What Explains the Recent Run-Up in Albanian House Prices? An Analysis with the LSTM Neural Network

Blerina VIKA

Department of Statistics and Applied Informatics,

Faculty of Economy, University of Tirana, Albania

Ilir VIKA

Research Department

Bank of Albania

Bank of Albania, “17th South-Eastern European Economic Research Workshop”, Tirana, December 4-5, 2023

Motivation

- Investigate the role of economic, financial and demographic indicators in recent rapid increase in house prices in Albania;

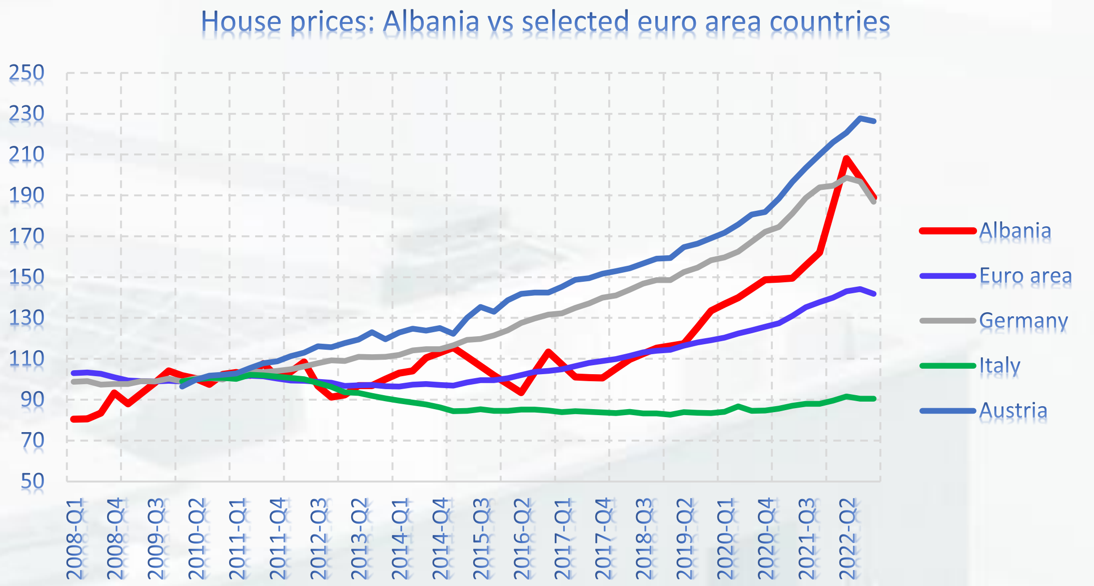
- Use the appealing deep learning method, LSTM – as special class of machine learning tools, incl. ANNs – which often gives more accurate results than conventional approaches in predicting prices;

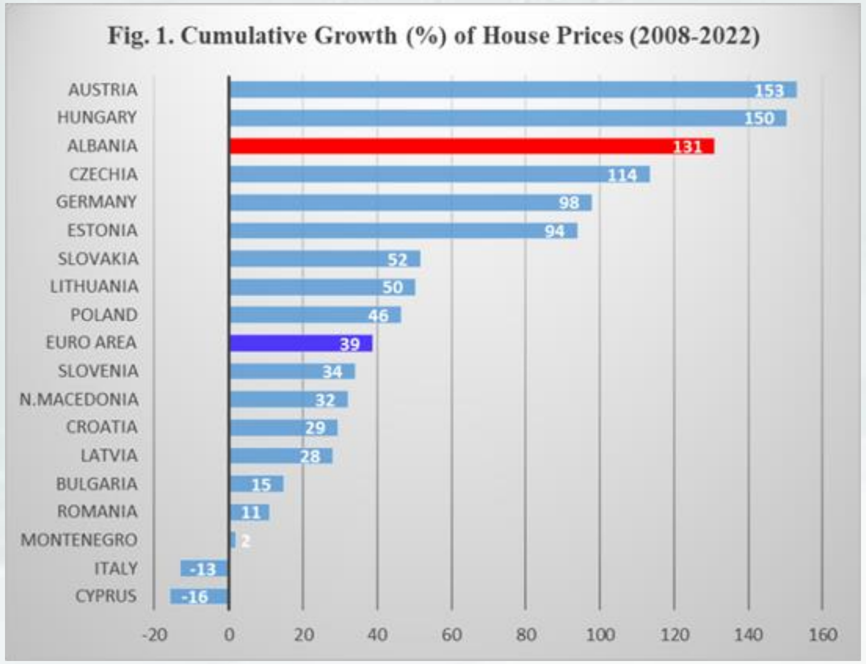
- Contribute to ANN literature w.r.t. model specification (selection);

- Help policymakers to understand factors driving house prices in order to legitimize their decisions.

Introduction

- Albanian housing market may be at an important juncture;
- House prices (HPs) have increased rapidly for nearly six years, before and after the pandemic period;
- This naturally raises the question of a speculative bubble in housing market;
- Since 2008, Albania’s HPs have been growing much faster than in Euro Area and Western Balkans neighbors.
- Beyond speculation or not, the concern is mostly related to a reverse in HPs amid stretched valuations and rising interest rates, which could result in adverse consequences on broader economy.

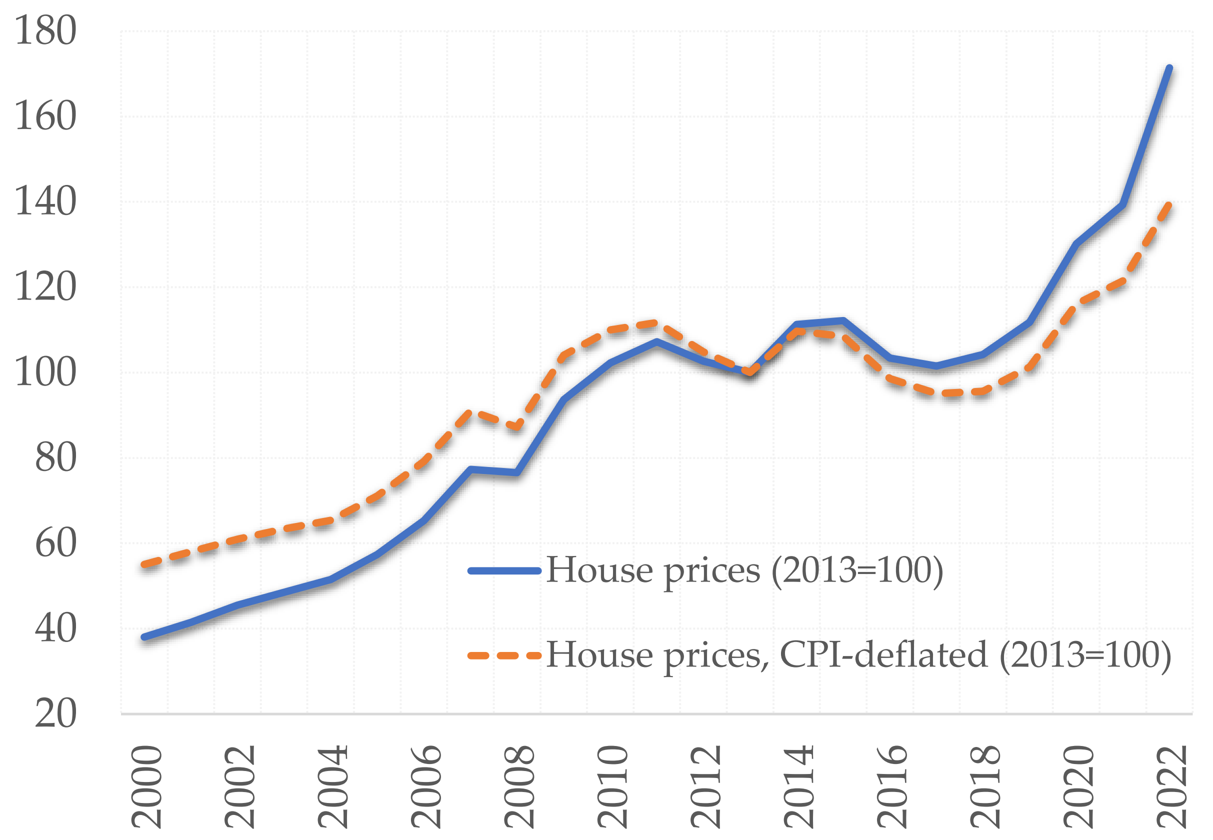




House price developments and long-run stylized facts

- HPs in Albania have increased significantly from 2000 to 2022, both in nominal and real terms.
- Its cumulative increase is about five times higher than that of CPI.
- Hwv, HP performance has not been the same over time.
- Whole period can be divided into
  i. rapid house price growth during 2000-09 (146%); followed by
  ii. price "stabilization", albeit fluctuating btw 2010-17; and then
  iii. strong upward HP trend reappears during 2018-22, prices rising 76%.

Figure 2. House price performance in Albania



Cumulative growth of house prices in the past two decades.

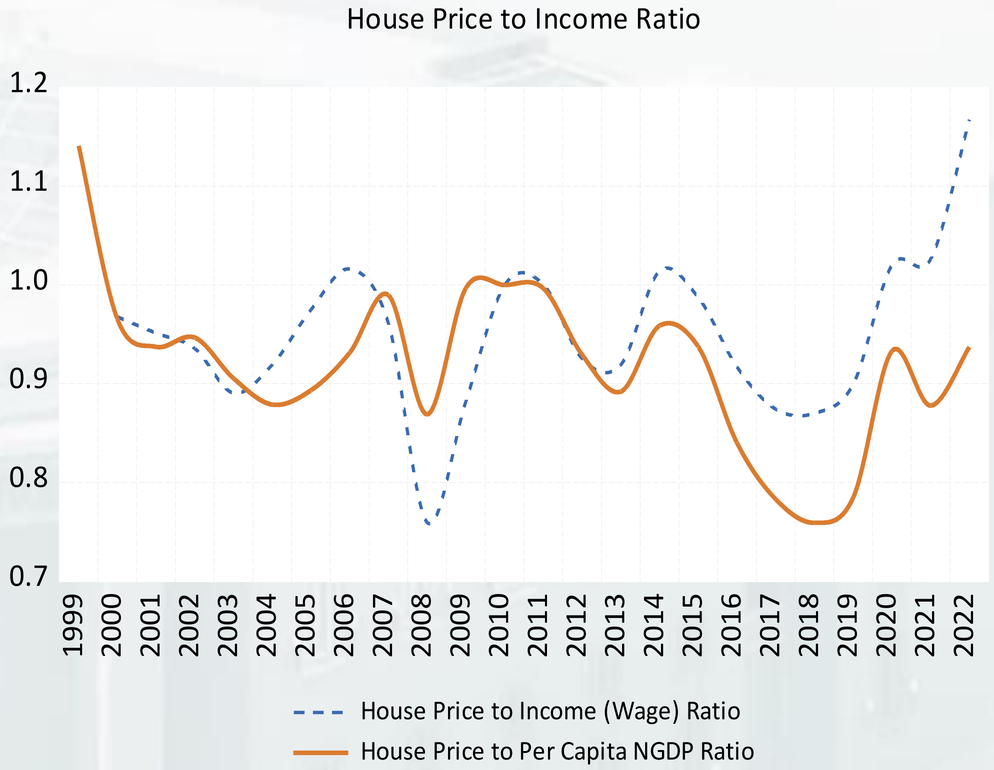
	Whole period 2000-2022	Rapid HPI growth 2000-2009	Relatively calm period 2010-2017	Return of strong HPI growth 2018-2022
HPI, cumul. increase (%)	401.7	146.5	1.9	76.3
HPI, st. dev. of yoy % chg	8.4	7.9	6.7	8.3
CPI, cumul. increase (%)	77.8	30.1	14.8	12.7
CCI, cumul. increase (%)	6.0	-6.5	3.3	8.7
GDP, nomin. cum. growth(%)	454.9	181.1	39.1	41.9

- In the long run, cumulative HPI (402%) seems to reflect nominal income, GDP (455%),
- It is less related to consumer inflation, CPI (78%) and …
- …even less to construction costs, CCI (12%).

Does the recent run-up in HPs suggest an adjustment with income growth?

Simple metrics of Price-to-Income and Price-to-Rent ratios raise concerns about possible exuberance of HPs in Albania.

- HP as ratio to per capita GDP suggests a "normal" HP level;
- Hwv, its ratio to Wages esp. in 2022 raises concerns for future demand for mortgage loans, house prices, etc. as house market may now be navigating in uncharted waters;
- Also, return on investment in housing (rent/price) is currently at all-time low.

