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ASSESSMENT INNOVATION & COLLABORATION WITH A FOCUS ON AI

One size fits all? Different applications of AVMs

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Automated Valuation Model (AVM)

- Definition AVM
  - “A mathematically based computer software program that market analysts use to produce an *estimate* of market value based on market analysis of location, market conditions, and real estate characteristics from information that was previously and separately collected.” (IAAO, Standard on Valuation Models, 2018)
- Market value
  - “the *estimated* amount for which an asset or liability should exchange on the *valuation date* between a willing buyer and a willing seller in an arm’s length transaction, after proper marketing and where the parties had each acted knowledgeably, prudently and without compulsion” (RICS, Red Book, Nov. 30, 2021)

Applications

- Focus on residential real estate
  - Owner-occupied market, not income producing properties
  - Using statistical models and Machine Learning algorithms
- Some applications

Application	Valuation date	Focus
Property tax	Past	Individual
Mortgage application	Now	Individual
Investment decision	Now	Individual
Risk management	Now	Portfolio
Price index construction	Past	Portfolio

Requirements

- **Consistency**
  - properties with the same characteristics have the same model value
- **Accuracy**
  - How close are *out-of-sample predictions* to realizations?
    - ***Aggregate*** measures: Bias / dispersion / vertical inequality (IAAO Standard ratio on studies)
    - ***Individual*** measures: prediction intervals (or density)
- **Interpretability**
  - “Interpretability is the degree to which a human can understand the cause of a decision.” (Miller, 2017)
  - Can differences in model values be attributed to differences in characteristics?

