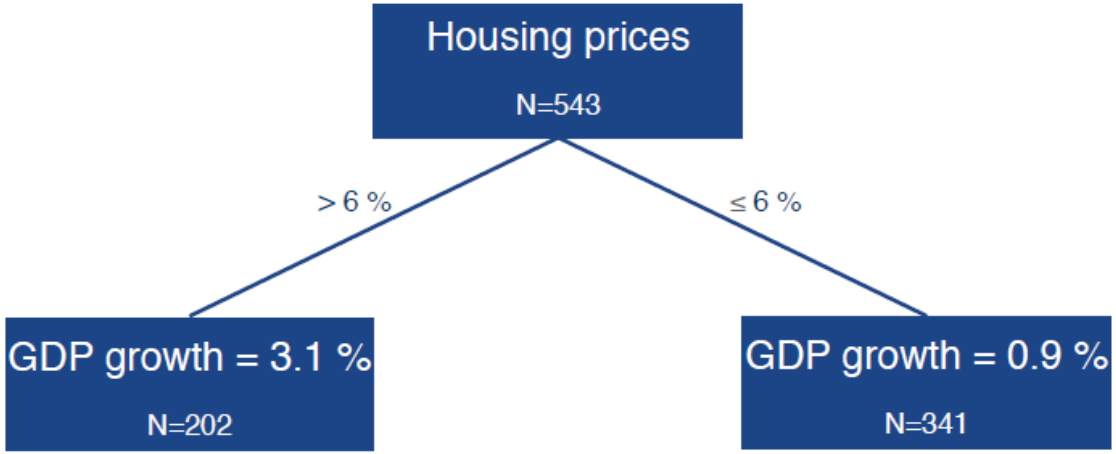
A non-linear approach to capture structural change in the economy

Adaptive Trees: two steps

1. Tackling *non-linearities* with regression trees

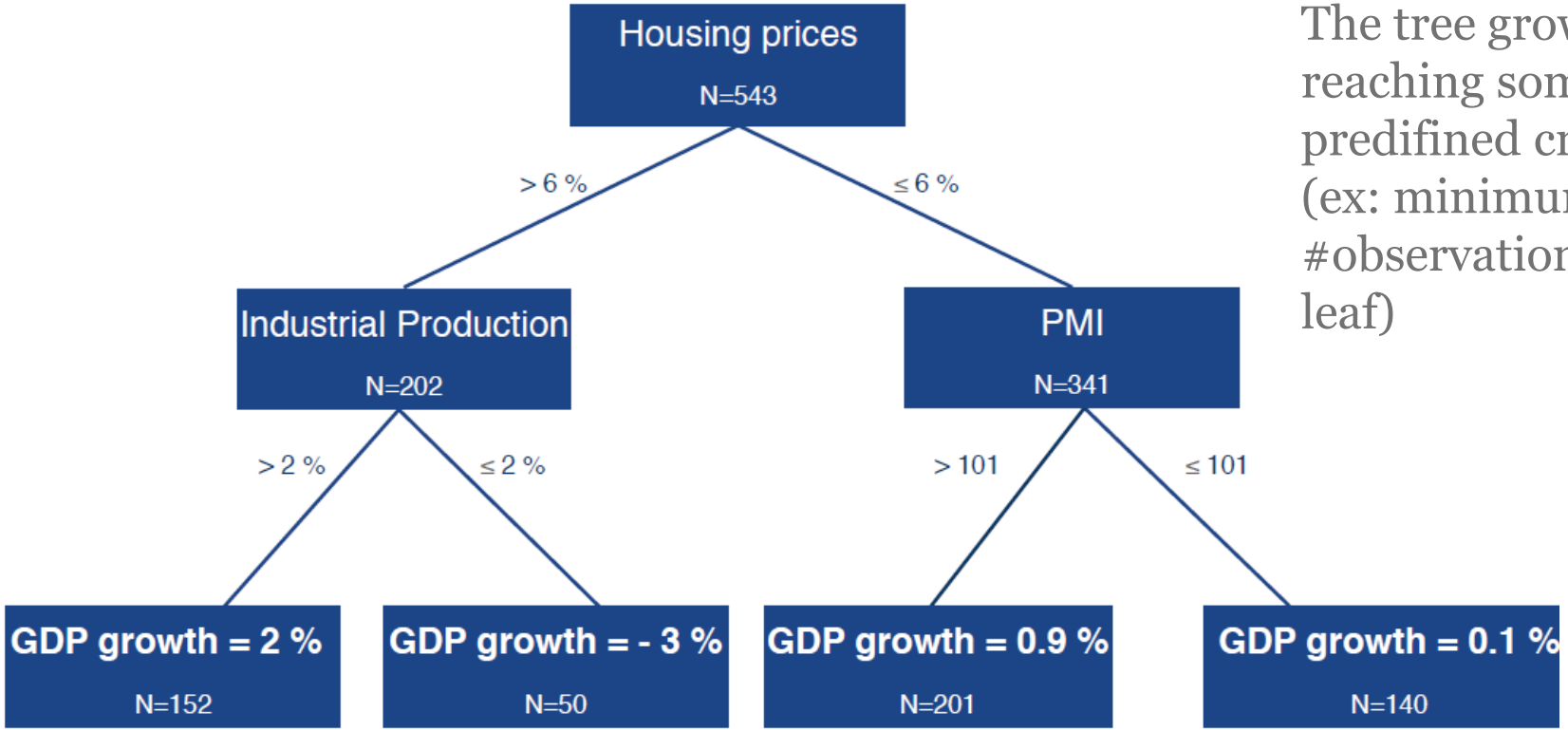
2. Adressing *structural change*: adaptive trees

Training regression trees



At each node, the algorithm selects the splitting variable + splitting point that minimises sub-group variance of GDP growth