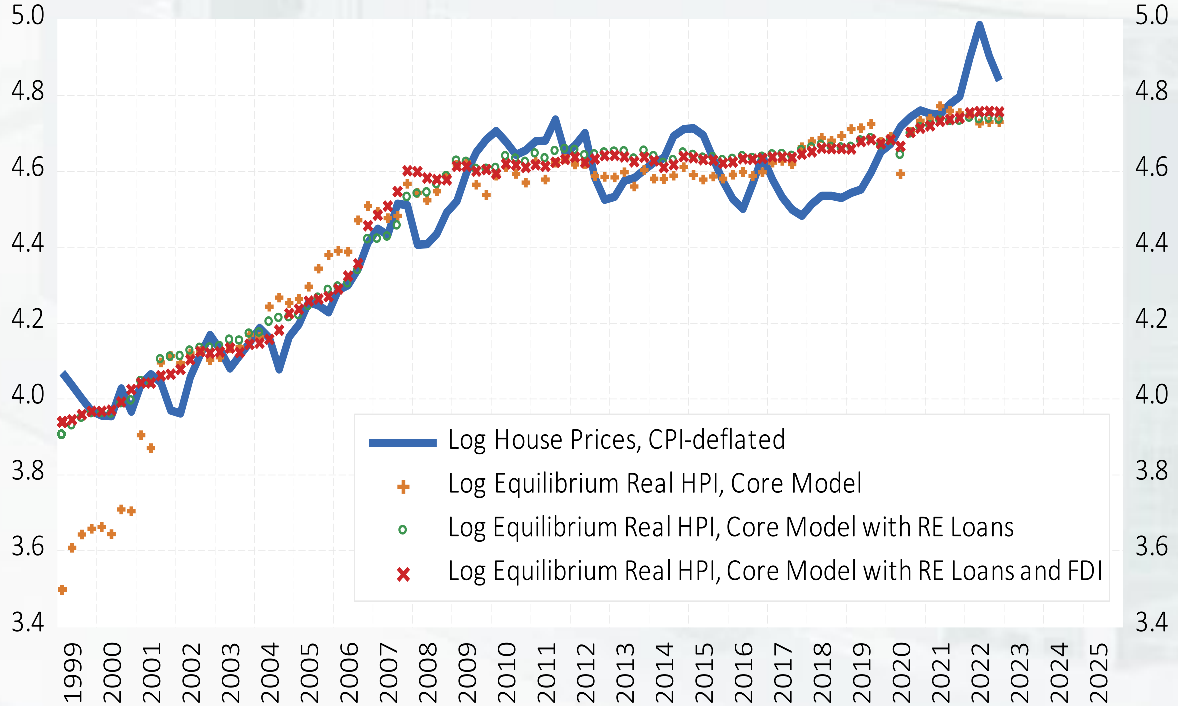


Albania: Percent Deviation from Long-Term Averages as Sustainable Levels (as of Last Quarter of 2022)				
	Relative to 7-Year MA	Relative to 10-Year MA	Relative to 15-Year MA	Relative to 20-Year MA
Price-to-Income (YNPC)	2.7	0.2	-3.2	-4.2
Price-to-Income (Wage)	7.1	6.9	9.0	9.0
Price-to-Rent	25.9	29.4	36.3	50.8

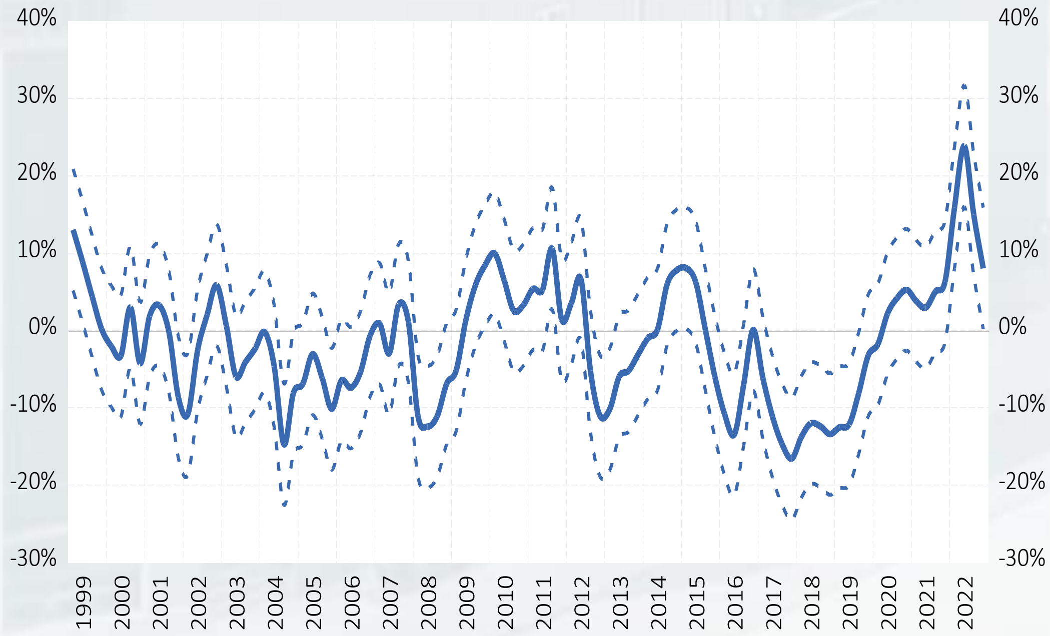
Source: Authors' calculations

Is rapid HPI growth in recent years in line with fundamental indicators?

- Vika (2023) analyzes the link of real HPI with a number of theoretically-related indicators such as GDP, rent, population, credit, and foreign investment; long-term relationship is estimated via ARDL method;
- Result from different ARDL specifications suggest similar equilibrium levels of real HPs, esp. after 2002;
- Real HP seem particularly undervalued btw 2017-2019, and unprecedentedly overvalued in mid-2022.



Real House Price Misalignment (+/- standard deviation)
(core model with RE loans and foreign investments)



Source: Vika, I. (2023). Whither house prices in Albania. Bank of Albania, Unpublished research document, May, 2023.

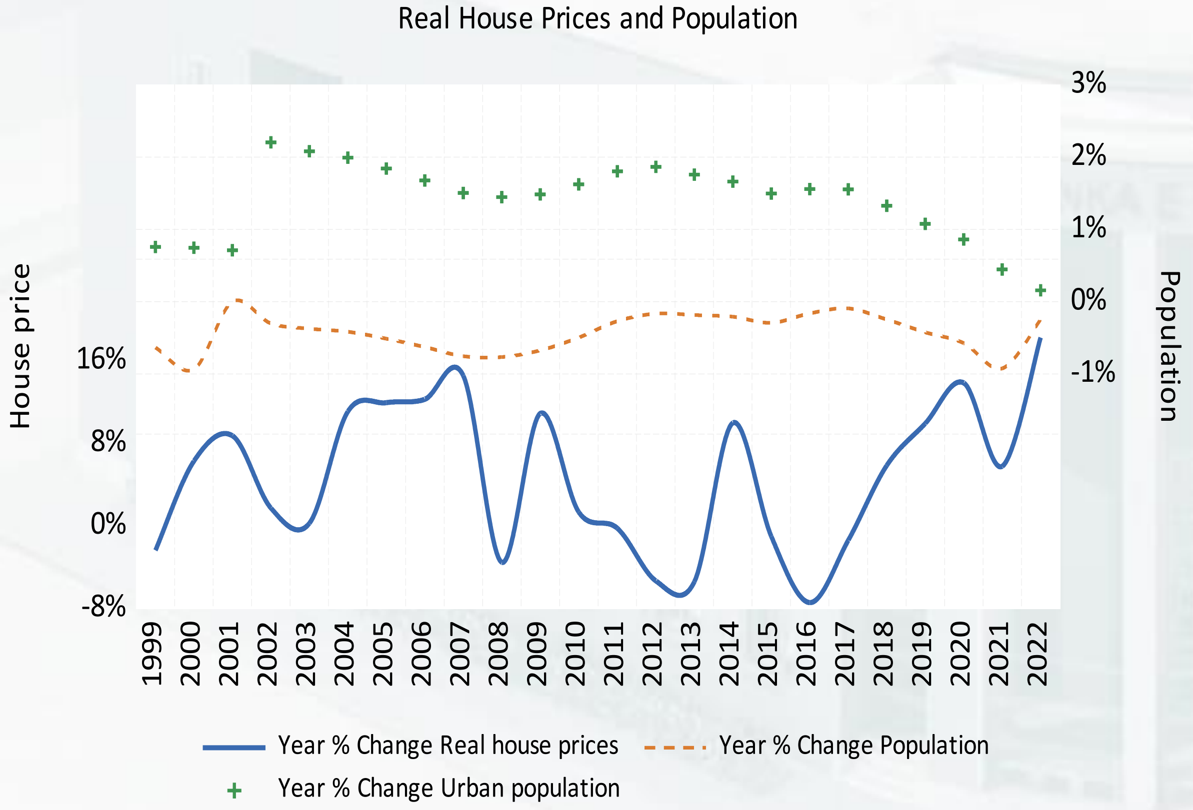
House Price Developments and Long-Run Stylized Facts

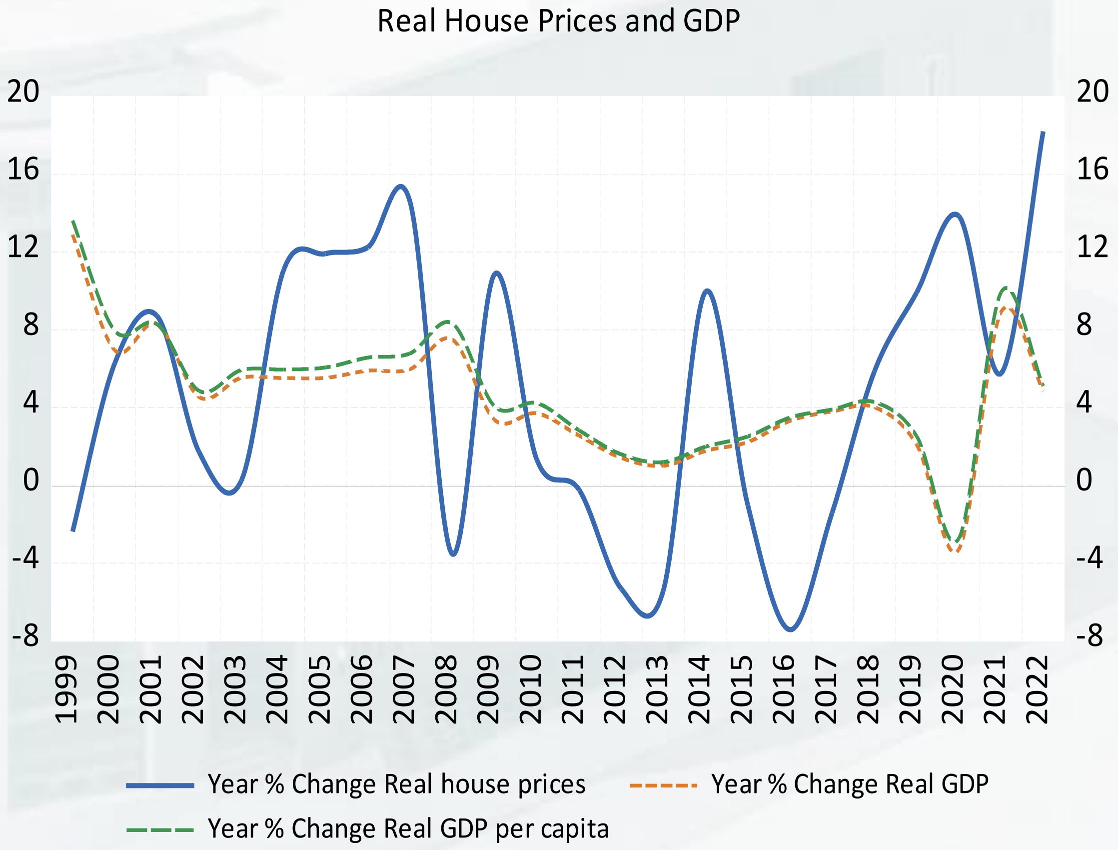
- Data availability issues:
  - Economic data for analyzing movements in house prices is not always available for Albania at quarterly frequency for the full period under investigation;
  - Most data series had to undergo certain manipulation in terms of interpolation from annual frequency or extrapolation in earlier periods by using supportive indicators.

