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BRUNO TAG SALES

IS CLIMATE CHANGE RELEVANT FOR THE REAL ESTATE MARKET? A MACHINE LEARNING APPROACH

Porto Alegre
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Work presented to the Undergraduate Program in Economics at the Faculdade de Ciências Econômicas of UFRGS, as a partial requirement for the Bachelor's degree in Economics.

Advisor: Prof. Dr. Hudson da Silva Torrent

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To my unwavering parents, who not only refrained from doubting me but also never faltered in their enduring support.

ABSTRACT

Climate change, a pressing global challenge, has wide-ranging implications for various aspects of our lives, including housing prices. This paper delves into the intricate relationship between climate change and housing prices in the United States. Using a comprehensive dataset and employing machine learning techniques, we analyze the relevance of climate variables for housing prices. Our findings suggest that climate change variables can influence housing prices, particularly in the short term, but the relationship varies by region. Understanding these dynamics is crucial for informed decision-making, sustainable urban development and climate risk mitigation.

Keywords: Climate finance. Housing market. Machine learning. Predictive modeling

RESUMO

As mudanças climáticas, um desafio global urgente, têm amplas implicações para vários aspectos de nossas vidas, incluindo os preços dos imóveis. Este estudo investiga a relação entre as mudanças climáticas e os preços dos imóveis nos Estados Unidos. Utilizando um conjunto de dados abrangente e empregando técnicas de machine learning, analisamos a relevância das variáveis climáticas para os preços dos imóveis. Nossos resultados sugerem que as variáveis das mudanças climáticas podem influenciar os preços dos imóveis, especialmente a curto prazo, mas a relação varia por região. Compreender essas dinâmicas é crucial para a tomada de decisões informadas, desenvolvimento urbano sustentável e mitigação dos riscos climáticos.

Palavras-chave: Finanças climáticas. Mercado imobiliário. Machine learning. Modelagem preditiva

CONTENTS

1 INTRODUCTION

Climate change significantly impacts various aspects of life, including extreme weather events and rising sea levels. It particularly affects housing prices by altering homebuyer preferences and increasing property damage from severe weather, thereby influencing economic decisions in the face of climate change (IPCC, 2021; Emanuel, 2017; Kousky, 2014).

The Earth's average surface temperature has risen by 1.1°C since the late 19th century due to human activities, affecting health, food systems, and water availability (IPCC, 2021; Trenberth et al., 2014). This warming contributes to economic challenges across infrastructure, agriculture, and energy sectors (Hsiang et al., 2017), underscoring the need for urgent global action.

In the housing sector, climate risks are increasingly factored into property values, with demand shifting based on an area's susceptibility to climate change (Heinen; Khadan; Strobl, 2019; Kim et al. 2022). This shift results in higher insurance premiums and affects housing affordability, especially in disaster-prone regions (Tucker, 1997).

The global real estate market, worth approximately $326.7 trillion in 2020, plays a critical role in the economy, with significant investments in real estate assets and mortgage-backed securities indicating its economic influence (Savills World Research, 2020; NAREIT, 2021; Federal Reserve, 2020). The housing market's health is a vital economic indicator, reflecting overall economic conditions and consumer confidence (U.S. Bureau of Economic Analysis, 2021; Case and Shiller, 2003).

This research delves into the intricate relationship between climate change and housing prices within the United States, drawing upon prior studies emphasizing climate-related variables such as temperature, precipitation, and humidity in shaping housing preferences and valuations (Sussman *et al*., 2014). Our objective is to comprehensively analyze this pivotal juncture, employing machine learning techniques to evaluate the impact of climate variables on housing returns. More specifically, the stepwise boosting was used, an iterative algorithm that by gradually incorporating variables seeks to balance complexity and overfitting risk.

This study incorporated decades of climate data, including temperature, precipitation, and drought. Additionally, it considered macroeconomic, financial, non-economic, non-financial factors, and measures of uncertainties to ensure a comprehensive analysis of the impact of climate change variables, while controlling for other factors. Multiple models were examined to evaluate the influence of climate change variables on predictive performance and to investigate their significance through selection rates within the boosting algorithm.

The significance of this research lies in its methodological and analytical approaches to understanding the relationship between climate change and the real estate market. The machine learning approach allows for a more sophisticated understanding of how various climate-related factors, such as temperature, precipitation, and drought, impact housing returns. The focus on specific climate variables and their direct impact on the housing market provides vital insights for stakeholders, including policymakers, real estate professionals, and the public. The empirical evidence presented in this study facilitates informed decision-making, promoting sustainable urban development and effective risk mitigation strategies in the face of climate change challenges. Furthermore, the examination of the economic implications of climate variables on housing markets enriches the understanding of broader economic indicators and consumer confidence, highlighting the critical role of the real estate sector in the global economy.

This paper is structured as follows: In Section 2, we discuss the impact of climate change on the real estate sector, drawing from multiple relevant studies. Section 3 outlines the empirical strategy used in this study, consisting of three sections. In Section 3.1, we present the data used, along with its descriptive statistics. Section 3.2 elaborates on the step-wise boosting algorithm. The forecasting procedures and model performance metrics employed are presented in Section 3.3. Sections 3.4 and 3.5 analyze the results pertaining to predictive accuracy and variable selection. Finally, Section 4 offers concluding thoughts and suggestions for future research.

2 CLIMATE CHANGE AND REAL ESTATE

The intricate interplay between climate change factors and the economy stands as a topic within the climate finance realm and its impact on various sectors have been subjects of extensive research and policy discussions. Several influential papers have offered crucial insights into this topic and this review seeks to offer a comprehensive amalgamation of extant research, accentuating the pertinence of climate change elements.

The Stern Review on the Economics of Climate Change (2006) delivered a foundational discovery, highlighting that the costs of inaction on climate change significantly outweigh those of mitigation. Acemoglu *et al*. (2012) contributed a key finding: environmental policies can direct technological change, leading to innovations that aid climate mitigation. Their work highlighted the importance of proactive policy measures in fostering sustainability.

Updating estimates of the social cost of carbon, Nordhaus (2017) reaffirmed its importance in guiding climate policy, emphasizing that accurate assessments of this parameter are vital for effective decision-making. A study by Burke, Hsiang, and Miguel (2015) revealed a nonlinear, negative impact of rising temperatures on economic production, suggesting that unchecked global warming could have severe global economic consequences.

Comprehensive reviews, such as Carleton and Hsiang's work (2016), have highlighted the extensive economic and social impacts of climate change. Their research underscores the urgency of mitigation and adaptation measures. Regarding the relationship between climate and economic development, Dell, Jones, and Olken (2014) noted its complexity and emphasized the need to understand how climate influences economic growth.

In the realm of uncertainty, Pindyck (2013) stressed that climate change economics models must acknowledge significant uncertainties, particularly regarding catastrophic events, which are crucial in policy formulation. In addressing the uncertainties inherent in climate change economics, Heal and Millner (2014) stressed the importance of considering risks and adaptation strategies in decision-making. Finally, Nordhaus (2018) revisited climate change modeling in the context of minimal climate policies, emphasizing the need to account for uncertain future climate outcomes.

Shifting our focus to the housing sector, climate change presents significant challenges. Numerous studies have highlighted vulnerabilities and potential consequences associated with a changing climate. The U.S. Global Change Research Program published a comprehensive assessment by Melilo *et al* (2014) outlining the impact of climate change on infrastructure in the United States. Key findings from this report emphasized increased risks of flooding, storm damage, and heat stress on roads, buildings, and industrial facilities, underscoring the urgent need for improved resilience measures, building codes, and land-use planning

The European housing sector also encounters climate-related challenges, as demonstrated by Domínguez-Amarillo, Samuel, *et al* (2019). In their research, they examine the performance of social housing in the face of temperature fluctuations. The study reveals that while ensuring comfort during cold weather is still a concern, the primary challenge lies in managing heat gain. This underscores the necessity for future intervention policies in urban centers in southern Europe.

Akbar and Kinnear (2010) studied the impact of climate change on coastal housing. This research, conducted in Queensland, Australia, examined the strain on coastal infrastructure and buildings due to changing climate conditions, including rising temperatures and extreme weather events. The findings underscored the intricate challenge of incorporating climate change adaptation and mitigation strategies into coastal housing policies while simultaneously aligning with the imperative of affordable housing goals. Significantly, the difficulty in achieving housing affordability in such contexts may stem from a heightened public awareness of climate change. This awareness, as illustrated by Duan and Li's (2022) research, appears to be influencing mortgage lenders to exercise greater caution in approving loans for homes situated in regions highly susceptible to sea-level rise.

Additionally, climate change has significant implications for housing conditions and health outcomes, with a pronounced effect on marginalized communities. Hales *et al.* (2007) highlighted that economic factors play a crucial role in determining vulnerability to extreme weather events. For instance, they pointed out that in the United

States, economically disadvantaged communities lacking access to air conditioning are particularly susceptible to the health consequences of heatwaves. Their research underscores the importance of energy-efficient cities as a critical component of ecologically sustainable development in the twenty-first century.

Investigations into the impact of climate change on housing values have brought to light multifaceted dynamics. Early inquiries, notably those conducted by Maddison and Bigano (2003) and Rehdanz and Maddison (2009), laid the groundwork by revealing that elevated average temperatures and milder winters tend to be seen as assets, while hotter and more humid summers are generally perceived as drawbacks. These initial insights suggest that climate change factors, such as fluctuations in temperature, can wield a considerable influence on housing markets.

Further examination of this correlation has expanded beyond mere temperature fluctuations. Kahn's (2009) influential study scrutinized climate amenity values by assessing home prices in major U.S. metropolitan areas. His research illuminated that anticipated shifts in temperature and precipitation could adversely affect housing prices, with certain cities experiencing declines exceeding 50%. These findings underscore the intricate ways in which climate change variables impact housing costs, encompassing both direct and indirect consequences.

Several research studies, including those conducted by Bernstein *et al*. (2019) and Baldauf *et al*. (2020), have highlighted a noteworthy finding: residences exposed to climate risks experience a reduction in their market value, often reaching up to 8.5%. This devaluation, as expounded by Shi and Varuzzo (2020), can be directly attributed to escalated repair and maintenance expenses, compounded by disruptions to infrastructure caused by weather-related disasters.

Beyond the tangible ramifications of climate change, the diversity of beliefs regarding long-term climate change risks has emerged as a significant factor influencing housing valuation (Baldauf *et al*., 2020). This dimension introduces an innovative perspective, emphasizing how individuals' beliefs concerning climate change can permeate dynamics within the housing market.

The intricacy of the relationship between climate and housing prices has spurred a variety of analytical approaches. Some studies have delved into exploring the connections between air pollutants, a climate change-related concern, and fluctuations in housing prices (Fong *et al*., 2020). Numerous statistical models and methodologies have been employed in the United States.

One frequently utilized approach is the hedonic pricing method, which posits that housing prices are influenced by a bundle of attributes, including climate-related factors like temperature and precipitation (Baldauf *et al*., 2020). This method has proven effective, uncovering substantial associations between housing costs and variables such as temperature, precipitation, and humidity.

Conversely, acknowledging the spatial disparities in housing prices, some researchers have embraced spatial econometric models, such as the spatial autoregressive model and geographically weighted regression (Zou *et al*., 2022). These models offer a more nuanced and precise estimation of the impact of climate change elements across various regions.

The incorporation of climate change scenarios into analyses has provided a vital perspective from which to examine the dynamics of housing prices. These scenarios allow researchers to envision potential futures and assess their repercussions on housing markets. Findings from such scenarios have revealed that the effects of climate change on housing prices exhibit significant variation across the United States (Sussman *et al*., 2014). These disparities are particularly pronounced between eastern counties and arid regions, influenced by factors like shifts in January temperature relative to July apparent temperature and alterations in annual average precipitation. These insights underscore the necessity of considering not only the presence of climate change but also its spatial variability when evaluating housing markets.

From a policy standpoint, these findings underscore the profound influence of climate change elements on housing markets. Policymakers and urban planners must take into account climate scenarios and spatial distinctions when formulating decisions related to land use, transportation, and climate mitigation strategies.

In conclusion, the prevailing literature emphasizes the profound and multifaceted impact of climate change factors on housing prices on a global scale. Ultimately, the insights derived from prior studies are indispensable for making informed decisions in a world increasingly shaped by the intricate forces of climate change.

3 EMPIRICAL ANALYSIS

The following section will cover the data and procedures applied in this work, as well as a discussion about the results and their relation to the current literature. In brief, the study analyzes data spanning several decades, incorporating climate-related variables such as anomalies in temperature, precipitation, and drought. To model housing returns, the paper utilizes stepwise boosting, an iterative algorithm that gradually integrates variables to balance model complexity and mitigate the risk of overfitting.

In assessing how climate change variables contribute to predictive performance, multiple models were tested, incorporating macroeconomic factors, financial factors, non-economic factors, non-financial factors, and measures of uncertainties. Finally, the study also examines the relevance of climate-related variables in housing return modeling, particularly by analyzing their selection rates within the boosting algorithm.