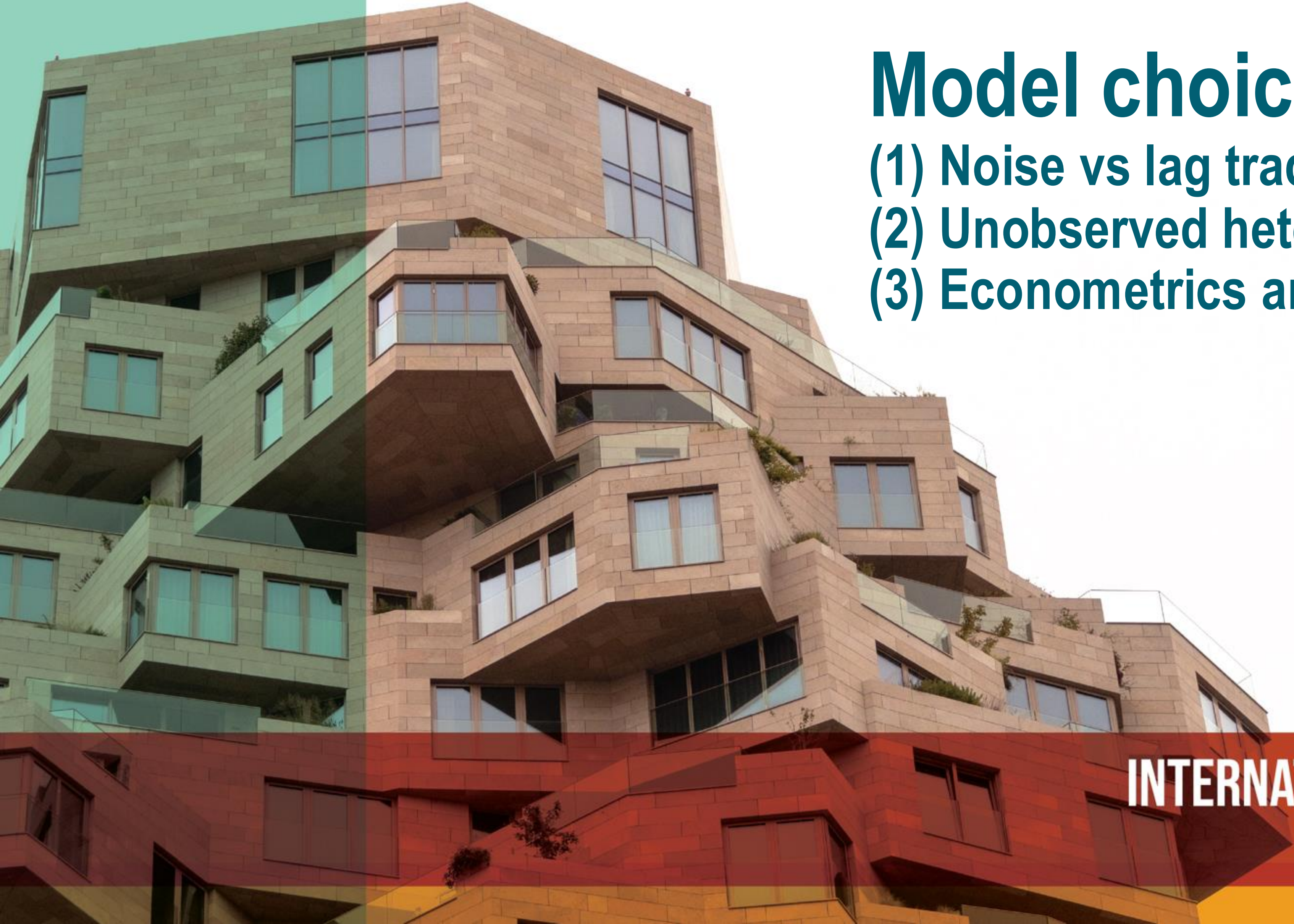
Applications and requirements

	Importance of		
Application	**Consistency**	**Interpretability**	**Accuracy**
Property tax	+	+	0
Mortgage application	-	-	+
Investment decision	-	+	+
Risk management	0	-	0
Price index construction	0	-	0

- The combination of *focus* (individual or portfolio), *valuation date* (past or now) and the importance of *consistency*, *interpretability*, and *accuracy* has consequences for the model setup.

Model choices

(1) Noise vs lag trade-off
(2) Unobserved heterogeneity
(3) Econometrics and Machine learning



1) Noise vs lag trade-off

Noise vs. lag trade-off

- You own a property. Would you rather have an estimate of value that is accurate to within ±10% with no lag bias, or to within ± 2%, but whose most likely value is what the property was worth 6 months ago?
- Your answer probably depends on how you are going to use the appraisal:
  - Are you just interested in the value of that *one property*?
  - Or will you be *combining* that property's valuation *with many others* to arrive at the value of an entire portfolio or index?
- In the latter case, the purely random error in the property valuation estimate will tend to cancel out with other errors and diversify away, but the temporal lag bias will not go away.

Noise vs. lag trade-off

Geltner et al. (2014) Two Possibilities:

1. Choose lagged and current information: use a large pool of properties
   - Standard error of model noise is small, but
   - Temporal lag bias ≠ 0
2. Choose current information only: small pool of properties
   - Standard error of model noise is high, but
   - Temporal lag bias = 0.

- Valuation
  - *Individual*: choose 1, because this option is founded on more information
  - *Portfolio*: choose 2, accuracy inversely proportional to number of properties
- Difference less relevant for valuation date in the past

Price index construction

Period-by-period regression

- Estimate a price model per period *t:* $\ln P_{it} = p_{it} = x'_{it}\beta_t + \varepsilon_{it}$
  - Gives $\hat{\beta}_t$
- Predict log prices of sales in period *t+1* based on the model in period *t*
  - Gives $\hat{p}_{i,t+1|t} = x'_{i,t+1}\hat{\beta}_t$, that is the log price level in period *t*
- Log price change:

$$\frac{1}{n_{t+1}}\left(p_{1,t+1} - \hat{p}_{1,t+1|t} + \cdots + p_{n_{t+1},t+1} - \hat{p}_{n_{t+1},t+1|t}\right)$$

- This method is frequently used by National Statistical Institutes

2) Unobserved heterogeneity

Price and market value

- P ≠ MV
  - P = Price, MV = Market Value
  - Market value is "estimated amount"
  - Illiquid, privately negotiated deals, unique assets in their entirety
  - Information asymmetry / negotiation skills / seller characteristics
    - Motivated sellers / home equity / loss aversion
- P = MV + TN
  - TN = Transaction Noise
  - E[P] = MV or equivalently E[TN] = 0
  - StDev(TN) around 7%, $\sigma_{TN}^2 = 0.07^2$
    - Goetzmann (1993) and Casametrics (Francke, 2010)
- TN cannot be modeled away, σ_{TN}^2 is a lower bound for model precision

Price, model value, transaction noise and model error

- $P = M + R$
  - M = model value
  - R = residual
- $R = ME + TN$
  - ME = Model Error
- $P = M + R = M +$ **TN** + **ME** (or $MV = M + ME$)
- Model Error ME due to
  - *errors in variables* (wrong input)
  - *missing variables* (missing input, omitted variable bias)
  - *specification error* (wrong functional form)
- Potential bias: $E[ME] \neq 0$

Dealing with unobserved heterogeneity

- Start with simple regression model

$$\ln P_{i,t} = \alpha + x'_{i,t}\beta + \varepsilon_{i,t},\ \varepsilon_{i,t} \sim N(0, \sigma^2)$$