Rapid HP growth in recent years seems in line with fundamental indicators

Despite negative growth of population in recent decades, internal migration to urban areas has been increasing…

… together with falling unemployment and rising GDP per capita, may have exerted pressure to raise housing prices.

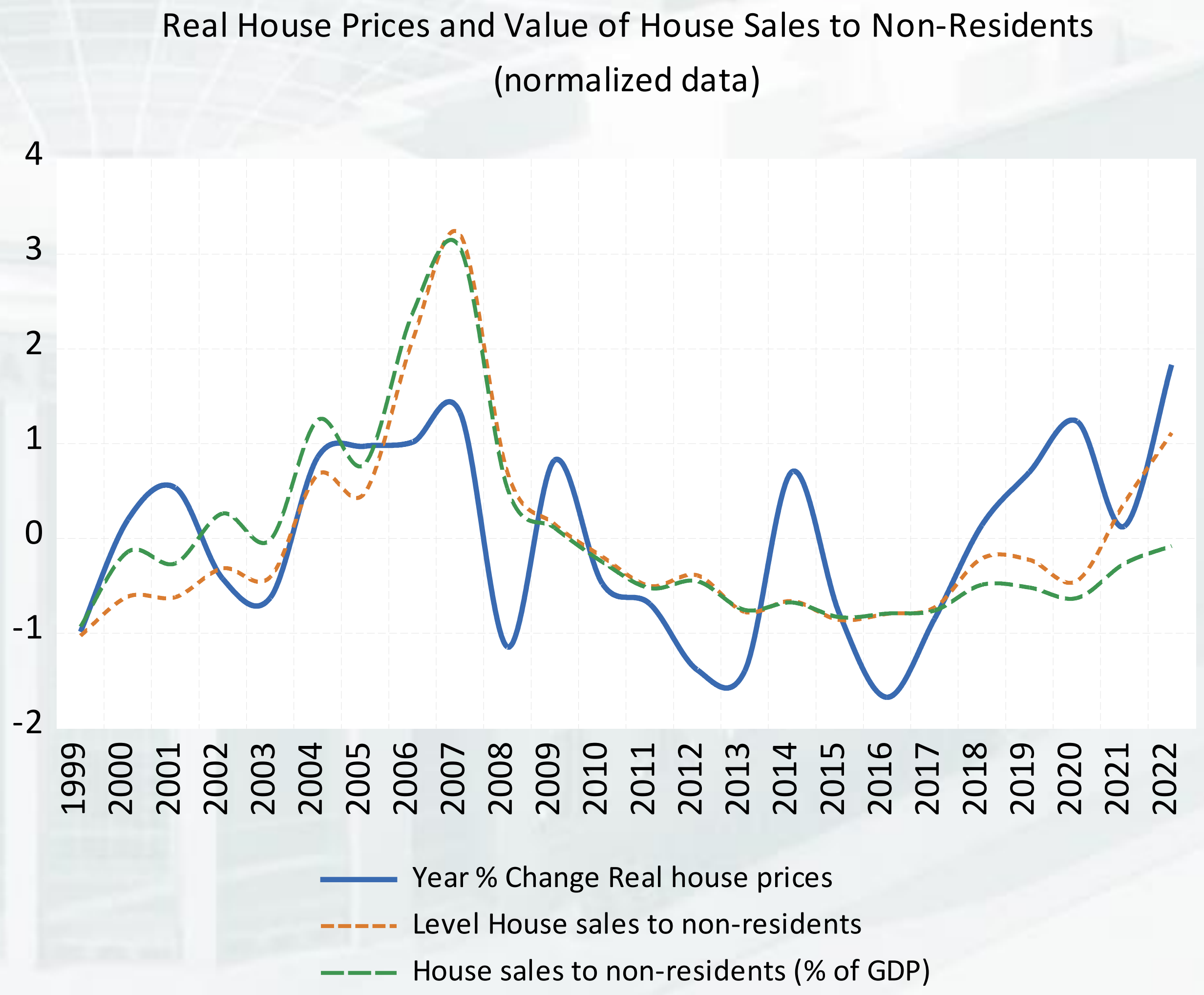




Source: Institute of Statistics (INSTAT), Bank of Albania and authors' calculations.

Rapid HP growth in recent years seems in line with fundamental indicators

Non-resident interest in investing directly in real estate in Albania has grown significantly over the past five years, jumping from an average of 0.36% of GDP over 2013-17 to 1.59% in 2022.

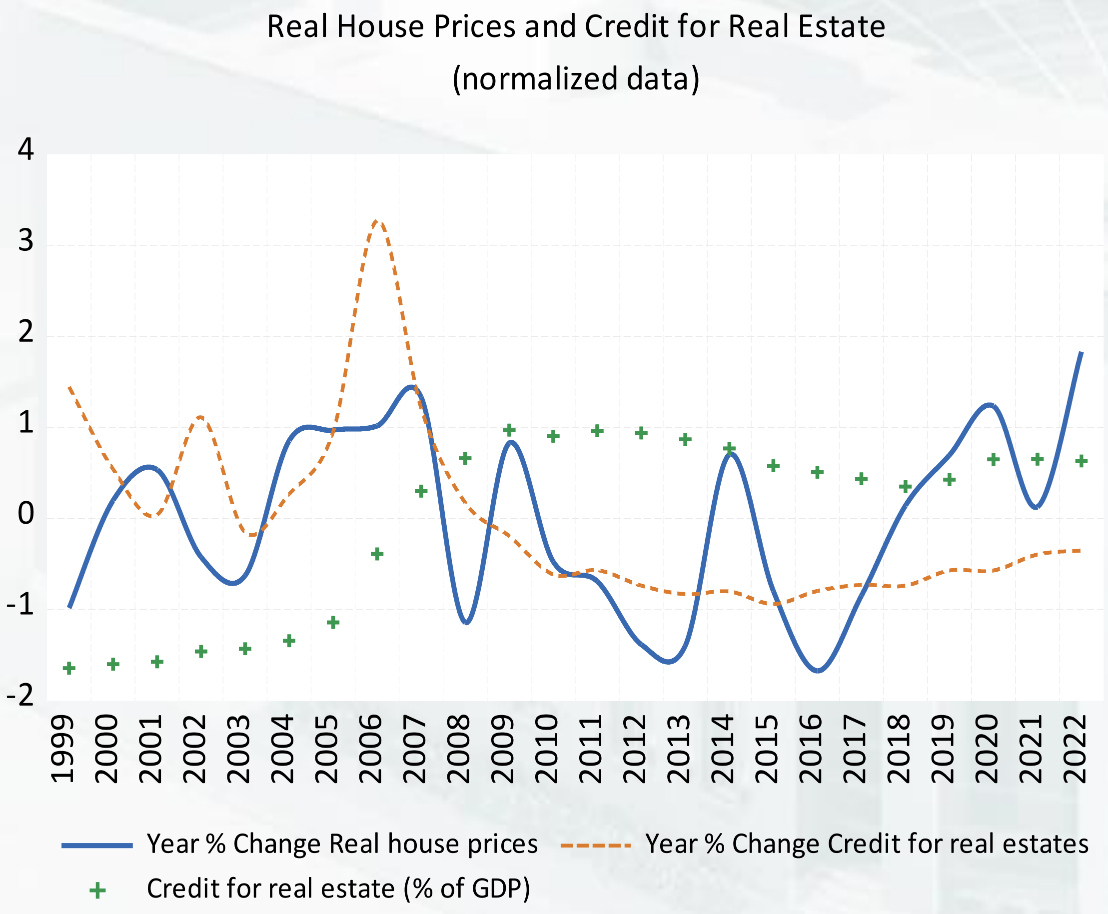


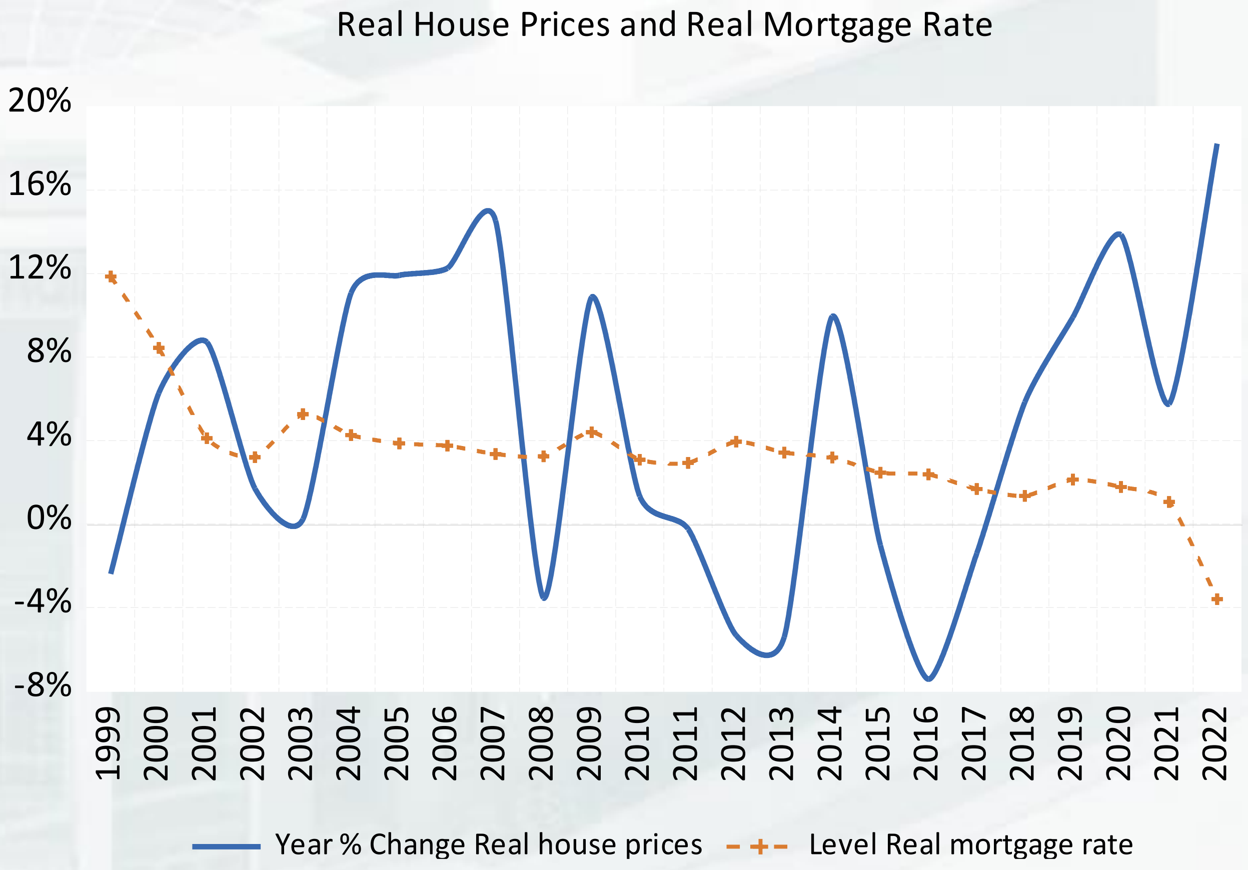
Source: Institute of Statistics (INSTAT), Bank of Albania and authors' calculations.

Similarly, banking system appears to have further stimulated demand in residential sector:

Increase in ratio of Real Estate Loans to GDP, …

… together with decline in real interest rate on new mortgage loans should have increased the affordability of housing purchases.