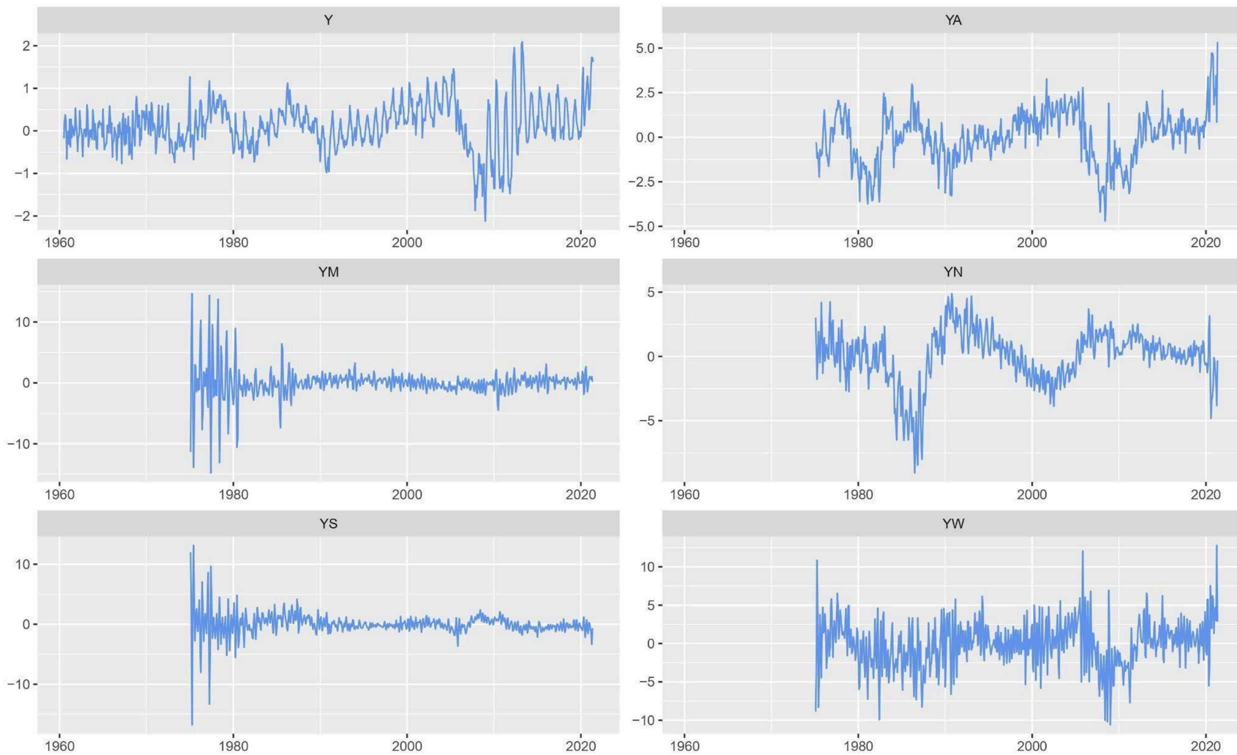
The modeling for this study was executed using R and R Studio. For the specific task of applying step-wise boosting, the mboost package was employed, adhering to the methodologies outlined by Hofner B, Mayr A, Robinzonov N, Schmid M (2014). Interested parties can find the datasets, scripts, detailed results, and a comprehensive description of the variables used in this study at the following GitHub repository: https://github.com/brunotag18/ClimateFinance-UFRGS.

3.1 DATA

In this study, we utilized a comprehensive set of six distinct dependent variables, each representing a measure of real housing returns, defined as the change in the housing index between two observations. The first of these variables encapsulated the entirety of real housing returns within the United States, spanning the temporal range from July 1960 to June 2021, and shall be denoted as "Y." Additionally, four other dependent variables were established to scrutinize housing returns within distinct regions of the United States: Northeast (YN), Midwest (YM), South (YS), and West (YW). The data for these regional variables spanned from February 1975 to May 2021.

Finally, an overarching aggregate variable (YA) was constructed, consolidating data from these four regional subsets, thus sharing an equivalent temporal scope.

Figure 1 – Real Housing Returns



Source: own elaboration based on data from the FHFA House Price Index (1960-2021).

The independent variables utilized in this study can be categorized into five distinct sets. The first set comprised eight macroeconomic factors outlined by Ludvigson and Ng (2009) collectively referred to as F1 through F8. The second and third sets pertained to macroeconomic and financial uncertainties resulting from both economic and non-economic factors, as expounded upon by Ludvigson *et al*. (2021). The variables in the second set were designated as MEU1, MEU3, MEU12, FEU1, FEU3, and FEU12, while the third set was characterized by NMEU1, NMEU3, NMEU12, NFEU1, NFEU3, and NFEU12.

The fourth set encompassed a collection of ten climate risk factors representing deviations in Average Temperature, Maximum Temperature, Minimum Temperature, Precipitation, Cooling Degree Days, Heating Degree Days, Palmer Drought Severity Index (PDSI), Palmer Hydrological Drought Index (PHDI), Palmer Modified Drought

Index (PMDI), and Palmer Z-Index. These indicators were extracted from the National Center for Environmental Information website and were denoted as CC1 through CC10. Lastly, the fifth set delineated the volatility associated with these climate anomalies, derived from a GARCH model, and was designated as CCV1 through CCV10. Moreover, to augment the analytical depth, eleven lagged values for each variable were incorporated into each set, resulting in a comprehensive assemblage of 480 independent variables for examination and assessment.

The primary characteristic of the variables within sets four and five is that they quantify climate-related anomalies rather than the variables themselves. This approach aligns with a substantial body of literature that associates climate change with alterations in precipitation patterns (Cook *et al.,* 2015; Trenberth, 2011; Huntington, 2006) and temperature (Coumou; Rahmstorf, 2012; Schär *et al*., 2004).

Table 1 - Descriptive statistics for the dependent and independent variables

Variables	Mean	St. Dev.	Min	Max
Dependent Variables				
Real Housing Returns (Y)	0.12	0.56	-2.12	2.09
Real Housing Returns - Northeast (YN)	0.00	2.11	-9.06	4.88
Real Housing Returns - Midwest (YM)	-0.02	2.44	-14.78	14.65
Real Housing Returns - Southwest (YS)	0.02	1.86	-16.75	13.12
Real Housing Returns - West (YW)	-0.02	3.17	-10.58	12.78
Real Housing Returns - Aggregate (YA)	0.00	1.48	-4.70	5.35
Macro and Financial Factors				
F1	0.00	0.40	-1.07	2.35
F2	0.00	0.27	-1.30	1.26
F3	0.00	0.26	-1.52	1.39
F4	0.00	0.23	-1.05	1.03
F5	0.00	0.21	-1.21	0.92
F6	0.00	0.20	-0.68	0.66
F7	0.00	0.17	-1.23	0.46
F8	0.00	0.15	-0.62	0.52
Macro and Financial Uncertainties				
MEU1	0.66	0.11	0.53	1.14
MEU3	0.79	0.12	0.65	1.30

MEU12	0.91	0.08	0.79	1.31
FEU1	0.90	0.16	0.60	1.55
FEU3	0.95	0.13	0.70	1.41
FEU12	0.98	0.04	0.89	1.11
Non-macro and Non-financial Uncertainties				
NMEU1	-0.01	0.01	-0.10	0.12
NMEU3	-0.01	0.01	-0.04	0.07
NMEU12	-0.01	0.01	-0.02	0.04
NFEU1	0.00	0.02	-0.01	0.17
NFEU3	0.00	0.01	-0.01	0.12
NFEU12	0.00	0.00	-0.01	0.03
Climate Change				
CC1	0.04	2.78	-10.35	9.38
CC2	0.05	3.16	-13.27	11.13
CC3	0.04	2.64	-10.08	9.27
CC4	0.00	0.65	-2.32	2.19
CC5	0.33	24.25	-88.00	96.00
CC6	-0.90	72.92	-286.00	283.00
CC7	-0.05	2.98	-8.72	8.78
CC8	-0.04	3.09	-8.72	8.78
CC9	-0.04	3.04	-8.72	8.78
CC10	-0.03	2.34	-7.80	8.98
Climate Change Volatility				
CCV1	7.80	3.32	5.72	30.99
CCV2	9.97	2.32	8.42	30.86
CCV3	7.24	4.65	4.38	42.05
CCV4	0.42	0.05	0.23	0.79
CCV5	904.18	1,461.41	183.09	11,091.93
CCV6	6,047.52	6,226.07	2,839.27	49,640.34
CCV7	9.04	10.57	0.56	71.73
CCV8	9.60	11.76	0.12	73.49
CCV9	9.25	10.69	0.37	70.93
CCV10	5.45	2.01	4.08	24.36

Source: own elaboration based on data from the FHFA House Price Index, Ludvigson and Ng (2009), Ludvigson et al. (2021), National Center for Environmental Information (1961-2021)

3.1.1 METHODOLOGY

In the subsequent section, we elucidate the partitioning of the dataset into training and test sets for the out-of-sample forecasting method, a pivotal component of our research framework. This methodological prerequisite stems from the need to rigorously assess the predictive performance of our model. However, a notable challenge arises when implementing this procedure within the context of our study. Namely, the resulting datasets exhibit more variables than observations. Consequently, the common practice of employing linear regression as a benchmark was unsuitable. Instead, we utilized an autoregressive AR(11) model for the response variable in certain predictive power analyses.

In response to this, we turn to the methodology of stepwise boosting. This approach demonstrates its mettle by crafting robust and consistent models even within a high-dimensional environment. One clear advantage, as delineated by the work of Zhang and Haghani (2015), is that the boosting learning algorithm not only aptly captures the intricate interplay between input variables and response variables but also offers insights into the relative significance of individual input variables. This discernment emerges organically through the iterative nature of the boosting procedure, fostering a deeper understanding of the relationships underpinning the data.

At the core of the stepwise boosting methodology lies the following logic. It seeks to construct a parsimonious yet highly effective linear model within the challenge of high-dimensional data. To circumvent the inconsistency, stepwise boosting constructs this model in an incremental fashion, systematically incorporating variables one by one. This iterative approach endeavors to arrive at the optimal model, one that encapsulates best the relationships between variables. The outcome is a function that aptly balances predictive accuracy and model simplicity. In this section, we delve into the intricacies of this stepwise boosting methodology and elucidate its application within the context of our research, culminating in a robust framework for predictive analysis.$\hat{f}(x_t) = \hat{y}_t$ that can be described as

$$\hat{f}(x_t) = \hat{f}^{(0)} + v \sum_{m=1}^{M} \hat{g}^{(m)} \qquad (1)$$

where x_t is the vector containing the dependent variables, $\hat{f}^{(0)}$ is a constant, known as the weak learner, v is shrinkage parameter that ranges from 0 to 1 and $\hat{g}^{(m)}$ is the learner estimated on each of the m iterations, which is also chosen arbitrarily.

In the realm of boosting algorithms, the selection of an appropriate weak learner constitutes a pivotal initial step, bearing profound consequences on the ensuing model's performance. Notably, the effectiveness of the boosting process is often accentuated when a sufficiently weak learner is employed, as this deliberate choice mitigates the risk of overfitting, an intrinsic peril in complex predictive modeling scenarios, as emphasized by Fuleky (2019). In this study, we designate the mean of the response variable as our chosen weak learner, representing the temporary model.

Subsequently, the boosting algorithm proceeds with its iterative refinement to enhance the predictive capabilities of our provisional model. To this end, we calculate the residuals from this provisional model. As these residuals signify what was unaccounted for by our initial model, a series of regressions against each predictor variable is executed to try and explain what the previous model couldn't. The next step is to assimilate a fraction v of the best regression outcomes, that meaning, the one yielding lower Sum of Squared Residuals (SSR), to the provisional model. These steps of iterative refinement and adaptation continue until the attainment of an optimal number of iterations m.

Briefly, the algorithm functions as follows.

a) start with the temporary model $\hat{f}^{(0)} = \bar{y}$;

b) obtain the residuals from such model $u_t = y_t - \hat{f}_t^{(m-1)}$;

c) perform a regression of these residuals against each independent variable x_i;

d) calculate the SRR for each one of these regression;

e) select the variable which model resulted in the smallest SRR;

f) define $\hat{g}^{(m)} = \hat{\beta}_{(i)} x_{(i)}$;

g) set the new model as $\hat{f}^{(m)} = \hat{f}^{(m-1)} + v\hat{g}^{(m)}$;

h) repeat the steps b through g for m iterations.

The parameter m represents the trade-off between model fitness and complexity, a foundational consideration in predictive modeling. Numerous metrics are available for quantifying this trade-off, including the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Cross-Validation. The main function of this parameter is to prevent overfitting of an excessive number of iterations. In this study, we opted for the AIC as the criterion of choice, applied within each prediction window, as it penalizes overparameterization more stringently, promoting the selection of simpler true models. These criteria are both asymptotically consistent and provide a robust framework for model evaluation (Bozdogan, 1987).

Also pivotal for the boosting algorithm quality, is the parameter v, commonly referred to as the "step". This numeric parameter, ranging from 0 to 1, assumes the role of a shrinkage factor in each iterative step. Its function is twofold. Firstly, it introduces a mere fraction of each predictor variable at every iteration, a form of regularization that imparts a controlled bias to the model while simultaneously curtailing its variance. This ensures that our model remains resilient against overfitting, making it a potent tool for predictive purposes.