Training regression trees

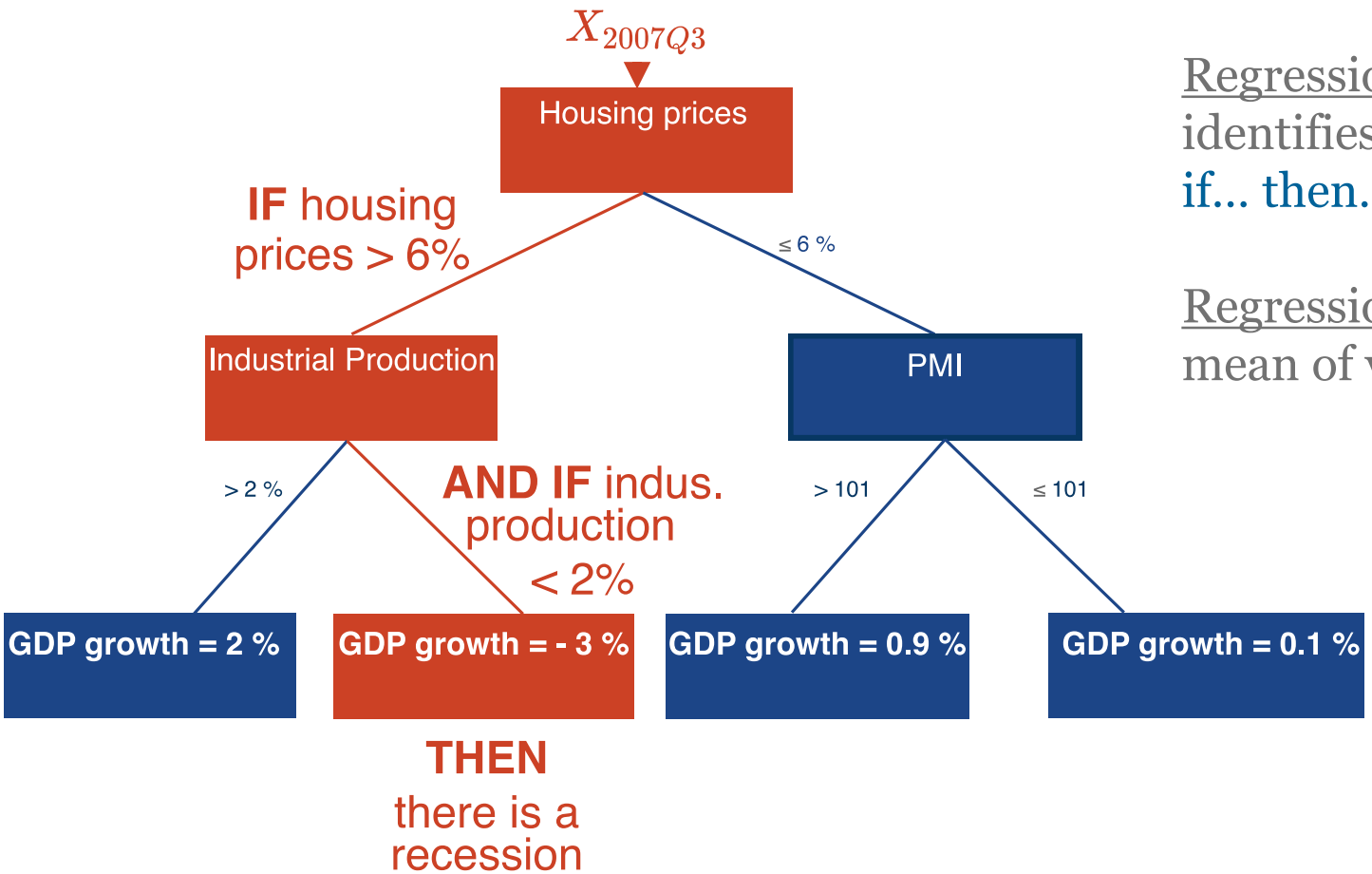


The tree grows until reaching some predifined criteria (ex: minimum #observations per leaf)

Train & Predict

The tree is grown using past data (training). Then it makes a prediction about the future (here, Q+1), using contemporaneous and past data.

Prediction



Regression trees: Prediction identifies complex structure: if… then…

Regression: simple weighted mean of variables

Adaptive Trees: two steps

1. Tackling *non-linearities* with regression trees

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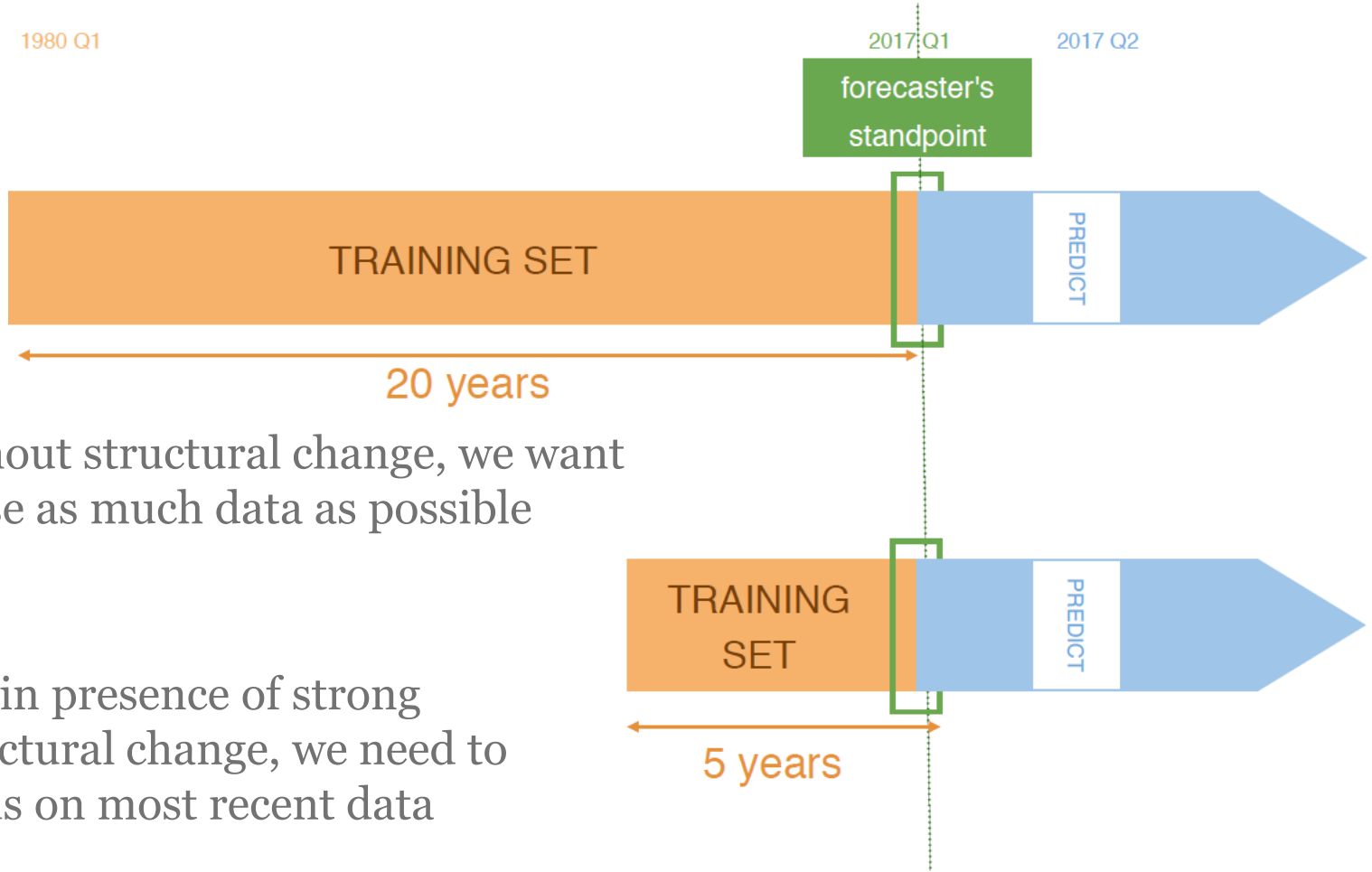
Trade off quantity/relevance