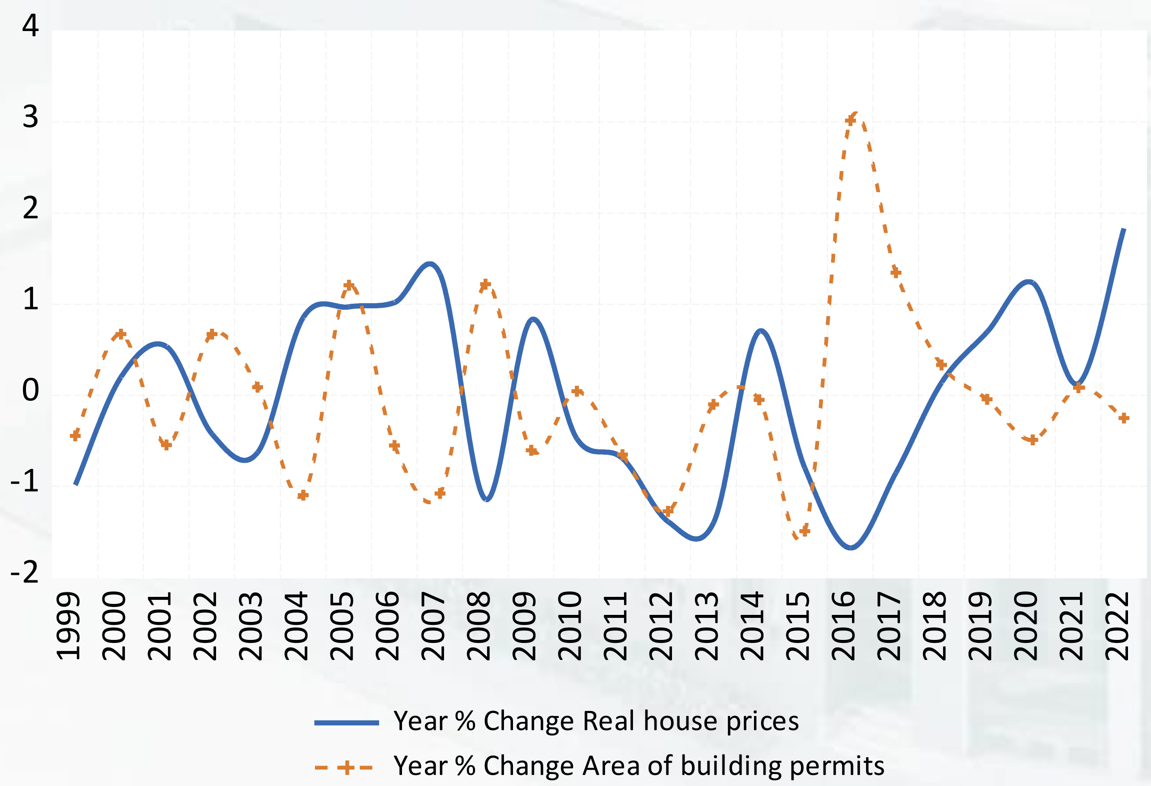


Source: Insttitute of Statistics (INSTAT), Bank of Albania and authors' calculations.

Supply side factors such as costs and building permits present a different picture

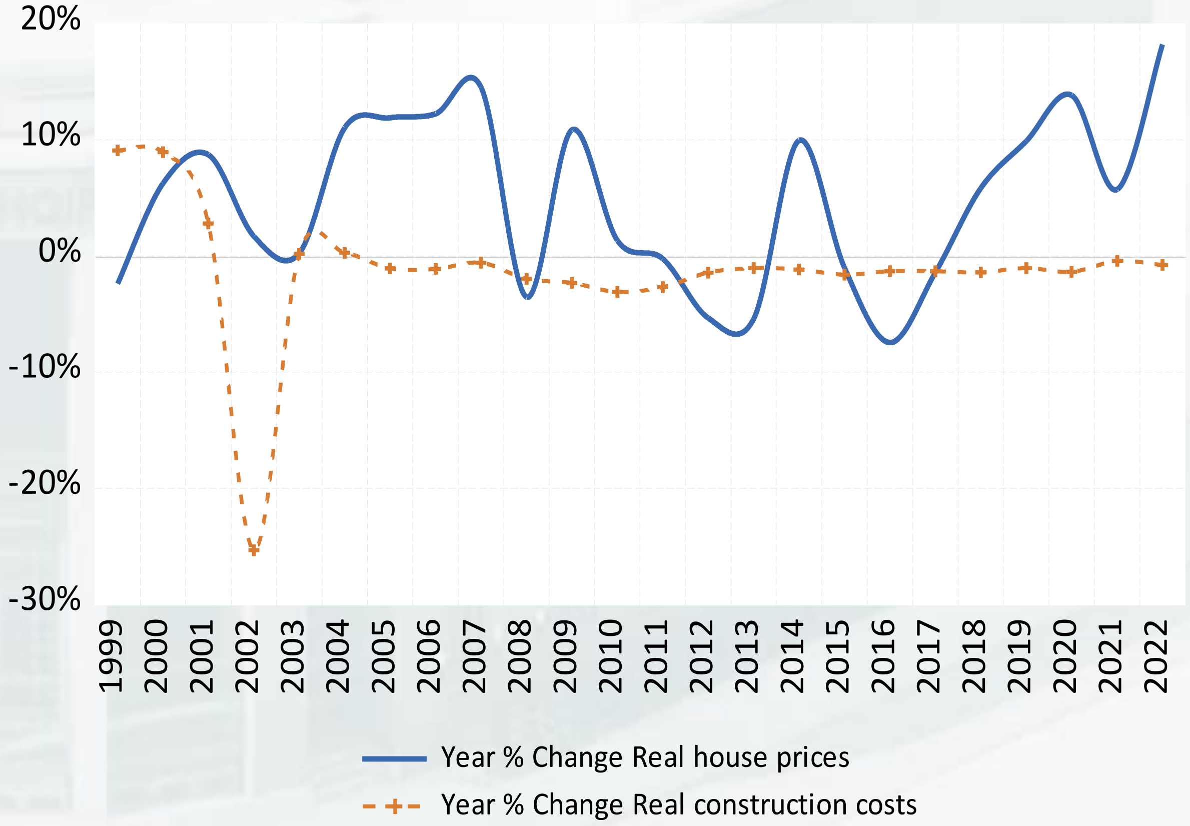
Influence of construction permits is not very clear

Real House Prices and Area for Building Permits
(normalized data)



Negative annual growth in real CCI, seem incapable to have influenced recent real HP upsurge

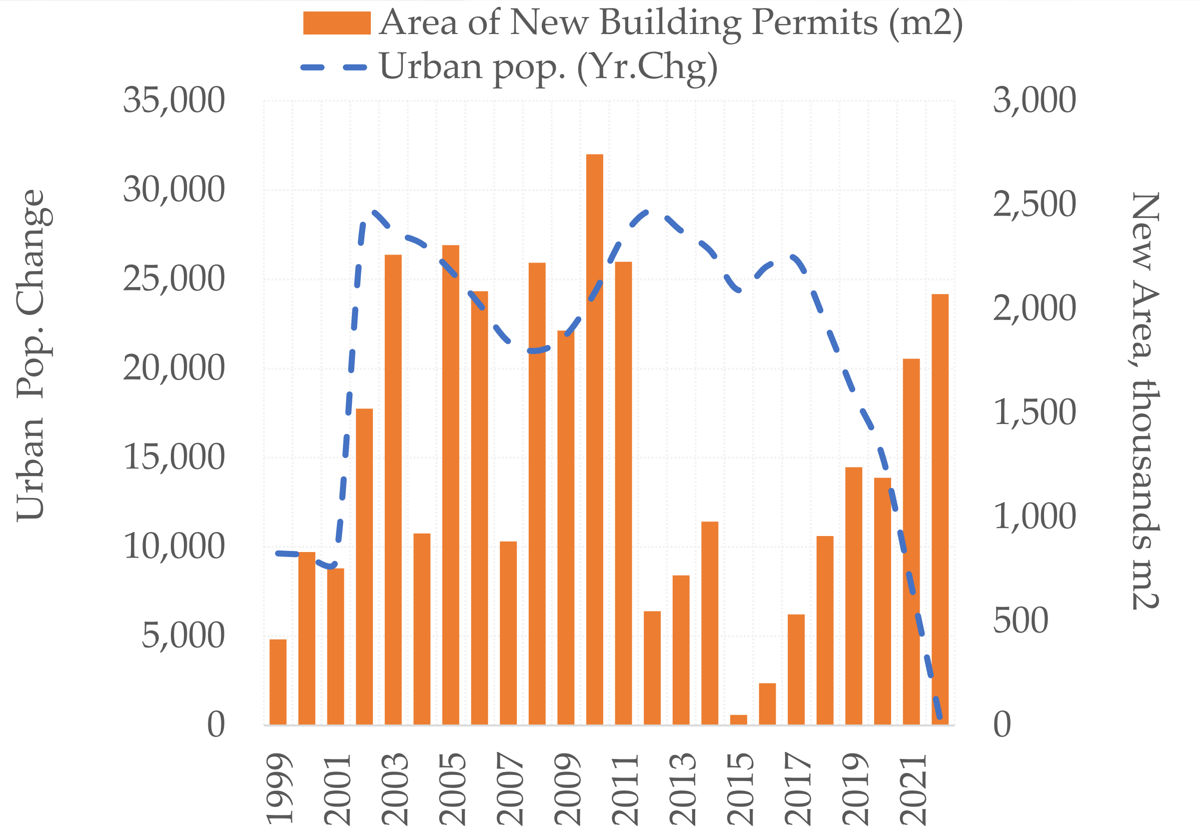
Real House Prices and Real Construction Costs



Source: Insttitute of Statistics (INSTAT), Bank of Albania and authors' calculations.

Housing demand and supply

- Permission to construct new houses contracted to just 3 km^2 during 2012-17, at a time when urban population increased over 159,000 people... this may have influenced fast HP increase in the subsequent period.
- Yet, demand pressures resulting from rising urban population should have eased somewhat during 2018-22 as building permits for dwellings (in km^2) started to increase… ratio of these indicators reached lowest level since 2002.



Urban population growth per km^2 of new house building area permits

Years	Urban population, cumul. growth (1)	Sum of house building area permits, in km^2 (2)	Ratio of column (1) over (2) (3)
2002-22	472,243	29.3	16,131
2002-12	277,204	19.6	14,130
2012-22	223,898	10.2	21,936
2012-17	159,416	3.0	52,526
2018-22	64,482	7.2	8,991

Source: Insttitute of Statistics (INSTAT) and authors' calculations.

Related work

- Relationshiop btw HPs and macro fundamentals has been overlooked in academic research… literature expanded after GFC when housing was understood to play determining role in HH wealth.

- Survey by Duca et al reveals 1) conventional theories seem insufficient to explain housing mkt dynamics; 2) HP-to-Rent models fail to capture variations in HPs; 3) Credit conditions are key driver of HP movements; 4) Land supply explain much of HP spatial variation; and 5) HP behavior during pandemic was different than in previous downturns.

- These findings caution against putting too much weight on interest rates and focus more on other macro-financial factors from both demand-side (e.g. income, wealth, fin. conditions) and supply-side (e.g. house availability) [Tsatsaronis & Zhu; Égert & Mihaljek; Agnello & Schuknecht; Cerutti, Dagher, & Dell’Ariccia].

- In Albania, a number of studies investigate housing mkt using linear traditional models: Yzeiraj constructs a “fundamental” HP index and finds prices overheated after 2006 and later entered a period of “correction” after 2012; Using VECM model, Suljoti finds HPs strongly linked to fin leverage and exch rate, but not so much with lending rates; Other studies focusing on HPI in Tirana find that most explanatory variables are consistent with hedonic pricing theory (Kraja et al), there is LR link with mortgage loans, LT lending rates and CCI (Marku et al) or remittances (Lleshaj & Korbi). Yet, others conclude it is difficult to find theoretically-relevant relationship with economic indicators (Koprencka et al) or their impact seems time-varying, esp. w.r.t. mortgage rates (Halili).

Related work (2)

- As such, forecasting HPs remains a challenging task due to the complex interactions among the economic, financial, and demographic indicators.
- Recent improvements in Machine-Learning (ML) methods have shifted attention of econometricians to new, promising techniques for macroeconomic forecasting.
- Several studies have applied ML models to predict HPs in advanced and developing economies [e.g., Mora-Garcia et al.; Wang & Li; Park & Bae; Banerjee et al.; Kok et al.; Ceh et al.; Fan et al.; Ho et al.; Chatzidis; Alfaro-Navarro et al.; Hong; Hacıevliyagil et al.].
- Their results outperformed traditional time series models by achieving better forecast accuracy.
- To the best of our knowledge, no research for Albania has yet taken advantage of artificial neural network (ANN) tools. Hence, another motivation for us to enrich the modest empirical literature for housing market in Albania with innovative and encouraging techniques that can deal with theoretical and statistical drawbacks, as well as data measurement challenges.