Moreover, v, by constraining the inclusion of individual variables to a fraction, also mitigates the risk of undue influence from any single variable, enhancing the predictive power. In this study, we adhere to the standard convention established in the literature to set the value of $v = 0.1$.

3.2 FORECASTING PROCEDURES AND PERFORMANCE

Our approach involved an examination of the predictive power of various sets of variables for each dependent variable and forecast horizon. This assessment was performed through a series of six distinct models. The primary objective of this endeavor was to evaluate the individual contributions of each set of variables toward enhancing predictive accuracy.

The suite of variables available for model selection expanded iteratively. Specifically, each subsequent model inherited the pool of variables from the preceding one, augmented by the introduction of a fresh set of variables. The initial model, used as the benchmark, had at its disposal only the lags of the dependent variable. In contrast, the sixth and final model had not only not only the lags of the dependent variable at its disposal but also the entirety of the five sets of variables enumerated earlier. This progression was designed to systematically probe the incremental value of each variable set.

Furthermore, a pivotal aspect of our methodology involved the normalization of variables within each training window. This step was implemented to safeguard against the inadvertent infiltration of test set information into the model. Achieved through the standardization of variables using mean and standard deviation, this normalization process ensured that our models operated untainted by data leakage from the test set. The step parameter was fixed at $v = 0.1$ across all models. The optimal number of iterations m for each window was determined through the AIC.

The forecasting procedure itself was executed through an out-of-sample rolling window approach. This entailed the training of a new model in each distinct window, with the objective of evaluating predictive performance. The forecasted periods varied according to the specific dependent variable and the forecast horizon. The predicted period for the overall real housing returns was from July 1991 to June 2021, from August 1991 to June 2021, from September 1991 to June 2021, and from December 1991 to June 2021 for the horizons of 1, 3, 6 and 12 months respectively. For regional housing returns and the aggregate the periods of forecast were from October 1998 to May 2021, from November 1998 to May 2021, from December 1998 to May 2021 and from March 1999 to May 2021 for the same horizons. These smaller data sets are a result of the division of the original data into training set and test set in a 1:2 ratio.

To gauge the efficacy of each model and elucidate the impact of different variable sets on predictive power, we employed four key statistical metrics. These included the Root Mean Square Error (RMSE) and the Mean Absolute Error (MAE). The RMSE quantifies the square root of the average squared prediction errors, offering insight into the magnitude of prediction deviations. Meanwhile, the MAE represents the mean of absolute prediction errors, serving as a robust measure of the overall prediction accuracy. Such statistic are described, respectively, as:

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}} \qquad (2)$$

and

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |\hat{y}_i - y_i| \qquad (3)$$

where $\hat{y}_i$ is the predicted value, y_i the actual value and n the total number of forecasts executed by the model.

The two-sided Giacomini-White test (GW) was also employed to assess the statistical difference between models, employing the first model as a benchmark. The test was used in two forms, the first using RMSE and the second MAE. Therefore, using the results of these metrics, we were able to make judgments about model superiority when statistically significant differences emerged.

Additionally, we incorporated the Model Confidence Set (MCS) (Hansen, Lunde, and Nason, 2011) as another statistical procedure within our analytical framework. The MCS, through a battery of tests involving forecasted and actual values, helps to delineate the best-performing model. It does so under the null hypothesis assumption of equal predictive power among the models under consideration. The MCS demonstrates the ability to discern a group of superior forecasting models from a pool, leveraging the information contained within the data, being adept at identifying models that outperform others efficiently (Hansen, Lunde, and Nason, 2003).

3.3 RESULTS

Table 2 provides an analysis of the performance of various predictive models with respect to overall real housing returns (Y), encompassing different predictive horizons. An examination of these results, particularly, when we focus on the short-term horizon (h = 1), Model 6, which incorporates climate change volatility variables, emerges as the frontrunner, displaying superior performance as indicated by RMSE, MAE, and the MCS Rank

In contrast, for longer horizons, the benchmark model (Model 1) consistently maintains its superiority, outperforming models that include climate change variables. Notably, only when h = 12 does another model (Model 3) manage to surpass the benchmark. In this specific case, the distinction becomes evident solely through the MCS Rank, as both Giacomini-White (GW) Tests show no statistically significant difference.

The results described above may shed light, at least in the short term, on the intricate relationship between housing prices and residents' environmental preferences as it is known to be the case in the realm of urban economics and the spatial equilibrium model (Zou *et al.*, 2022, Albouy, 2016). These studies have underscored the ability of housing prices to serve as indicators of the value people place on their surroundings. Similarly, in the context of predicting future trends, an intriguing pattern emerges, as for longer horizons, none of the models incorporating climate change variables manages to surpass the performance of the benchmark. These findings emphasize the nuanced nature of predictive modeling, where certain variables can wield significant influence in specific circumstances, while the broader context may reveal different dynamics.

Table 2 - Statistics on the predictive power for the overall real housing returns (Y)

h = 1

Model	RMSE	MAE	GW Test MSE	GW Test Mae	MCS Rank M	MCS Rank R
Model 1	0.2925	0.2104			E	E
Model 2	0.2692	0.1949	0.3211	0.3189	5	5
Model 3	0.2644	0.1914	0.1784	0.1769	3	3
Model 4	0.2743	0.1912	0.0069*	0.0067*	2	2
Model 5	0.2739	0.1924	0.0053*	0.0052*	4	4
Model 6	**0.2693**	**0.1885**	0.0116*	0.0115*	**1**	**1**

h = 3

Model	RMSE	MAE	GW Test MSE	GW Test Mae	MCS Rank M	MCS Rank R
Model 1	**0.4035**	**0.2903**			**1**	**1**
Model 2	0.4349	0.3063	0.5233	0.5151	4	4
Model 3	0.4226	0.2983	0.1797	0.1759	2	2
Model 4	0.4354	0.3068	0.0021*	0.0019*	3	3
Model 5	0.4478	0.3252	0.0169*	0.0160*	E	E
Model 6	0.4856	0.3429	0.0059*	0.0058*	E	E

h = 6

Model	RMSE	MAE	GW Test MSE	GW Test Mae	MCS Rank M	MCS Rank R
Model 1	**0.4092**	**0.2938**			**1**	**1**
Model 2	0.4425	0.3210	0.5147	0.5006	3	3
Model 3	0.4403	0.3212	0.1243	0.1210	2	2
Model 4	0.4844	0.3380	0.0006*	0.0005*	4	4
Model 5	0.4952	0.3528	0.0006*	0.0006*	E	E
Model 6	0.5811	0.4077	0.0005*	0.0005*	E	E

h = 12

Model	RMSE	MAE	GW Test MSE	GW Test Mae	MCS Rank M	MCS Rank R
Model 1	0.3845	0.2759			4	2
Model 2	0.3829	0.2719	0.3720	0.3791	2	3
Model 3	**0.3770**	**0.2689**	0.7120	0.7118	**1**	**1**
Model 4	0.3852	0.2740	0.2699	0.2462	3	4
Model 5	0.3882	0.2778	0.3605	0.3366	5	5
Model 6	0.3905	0.2809	0.2873	0.2708	6	6

Source: own elaboration

Notes: * Statistical difference at 5%

Turning our attention to the aggregate variable encompassing data from all four regions (YA), Table 3 shows that both GW Tests indicate no statistically significant difference between the models in any horizon. However, the MCS Ranks consistently excludes the first model across various horizons. Instead, models 2, 3, and 4 emerge as the preferred choices under specific h values.

Table 3 - Statistics on the predictive power for the real housing returns - Aggregate (YA)

h = 1

Model	RMSE	MAE	GW Test MSE	GW Test Mae	MCS Rank M	MCS Rank R
Model 1	0.9064	0.6730			E	E
Model 2	**0.6571**	**0.4380**	0.8519	0.8679	2	2
Model 3	0.6638	0.4357	0.8233	0.8402	**1**	**1**
Model 4	0.7145	0.4485	0.9420	0.9643	5	4
Model 5	0.6981	0.4440	0.8627	0.8821	3	3
Model 6	0.6805	0.4455	0.9897	0.9728	4	5

h = 3

Model	RMSE	MAE	GW Test MSE	GW Test Mae	MCS Rank M	MCS Rank R
Model 1	1.0986	0.8608			E	E
Model 2	**0.8498**	0.6354	0.8740	0.8554	4	4
Model 3	0.8547	0.6342	0.5518	0.5696	3	3
Model 4	0.8723	**0.6295**	0.7125	0.7587	**1**	**1**
Model 5	0.8692	0.6362	0.7237	0.7679	5	5
Model 6	0.8718	0.6316	0.8940	0.9342	2	2

h = 6

Model	RMSE	MAE	GW Test MSE	GW Test Mae	MCS Rank M	MCS Rank R
Model 1	1.1682	0.8918			E	E
Model 2	0.8910	**0.6894**	0.8023	0.7989	**1**	**1**
Model 3	**0.8798**	0.6935	0.3748	0.3706	2	2
Model 4	0.9899	0.7117	0.8936	0.9697	3	3
Model 5	0.9993	0.7522	0.7361	0.7950	E	E
Model 6	1.0459	0.7826	0.5748	0.5190	E	E

h = 12

Model	RMSE	MAE	GW Test MSE	GW Test Mae	MCS Rank M	MCS Rank R
Model 1	1.3685	1.0059			E	E
Model 2	1.1445	0.8390	0.8003	0.8257	3	3
Model 3	**1.0956**	**0.8076**	0.2964	0.3215	**1**	**1**
Model 4	1.1721	0.8349	0.8897	0.7484	2	2
Model 5	1.1821	0.8614	0.9200	0.7834	4	4
Model 6	1.2138	0.8780	0.6368	0.5052	5	5

Source: own elaboration
Notes: * Statistical difference at 5%

For the regional variables, the results are presented in Appendix B. None of the models incorporating climate change variables manage to surpass the benchmark model in any of the statistical metrics employed. The first model consistently outperforms the others, as evidenced by all measurement criteria, except for the West (YW) region. Here, models 2 and 3 consistently secure the top position in the MCS Rank, despite statistical differences in RMSE only appearing at h = 12.

The results for the regional dependent variables may exhibit some similarity to those reported by Sussman *et al.* (2014). In their study, they explored different scenarios and observed varying housing prices in the western, eastern, and northern counties of the United States. These variations ranged from increases to decreases, suggesting that the impact of climate change variables on a regional level may not be straightforward.

However, it is noteworthy that the mean change in housing prices for all counties remained consistent across all scenarios examined by the authors. This finding also corresponds with our results concerning overall housing returns, at least in the short term.

3.4 VARIABLE SELECTION

As the selection of variables holds paramount importance in the context of step-wise boosting, this section seeks to evaluate the relevance of climate change variables in the modeling of housing returns by looking at its selection rate. In this regard, it is pertinent to note that the variables selected for Model 1 are not explicitly delineated in our results. This omission stems from the fact that Model 1 exclusively incorporated the lags of the dependent variable, thereby providing limited insights into the relative importance of each variable set under consideration.

The first noteworthy result is that, as presented in Table 4, for the overall real housing returns, in Model 6, a significant proportion of the 15 most frequently selected variables are associated with Climate Change Volatility. This result may point in part to the significance of climate change factors as an explanation for the superior performance of Model 6, as demonstrated in the preceding section. Notably, the lags of Cooling Degree Days Anomaly and Heating Degree Days Anomaly stand out as key contributors within this subset. It is pertinent to underscore that, apart from the lags of housing returns, only the variables from the first set, specifically the macro factors, consistently feature among the top 15 variables in Models 2 through 4. Only with the introduction of climate change factors in Models 5 and 6 can we see a shift in this trend.

The analysis of the frequency of variable selection reveals an interesting pattern, with select climate change variables exhibiting frequencies exceeding 80% for specific horizons of prediction. Notably, the tenth lag of Cooling Degree Days Anomaly Volatility and the fourth lag of Heating Degree Days Anomaly Volatility were consistently selected in 100% of instances when h = 6.

As Cooling Degree Days and Heating Degree Days quantify the energy demand for cooling or heating buildings respectively, these metrics are highly relevant to current literature. Specifically, in the context of social housing in Europe, Domínguez-Amarillo, Samuel, et al. (2019) observed that while maintaining comfort during cold weather remains important, the primary challenge has shifted towards managing heat gain. Furthermore, in the pursuit of ecologically sustainable urban development, Hales et al. (2007) emphasized the importance of energy-efficient cities. This is particularly crucial for economically disadvantaged communities who, lacking access to air conditioning, are more vulnerable to the health risks posed by heatwaves.

These nuanced observations underscore the potential influence of climate change variables on our modeling efforts, particularly in scenarios where specific lagged values manifest recurrently.