- Dealing with time-invariant unobserved heterogeneity (omitted variable bias)
  - **1) Adding property random effects**

$$\mu_i \sim N(0, \sigma_\mu^2)$$

    - Some properties need to have more than 1 sale
    - Can also be estimated for one-only sales
    - Magnitude of μ_i depends on included variables *x*
  - **2) Adding spatial random effects** (Besag, 1974)

$$\theta_i | \theta_{-i} \sim N\left(\sum_{j \neq i} w_{i,j}\theta_j, \frac{\sigma_\theta^2}{\sum_{j \neq i} w_{i,j}^*}\right)$$

    - Spatial effect of property *i* depends on its neighbors $j \neq i$
    - No need for repeat sales

Decomposition

- Property and spatial random effects (Francke and van de Minne, 2021)

$$\ln P_{i,t} = \alpha + x_{i,t}'\beta + \mu_i + [\theta_i] + \varepsilon_{i,t},\ \varepsilon_{i,t} \sim N(0, \sigma^2)$$

- Application Heemstede
  - Expensive Dutch city, large houses, heterogeneous
  - Approx. 2500 sales of 2000 single-family homes
  - Period from 2001 to 2017
  - Source: Dutch brokerage organization (NVM)
  - Extensive set of variables

Property random effects	No	Yes
RMSE: σ^2	0.171^2	0.102^2
Property random effects: σ_μ^2		0.139^2
Total	**0.171^2**	**0.172^2**
Transaction noise σ_{TN}^2	0.070^2	0.070^2
Remaining error σ^2-σ_μ^2-σ_{TN}^2	0.156^2	0.074^2

Out-of-sample performance

- Improves out-of-sample performance
  - Mean absolute residual (in logs, leave-one-out)
  - Property random effects help for repeat sales
  - Individual spatial random effects also help for one-only sales

Property and spatial effects	No	Property	Property & Spatial	Number of sales
sales per property in training set				
0	0.139	0.139	0.108	1703
1	0.129	0.102	0.090	644
2	0.120	0.091	0.087	117
Total	0.137	0.133	0.105	2468

Property and individual spatial random effects

Adding property and individual spatial random effects

- *Consistency* (--)
  - Properties with identical observed characteristics can have different values
- *Interpretability* (-)
  - Differences in property value can’t be explained by differences in observed characteristics
- *Accuracy*
  - Aggregate (++)
  - Individual (++)

Unobserved heterogeneity

- Simpler and less accurate version of property random effects
  - Indexation of past sale price
- Adding more variables to reduce unobserved heterogeneity
- Reducing remaining error
  - Errors in variables -> better data cleaning
  - Time-varying unobserved heterogeneity
  - Specification error -> flexible functional forms

3) Econometrics and Machine learning

Econometrics

- Econometric models have been in use for many years
  - Define a model structure prior to parameter estimation: functional form, error distribution, included features, and their transformations and interactions
  - Given a model's structure definition and the assumed statistical distribution of the error term, one can estimate β from observed data
    - sale prices *p* and variables *X*, e.g. $p = X\beta + \varepsilon$
  - Requires in-depth statistical knowledge
  - It allows one to perform statistical inference and to make statements on the statistical significance of parameters
  - Econometric models revolve around correctly estimating parameters $\hat{\beta}$ and even causality (Mullainathan and Spiess, 2017)

Econometrics

- Provides not only a point estimate, the predicted value, but also prediction intervals (or even a density)
  - Heterogeneous: Interval width depends on property characteristics
  - Asymmetric: point estimate not necessarily in the middle of the interval
- Real estate property transaction data
  - Cross-sectional
  - Spatial dependence
  - Temporal dependence
  - Repeat observations
- Econometric models can deal with complex correlation structures

Machine learning

Supervised	Unsupervised
Regression	Clustering
Classification	Dimensionality Reduction

- Simultaneously search for a functional form and parameter values
- Are data hungry: NO BIG DATA in real estate transaction data
- Calibration
  - Minimize "distance" between observed p and predicted values $\hat{p}$, defined by a loss function
  - Which loss function?
  - Expectation of identification function = 0
  - Solution is optimal for only 1 loss function

Loss function	Identification function
$\lvert p-\hat{p}\rvert$	$0.5 - \mathbf{1}[p \geq \hat{p}]$
$(p-\hat{p})^2$	$p-\hat{p}$
$\left(\frac{p-\hat{p}}{\sqrt{p}}\right)^2$	$\frac{p-\hat{p}}{p}$