Modeling framework

- HPs are usu. modelled in terms of various housing demand and supply variables;
- On demand-side, typical key factors include expected HP, income, housing loans rate, fin. wealth, demographic and labor market factors, expected return on housing, and other demand shifters such as location, state of house, or institutional factors;
- On supply-side, HPs are usu. taken to depend positively on profitability, which can in turn depend positively on HPs and negatively on real cost of construction.
- Assuming that housing mkt is in equilibrium (with demand equal to supply at all times), we express HPs as a reduced-form model with factors relevant to housing market in Albania's urban area:
  - $RHP = f\,(RHP_{t-p}, YPC_{t-p}, CRE_{t-p}, FIRE_{t-p}, REN_{t-p}, RI2Y_{t-p}, RCC_{t-p}, POPCM_{t-p})$

  where RHP = HPI, CPI-deflated, in lek, seas. adj.; YPC = real GDP per capita; CRE = bank lending for real estate (annual change in stock, as % of GDP); FIRE = Real Estate sales to non-residents (4-quarter cumulative sales in % of GDP); REN=house rental, CPI-deflated; RI2Y = 2Y gov. bond rate, CPI-deflated; RCC = Construction costs, CPI-deflated, SA; POPCM = Ratio of urban population change to new house building permits.

Methodology: Neural networks

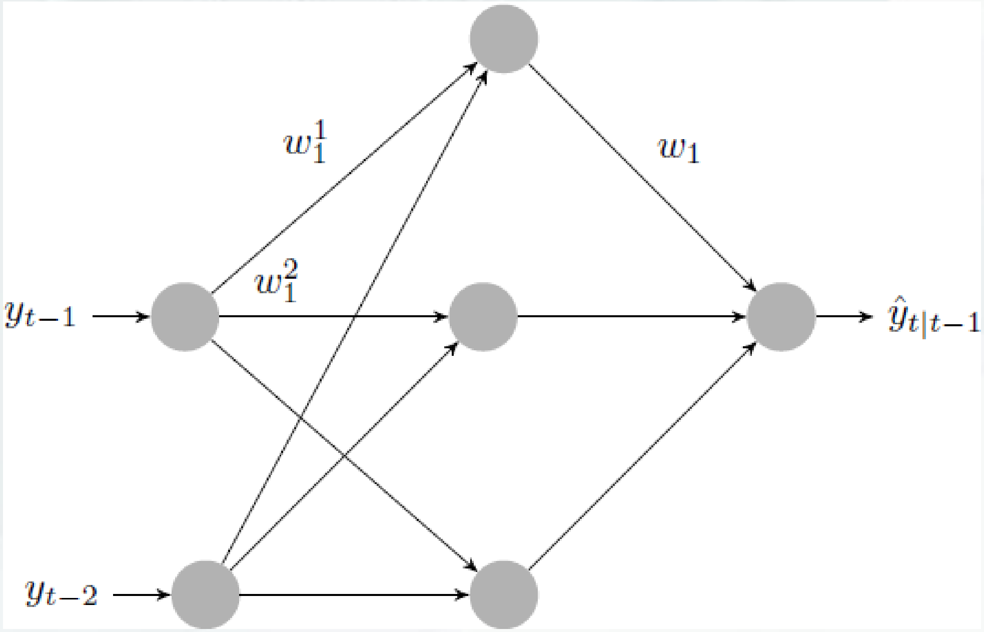
- Dorsey (2000) argues that "ANN can provide a completely flexible mapping that can approximate highly nonlinear functions to any degree of desired accuracy as long as a sufficient number of hidden nodes are included."

- A simple fully-connected neural network can be written as:

$$\hat{y}_{t|t-1} = b + \sum_{n=1}^{N} w_n \cdot \sigma\left(b^n + \sum_{\tau=1}^{P} w_\tau^n y_{t-\tau}\right)$$

where
σ(·) is a non-linear activation function,
b is a bias of the output and
b^n is a bias of the hidden nodes *n*,
ω^n is a weight from the hidden node *n* to the output,
ω_τ^n is a weight from the lag τ to the hidden node *n*.

A simple NN model (biases are ignored)



Methodology: Recurrent Neural Networks

- An extended form of feed-fwd networks is the recurrent neural network, which allows network activations to feedback as inputs to units within same or preceding layer(s).

- Thus, difference btw FF-NN and RNN comes from its recurrent nature: RNN consists of NN that is repeated... prediction is computed sequentially after each step... model's output (prediction) from previous period is used as additional input to model at time *t*, along with current inputs.

- In RNNs: i) more recent lags might be more important for final prediction (in contrast to NN that treats all lags equally); ii) network remembers info about distant input lags, e.g. in text analysis, first few words inform RNN if sentiment is positive or negative; iii) input lags, *p*, do not have to be of the same length.

Methodology: LSTM Neural Network

- Yet, basic RNNs suffer from “short-term memory” problem: they utilize data from recent history to forecast, but if a sequence is long enough, it cannot carry relevant info from earlier periods to later ones.

- Long Short-Term Memory networks (LSTMs) mitigate the “short-term memory” problem by introducing gates that enable the preservation of relevant “long-term memory” and combining it with most recent data (Hochreiter & Schmidhuber, 1997).

- As such, LSTM has the ability to «memorize» or «forget» information thru the use of special memory cell state, carefully regulated by three gates: input gate, forget gate and output gate, which together regulate the flow of information into and out of the memory cell state.

- Their capability to model complex systems even without precise knowledge of underlying rules makes LSTM network a suitable tool to address obstacles faced in analyzing and forecasting HPs in Albania, stemming from e.g. absence of a consensus model, disputes over included variables, and data measurement challenges.

Methodology: Neural Network Estimation

- Parameters of NNs are estimated by minimizing loss function btw fitted and actual values in in-sample period.
- Literature on NN usu. applies (stochastic) gradient descent method of optimization, where parameters are updated iteratively at a learning rate which determines the size of the step towards optimization.
- We employ Adam optimization algorithm (extension of gradient descent) that features an adaptive learning rate.
- Another important concept in training with machine learning methods is the epoch, defined as no. of passes thru the algorithm of all observations in the training set. We initially try 600 epochs.
- To help tackle overfitting, three methods are employed:

i. *Weight regularization*. This penalizes large values of network weights. Common practice is to transform input variables to have same scale.

ii. *Dropout regularization*. Drop some neurons during training, or assign a probability so that to temporarily ignored them from calculations. We use latter technique, setting Dropout Rate = 0.2.

iii. *Early Stopping regularization*. After trying 600 epochs, we screen out model loss values during training and validation samples and adjust no. of epochs if there are clear signs of under-, or over-fitting.

LSTM Model: Selection of Hyperparameters

- The process of establishing a neural network's architecture is similar to curve fitting, with no. of input lags, hidden layers and neurons determining model's complexity. Empirical practice suggests that NN are able to handle estimations with much larger no. of parameters than observations.

- Yet, using just a few lags, layers or nodes may lead to poor fit and prediction, while using too many of them may result in overfitting.

- We let vary the number of input lags (p), hidden layers (h) and nodes (n) in order to choose the combinations that are more appropriate to our data. Different candidate structures are tested:
  - $p = \{2,4,8,16\}$;
  - $h = \{1,2,3,4\}$;
  - $n = \{16,32,64,128,256,512,1024\}$.

- Keeping the no. of nodes equal in each hidden layer, the above candidates result in 112 NN structures.