Table 4 - Step-wise boosting variable selection rate for the overall real housing returns (Y)

h = 1

Model 2		Model 3		Model 4		Model 5		Model 6	
F2	100.00%	F2	100.00%	F2	100.00%	F3	100.00%	F3	100.00%
F3	100.00%	F3	100.00%	F3	100.00%	Y_L1	100.00%	Y_L1	100.00%
Y_L1	100.00%	Y_L1	100.00%	Y_L1	100.00%	Y_L10	100.00%	Y_L10	100.00%
Y_L10	100.00%	Y_L10	100.00%	Y_L10	100.00%	F2	99.72%	F2	98.06%
Y_L11	99.17%	Y_L11	99.17%	Y_L11	98.61%	Y_L11	98.33%	Y_L11	91.67%
F7_L8	89.44%	F7_L8	88.06%	F7_L8	88.33%	F7_L8	78.06%	**CCV6_L3**	90.56%
F3_L9	80.00%	F3_L9	81.94%	F3_L9	82.22%	F4_L4	73.06%	F4_L4	63.06%

F7_L11	75.56%	F4_L4	76.67%	F4_L4	74.72%	F3_L9	72.22%	**CCV6_L11**	60.28%
F4_L4	75.00%	F7_L11	74.72%	F7_L11	74.17%	F7_L11	65.83%	**CCV5_L7**	59.17%
F8	65.83%	F4_L5	70.28%	F4_L5	65.00%	F8	59.44%	**CCV5_L8**	58.89%
F4_L5	62.22%	F8	68.89%	F8	64.44%	F4_L3	54.44%	**CCV5_L10**	56.94%
F7_L2	61.39%	F8_L2	67.22%	Y_L3	59.72%	Y_L3	53.61%	F7_L11	54.17%
F8_L2	60.83%	F7_L2	65.83%	F4_L3	57.22%	F4_L5	53.33%	F7_L8	54.17%
Y_L3	59.17%	Y_L3	61.94%	F7	54.44%	F7	51.39%	**CCV5_L1**	52.50%
F4_L3	57.22%	F4_L3	58.61%	F7_L10	53.06%	**CC5_L9**	50.83%	F8	52.50%

h = 3

Model 2		Model 3		Model 4		Model 5		Model 6	
F3	100.00%	F3	100.00%	F2_L4	100.00%	Y_L1	100.00%	Y_L1	100.00%
F3_L1	100.00%	F3_L1	100.00%	F3	100.00%	Y_L10	100.00%	Y_L10	100.00%
F3_L2	100.00%	F3_L2	100.00%	F3_L1	100.00%	Y_L3	100.00%	Y_L3	100.00%
F8	100.00%	F8	100.00%	F3_L2	100.00%	F8	98.89%	F8	83.57%
Y_L1	100.00%	Y_L1	100.00%	F8	100.00%	F2_L4	95.26%	F3_L2	82.17%
Y_L10	100.00%	Y_L10	100.00%	Y_L1	100.00%	F3_L2	90.53%	**CCV5_L8**	81.06%
Y_L3	100.00%	Y_L3	100.00%	Y_L10	100.00%	F8_L1	83.84%	F2_L4	80.78%
F7	99.72%	F2_L4	99.16%	Y_L3	100.00%	F3_L1	81.62%	F8_L1	76.60%
F2_L4	99.16%	F7	98.89%	F2	98.61%	F2_L1	81.06%	F3	73.26%
F8_L1	97.77%	F8_L1	97.77%	F3_L10	94.15%	**CC5_L10**	80.22%	F4_L11	72.42%
F2	97.49%	F2	97.49%	Y_L4	91.64%	F3	78.27%	F2_L1	71.87%
Y_L4	96.94%	F2_L1	97.21%	F8_L1	91.09%	F4_L5	76.60%	F3_L1	71.03%
F3_L10	96.38%	F3_L10	96.10%	F7	89.97%	F7	76.60%	**CCV6_L4**	70.19%
F2_L1	82.73%	Y_L4	92.20%	F2_L1	89.69%	F2_L3	74.09%	F2_L3	68.25%
F8_L2	81.89%	F2_L2	82.17%	F2_L2	86.07%	F4	69.08%	F7	67.97%

h = 6

Model 2		Model 3		Model 4		Model 5		Model 6	
F3	100.00%	F3	100.00%	F2_L7	100.00%	F2_L7	100.00%	**CCV5_L10**	100.00%

F3_L5	100.00%	F3_L5	100.00%	F3	100.00%	F3_L5	100.00%	**CCV6_L4**	100.00%
F7_L2	100.00%	F7_L2	100.00%	F3_L5	100.00%	F8_L3	100.00%	Y_L1	100.00%
F8_L3	100.00%	F8_L3	100.00%	F8_L3	100.00%	Y_L1	100.00%	F8_L3	99.72%
Y_L1	100.00%	Y_L1	100.00%	Y_L1	100.00%	Y_L10	100.00%	Y_L10	98.60%
Y_L10	100.00%	Y_L10	100.00%	Y_L10	100.00%	Y_L4	100.00%	**CCV5_L4**	97.77%
Y_L11	100.00%	Y_L4	100.00%	Y_L4	100.00%	Y_L8	100.00%	F2_L7	97.21%
Y_L3	100.00%	Y_L8	100.00%	Y_L8	100.00%	Y_L9	100.00%	**CCV6_L3**	93.02%
Y_L4	100.00%	Y_L9	100.00%	Y_L9	100.00%	F3	90.22%	Y_L8	92.46%
Y_L8	100.00%	Y_L11	98.88%	Y_L11	98.88%	Y_L11	89.11%	F3_L5	89.66%
Y_L9	100.00%	Y_L3	98.88%	Y_L3	98.60%	**CC5_L10**	85.75%	Y_L9	89.39%
F2_L7	99.16%	F2_L7	98.60%	F2_L1	97.49%	F2_L1	84.92%	**CCV5_L3**	86.31%
F8_L2	98.32%	F2_L1	96.37%	F7_L2	95.81%	F8_L1	84.64%	Y_L4	84.08%
F2_L1	97.49%	F8_L2	95.53%	F8_L2	89.94%	Y_L3	83.52%	**CC5_L10**	83.52%
F8_L1	91.90%	F8_L1	86.03%	F2	89.11%	F8_L2	83.24%	F3	83.52%

h = 12

Model 2		Model 3		Model 4		Model 5		Model 6	
F3_L11	100.00%	F3_L11	100.00%	F3_L11	100.00%	F3_L11	100.00%	F3_L11	100.00%
Y_L1	100.00%	Y_L1	100.00%	Y_L1	100.00%	Y_L1	100.00%	Y_L1	100.00%
Y_L11	100.00%	Y_L11	100.00%	Y_L11	100.00%	Y_L11	100.00%	Y_L11	100.00%
F8_L3	99.72%	F8_L3	97.75%	F2_L11	94.37%	**CC3_L1**	94.08%	F7_L11	85.92%
F8	94.65%	F7_L11	93.80%	F7_L11	93.24%	F7_L11	87.89%	**CC3_L1**	83.10%
F7_L11	92.68%	F8	92.96%	F2	86.48%	F8	83.10%	**CC5_L9**	79.15%
F4	86.76%	F2_L1	89.30%	F3	83.94%	F8_L3	80.85%	F8_L3	75.21%
F8_L1	82.25%	F4	85.92%	F3_L10	83.94%	**CC5_L10**	78.87%	F3	74.93%
F3	81.41%	F2	81.41%	F8_L3	83.38%	**CC5_L9**	78.87%	F8	74.08%
F2	78.31%	F4_L5	80.56%	F4	81.97%	F2_L11	77.18%	**CC5_L10**	71.83%
F3_L10	78.03%	F3	78.87%	F4_L5	81.69%	F4_L5	76.90%	F2_L1	63.94%
F2_L1	76.62%	F3_L10	78.59%	F8	81.41%	F3	76.62%	F3_L10	62.54%
Y_L10	76.34%	F8_L1	75.77%	F3_L8	79.15%	**CC5**	75.21%	F4_L4	60.28%
F2_L11	75.49%	F7_L2	74.93%	F7_L2	75.21%	F4	74.65%	F4_L5	58.59%

F7_L2	75.49%	F7_L1	72.96%	F8_L11	75.21%	F3_L10	71.27%	**CCV6_L4**	57.75%

Source: own elaboration

Table 5 presents the outcomes of our variable selection process for aggregate housing returns. In this context, the prevalence of climate change variables is notably less pronounced compared to the previous case. An extreme instance of this phenomenon occurs at h = 6, where only a single climate change variable finds its way into the selection.

Interestingly, our analysis reveals the emergence of diverse factors beyond the Cooling Degree Days Anomaly and Heating Degree Days Anomaly within the top 15 selected variables. These include Precipitation Anomaly, PDSI Anomaly, PMDI Anomaly, and Z-Index Anomaly. Nevertheless, it remains a consistent pattern that climate change factors continue to be the predominant representatives from variable sets beyond the first one in the selection.

Table 5 - Step-wise boosting variable selection rate for the real housing returns - Aggregate (YA)

h = 1

Model 2		Model 3		Model 4		Model 5		Model 6	
F2	100.00%	F2	100.00%	F2	100.00%	F2	100.00%	F2	100.00%
F3	100.00%	F3	100.00%	F3	100.00%	F3	100.00%	F3	100.00%
F4_L1	100.00%	F4_L1	100.00%	F4_L1	100.00%	F4_L1	100.00%	F4_L1	100.00%
F4_L2	100.00%	F4_L2	100.00%	YA_L1	100.00%	YA_L1	100.00%	YA_L1	100.00%
YA_L1	100.00%	YA_L1	100.00%	YA_L9	100.00%	YA_L9	100.00%	YA_L9	100.00%
YA_L9	100.00%	YA_L9	100.00%	F4_L2	99.26%	F4_L2	93.01%	**CCV7_L9**	88.97%
F3_L2	98.53%	F3_L2	94.12%	F3_L1	94.12%	F3_L1	86.76%	F6_L1	83.09%
F3_L1	92.28%	F3_L1	93.01%	F3_L2	89.71%	F6_L1	80.88%	**CCV10_L6**	82.35%
F6_L1	84.93%	F6_L1	84.93%	F6_L1	84.19%	YA_L6	76.84%	YA_L6	81.99%
YA_L2	78.68%	F3_L11	77.21%	F5	79.41%	F4	72.06%	F3_L1	72.06%
YA_L6	77.94%	YA_L6	77.21%	YA_L6	76.84%	YA_L2	70.96%	YA_L2	70.96%
F4	72.43%	F4	74.63%	F3_L11	76.10%	**CC4_L5**	68.38%	F4	67.65%

F3_L11	70.59%	F5	74.63%	F4	73.90%	**CC6_L10**	66.18%	F8_L3	65.07%
F5	70.59%	F8_L3	73.53%	F8_L3	72.06%	F5	65.81%	F4_L2	61.40%
F8_L3	70.59%	YA_L2	71.32%	YA_L2	69.85%	F8_L3	64.34%	F3_L11	55.51%
h = 3									
Model 2		Model 3		Model 4		Model 5		Model 6	
F2	100.00%	F2	100.00%	F2	100.00%	F2	100.00%	F2	100.00%
F2_L1	100.00%	F2_L1	100.00%	F2_L1	100.00%	F2_L1	100.00%	F2_L1	100.00%
F2_L2	100.00%	F2_L2	100.00%	F2_L2	100.00%	F2_L2	100.00%	F2_L2	100.00%
F3	100.00%	F3	100.00%	F3	100.00%	F3	100.00%	F3	100.00%
F3_L1	100.00%	F3_L1	100.00%	F3_L1	100.00%	F3_L1	100.00%	F3_L1	100.00%
F3_L2	100.00%	F3_L2	100.00%	F3_L2	100.00%	F3_L2	100.00%	F3_L2	100.00%
F4_L1	100.00%	F4_L1	100.00%	F4_L1	100.00%	F4_L1	100.00%	F4_L1	100.00%
F4_L2	100.00%	F4_L2	100.00%	F4_L2	100.00%	YA_L1	100.00%	F4_L2	100.00%
YA_L1	100.00%	YA_L1	100.00%	YA_L1	100.00%	F4_L2	99.63%	YA_L1	100.00%
YA_L6	97.05%	YA_L3	97.79%	F3_L11	98.52%	F3_L11	89.67%	F3_L11	96.68%
F4	96.68%	F3_L11	96.68%	YA_L3	93.36%	F4	69.74%	**CCV7_L10**	72.69%
F3_L11	95.94%	YA_L6	91.51%	YA_L6	92.62%	**CC10_L1**	69.00%	F4	71.22%
YA_L3	95.20%	F4_L4	90.77%	F4_L4	88.19%	F4_L4	65.31%	**CC10_L1**	70.85%
F3_L3	91.88%	F3_L3	86.35%	NFEU1_L6	87.08%	YA_L7	63.10%	**CC10_L2**	67.53%
F1_L3	87.08%	F5_L3	85.61%	F5_L3	83.76%	**CC10_L8**	61.25%	**CCV2_L9**	64.21%