Without structural change, we want to use as much data as possible

But in presence of strong structural change, we need to focus on most recent data

Structural change

- The economy is ever-changing**.** That is part of « economic complexity ».
- Consequence: recent past more informative about near future than remote past
- There may be **sudden structural breaks** (during crises), or **incremental structural change**
- We tackle structural change using an original technique that we developped for the purpose of economic forecasting: « Adaptive Trees »

Adaptive Trees

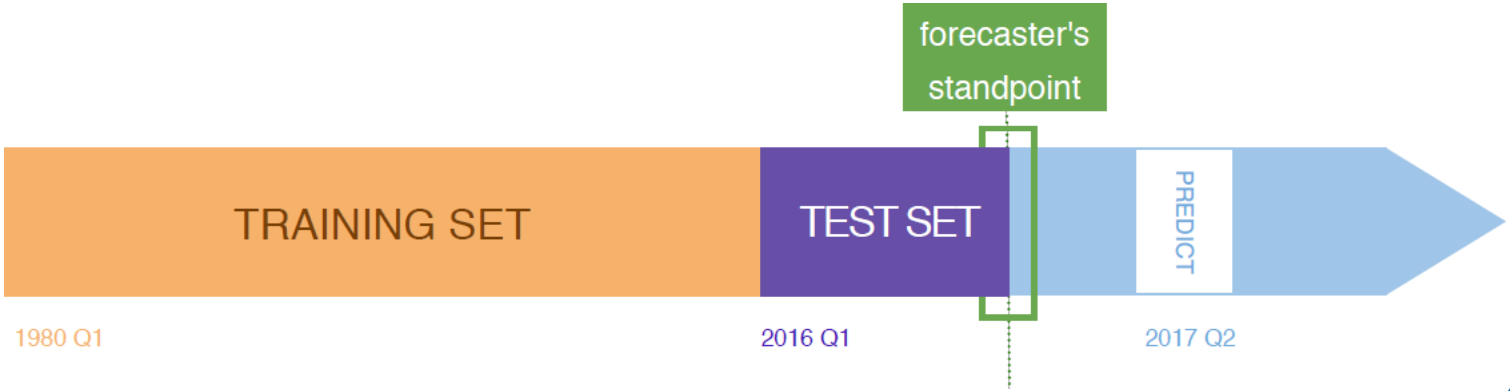
Adaptive Trees are a transformation of the Gradient Boosting algorithm

Tackling incremental structural change:

- Give more weight to the recent past

Tackling sudden structural change:

- Detect structural change: measuring how accurately the algorithm trained on the training set can predict the latest observations
- If not well: gives even more weight to the recent observations that are hard to predict



III. PROOF OF CONCEPT

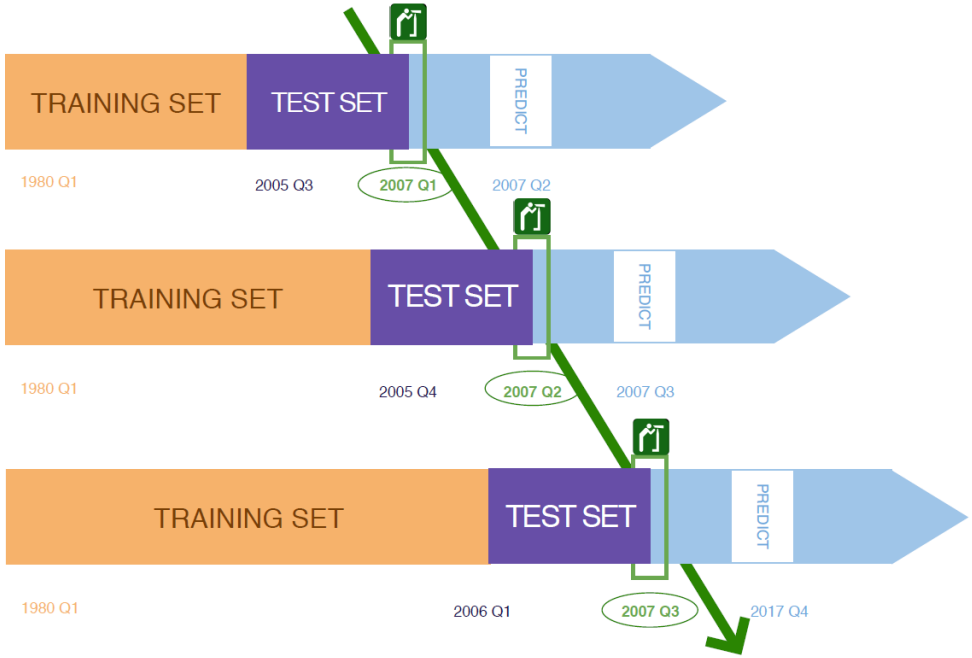
FORECAST OF GDP GROWTH IN G6 COUNTRIES

1. Forecast simulations
2. Comparison with OECD forecasts
3. Comparison with Consensus forecast

Setting of forecast simulations

- Simulations in pseudo-real time of a forecast of GDP growth in G6 countries

- Using the exact same data as benchmark OECD Indicator Model (housing prices, indutrial production, PMI…) so as to provide a *methodological benchmark*



Benchmark forecasts

Compare with two benchmark forecasts:			
OECD Indicator Model	M+3 & M+6	VAR	2007 – 2016, quarterly, q-o-q
Consensus Forecast	Y+1	Average of expert forecasts	2010 – 2016, yearly, y-o-y

Measuring performance:

- Accuracy: Root Mean Square Error (RMSE)
- Forecast Directional Accuracy (FDA): % times forecasts right direction