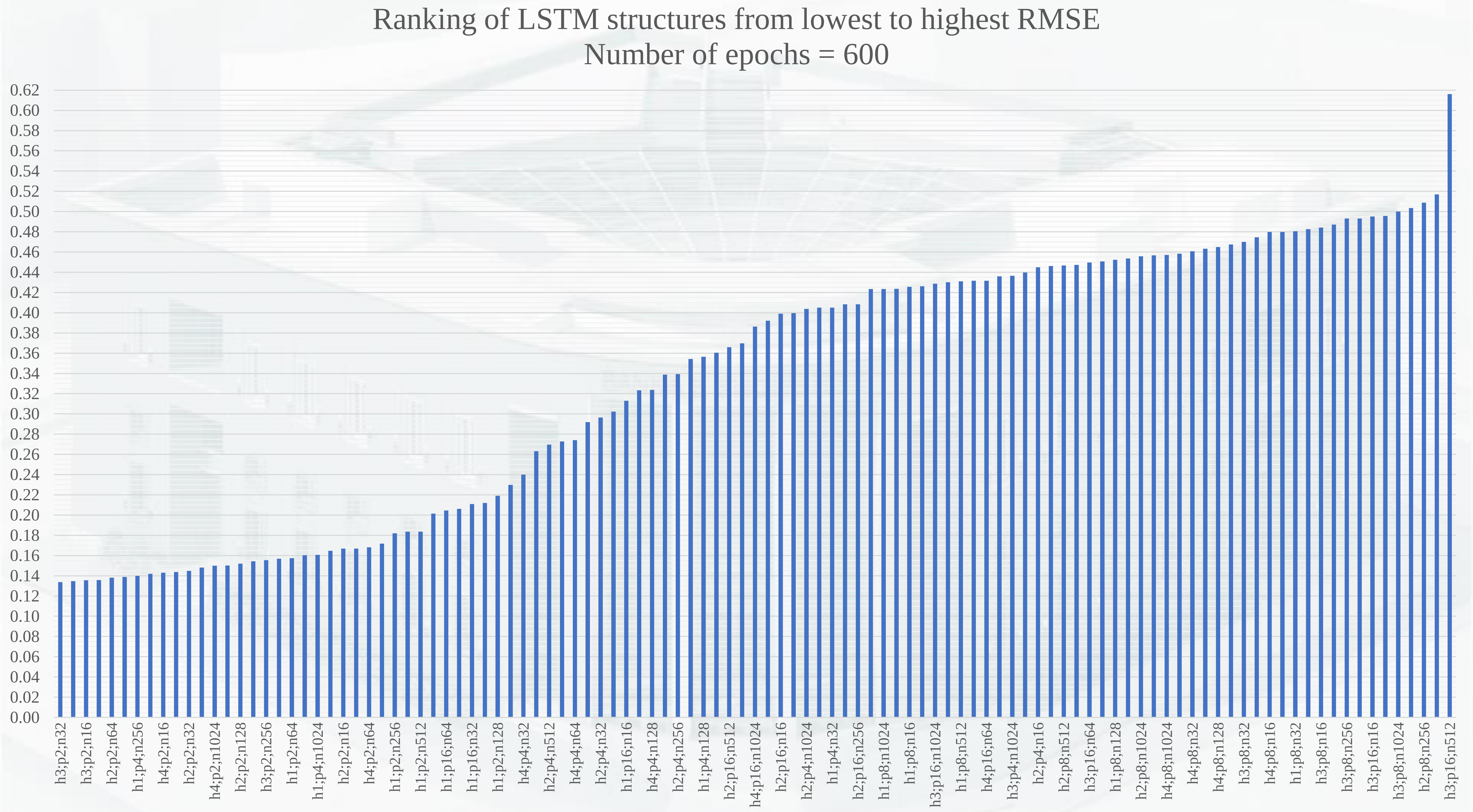
LSTM Modeling Strategy

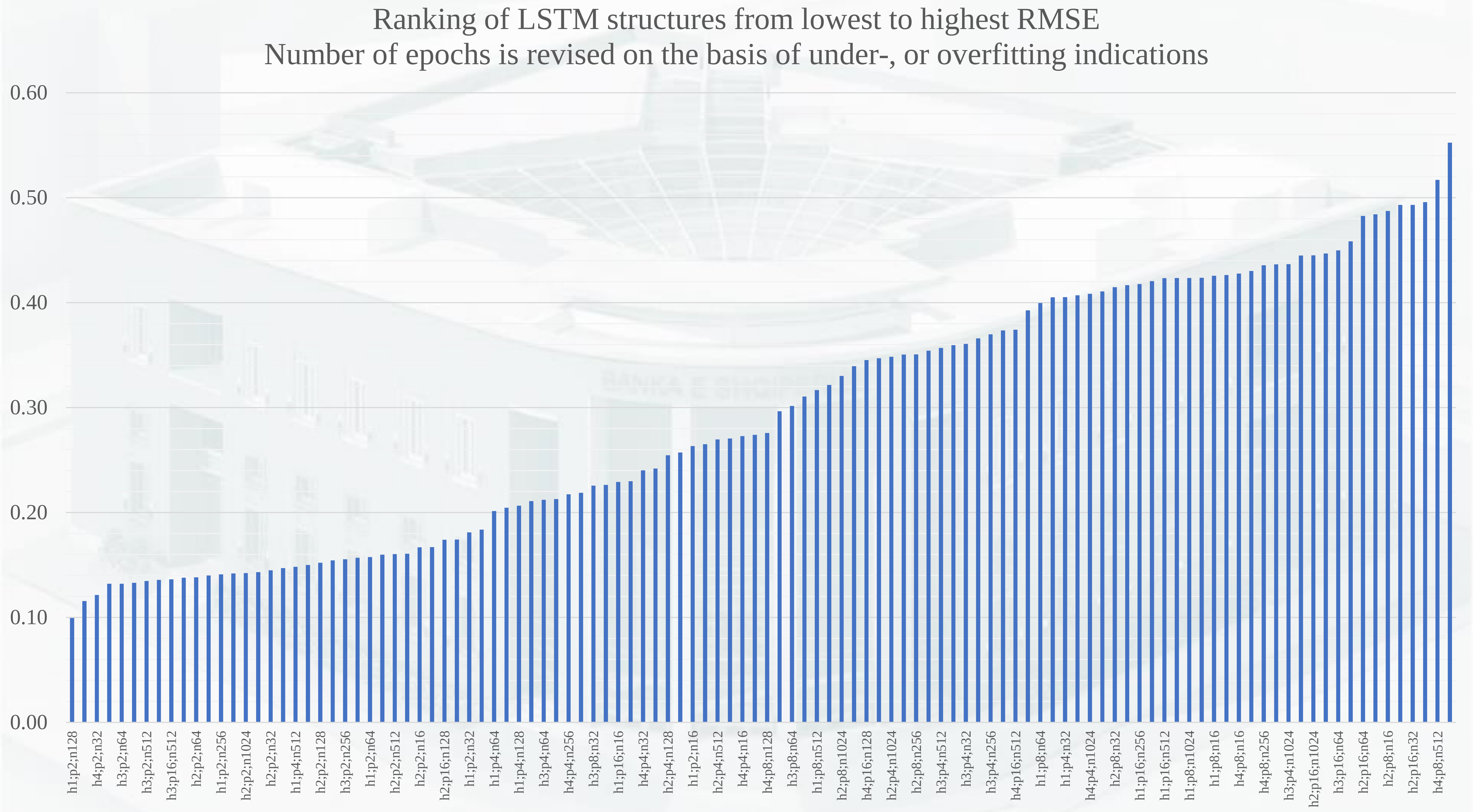
- All input variables enter the model in levels;
- Selection of hyperparameters is implemented by choosing the set of hyperparameters that yields lowest out-of-sample error (MSE) over a validation sample.
- More specifically, application is as follows: a) split data into three consecutive samples: training, validation, and (out-of-sample) test set; b) estimate each LSTM specification over training sample (1998q1-2012q4) and predict over the validation sample (2013q1-2016q4); c) repeat this process for 600 epochs (if there are signs of overfitting, stop earlier at the point where MSE curve is decreasing for training period but is not increasing for the validation set;
- Finally, we evaluate forecast ability during the out-of-sample period 2017q1-2023q2, and rank accordingly from best to worse performing networks.
- RHP predictions are evaluated over a horizon of 2 years ahead, which largely coincides with banking sector stress-testing period at BoA.

Number of trials for:

- $h_i = 28$;
- $p_i = 28$;
- $n_i = 16$.

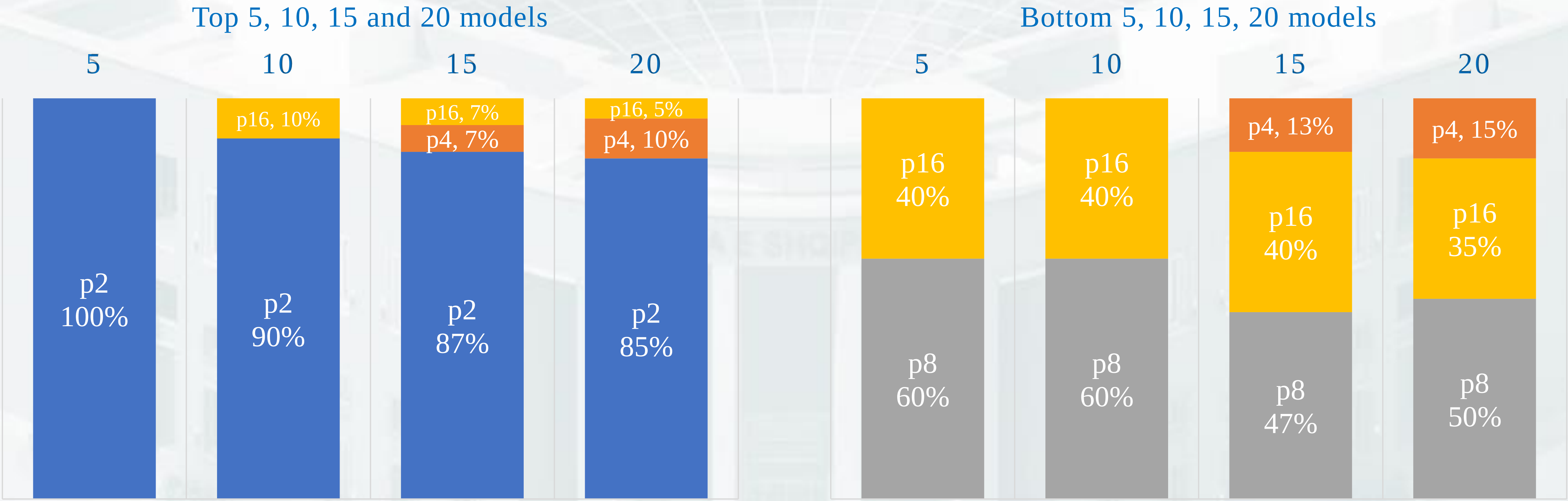
Table. Summary List of All LSTM Network Specifications							
Legend: h = hidden layers; p = lags; n = nodes in h.							
Model No.	NN Structure	Model No.	NN Structure	Model No.	NN Structure	Model No.	NN Structure
1	h1;p2;n16	29	h2;p2;n16	57	h3;p2;n16	85	h4;p2;n16
2	h1;p2;n32	30	h2;p2;n32	58	h3;p2;n32	86	h4;p2;n32
3	h1;p2;n64	31	h2;p2;n64	59	h3;p2;n64	87	h4;p2;n64
4	h1;p2;n128	32	h2;p2;n128	60	h3;p2;n128	88	h4;p2;n128
5	h1;p2;n256	33	h2;p2;n256	61	h3;p2;n256	89	h4;p2;n256
6	h1;p2;n512	34	h2;p2;n512	62	h3;p2;n512	90	h4;p2;n512
7	h1;p2;n1024	35	h2;p2;n1024	63	h3;p2;n1024	91	h4;p2;n1024
8	h1;p4;n16	36	h2;p4;n16	64	h3;p4;n16	92	h4;p4;n16
9	h1;p4;n32	37	h2;p4;n32	65	h3;p4;n32	93	h4;p4;n32
10	h1;p4;n64	38	h2;p4;n64	66	h3;p4;n64	94	h4;p4;n64
11	h1;p4;n128	39	h2;p4;n128	67	h3;p4;n128	95	h4;p4;n128
12	h1;p4;n256	40	h2;p4;n256	68	h3;p4;n256	96	h4;p4;n256
13	h1;p4;n512	41	h2;p4;n512	69	h3;p4;n512	97	h4;p4;n512
14	h1;p4;n1024	42	h2;p4;n1024	70	h3;p4;n1024	98	h4;p4;n1024
15	h1;p8;n16	43	h2;p8;n16	71	h3;p8;n16	99	h4;p8;n16
16	h1;p8;n32	44	h2;p8;n32	72	h3;p8;n32	100	h4;p8;n32
17	h1;p8;n64	45	h2;p8;n64	73	h3;p8;n64	101	h4;p8;n64
18	h1;p8;n128	46	h2;p8;n128	74	h3;p8;n128	102	h4;p8;n128
19	h1;p8;n256	47	h2;p8;n256	75	h3;p8;n256	103	h4;p8;n256
20	h1;p8;n512	48	h2;p8;n512	76	h3;p8;n512	104	h4;p8;n512
21	h1;p8;n1024	49	h2;p8;n1024	77	h3;p8;n1024	105	h4;p8;n1024
22	h1;p16;n16	50	h2;p16;n16	78	h3;p16;n16	106	h4;p16;n16
23	h1;p16;n32	51	h2;p16;n32	79	h3;p16;n32	107	h4;p16;n32
24	h1;p16;n64	52	h2;p16;n64	80	h3;p16;n64	108	h4;p16;n64
25	h1;p16;n128	53	h2;p16;n128	81	h3;p16;n128	109	h4;p16;n128
26	h1;p16;n256	54	h2;p16;n256	82	h3;p16;n256	110	h4;p16;n256
27	h1;p16;n512	55	h2;p16;n512	83	h3;p16;n512	111	h4;p16;n512
28	h1;p16;n1024	56	h2;p16;n1024	84	h3;p16;n1024	112	h4;p16;n1024


Ranking of LSTM structures from lowest to highest RMSE
Number of epochs = 600
0.62
0.60
0.58
0.56
0.54
0.52
0.50
0.48
0.46
0.44
0.42
0.40
0.38
0.36
0.34
0.32
0.30
0.28
0.26
0.24
0.22
0.20
0.18
0.16
0.14
0.12
0.10
0.08
0.06
0.04
0.02
0.00
h3;p2;n32
h3;p2;n16
h2;p2;n64
h1;p4;n256
h4;p2;n16
h2;p2;n32
h4;p2;n1024
h2;p2;n128
h3;p2;n256
h1;p2;n64
h1;p4;n1024
h2;p2;n16
h4;p2;n64
h1;p2;n256
h1;p2;n512
h1;p16;n64
h1;p16;n32
h1;p2;n128
h4;p4;n32
h2;p4;n512
h4;p4;n64
h2;p4;n32
h1;p16;n16
h4;p4;n128
h2;p4;n256
h1;p4;n128
h2;p16;n512
h4;p16;n1024
h2;p16;n16
h2;p4;n1024
h1;p4;n32
h2;p16;n256
h1;p8;n1024
h1;p8;n16
h3;p16;n1024
h1;p8;n512
h4;p16;n64
h3;p4;n1024
h2;p4;n16
h2;p8;n512
h3;p16;n64
h1;p8;n128
h2;p8;n1024
h4;p8;n1024
h4;p8;n32
h4;p8;n128
h3;p8;n32
h4;p8;n16
h1;p8;n32
h3;p8;n16
h3;p8;n256
h3;p16;n16
h3;p8;n1024
h2;p8;n256
h3;p16;n512