h = 6									
Model 2		Model 3		Model 4		Model 5		Model 6	
F2_L5	100.00%	F2_L6	100.00%	F2_L4	100.00%	F2_L4	100.00%	**CCV9_L10**	100.00%
F2_L6	100.00%	F3	100.00%	F2_L5	100.00%	F2_L5	100.00%	F2_L6	100.00%
F3	100.00%	F3_L1	100.00%	F2_L6	100.00%	F2_L6	100.00%	F3	100.00%
F3_L1	100.00%	F3_L2	100.00%	F3	100.00%	F3	100.00%	F3_L1	100.00%
F3_L2	100.00%	F3_L5	100.00%	F3_L1	100.00%	F3_L1	100.00%	F3_L5	100.00%
F3_L5	100.00%	F3_L6	100.00%	F3_L5	100.00%	F3_L5	100.00%	YA_L1	100.00%
F3_L6	100.00%	YA_L1	100.00%	YA_L1	100.00%	YA_L1	100.00%	F2_L5	99.26%
F3_L7	100.00%	F2_L4	99.63%	F3_L2	99.63%	F3_L6	99.26%	F3_L2	93.70%
F4_L2	100.00%	F2_L5	99.63%	F2_L7	99.26%	F3_L2	98.15%	F2_L7	91.48%
YA_L1	100.00%	F3_L7	99.63%	F3_L6	99.26%	F2_L7	97.78%	F3_L11	90.37%
F2_L4	99.63%	F4_L1	99.63%	F3_L7	98.52%	F2_L3	95.56%	F3_L6	83.70%
F4_L1	99.63%	YA_L4	99.63%	F2_L3	97.41%	F4_L2	95.56%	F2_L4	82.96%
YA_L4	99.63%	F3_L8	98.89%	F4	95.93%	F3_L8	93.70%	F4	78.89%
F2_L3	99.26%	F4	98.52%	F3_L8	95.56%	F3_L7	90.37%	F4_L2	71.48%
F4_L3	99.26%	F4_L2	98.15%	YA_L4	95.19%	F4_L4	90.00%	F6	69.63%
h = 12									
Model 2		Model 3		Model 4		Model 5		Model 6	
F2	100.00%	F2_L10	100.00%	F2_L10	100.00%	F2_L11	100.00%	F2_L11	100.00%
F2_L10	100.00%	F2_L11	100.00%	F2_L11	100.00%	F3	100.00%	F3	100.00%
F2_L11	100.00%	F3	100.00%	F3	100.00%	F3_L1	100.00%	F3_L1	100.00%
F3	100.00%	F3_L1	100.00%	F3_L1	100.00%	F3_L11	100.00%	F3_L11	100.00%
F3_L1	100.00%	F3_L11	100.00%	F3_L11	100.00%	F3_L2	100.00%	F3_L2	100.00%
F3_L11	100.00%	F3_L2	100.00%	F3_L2	100.00%	YA_L1	100.00%	YA_L1	100.00%
F3_L2	100.00%	F3_L9	100.00%	YA_L1	100.00%	F2_L10	99.63%	F3_L10	99.63%
YA_L1	100.00%	YA_L1	100.00%	F3_L10	98.88%	F3_L10	99.25%	F2_L10	94.76%
YA_L11	100.00%	F4_L1	98.88%	F3_L9	97.38%	F3_L9	94.38%	F3_L9	90.26%
F4_L1	99.25%	F3_L10	98.50%	F2	96.63%	F4_L1	91.76%	F8	89.51%
F4_L2	99.25%	YA_L11	98.13%	F4	96.63%	F4	87.64%	F4_L1	86.89%
F3_L10	98.50%	F2	97.38%	F8_L11	95.13%	F8_L6	87.64%	F8_L6	86.89%
F3_L9	98.50%	F4_L2	97.38%	F4_L1	94.38%	F8	86.14%	**CC6_L1**	81.27%
F4	97.75%	F4	96.63%	F8	92.13%	**CC6_L1**	84.64%	F4	79.03%
F8	96.63%	F8	94.38%	F8_L6	89.89%	F2	82.77%	F8_L3	77.15%

Source: own elaboration:

The results of regional housing returns are presented in Appendix B. While a definitive pattern is not observed it is evident that climate change variables bear significance, albeit in a nuanced manner. Notably, for the Midwest (YM) region, climate change variables seem to have some importance, particularly at h = 1, 3, and 12. Similarly, for the Northeast region, climate change variables exhibit relevance at h = 3, 6, and 12.

Examining the frequency of variable selection, certain climate change factors consistently emerge with selection frequencies surpassing 80%. This recurring selection, despite models containing these factors not consistently demonstrating substantial improvements in forecasting accuracy, might be an indicator of the importance of such factors.

As examined by (Sussman *et al*., 2014) the impact of climate change variables on housing prices varies depending on different assumptions and the regional-level effects may not be as evident as those observed in a broader context. Nevertheless, our results from variable selection for certain time horizons indicate that these variables still exhibit some degree of relevance, as occurs with the results by these authors.

4 CONCLUSION

This paper intended to shed light on the intricate relationship between climate change and housing prices within the United States. The study underscores the profound and multifaceted influence of climate change factors on housing prices, revealing nuanced patterns in different regions and time horizons.

The findings demonstrate that climate change variables, particularly climate change volatility factors, can significantly impact short-term housing price predictions. However, the influence of these variables diminishes for longer forecasting horizons. This suggests that while climate-related factors play a role in shaping housing prices, other economic and financial factors may retain greater importance in longer-term predictions.

Moreover, the analysis of variable selection frequency highlights the relevance of certain climate change variables in predicting housing returns, especially those related to Cooling Degree Days and Heating Degree Days. While not always leading to substantial improvements in forecasting accuracy, the consistent selection of these variables underscores their potential influence.

Overall, this research contributes to a deeper understanding of how climate change influences housing prices, providing critical insights for policymakers, real estate professionals, urban planners, and investors. It underscores the importance of integrating climate change considerations into urban planning and policy formulation, highlighting the need for climate-resilient infrastructure to mitigate the adverse effects on housing markets. This study also points towards the importance of climate mitigation and adaptation strategies in the real estate sector, promoting measures that reduce carbon footprints and enhance community resilience. Furthermore, it suggests that real estate investors and professionals can use these insights for better risk assessment and management, particularly by considering the short-term impacts of climate change variables like Cooling Degree Days and Heating Degree Days on housing prices.

In the realm of investment strategies and market forecasting, the findings suggest that while climate change variables have a significant impact on short-term housing price predictions, their influence wanes over longer forecasting horizons. This indicates the necessity for a broader consideration of economic and financial factors in long-term investment decisions, while still accounting for the potential future scenarios of climate change. Moreover, the study enhances forecasting models by demonstrating the potential of machine learning approaches in capturing the complex dynamics between climate change and housing prices. Lastly, these insights can help inform public discourse and awareness about the interconnectedness of climate change, urban development, and economic stability, driving collective action and support for sustainable and resilient housing market policies.

To advance our understanding of this issue through empirical evidence, a recommendation would be adopting a similar methodology across different countries, with a specific emphasis on regions where climate change poses a more acute threat. This targeted approach may encompass island nations and rapidly growing economies that are especially vulnerable to climate-related challenges.

Furthermore, a crucial improvement worth exploring involves analyzing how the relevance and impact of climate change variables evolve in the aftermath of extreme weather events like floods, hurricanes, and droughts. This analysis can provide valuable insights into the dynamic relationship between climate change and housing markets, shedding light on the immediate and long-term effects of such events on property values and market dynamics.

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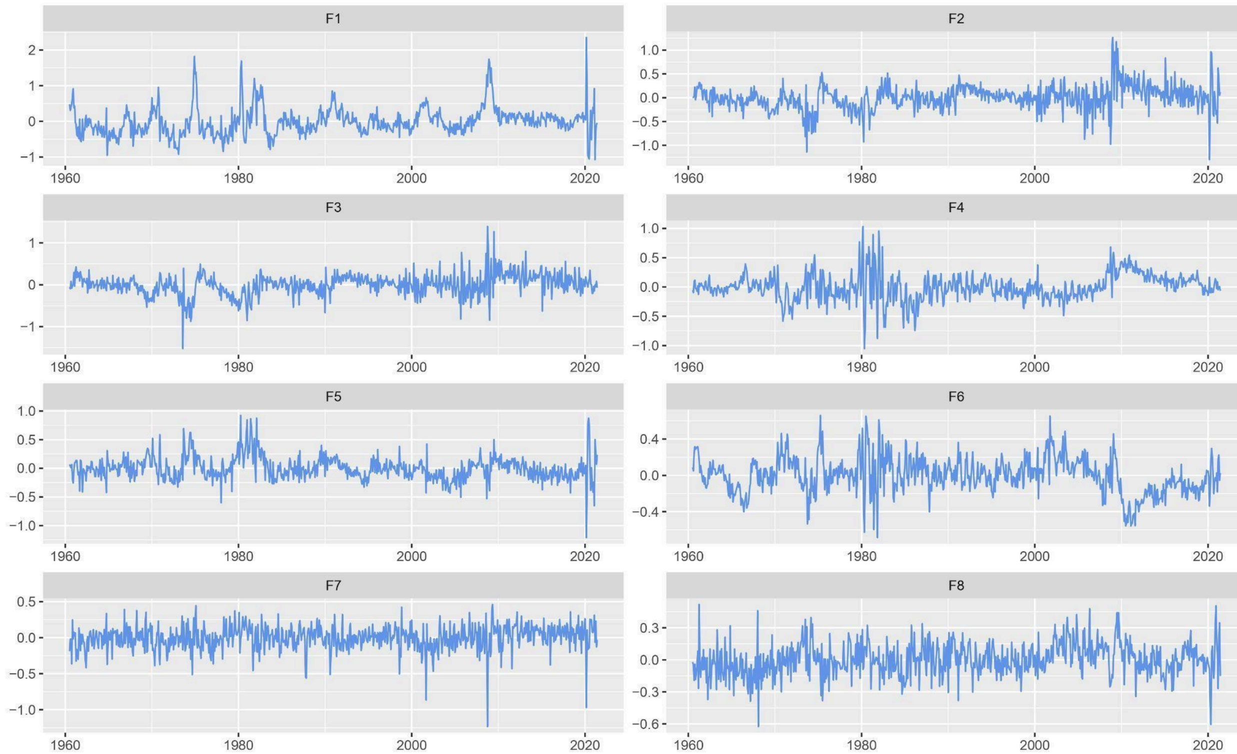
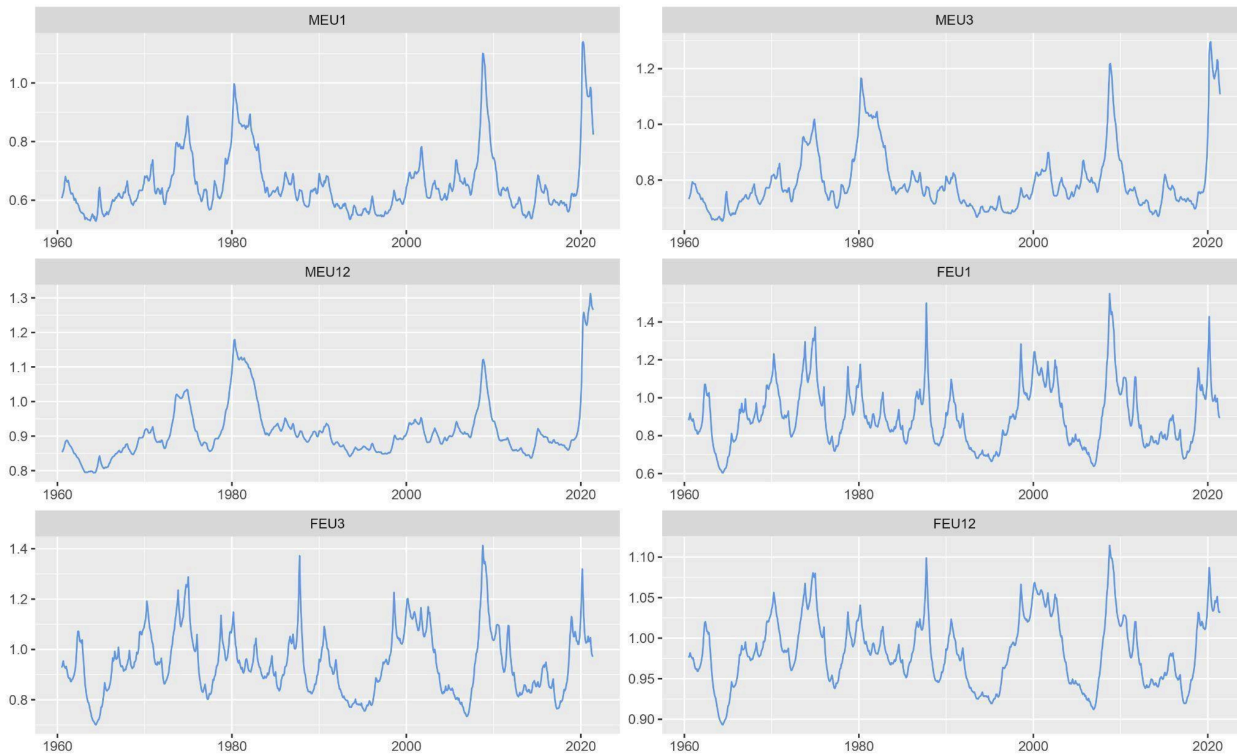
APPENDIX A - DEPENDENT VARIABLES

Figure 1 – Macroeconomic and Financial Factors



Source: own elaboration based on data from Ludvigson and Ng. (2009) (1960-2021).