Machine Learning

- ML algorithms are much easier to calibrate
- ML algorithms are prone to overfitting: train & out-of-sample test set
  - Regularization can mitigate overfitting by penalizing the complexity of the algorithm
- Each algorithm requires a set of algorithm-specific hyperparameters.
  - They are usually “tuned” to select the best-performing model.
- Easy dealing with missing values and many variables (algorithm dependent)
- Black box
  - iML / causal ML are still in their infancy, although a lot of research is being done
  - ML predictions often a combination of many algorithms

Machine Learning

- ML focuses on best predictions $\hat{p}$ (Mullainathan and Spiess, 2017)
- Off-the-shelf ML algorithms assume that observations are independently and identically distributed
  - Do not consider spatial and temporal correlations and repeat observations
  - An evolving field of research
    - Regularization by graph Laplacian in regression models (Sijp et al., 2024)
    - Graph Neural Networks
- Prediction intervals (densities) are not a by-product of the algorithm, a separate algorithm is needed for this
  - Even then they sometimes produce homogeneous and symmetric intervals
  - Francke et al. (2024) for a comparison of different algorithms

Econometrics and Machine Learning

Econometrics	Machine Learning
Pre-defined model specification	Algorithm determines function form
Imposed structure limits data needs	Flexibility of algorithm requires lots of data
Requires specialized statistical knowledge	Relatively easy to implement
Focus on explaining	Focus on prediction
Explainable (to other specialists)	Black box (iML is a large research area)
Gives accuracy of predictions	Separate algorithm needed to determine accuracy
Can deal with correlation structures (time, space, panel, repeat observations)	Standard ML algorithms assume that observations are independent and identically distributed

Econometrics and Machine learning

- Do ML algorithms outperform econometric models?
  - Not really, but easier to implement (ML needs lots of data, not available in real estate)
- Econometrics
  - Consistency: 0 (depends on specification)
  - Interpretability: +
  - Individual accuracy: +
- Machine learning
  - Consistency: 0
  - Interpretability: -
  - Individual accuracy: 0 (needs additional algorithm)
- ML algorithms can be used as second opinion in case interpretability is key

Machine learning and feature engineering

- ML algorithms can be used for feature engineering
  - extract information from (previously inaccessible) sources: images and text
- Examples Google Streetview
  - Naik et al. (2017)
    - Measuring changes in physical appearance of streets
    - Baltimore, Boston, Detroit, New York, Washington DC
    - Image classes: ground, buildings, trees, sky
    - Street score: 0 – 25
    - Validation by surveys
  - Lindenthal and Johnson (2021)
    - Detect architectural styles (Gerogian, early/late Victorian, interwar, …)
- The extracted features can then be used in an AVM

Combining Econometrics and Machine Learning

- Combining
  - Flexibility of ML
  - Interpretability of econometrics: How much does the property value change
    - as you move it around the map: location value
    - over time: price indexes
- Put (econometric) structure on time & location, repeat observations

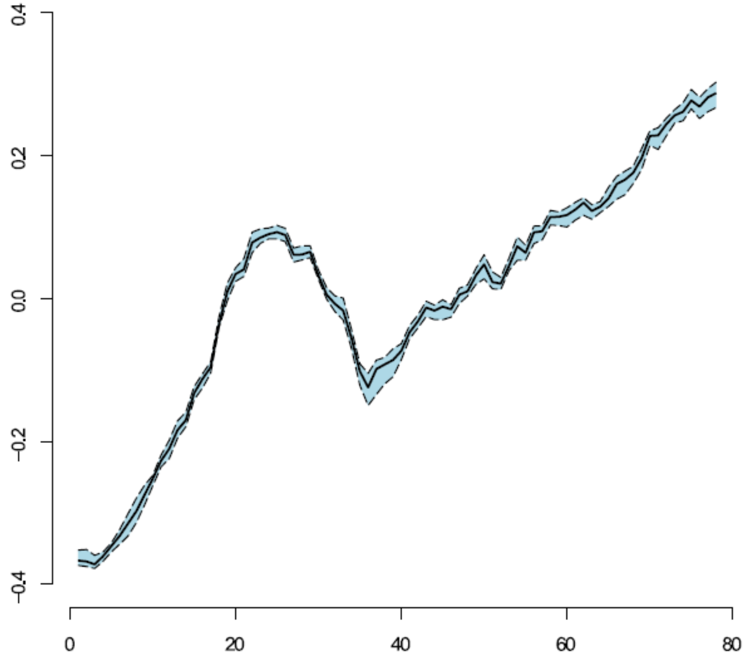
$$\ln P_{i,j,t} = f(x_{i,j,t}, \beta) + \gamma_t + \delta_{jt} + \mu_i + \theta_i + \varepsilon_{i,j,t}$$