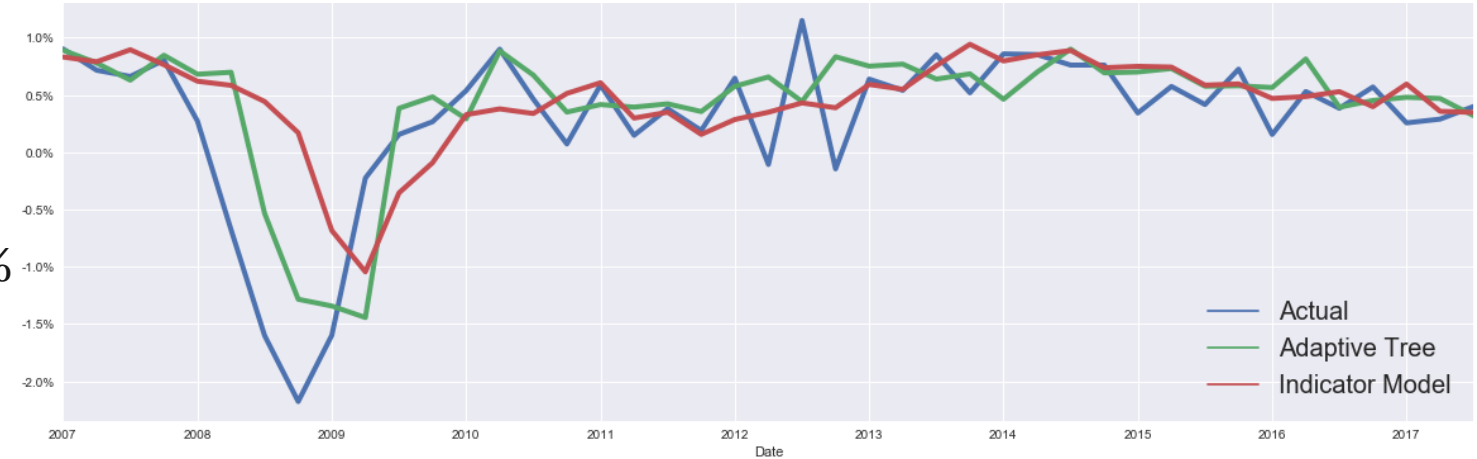
Quantitative

Qualitative

Comparison with OECD Indicator Model

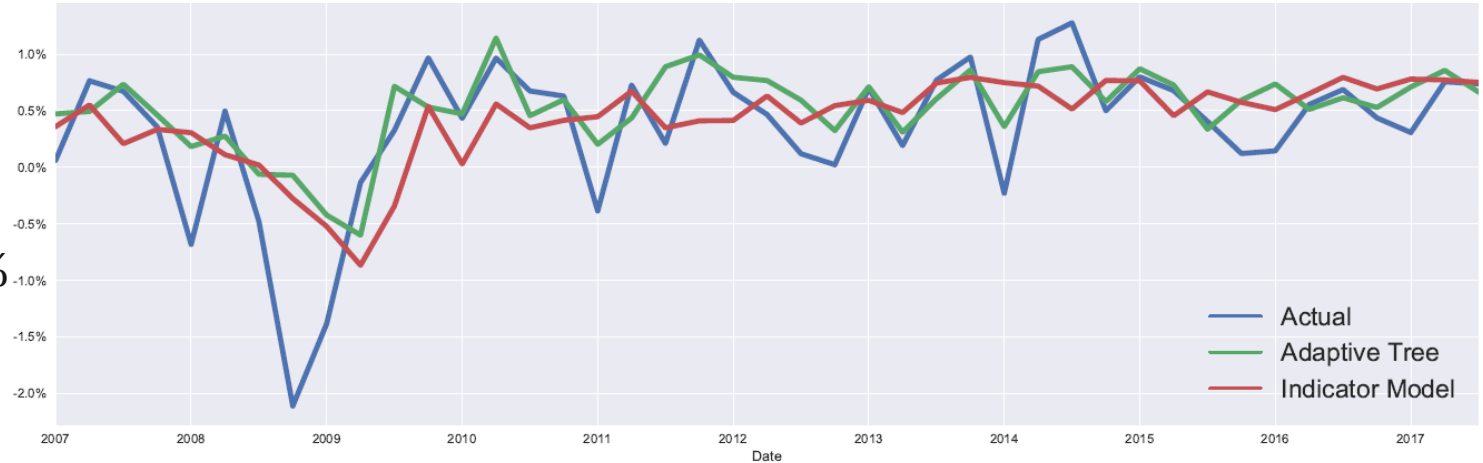
1. UK, M+3

Accuracy: +25 %
Dir. Accuracy: +4 %



2. USA, M+3

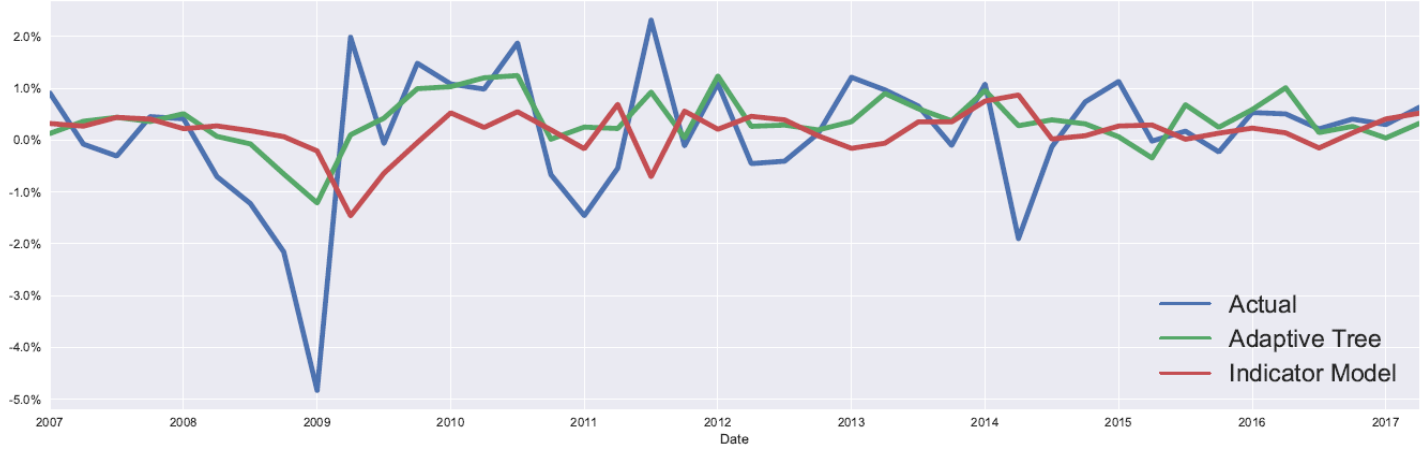
Accuracy: +9 %
Dir. Accucacy: +32 %



Comparison with OECD Indicator Model

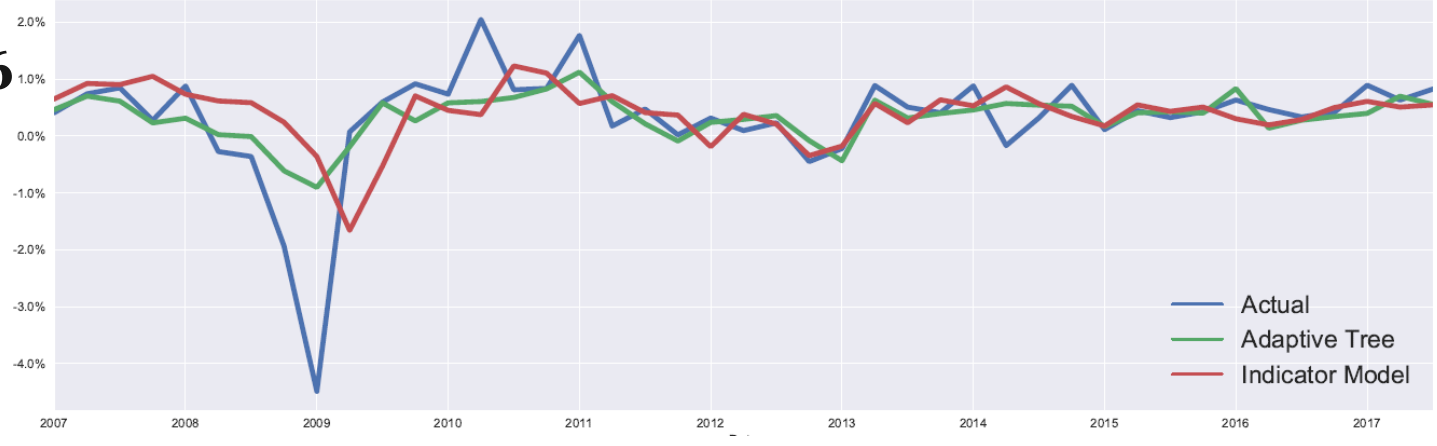
3. Japan, M+6

Accuracy: + 29 %
Dir. Accuracy: + 42 %



4. Germany, M+6

Accuracy: + 25 %
Dir. Accuracy: + 18 %

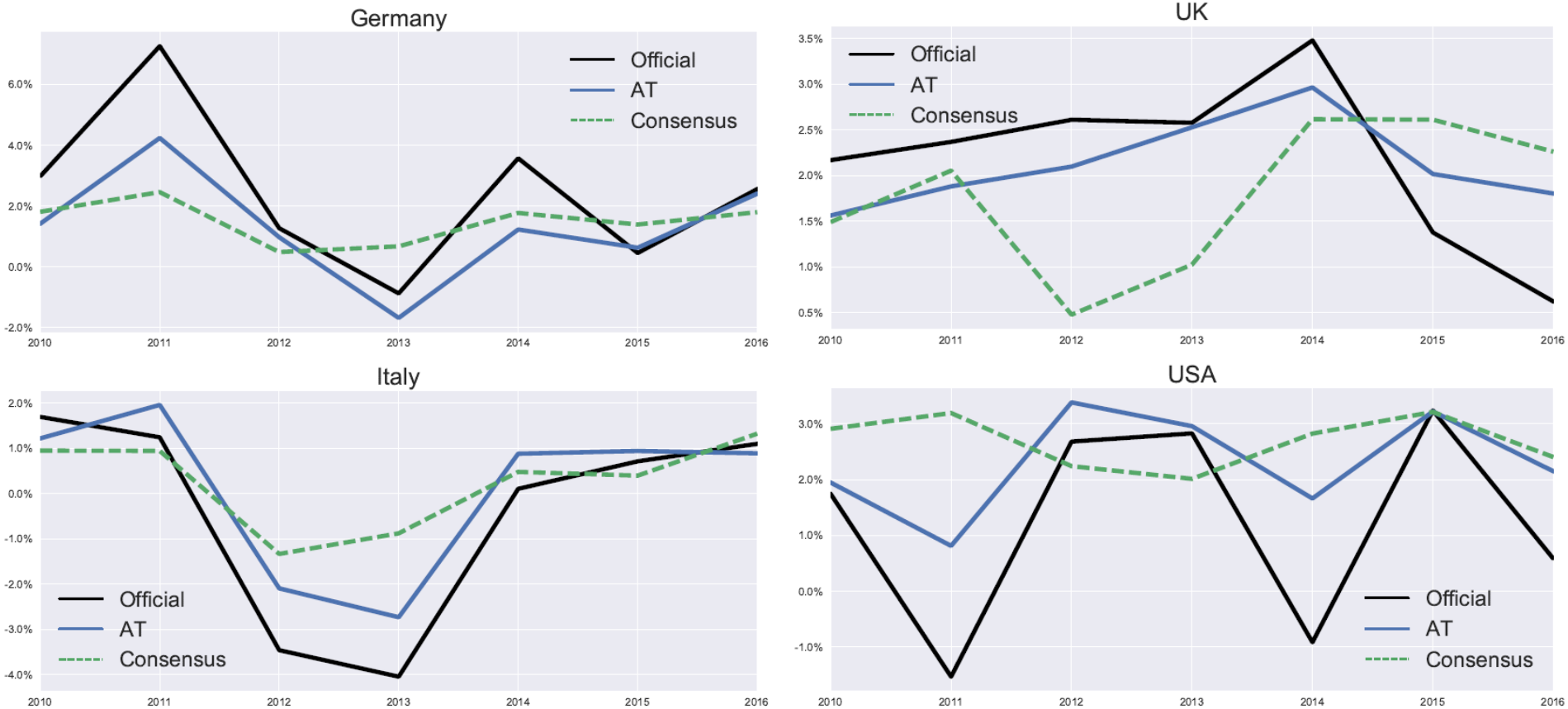


Overall improvement from Indicator Model

G6	RMSE	FDA
M+3	12%	27%
M+6	23%	32%

Adaptive Tree forecast consistently has better accuracy, and much better directional accuracy than the Indicator Model, while using the exact same data.

Comparison with Consensus forecast



Comparison with Consensus forecast

Y+1	Gain in accuracy	Gain in directional accuracy
UK	51%	25%
USA	40%	150%
France	6%	20%
Japan	24%	50%
Germany	25%	20%
Italy	43%	0%
Overall	***32%***	***44%***

At Y+1 from 2010 to 2016, Adaptive trees are on average **32% more accurate** and **44% more directionally accurate** than the Consensus Forecast.

IV. CONCLUSION

Economics & machine learning

- Great tool to explore the complexity of the economy

- Performance:

- At M+6, Adaptive Trees are 23% more accurate and 32% more directionally accurate than the **Indicator Models**, using the exact same data

- At Y+1, Adaptive Trees are 32% more accurate and 44% more directionally accurate than the **Consensus**

- Numerous possible extensions using broader set of variables

THANK YOU

Questions ?