Figure 2 – Macroeconomic and Financial Uncertainties Factors



Source: own elaboration based on data from Ludvigson et al. (2021) (1960-2021)

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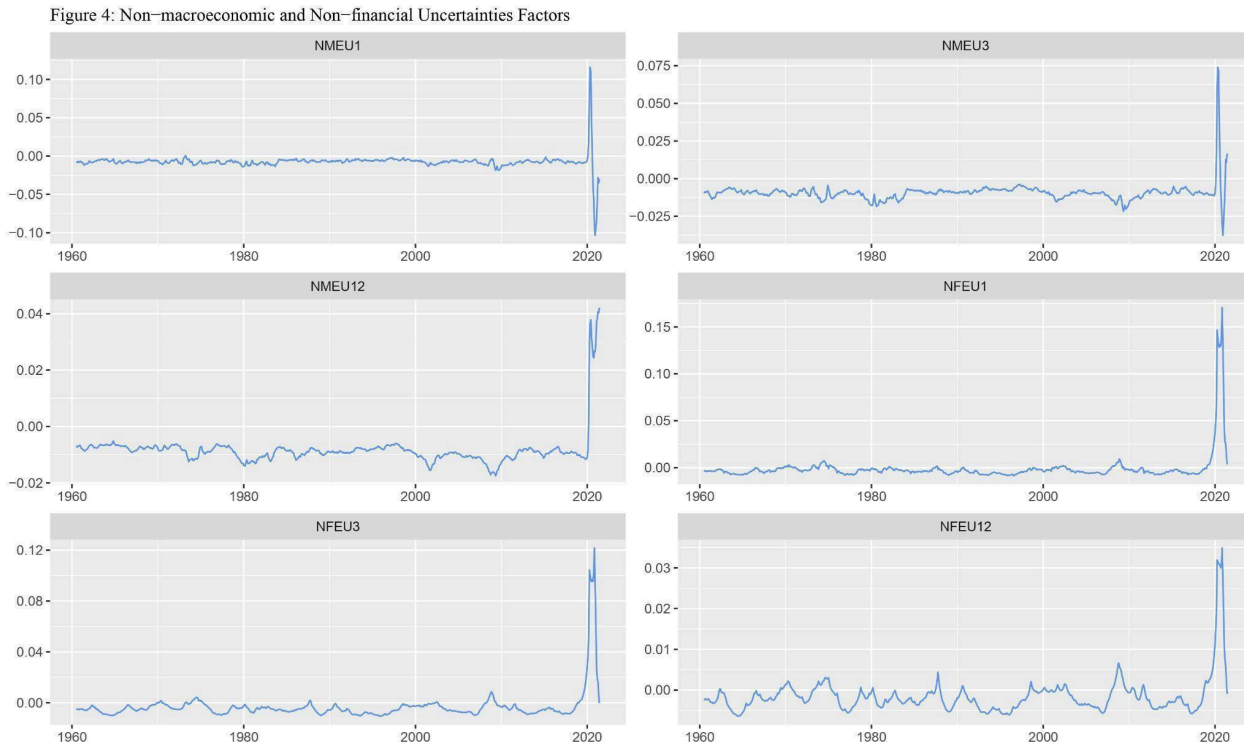
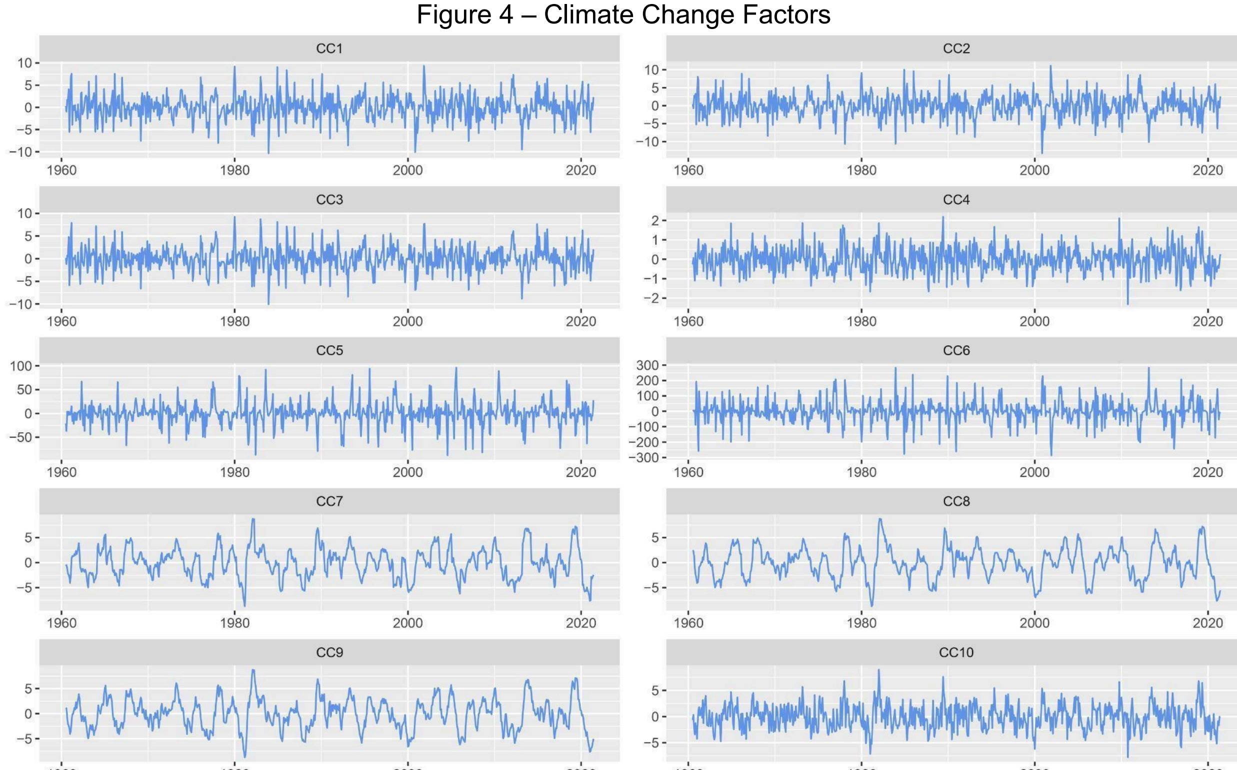
Figure 3 – Non-macroeconomic and Non-financial Uncertainties Factors



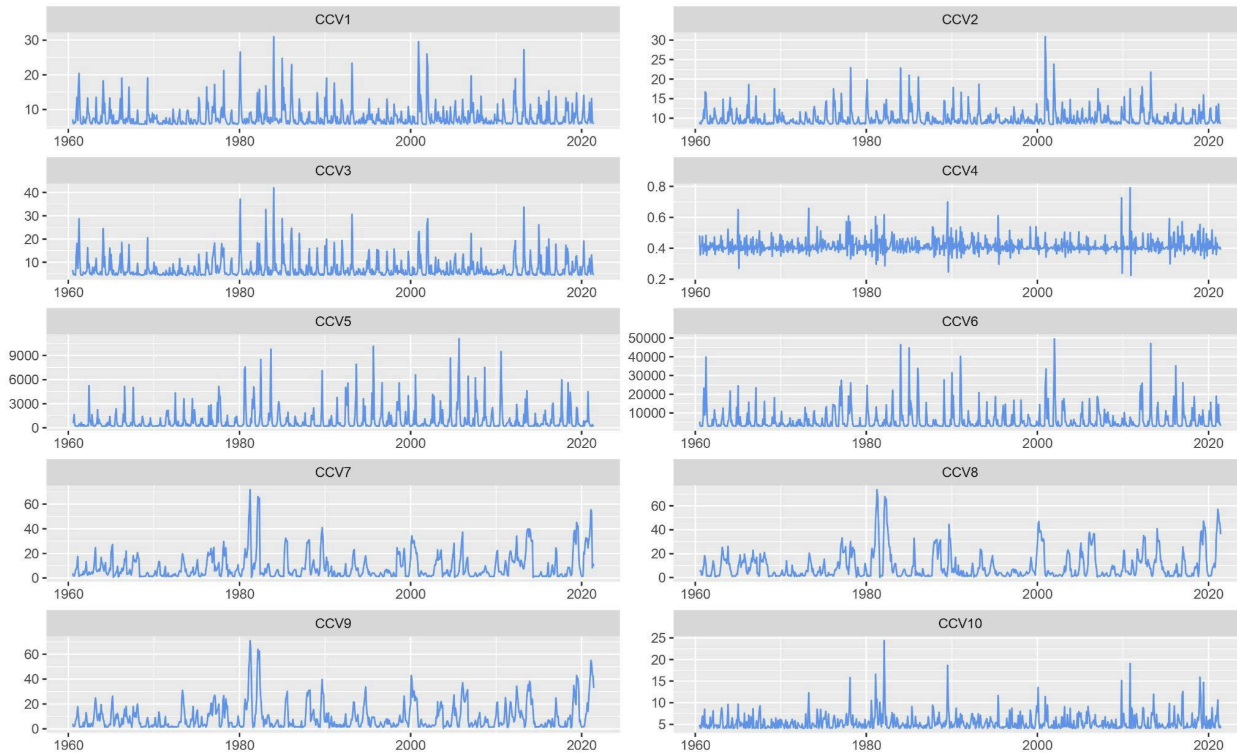
Source: own elaboration based on data from Ludvigson et al. (2021) (1960-2021).

Figure 4 – Climate Change Factors



Source: own elaboration based on data from the National Center for Environmental Information (1960-2021).

Figure 5 – Climate Change Factors Volatility



Source: own elaboration based on data from the National Center for Environmental Information (1960-2021).

APPENDIX B - REGIONAL RESULTS

Table 1 - Statistics on the predictive power for the real housing returns - Midwest (YM)

h = 1

Model	RMSE	MAE	GW Test MSE	GW Test MAE	MCS Rank M	MCS Rank R
Model 1	**0.5174**	**0.3953**			**1**	**1**
Model 2	0.5850	0.4489	0.0002*	0.0002*	E	E
Model 3	0.5964	0.4585	0.0509	0.0512*	E	E
Model 4	0.6279	0.4806	0.1273	0.1270	E	E
Model 5	0.6583	0.5099	0.0351*	0.0353*	E	E
Model 6	0.6661	0.5165	0.0129*	0.0130*	E	E

h = 3

Model	RMSE	MAE	GW Test MSE	GW Test Mae	MCS Rank M	MCS Rank R
Model 1	**0.7393**	**0.5705**			**1**	**1**
Model 2	0.8321	0.6420	0.0017*	0.0017*	E	E
Model 3	0.8509	0.6683	0.1342	0.1377	E	E
Model 4	0.8828	0.6974	0.2853	0.2869	E	E
Model 5	0.9600	0.7717	0.1481	0.1480	E	E
Model 6	1.0380	0.8244	0.1179	0.1194	E	E

h = 6

Model	RMSE	MAE	GW Test MSE	GW Test Mae	MCS Rank M	MCS Rank R
Model 1	**0.9348**	**0.7428**			**1**	**1**
Model 2	1.0095	0.8007	0.0014*	0.0015*	E	E
Model 3	1.0293	0.8177	0.0145*	0.0155*	E	E
Model 4	1.0626	0.8354	0.0194*	0.0203*	E	E
Model 5	1.1345	0.9115	0.0206*	0.0214*	E	E
Model 6	1.2329	0.9773	0.0412*	0.0437*	E	E

h = 12

Model	RMSE	MAE	GW Test MSE	GW Test Mae	MCS Rank M	MCS Rank R
Model 1	**1.1144**	**0.8298**			**1**	**1**
Model 2	1.2120	0.9297	0.1065	0.1140	E	E
Model 3	1.2290	0.9434	0.4062	0.4412	E	E
Model 4	1.2745	0.9785	0.0558	0.0599	E	E

Model 5	1.4100	1.0855	0.0043*	0.0046*	E	E
Model 6	1.4437	1.1188	0.1966	0.2069	E	E

Source: own elaboration
Notes: * Statistical difference at 5%

Table 2 - Statistics on the predictive power for the real housing returns - Northeast (YN)

h = 1

Model	RMSE	MAE	GW Test MSE	GW Test Mae	MCS Rank M	MCS Rank R
Model 1	**0.6947**	**0.5038**			**1**	**1**
Model 2	0.7189	0.5286	0.0352*	0.0339*	2	2
Model 3	0.7557	0.5494	0.0013*	0.0013*	4	4
Model 4	0.7856	0.5615	0.1344	0.1261	5	5
Model 5	0.7728	0.5466	0.2729	0.2633	3	3
Model 6	0.8154	0.5772	0.6171	0.6080	6	6

h = 3

Model	RMSE	MAE	GW Test MSE	GW Test Mae	MCS Rank M	MCS Rank R
Model 1	**0.9493**	**0.7030**			**1**	**1**
Model 2	0.9598	0.7228	0.0134*	0.013*	2	2
Model 3	1.0002	0.7499	0.0013*	0.0012*	3	3
Model 4	1.0465	0.7645	0.0221*	0.019*	E	E
Model 5	1.1157	0.8236	0.1042	0.0931	E	E
Model 6	1.2765	0.9341	0.3917	0.3695	E	E

h = 6

Model	RMSE	MAE	GW Test MSE	GW Test Mae	MCS Rank M	MCS Rank R
Model 1	**1.0997**	**0.8368**			**1**	**1**
Model 2	1.1739	0.8965	0.3012	0.2912	2	2
Model 3	1.2279	0.9262	0.028*	0.0247*	4	3
Model 4	1.2872	0.9548	0.2138	0.1796	6	4
Model 5	1.2342	0.9204	0.9377	0.9122	3	5
Model 6	1.2851	0.9661	0.4999	0.4821	5	6

h = 12

Model	RMSE	MAE	GW Test MSE	GW Test Mae	MCS Rank M	MCS Rank R
Model 1	**1.2368**	0.9591			2	2
Model 2	1.2373	**0.9503**	0.0498*	0.0506	**1**	**1**
Model 3	1.2829	0.9865	0.0122*	0.013*	3	3
Model 4	1.2964	0.9962	0.1821	0.1517	4	4
Model 5	1.3187	1.0404	0.2999	0.2900	E	E
Model 6	1.3426	1.0646	0.0954	0.1030	E	E