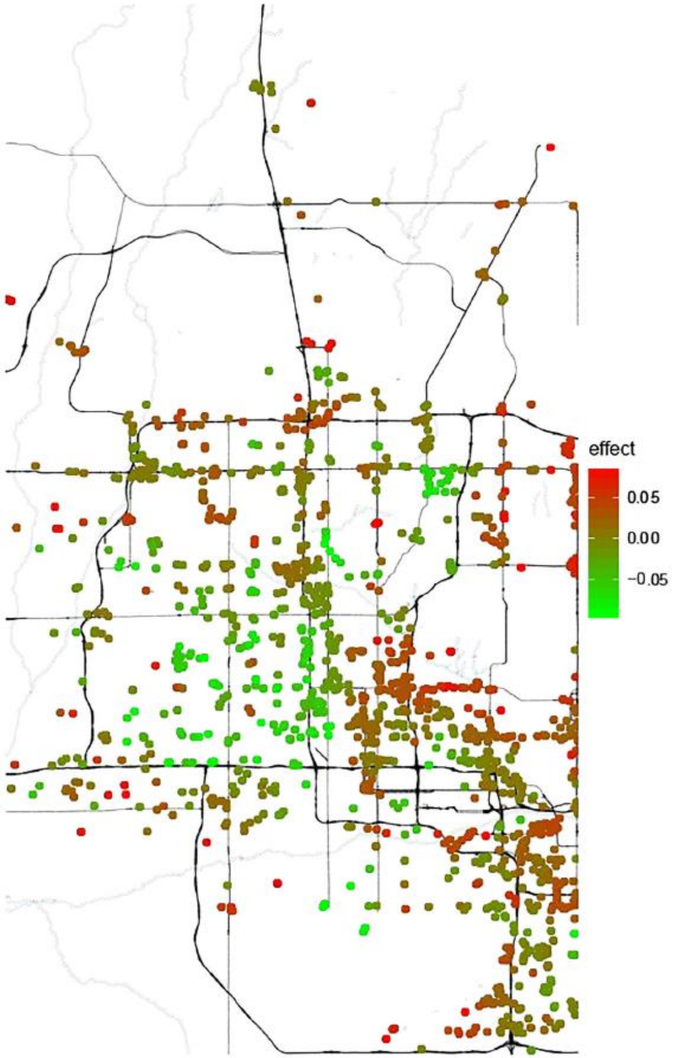
  - $f(x_{i,j,t}, \beta)$ ML part (NN / SVM / RT / GBM), replacing $x'_{i,j,t}\beta$
  - γ_t is common price index, δ_{jt} is property type *j* specific index
  - μ_i is property random effect, θ_i is an individual spatial effect
- Calibrate all at once or iteratively

Hybrid model

- Application (Francke and Van de Minne, 2024)
  - Commercial real estate in Phoenix: apartment, industrial, office, retail
  - 2,652 sales over the period 2001 – 2021
  - Sale price: above $ 2.5 mln
  - Included variables
    - Net operating income
    - Building size
    - Building age
    - Walk score

Price Index and Location Values (econometrics part)





Out-of-sample prediction results

TABLE 2 Main results for Phoenix.

	(1) NN	(2) REM	(3) fNNREM	(4) iNNREM
MAPE, out of sample, all	0.139	0.147	0.111	0.109
MAPE, out of sample, $k = 0$	0.142	0.157	0.111	0.114
MAPE, out of sample, $k = 1$	0.136	0.138	0.113	0.106
MAPE, out of sample, $k > 1$	0.133	0.117	0.102	0.090
MAPE, in sample, all	0.127	0.095	0.104	0.079
Obs, all	2652	2652	2652	2652
Obs, $k = 0$	1685	1694	1694	1694
Obs, $k = 1$	659	647	647	647
Obs, $k > 1$	308	311	311	311

- (1): Neural Network
- (2): Random effect model with linear characteristic's specification
- (3) and (4): Hybrid models
- MAPE = Mean absolute percentage error

Concluding remarks

- ML is not a replacement for current valuation methods
- ML algorithms
  - Relatively easy to implement
  - Require lots of data, but no Big Data in real estate (sales and rentals limited)
  - Added value: Creating new variables from text or pictures
  - Out-of-sample performance comparable to or better than advanced econometric models
  - Importance of loss function
  - Explainability is limited
  - Determining prediction accuracy is not a standard output
  - Hybrid approach seems superior

Questions?