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ADDITIONAL MATERIAL

Comparison with Consensus forecast

Table 1: Comparison of forecast accuracies, y-o-y

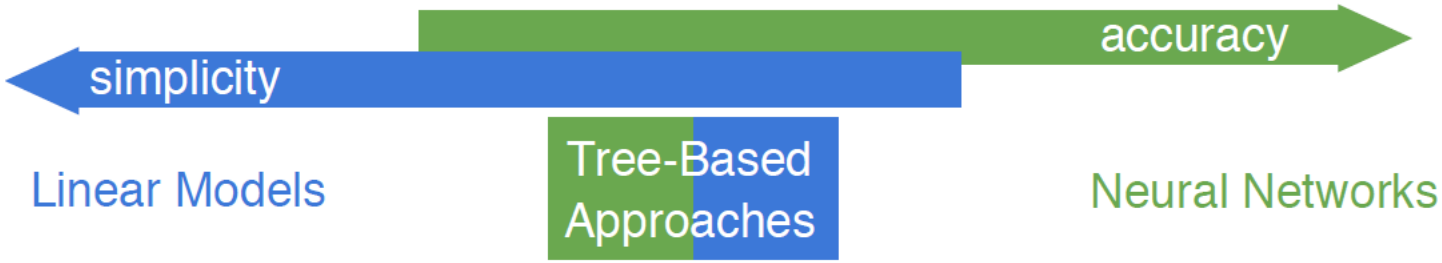
Y+1	AT	Consensus	*Gain from consensus*
UK	0.648	1.335	***51%***
USA	1.472	2.447	***40%***
France	1.106	1.178	***6%***
Japan	2.917	3.820	***24%***
Germany	1.597	2.143	***25%***
Italy	0.848	1.489	***43%***
Overall	*1.431*	*2.069*	***32%***

Table 2: Comparison of forecast directional accuracies, y-o-y

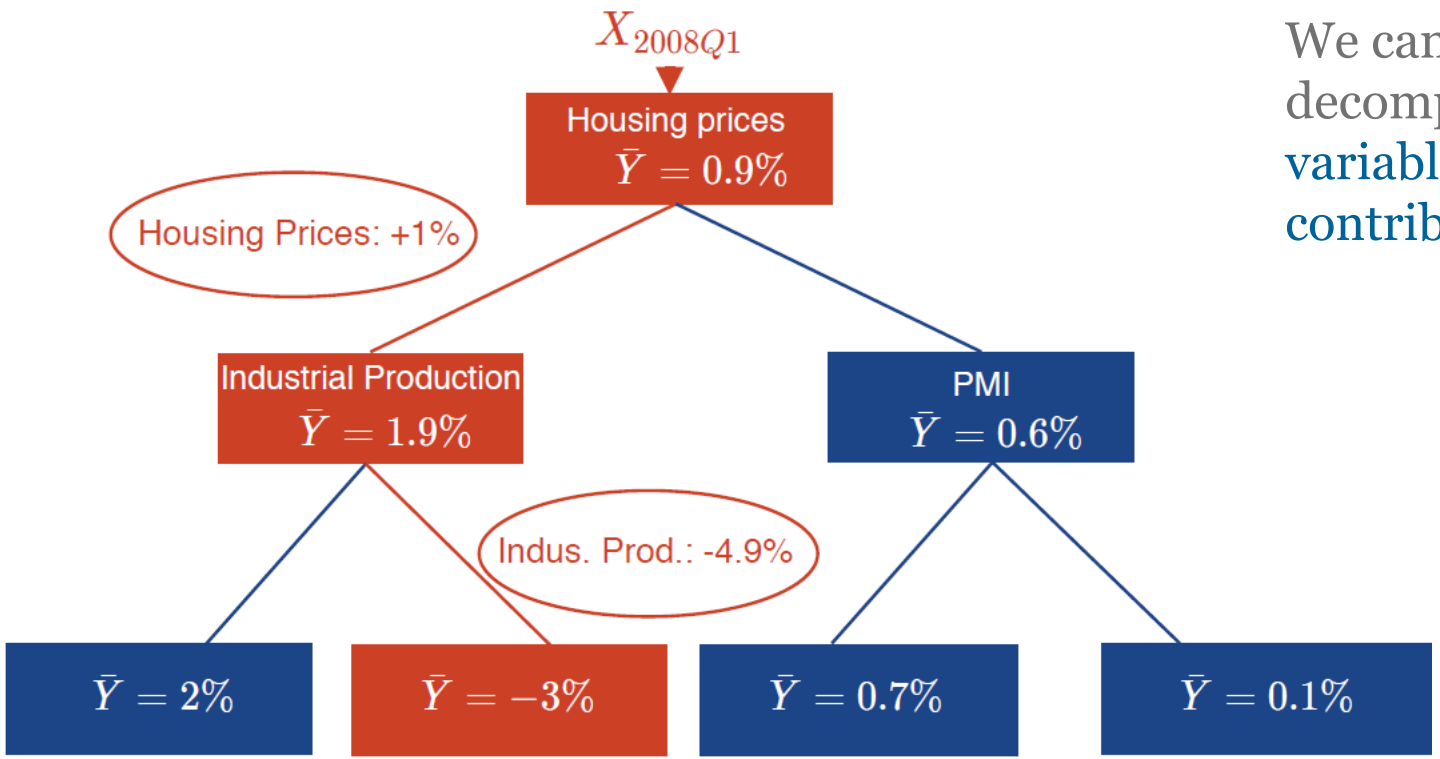
Y+1	AT	Consensus	*Gain from consensus*
UK	83%	67%	***25%***
USA	83%	33%	***150%***
France	100%	83%	***20%***
Japan	50%	33%	***50%***
Germany	100%	83%	***20%***
Italy	67%	67%	***0%***
Overall	*81%*	*61%*	***44%***

Problem: interpretability

- Modelling complexity requires more complex models
- Trade off simplicity/accuracy:
  - Too much simplicity: fail to capture important variations
  - Too much complexity: fail to produce a sensible story