Source: own elaboration
Notes: * Statistical difference at 5%

Table 3 - Statistics on the predictive power for the real housing returns - South (YS)

h = 1

Model	RMSE	MAE	GW Test MSE	GW Test Mae	MCS Rank M	MCS Rank R
Model 1	**0.5055**	**0.3898**			2	**1**
Model 2	0.5431	0.4016	0.8982	0.8901	**1**	2
Model 3	0.5628	0.4114	0.0336*	0.0326*	3	4
Model 4	0.6067	0.4327	0.0660	0.0628	4	3
Model 5	0.6142	0.4341	0.0123*	0.0118*	E	E
Model 6	0.6227	0.4381	0.0258*	0.0251*	E	E

h = 3

Model	RMSE	MAE	GW Test MSE	GW Test Mae	MCS Rank M	MCS Rank R
Model 1	**0.6319**	**0.5009**			**1**	**1**
Model 2	0.7307	0.5534	0.8841	0.9058	E	E
Model 3	0.7448	0.5720	0.0294*	0.0274*	E	E
Model 4	0.7995	0.6020	0.0249*	0.0214*	E	E
Model 5	0.8175	0.6262	0.0043*	0.0037*	E	E
Model 6	0.8408	0.6295	0.0019*	0.0017*	E	E

h = 6

Model	RMSE	MAE	GW Test MSE	GW Test Mae	MCS Rank M	MCS Rank R
Model 1	**0.8035**	**0.6486**			**1**	**1**
Model 2	0.9407	0.7275	0.7062	0.7422	E	E
Model 3	0.9625	0.7423	0.0354*	0.0315*	E	E
Model 4	1.0394	0.7718	0.0929	0.0773	E	E
Model 5	1.0501	0.8020	0.0407*	0.0344*	E	E
Model 6	1.0909	0.8311	0.2263	0.2055	E	E

h = 12

Model	RMSE	MAE	GW Test MSE	GW Test Mae	MCS Rank M	MCS Rank R
Model 1	**0.9605**	**0.7547**			**1**	**1**
Model 2	1.0433	0.8205	0.7404	0.7621	2	2
Model 3	1.0587	0.8394	0.0796	0.0735	4	3
Model 4	1.1341	0.8848	0.0689	0.0578	E	E
Model 5	1.0830	0.8479	0.0189*	0.0154*	3	4
Model 6	1.0902	0.8649	0.0354*	0.0302*	E	E

Source: own elaboration
Notes: * Statistical difference at 5%

Table 4 - Statistics on the predictive power for the real housing returns - West (YW)

h = 1

Model	RMSE	MAE	GW Test MSE	GW Test Mae	MCS Rank M	MCS Rank R
Model 1	1.9742	1.5002			5	4
Model 2	1.8697	**1.3172**	0.8355	0.8077	2	**1**
Model 3	**1.8691**	1.3250	0.6815	0.6502	**1**	2
Model 4	2.0024	1.3743	0.9015	0.9473	3	3
Model 5	2.0360	1.4357	0.8275	0.8664	4	5
Model 6	2.0851	1.5205	0.5948	0.6153	E	E

h = 3

Model	RMSE	MAE	GW Test MSE	GW Test Mae	MCS Rank M	MCS Rank R
Model 1	**0.9493**	**0.7030**			**1**	**1**
Model 2	0.9598	0.7228	0.0134*	0.013*	2	2
Model 3	1.0002	0.7499	0.0013*	0.0012*	3	3
Model 4	1.0465	0.7645	0.0221*	0.019*	E	E
Model 5	1.1157	0.8236	0.1042	0.0931	E	E
Model 6	1.2765	0.9341	0.3917	0.3695	E	E

h = 6

Model	RMSE	MAE	GW Test MSE	GW Test Mae	MCS Rank M	MCS Rank R
Model 1	**1.0997**	**0.8368**			**1**	**1**
Model 2	1.1739	0.8965	0.3012	0.2912	2	2
Model 3	1.2279	0.9262	0.028*	0.0247*	4	3
Model 4	1.2872	0.9548	0.2138	0.1796	6	4
Model 5	1.2342	0.9204	0.9377	0.9122	3	5
Model 6	1.2851	0.9661	0.4999	0.4821	5	6

h = 12

Model	RMSE	MAE	GW Test MSE	GW Test Mae	MCS Rank M	MCS Rank R
Model 1	3.5085	2.7329			E	E
Model 2	2.9756	2.2056	0.1591	0.1744	2	2
Model 3	**2.9306**	**2.2041**	0.0419*	0.0526	**1**	**1**
Model 4	3.0387	2.2526	0.1849	0.2991	3	3
Model 5	3.0976	2.3876	0.2268	0.3338	4	4
Model 6	3.1078	2.3996	0.1885	0.2719	5	5

Source: own elaboration

Notes: * Statistical difference at 5%

Table 5 - Step-wise boosting variable selection rate for the real housing returns - Midwest (YM)

h = 1									
Model 2		Model 3		Model 4		Model 5		Model 6	
YM_L1	100.00%	YM_L1	100.00%	YM_L1	100.00%	YM_L1	100.00%	YM_L1	100.00%
YM_L2	100.00%	YM_L2	100.00%	YM_L2	100.00%	YM_L2	100.00%	YM_L2	100.00%
YM_L3	100.00%	YM_L3	100.00%	YM_L3	100.00%	YM_L3	100.00%	YM_L3	98.90%
YM_L7	100.00%	F8_L2	98.53%	YM_L5	98.53%	YM_L9	87.87%	YM_L7	94.49%
F8_L2	97.79%	YM_L5	98.53%	F8_L2	97.06%	YM_L5	86.76%	YM_L9	87.50%
YM_L5	97.43%	YM_L7	91.18%	YM_L7	90.81%	YM_L7	85.66%	F3	84.19%
YM_L6	94.85%	F7_L9	90.81%	YM_L9	88.60%	F8_L2	84.93%	F8_L2	80.88%
YM_L9	93.38%	YM_L9	88.60%	F7_L9	87.13%	F3	84.56%	YM_L5	74.63%
YM_L4	93.01%	F4_L6	85.29%	F3	85.29%	F8_L7	70.96%	F8_L7	68.38%
F7_L9	91.18%	F3	84.56%	F2_L11	78.31%	YM_L10	66.91%	YM_L10	67.28%
F4_L4	90.07%	F7_L1	82.35%	F8_L7	77.94%	**CC7_L5**	66.18%	**CC5_L5**	58.46%
F2_L3	88.60%	F2_L3	80.88%	F7_L1	77.57%	**CC5_L5**	65.81%	YM_L4	56.99%
F7_L1	87.87%	YM_L4	80.51%	F2_L3	76.47%	**CC5_L6**	64.34%	**CC5_L6**	53.68%
F2_L11	86.03%	YM_L6	79.41%	F4_L4	75.37%	**CC5_L9**	64.34%	**CC7_L5**	52.57%
F7_L7	84.56%	F4_L4	78.68%	YM_L4	75.37%	**CC4_L8**	63.97%	**CC4_L8**	50.74%
h = 3									
Model 2		Model 3		Model 4		Model 5		Model 6	
YM_L1	100.00%	YM_L1	100.00%	YM_L1	100.00%	YM_L1	100.00%	YM_L1	100.00%
YM_L2	100.00%	YM_L2	100.00%	YM_L2	100.00%	YM_L2	100.00%	YM_L2	100.00%
YM_L3	100.00%	YM_L3	100.00%	YM_L3	100.00%	YM_L4	100.00%	YM_L4	100.00%
YM_L4	100.00%	YM_L4	100.00%	YM_L4	100.00%	YM_L5	100.00%	YM_L8	98.89%
YM_L5	100.00%	YM_L5	100.00%	YM_L5	100.00%	YM_L8	98.52%	YM_L5	97.79%
YM_L7	100.00%	YM_L7	100.00%	YM_L7	100.00%	YM_L9	98.15%	YM_L9	85.61%
YM_L9	100.00%	YM_L9	100.00%	YM_L9	100.00%	YM_L3	97.05%	F8	72.69%
YM_L8	98.89%	F8	98.52%	YM_L8	98.89%	YM_L7	96.31%	**CC5_L6**	70.85%

F8	98.52%	YM_L8	97.79%	F8	98.15%	**CC5_L6**	86.72%	F8_L8	70.85%
F5	89.30%	F5	90.04%	F5	90.04%	YM_L6	86.35%	**CC4_L9**	70.11%
F3_L10	87.82%	YM_L6	89.67%	YM_L6	90.04%	**CC4_L9**	84.87%	**CC7_L5**	66.05%
F8_L8	87.45%	F3_L10	88.19%	F3_L10	88.19%	**CC7_L5**	84.87%	F3_L1	63.84%
F4	86.72%	F8_L8	85.24%	F4	82.29%	F8	81.18%	YM_L6	63.84%
F4_L4	86.35%	F4	81.55%	F8_L8	82.29%	F8_L8	77.86%	YM_L3	60.89%
F8_L5	78.60%	F8_L5	78.97%	F8_L5	78.60%	**CC5_L5**	76.38%	F5	60.15%
h = 6									
Model 2		Model 3		Model 4		Model 5		Model 6	
YM_L1	100.00%	YM_L1	100.00%	YM_L1	100.00%	YM_L1	100.00%	YM_L1	100.00%
YM_L2	100.00%	YM_L2	100.00%	YM_L2	100.00%	YM_L4	100.00%	YM_L4	100.00%
YM_L3	100.00%	YM_L3	100.00%	YM_L3	100.00%	YM_L6	100.00%	YM_L8	100.00%
YM_L4	100.00%	YM_L4	100.00%	YM_L4	100.00%	YM_L8	100.00%	YM_L6	99.26%
YM_L5	100.00%	YM_L5	100.00%	YM_L5	100.00%	YM_L2	99.63%	YM_L2	95.56%
YM_L8	100.00%	YM_L8	100.00%	YM_L8	100.00%	YM_L5	84.44%	F5	75.19%
YM_L6	98.15%	YM_L6	99.63%	YM_L6	99.26%	F5	83.70%	F8_L3	73.70%
F5	93.33%	F5	94.07%	F5	94.07%	YM_L3	82.59%	F8_L5	72.59%
YM_L7	92.59%	YM_L7	91.85%	YM_L7	87.41%	F8_L5	80.74%	F8_L10	71.11%
F2_L4	88.89%	F3_L2	85.19%	F1_L3	82.96%	**CC5_L9**	78.52%	F8_L11	71.11%
F8_L3	86.67%	F1_L3	84.44%	F8_L5	82.96%	F8_L3	76.67%	F3	67.41%
F3_L2	85.93%	F8_L3	83.70%	F8_L3	81.11%	F8_L10	74.07%	F3_L1	60.00%
F8_L5	84.44%	F2_L4	83.33%	F3_L2	80.00%	**CC5_L10**	73.70%	**CC4_L3**	59.63%
F8_L10	82.22%	F8_L5	83.33%	F3_L4	79.26%	F3	72.96%	F8_L8	58.89%
F8_L2	81.48%	F8_L8	78.52%	F4_L10	77.41%	F8_L11	72.22%	**CCV10_L2**	57.04%
h = 12									
Model 2		Model 3		Model 4		Model 5		Model 6	
YM_L1	100.00%	YM_L1	100.00%	YM_L1	100.00%	YM_L1	100.00%	YM_L1	100.00%
YM_L11	100.00%	YM_L11	100.00%	YM_L11	100.00%	YM_L4	100.00%	YM_L4	100.00%