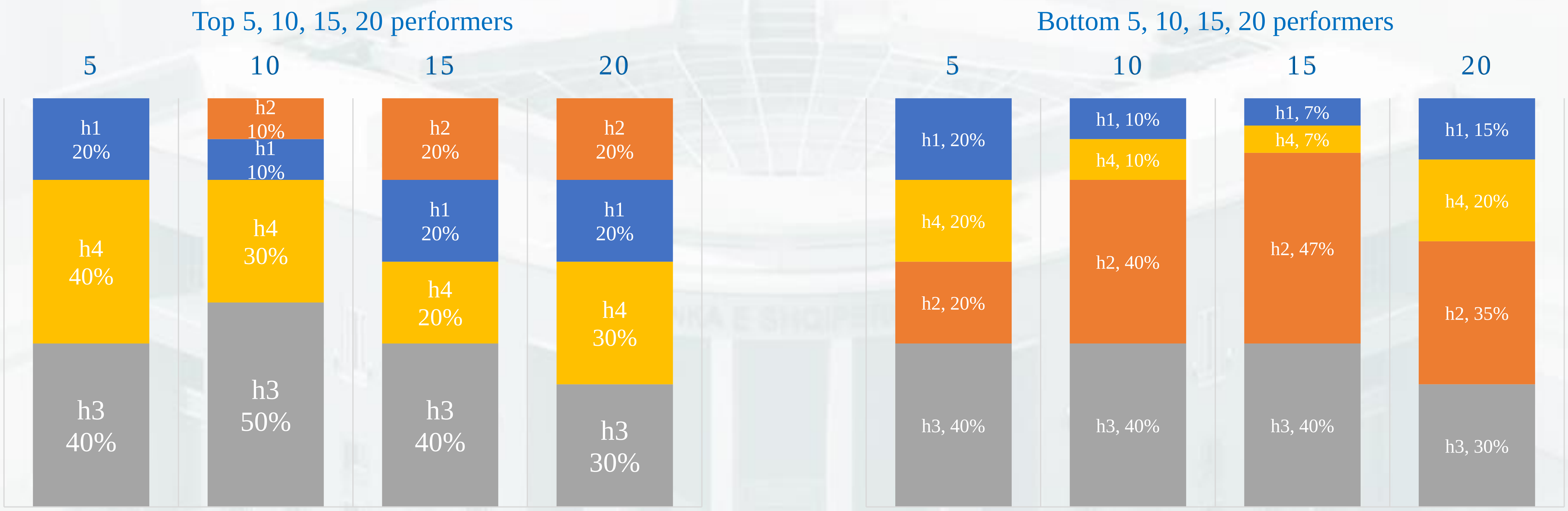


Ranking of LSTM structures from lowest to highest RMSE
Number of epochs is revised on the basis of under-, or overfitting indications
0.60
0.50
0.40
0.30
0.20
0.10
0.00
h1;p2;n128
h4;p2;n32
h3;p2;n64
h3;p2;n512
h3;p16;n512
h2;p2;n64
h1;p2;n256
h2;p2;n1024
h2;p2;n32
h1;p4;n512
h2;p2;n128
h3;p2;n256
h1;p2;n64
h2;p2;n512
h2;p2;n16
h2;p16;n128
h1;p2;n32
h1;p4;n64
h1;p4;n128
h3;p4;n64
h4;p4;n256
h3;p8;n32
h1;p16;n16
h4;p4;n32
h2;p4;n128
h1;p2;n16
h2;p4;n512
h4;p4;n16
h4;p8;n128
h3;p8;n64
h1;p8;n512
h2;p8;n1024
h4;p16;n128
h2;p4;n1024
h2;p8;n256
h3;p4;n512
h3;p4;n32
h3;p4;n256
h4;p16;n512
h1;p8;n64
h1;p4;n32
h4;p4;n1024
h2;p8;n32
h1;p16;n256
h1;p16;n512
h1;p8;n1024
h1;p8;n16
h4;p8;n16
h4;p8;n256
h3;p4;n1024
h2;p16;n1024
h3;p16;n64
h2;p16;n64
h2;p8;n16
h2;p16;n32
h4;p8;n512

Model Selection: Distribution of Lags (p) in Best & Worse NN Perfomers (in %)



Model Selection: Distribution of Hidden Layers (h) in Best & Worse NN Perfomers (in %)



Model Selection: Distribution of Nodes (n) in Best & Worse NN Perfomers (in %)

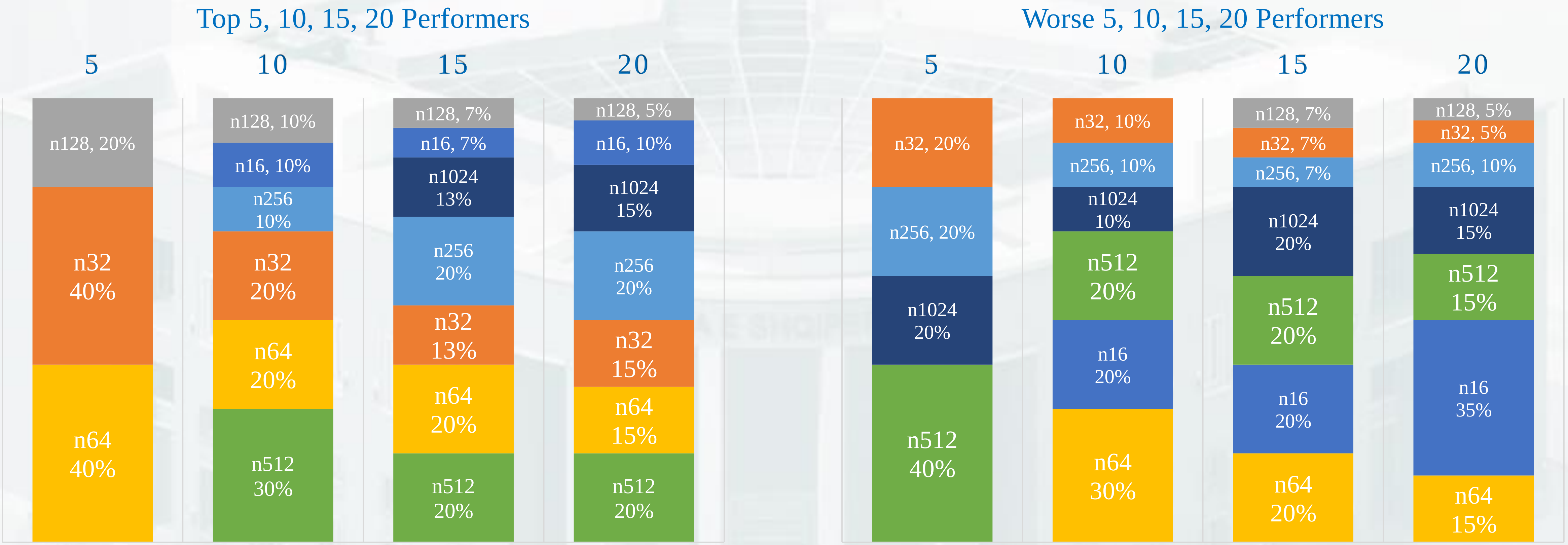


Table. Candidate and Optimal Values for Hyperparameters		
	Candidates	Optimal
Lags, p	2,4,8,16	2
Hidden layers, h	1,2,3,4	3
Nodes, n	16,32,64,128,256,512,1024	32,64
Parameters		~67,600
Epochs	600, Revised	Revised*)

*) No. of epochs needed to be revised for about half of the estimated models (57/112).

Table. Best LSTM perfomers in relation to an autoregressive AR forecast

	RMSE	Bias#)	Variance#)	Epoch #	Total Params
Benchmark, AR(1)*)	1.00	0.39	0.16		
LSTM(h1; p2; n128)	0.81	0.06	0.64	123	67,592
LSTM(h3; p2; n32)	0.95	0.12	0.70	167	21,256
LSTM(h4; p2; n32)	1.02	0.20	0.68	121	29,576
LSTM(h4; p2; n64)	1.03	0.02	0.49	179	116,488
LSTM(h3; p2; n64)	1.09	0.24	0.49	173	83,464

Table notes. LSTM legend: h = hidden layers; p = lags; n = nodes in h.

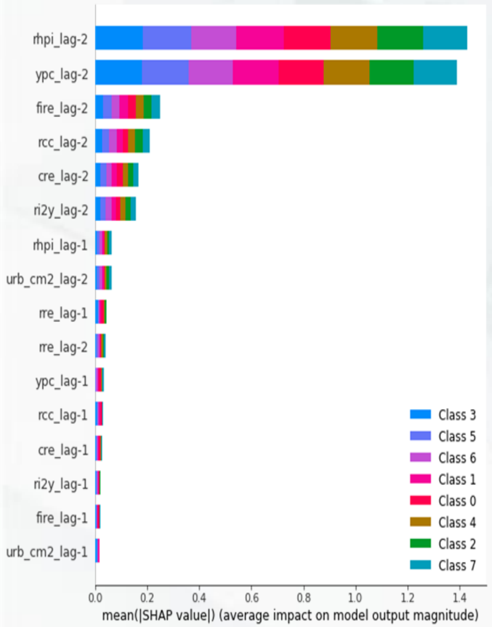
#) Bias and Variance proportions of Mean Squared Forecast Errors.

*) The benchmark forecast is derived from an autoregressive (AR) model of order p=1. Stationarity tests suggested that RHP is integrated of order I(1), thus entering the AR model in first difference. AR is estimated by least squares and p is selected in accordance with Bayesian information criterion. Benchmark forecast RMSE=12.55; it refers to a horizon of 8 quarters ahead, same with LSTM models.

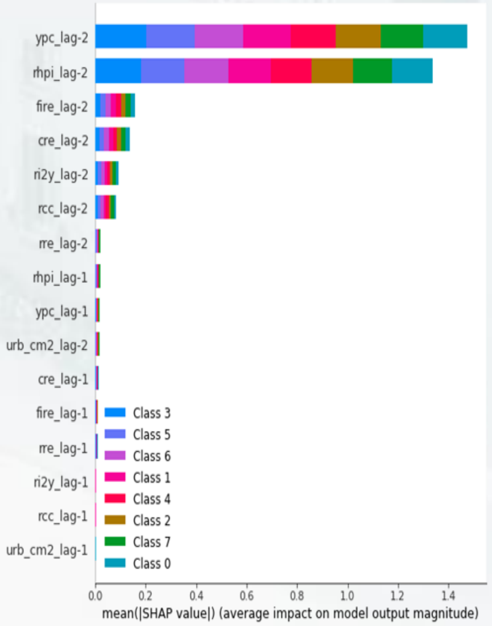
Understanding the Drivers of Recent Surge in House Prices

- In search of factors behind recent run-up in HPs, we calculate Shapley values from top LSTM performers over a forecast horizon of 2Y during the out-of-sample period 2017q1-2023q2;
- Sorting the impact on model prediction (SHAP value) from most to less important suggests that past HP performance a.w.a. per capita income are two essential variables in explaining recent HP rise… other beneficial indicators could be foreign purchases, bank lending, construction costs, and gov. bond rates;
- Contrary to many perceptions, house renting and urban population growth (in relation to permissions for new house building area) are found with only little influence;
- Interestingly, second lag is shown to carry decisive information for most indicators, while first lag shows little power to determine the outcome.

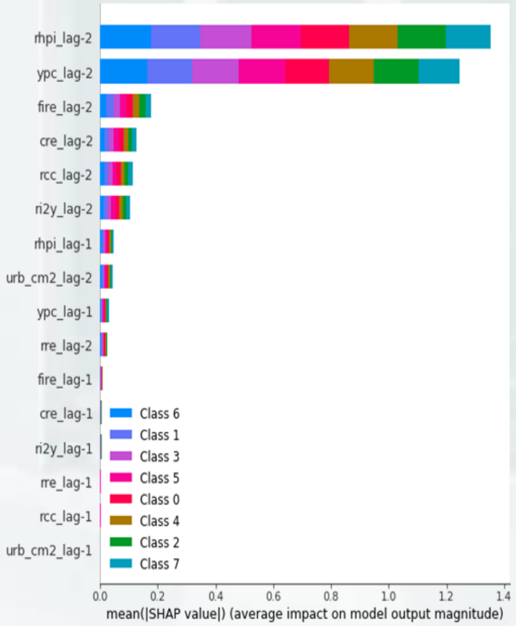
LSTM(p=2;h=1;n=128)



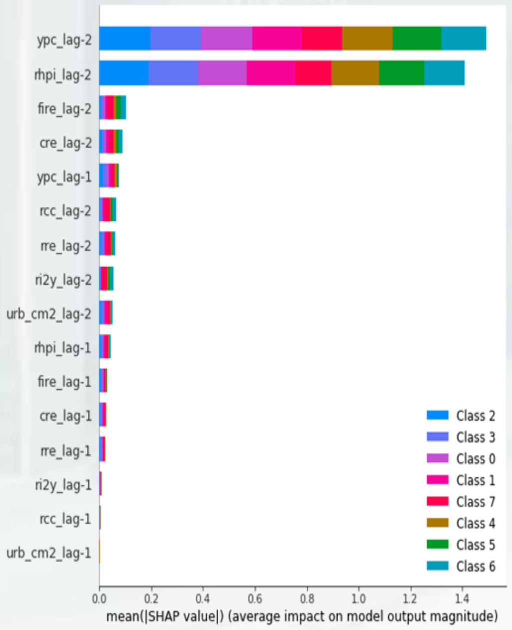
LSTM(p=2;h=3;n=32)



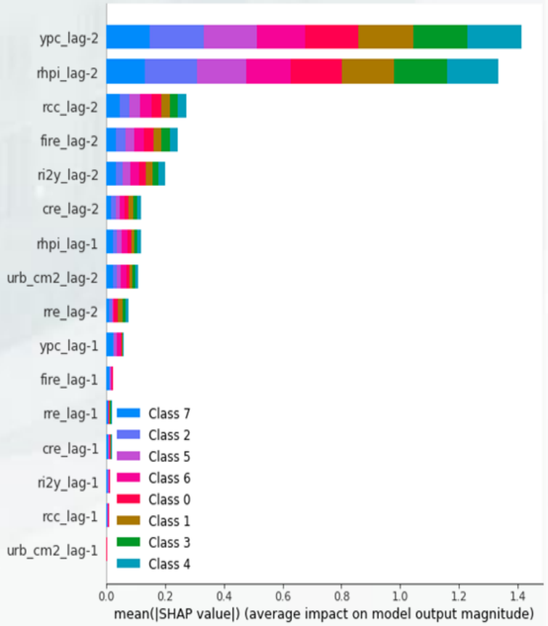
LSTM(p=2;h=4;n=32)