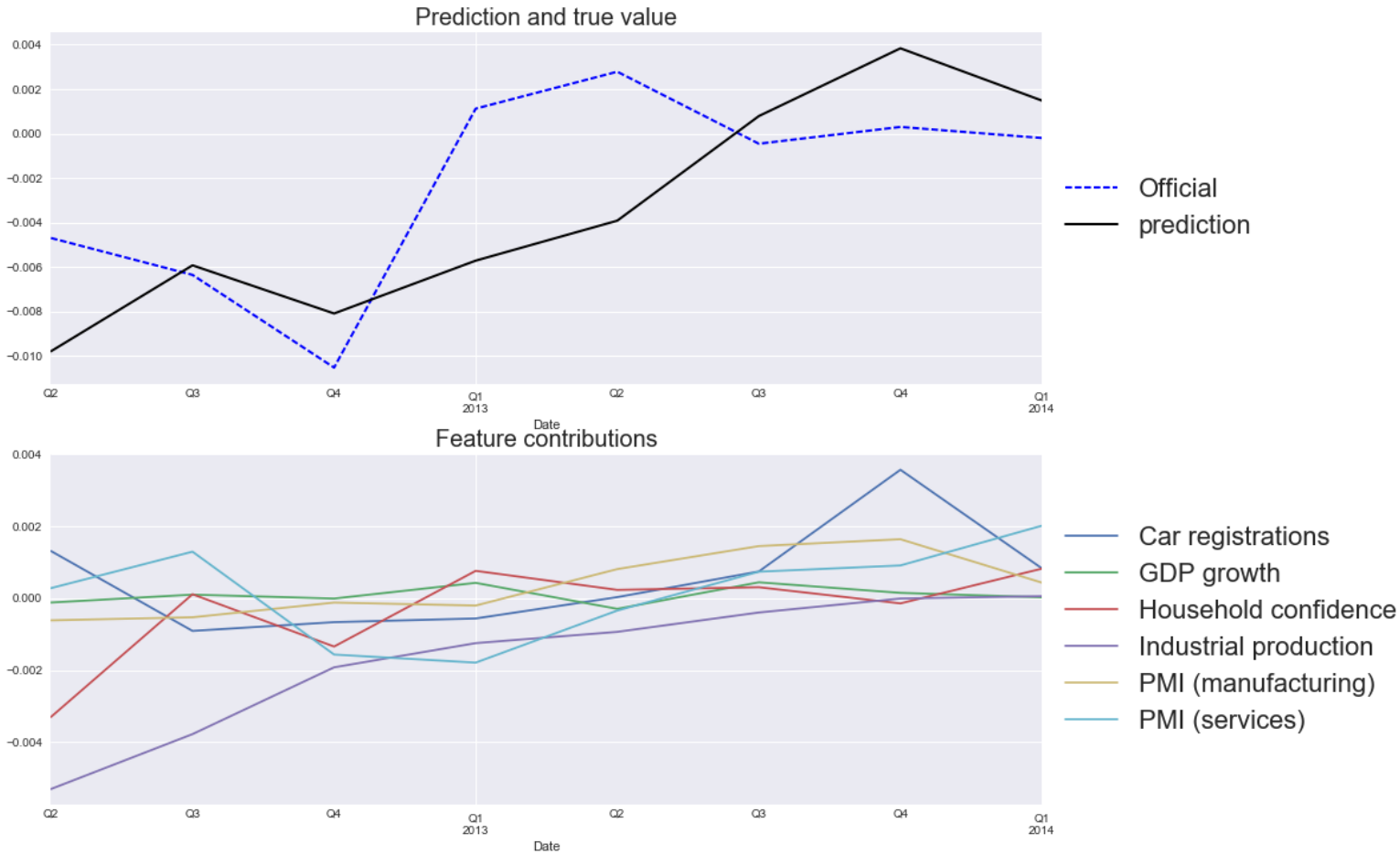
Interpretability



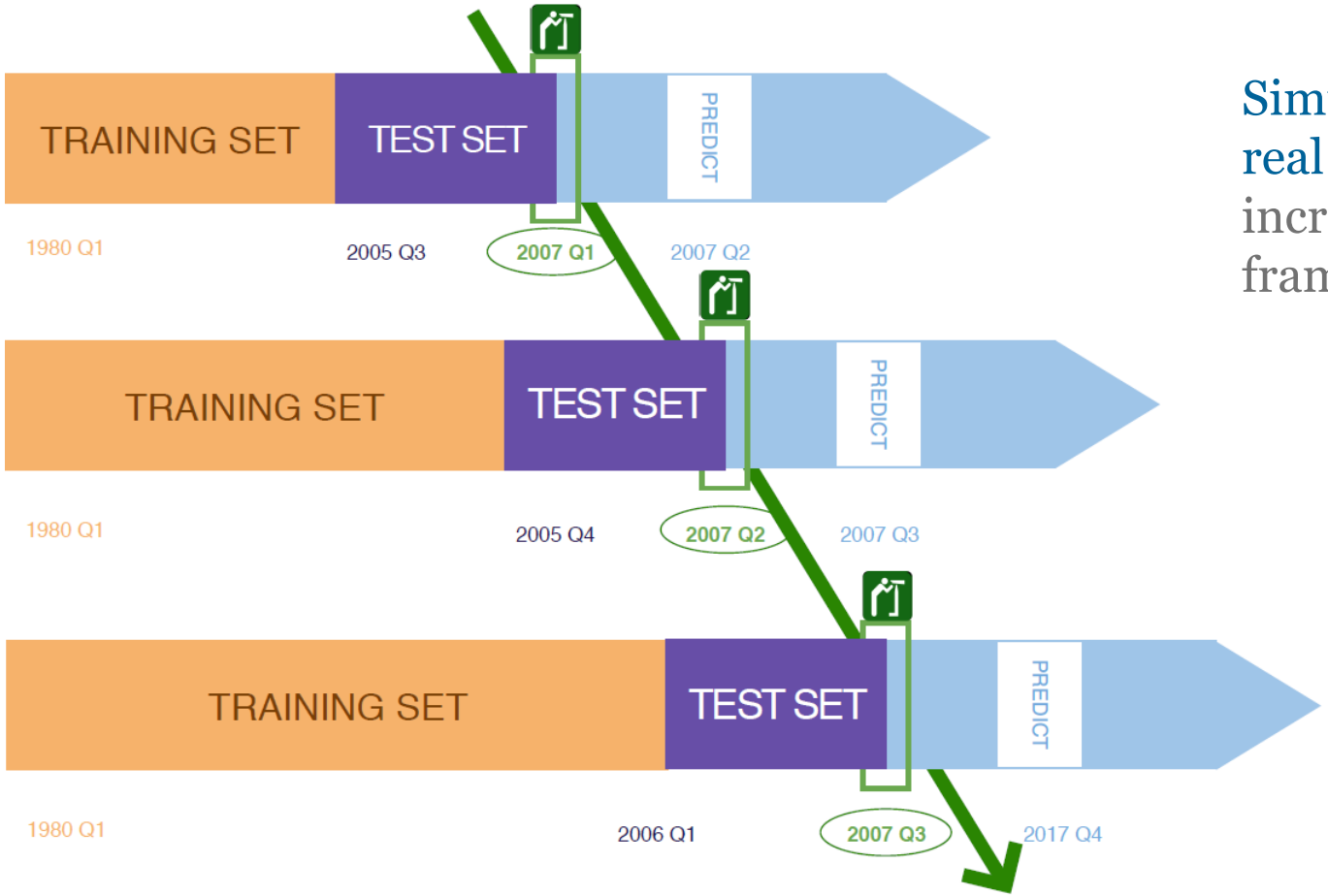
We can easily decompose in variable's contribution

$$\hat{Y} = 0.9\% + \sum Feature\ Contributions$$

Variable contributions, Italy M+3



Simulations



Simulations in pseudo-real time using an incremental learning framework

Variable selection

- For each variable:
  - What relevant lag : M-1, M-2, M-12, M-24 ?
  - In level ? In growth rate ?

- Data-driven variable selection:
  - Based on variable importance
  - Variable importance: a variable is all the more important that it is **high in the tree**, close to the root
  - Accounts for multiple interactions (can keep a variable that is loosely correlated with the GDP but that provides relevant interactions. Ex: price of gold)

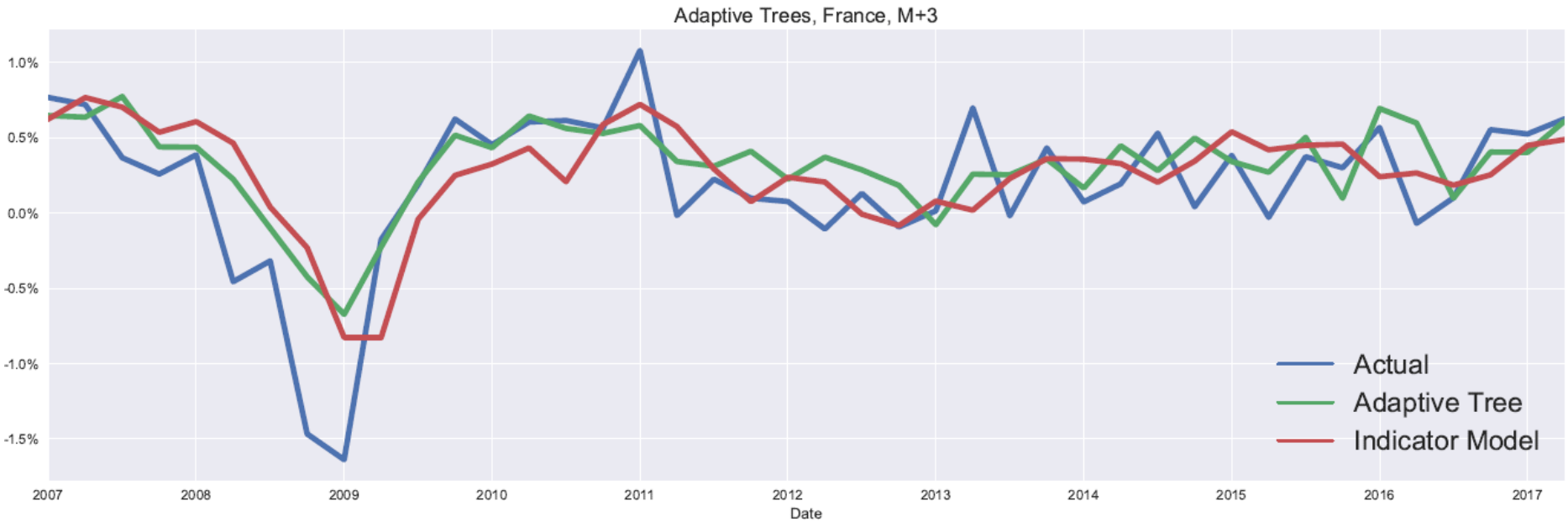
Complexity v. Bayesian econometrics

- In a regression with 10 variables, should we want to test all possible multiple interactions : 10^{10} possibilities

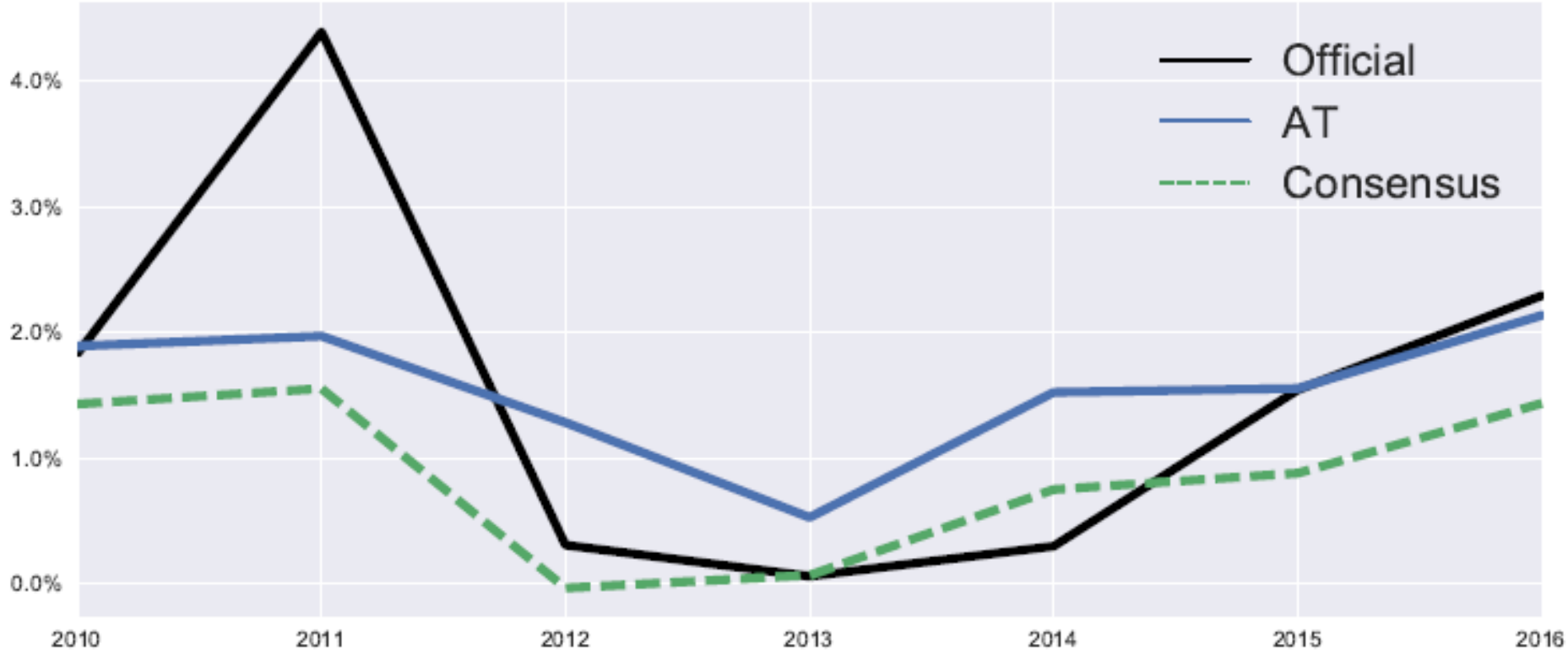
- With tree-based approaches, we explore all possible interactions with 120 variables

- Amount of prior knowledge:
  - Linear econometrics: we know the form of the relationship
  - Bayesian econometrics: we know the relationship can take any of the know forms
  - Machine learning: we know nothing

France, M+3


Adaptive Trees, France, M+3
1.0%
0.5%
0.0%
-0.5%
-1.0%
-1.5%
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
Date
Actual
Adaptive Tree
Indicator Model

France, Y+1


Official
AT
Consensus
4.0%
3.0%
2.0%
1.0%
0.0%
2010
2011
2012
2013
2014
2015
2016