LSTM(p=2;h=4;n=64)



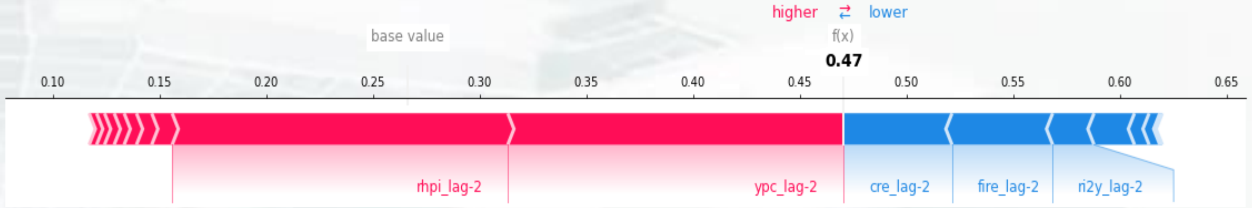
LSTM(p=2;h=3;n=64)



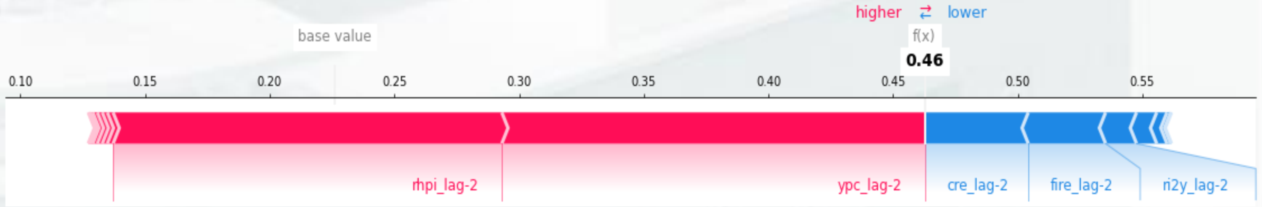
Understanding the Drivers of Recent Surge in House Prices

- "Force plotting" the results enables us to look deeper into the impact of each variable in pushing predicted value farther or closer to average contributions (base value).
- It seems that the two highest contributors – past HPs and income – have put upward pressure on future HPs.
- On the other hand, bank credit, foreign purchases, and gov bond rates have contributed on downward side to HP growth;

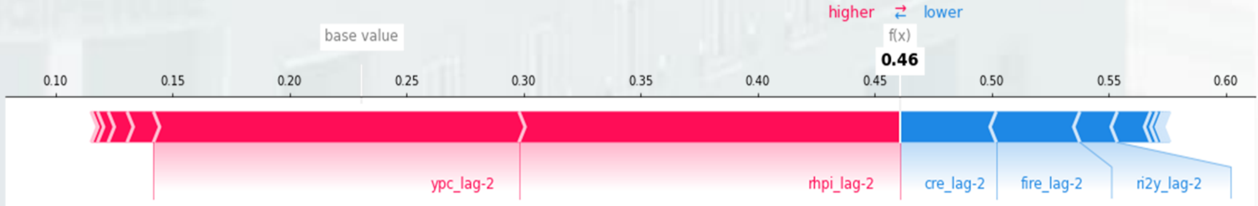
NN(p=2;h=1;n=128)



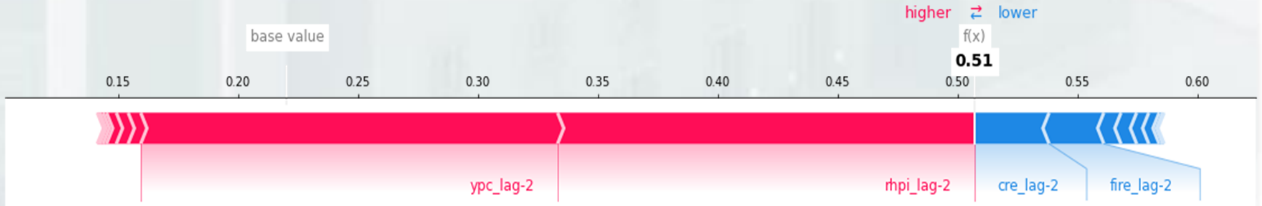
NN(p=2;h=3;n=32)



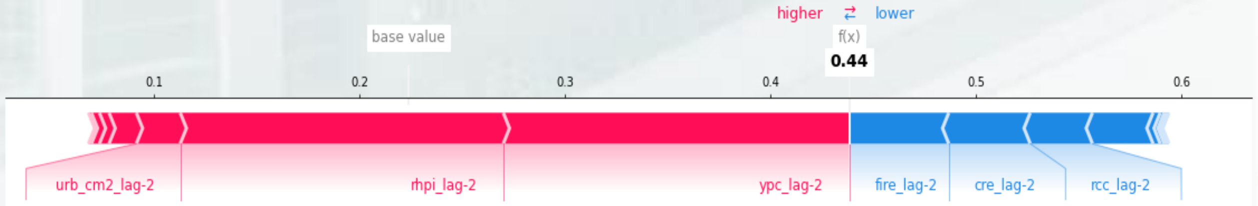
NN(p=2;h=4;n=32)



NN(p=2;h=4;n=64)



NN(p=2;h=3;n=64)



Concluding remarks

- Although HPs appear to be generally in line with its “sustainable” levels as derived from cointegration methods (Vika, 2023), fear about a potential price correction necessitates a rigorous monitoring and understanding of the key factors influencing the risks of housing price decline.
- This study attempts to provide a granular investigation of HP developments;
- It delves into economic, financial and demographic determinants of HPs and tries to draw policy implications.
- Our prediction-based analysis demonstrates important role for fundamental indicators in predicting HPI in Albania.
- Their information content improves upon AR model forecasts in the mid-term horizon of two years, in line with most relevant factors identified in Vika & Vika (2024).
- Albanian financial sector currently appears relatively strong and resilient;
- Yet, gov. institutions should be attentive to residential market trends and its related economic fundamentals in order to ensure the stability of both housing and finance.

References

- Duca, J. V.; Muellbauer, J.; Murphy, A. (2021). What drives house prices cycles? International experience and policy issues. *Journal of Economic Literature* 59 (3): 773-864.
- Tsatsaronis, K.; Zhu, H. (2004). What drives housing price dynamics: cross-country evidence. *BIS Quarterly Review*, March.
- Egert, B.; Mihaljek, D. (2007). Determinants of house prices in Central and Eastern Europe. *Comparative Economic Studies*, Vol. 49, pp. 367-388.
- Agnello, L.; Schuknecht, L. (2011). Booms and busts in housing markets: determinants and implications. *Journal of Housing Economics*, Vol. 20, pp. 171-190.
- Cerruti, E.; Dagher, J.; Dell'Ariccia, G. (2015). Housing finance and real-estate booms: a cross-country perspective. *IMF Discussion Note* No. 15/12.
- Yzeiraj, Endrit (2016). House prices in Albania: deviations from the equilibrium? *Bank of Albania working paper* 20 (59) 2016.
- Suljoti, Erjona (2017). The implications of financial conditions in the housing market – a cointegrated analysis. *Bank of Albania Working Paper* 27 (66) 2017.
- Kraja, I.; Sejdini, M.; Sejdini, A. (2018). Tregu i banesave në Shqipëri: regresioni hedonik. *INSTAT Revista e Statistikave dhe Analizave Social Ekonomike* Nr. 1/2018. Available online: https://www.instat.gov.al/media/4268/4-the-housing-market-in-albania.pdf (accessed on 30 April 2023).
- Marku, E.; Lleshaj, Ll.; Lleshaj, A. (2020). VECM analysis of house price index. Case of Tirana. *European Journal of Marketing and Economics*, Vol. 3, Issue 1, January-June 2020.
- Lleshaj, Ll.; Korbi, A. (2019). VAR model for short-run endogenous factors in real estate market: case of Albania. *American Research Journal Of Humanities Social Science*, Vol. 02, Issue 10, pp. 29-36, October 2019.
- Koprencka, L. K.; Bundo, Sh.; Qarri, A. (2014). Factorial analysis of Albanian housing market. Acta Universitatis Danubius, *Economica*, Vol 10, No 4 (2014).
- Halili, F. (2022). The Impact of Macroeconomic Factors on the Change of Residential Prices – The Case Study of Albania. *International Journal of Applied Research in Management and Economics*, 5(4): 29-44.
- Mora-Garcia, R.-T.; Cespedes-Lopez, M.-F.; Perez-Sanchez, V.R. (2022). Housing Price Prediction Using Machine Learning Algorithms in COVID-19 Times. *Land* 2022, 11, 2100.
- Wang, D.; Li, V.J. (2019). Mass appraisal models of real estate in the 21st century: a systematic literature review. *Sustainability* 2019, 11 7006.
- Park, B.; Bae, J.K. (2015). Using machine learning algorithms for housing price prediction: the case of Fairfax County, Virginia housing data. *Expert Syst. Appl.* 2015, 42, 2928-2934.
- Banerjee, D.; Dutta, S. (2017). Predicting the housing price direction using machine learning techniques. Proceedings of the 2017 IEEE International Conference on Power, Control, Signals and Instrumentation Engineering (ICPCSI), Chennai, India, 21–22 September 2017; pp. 2998–3000.
- Kok, N.; Koponen, E.-L.; Martínez-Barbosa, C.A. (2017). Big Data in Real Estate? From Manual Appraisal to Automated Valuation. *J. Portf. Manag.* 2017, 43, 202–211.
- Ceh, M.; Kilibarda, M.; Lisec, A.; Bajat, B. (2018). Estimating the Performance of Random Forest versus Multiple Regression for Predicting Prices of the Apartments. *ISPRS Int. J. Geo-Inf.* 2018, 7, 168.
- Fan, C.; Cui, Z.; Zhong, X. (2018). House Prices Prediction with Machine Learning Algorithms. Proceedings of the 2018 10th International Conference on Machine Learning and Computing, Macau, China, 26–28 February 2018; pp. 6–10.
- Ho, W.K.O.; Tang, B.-S.; Wong, S.W. (2021). Predicting property prices with machine learning algorithms. *J. Prop. Res.* 2021, 38, 48–70.
- Chatzidis, I.V. (2019). Prediction of Housing Prices based on Spatial & Social Parameters using Regression & Deep Learning Methods. Master's Thesis, University of Thessaloniki, Thessaloniki, Greece, 2019.
- Alfaro-Navarro, J.-L.; Cano, E.L.; Alfaro-Cortés, E.; García, N.; Gámez, M.; Larraz, B. (2020). A Fully Automated Adjustment of Ensemble Methods in Machine Learning for Modeling Complex Real Estate Systems. *Complexity* 2020, 2020, 5287263.
- Hong, J. (2020). An Application of XGBoost, LightGBM, CatBoost Algorithms on House Price Appraisal System. *Hous. Financ. Res.* 2020, 4, 33–64.
- Hacıevliyagil, N.; Drachal, K.; Eksi, I.H. (2022). Predicting House Prices Using DMA Method: Evidence from Turkey. *Economies* 10: 64. Available online: https://doi.org/10.3390/economies10030064 .
- Gedeshi, I. (2002). The role of remittances from Albanian emigrants and their influence in the country's economy. In Kotios and Petrakos (eds.) Restructuring and Development in Southeastern Europe, University of Thessaly Press, SEED, 2002.
- Ghysels, E.; Marcellino, M. (2018). Applied Economic Forecasting Using Time Series Methods. Book published by Oxford University Press, 2018.
- Nair, V.; Hinton, G. E. (2010). Rectified linear units improve restricted Boltzmann machines. Proceedings of the 27th international conference on machine learning (ICML-10), pp. 807-814.
- Ruder, S. (2017). An overview of gradient descent optimization algorithms. arXiv:1609.04747v2 [cs.LG] 15 Jun 2017.
- Vika, I. (2023). Whither house prices in Albania. *Bank of Albania*, Unpublished research document, May, 2023.
- Vika, B.; Vika, I (2024). Forecasting house prices in Albania with the deep learning LSTM network. Article forthcoming in Journal of Economics and Business Issues, in Ferbruaray, 2024.