YM_L2	100.00%	YM_L2	100.00%	YM_L2	100.00%	F3	82.40%	F3	76.40%
YM_L4	100.00%	YM_L4	100.00%	YM_L4	100.00%	YM_L11	82.40%	F8_L3	75.66%
F8_L2	95.88%	F8_L8	94.76%	F8_L8	90.26%	YM_L2	81.65%	YM_L11	71.54%
F8_L8	95.51%	F8_L2	92.51%	YM_L9	87.64%	F8_L3	74.91%	F8_L2	65.92%
F7_L9	88.01%	F7_L9	89.51%	F8_L2	86.89%	F6_L7	70.79%	**CC6_L10**	65.54%
YM_L9	86.14%	F4	89.14%	F5	85.39%	F8_L2	70.79%	**CCV7**	64.42%
F3	83.52%	F4_L10	87.64%	F3	84.27%	**CC2_L6**	70.04%	F6_L7	59.55%
F5	83.15%	F5	86.52%	F7_L9	82.77%	**CC6_L10**	67.79%	F5	57.68%
F4_L10	82.40%	YM_L9	85.39%	F4_L10	81.65%	F7_L10	67.79%	F8_L8	56.18%
F7_L10	81.65%	F3	83.52%	F8_L3	76.78%	F8_L8	64.42%	**CC4_L3**	53.93%
F2_L3	79.78%	F7_L10	81.27%	F8_L5	74.53%	**CC2_L7**	62.92%	**CCV3_L10**	53.93%
F4	77.90%	F2_L3	78.65%	F4	73.78%	F7_L9	62.92%	**CC4_L7**	51.69%
F7_L8	77.90%	F8_L3	74.91%	F3_L1	72.66%	**CC5_L7**	62.55%	F8_L7	50.94%

Source: own elaboration

Table 6 - Step-wise boosting variable selection rate for the real housing returns - Northeast (YN)

h = 1									
Model 2		Model 3		Model 4		Model 5		Model 6	
F3	100.00%	F2	100.00%	F2	100.00%	F2	100.00%	YN_L1	100.00%
YN_L1	100.00%	F3	100.00%	F3	100.00%	YN_L1	100.00%	YN_L4	100.00%
YN_L2	100.00%	YN_L1	100.00%	YN_L1	100.00%	YN_L4	100.00%	YN_L6	100.00%
YN_L4	100.00%	YN_L2	100.00%	YN_L2	100.00%	YN_L6	100.00%	F3	98.16%
YN_L6	100.00%	YN_L4	100.00%	YN_L4	100.00%	F3	99.63%	F2	97.43%
YN_L9	100.00%	YN_L6	100.00%	YN_L6	100.00%	YN_L2	93.38%	F3_L2	94.12%
YN_L3	98.90%	YN_L9	98.90%	F3_L2	97.06%	F3_L2	91.91%	YN_L9	83.82%
F2	98.53%	YN_L3	97.06%	YN_L9	95.96%	YN_L9	91.18%	YN_L2	61.76%
F3_L2	97.79%	F3_L2	96.32%	YN_L3	95.22%	F8_L9	72.06%	F4_L4	56.25%
F8_L9	95.59%	F8_L9	94.49%	F8_L2	83.82%	YN_L3	70.59%	**CCV8**	55.88%
F8_L2	88.24%	F8_L2	86.40%	F8_L9	83.09%	**CC6_L1**	68.01%	**CC4_L2**	54.04%
F7_L7	81.99%	F7_L7	81.99%	F7_L7	75.37%	F2_L2	67.28%	YN_L10	51.10%
F3_L1	80.51%	F8_L1	77.21%	F8_L1	73.16%	F8_L2	65.07%	F3_L1	44.49%
F8_L1	76.10%	F4_L1	73.90%	F8_L7	69.49%	F7_L7	62.13%	F2_L1	43.01%
F4_L1	73.53%	F8_L7	71.69%	F4_L4	65.44%	**CC4_L2**	61.40%	F8_L9	43.01%
h = 3									
Model 2		Model 3		Model 4		Model 5		Model 6	
YN_L1	100.00%	YN_L1	100.00%	YN_L1	100.00%	YN_L1	100.00%	YN_L1	100.00%
YN_L2	100.00%	YN_L2	100.00%	YN_L2	100.00%	YN_L2	100.00%	YN_L5	100.00%
YN_L4	100.00%	YN_L5	100.00%	YN_L5	100.00%	YN_L5	100.00%	F2_L1	98.89%
YN_L5	100.00%	YN_L4	99.63%	YN_L4	98.52%	F2_L1	99.63%	YN_L2	96.31%
F8_L2	98.15%	F8_L2	98.89%	F2_L1	98.15%	YN_L9	98.15%	YN_L9	96.31%
F2_L1	95.94%	F2_L1	98.52%	F8_L2	97.42%	F8_L2	94.83%	F8_L9	91.88%
YN_L9	93.36%	F3_L5	93.36%	F3_L5	94.83%	F4_L8	94.46%	**CCV10_L1**	84.50%

F2_L3	90.04%	YN_L9	91.14%	YN_L9	92.62%	**CC10_L2**	87.08%	**CCV10_L11**	80.44%
F3_L5	88.19%	F4_L8	85.61%	F2_L3	85.98%	F8_L8	84.50%	**CC4**	77.86%
F8_L8	87.08%	F8_L8	85.61%	F4_L8	82.66%	F2_L3	82.66%	F8_L8	77.86%
F3_L3	81.92%	F2_L3	84.87%	F8_L3	80.44%	**CC6_L2**	80.44%	F2_L3	74.54%
F8_L1	79.70%	F2	81.18%	F8_L8	80.44%	**CC4**	78.97%	**CCV6_L11**	73.06%
F2	77.86%	F8_L1	78.23%	F3_L1	76.01%	F8_L3	78.97%	**CC5_L9**	72.32%
F4_L8	76.75%	F8_L3	77.12%	F2	75.65%	YN_L4	77.49%	F8_L2	72.32%
F3_L1	74.54%	F3_L1	76.38%	F8_L9	71.59%	**CC5_L9**	74.17%	**CC10_L2**	70.85%

h = 6

Model 2		Model 3		Model 4		Model 5		Model 6	
YN_L1	100.00%	F8_L11	100.00%	YN_L1	100.00%	YN_L1	100.00%	YN_L1	100.00%
F8_L11	99.63%	YN_L1	100.00%	F8_L11	99.26%	F3_L5	97.41%	F8_L11	96.30%
F3_L5	98.89%	F3_L5	98.89%	F3_L5	98.15%	F8_L11	95.93%	F2_L1	89.63%
F2_L1	88.15%	F2_L1	89.26%	F2_L1	87.78%	F2_L7	79.63%	F3_L5	89.63%
F2_L7	80.74%	F2_L7	85.93%	F2_L7	85.19%	F2_L1	77.41%	**CC10_L8**	74.44%
F8_L10	79.26%	F8_L10	80.37%	F3_L4	73.33%	**CC10_L8**	73.70%	**CCV8**	73.33%
F3_L4	78.89%	F3_L4	76.67%	F6	69.63%	F4_L8	68.15%	F2_L7	71.85%
F6	73.33%	F2	75.19%	F2	65.19%	F3_L4	59.26%	**CCV10_L11**	61.85%
F6_L1	72.96%	F6	73.33%	F4_L8	65.19%	**CC6_L2**	58.15%	**CC6_L2**	61.48%
F2_L6	71.48%	F8_L2	70.37%	F6_L1	61.85%	F6	57.78%	F8	54.44%
F8_L2	71.48%	F4_L8	67.04%	F8	61.11%	**CC5_L10**	53.70%	F4_L8	53.70%
F2	68.52%	F6_L1	64.81%	F6_L11	60.00%	F8	52.22%	F6	53.70%
F6_L11	65.56%	F6_L11	63.33%	F8_L10	60.00%	F6_L1	51.85%	F8_L10	53.33%

F4_L8	62.59%	F2_L6	62.59%	F8_L2	58.52%	F8_L10	51.85%	**CCV8_L11**	51.48%
F8	58.52%	F8	60.74%	NMEU1_L10	54.44%	F4_L7	50.00%	F3_L4	48.52%
h = 12									
Model 2		Model 3		Model 4		Model 5		Model 6	
YN_L1	100.00%	YN_L1	100.00%	YN_L1	100.00%	YN_L1	100.00%	YN_L1	100.00%
YN_L11	90.26%	F3_L11	88.76%	F3_L11	88.39%	F3_L11	90.26%	**CCV8**	95.13%
F8_L2	88.01%	YN_L11	86.89%	F6_L11	85.39%	F6_L11	83.52%	F3_L11	90.26%
F6_L11	86.89%	F6_L6	85.39%	YN_L11	83.90%	**CC10_L2**	81.27%	**CCV10**	85.77%
F6_L6	84.27%	F6_L7	85.02%	F3_L1	80.52%	F6_L7	79.03%	F6_L11	79.03%
F6_L7	82.40%	F6_L11	83.52%	F6_L7	79.78%	F3_L1	78.65%	F3_L1	77.15%
F3_L11	81.65%	F8_L2	83.15%	F6_L6	78.65%	F6_L6	78.28%	F6_L7	73.03%
F3_L1	80.52%	F7_L7	82.02%	F8_L2	78.28%	FEU12	69.66%	**CCV6_L10**	71.54%
F7_L7	71.54%	F3_L1	80.52%	F7_L7	73.03%	**CC4**	67.79%	FEU12	68.91%
F3	65.17%	F3_L10	70.04%	FEU12	69.29%	F7_L7	65.92%	**CC4**	67.79%
F8_L8	64.79%	FEU12	69.29%	F3_L10	67.04%	F8_L2	64.79%	**CC5_L9**	66.67%
F6_L10	58.05%	F3	64.42%	F3	65.17%	**CC5_L9**	62.17%	**CC10_L2**	66.29%
F8_L10	58.05%	F4_L4	54.31%	F4_L4	53.93%	YN_L11	61.80%	F6_L6	65.92%
F8_L1	57.68%	F2	52.81%	F6_L10	53.93%	**CC2_L3**	60.67%	**CCV7_L7**	62.17%
F3_L10	57.30%	F8_L10	52.81%	F8_L7	49.44%	F3	58.80%	F7_L7	61.42%

Source: own elaboration

Table 7 - Step-wise boosting variable selection rate for the real housing returns - South (YS)

h = 1									
Model 2		Model 3		Model 4		Model 5		Model 6	
F3	100.00%	F3	100.00%	F3	100.00%	F8	100.00%	YS_L1	100.00%
F4_L6	100.00%	F4_L6	100.00%	F4_L6	100.00%	YS_L1	100.00%	YS_L2	100.00%
F6_L11	100.00%	F8	100.00%	F8	100.00%	YS_L2	100.00%	YS_L3	100.00%
F8	100.00%	YS_L1	100.00%	YS_L1	100.00%	YS_L3	100.00%	F3	99.63%
YS_L1	100.00%	YS_L2	100.00%	YS_L2	100.00%	F3	99.63%	F8	99.63%
YS_L2	100.00%	YS_L3	100.00%	YS_L3	100.00%	YS_L6	98.53%	F2	97.79%
YS_L3	100.00%	YS_L4	100.00%	YS_L6	100.00%	F2	98.16%	YS_L6	96.32%
YS_L4	100.00%	YS_L6	100.00%	F2	98.53%	YS_L4	96.32%	YS_L4	94.12%
YS_L6	100.00%	F2	99.63%	F7	98.53%	F4_L6	91.18%	F7	79.41%
F2	99.63%	F7	98.90%	YS_L4	98.53%	F7	82.35%	F4_L1	72.06%
F7	99.26%	YS_L11	95.96%	YS_L11	94.12%	**CC10_L6**	78.31%	**CCV7_L11**	70.59%
F2_L7	97.43%	F2_L5	95.59%	F7_L8	93.01%	F6_L11	77.94%	F4_L6	62.13%
YS_L11	96.69%	F6_L11	94.85%	F6_L11	88.24%	F7_L8	77.21%	F5_L8	61.03%
F7_L8	94.85%	F7_L8	93.38%	F7_L3	84.56%	F4_L1	75.00%	F6_L11	61.03%
F2_L5	91.91%	F2_L7	92.28%	F2_L7	84.19%	F7_L3	75.00%	F5_L5	60.66%
h = 3									
Model 2		Model 3		Model 4		Model 5		Model 6	
F3_L1	100.00%	F3_L1	100.00%	F3_L1	100.00%	F8	100.00%	YS_L1	100.00%
F8	100.00%	F8	100.00%	F8	100.00%	YS_L1	100.00%	YS_L2	100.00%
YS_L1	100.00%	YS_L1	100.00%	YS_L1	100.00%	YS_L2	100.00%	YS_L4	100.00%
YS_L2	100.00%	YS_L2	100.00%	YS_L2	100.00%	YS_L4	100.00%	F8	99.26%
YS_L3	100.00%	YS_L3	100.00%	YS_L4	100.00%	F3_L1	99.63%	F3_L1	98.52%
YS_L4	100.00%	YS_L4	100.00%	YS_L3	99.63%	**CC10_L7**	97.05%	F8_L1	90.41%

YS_L5	100.00%	YS_L5	100.00%	YS_L5	99.63%	F8_L1	91.14%	**CC10_L7**	85.24%
F3	92.99%	F8_L1	95.94%	F8_L1	92.99%	F3_L2	87.82%	F3_L2	83.76%
F7	92.99%	F2_L1	89.67%	F3_L2	86.35%	F4_L2	84.13%	F2_L2	75.28%
F8_L1	87.45%	F3	88.93%	F3	85.98%	F3	79.34%	F3	75.28%
F2_L2	85.24%	F2_L2	84.13%	F2_L5	83.03%	F2_L2	78.60%	F4_L2	74.54%
F6_L10	83.76%	F7_L11	83.76%	YS_L7	83.03%	F2_L5	75.28%	NFEU1	68.63%
YS_L7	83.39%	F4_L1	81.55%	F2_L2	80.07%	F2_L1	70.11%	F2_L1	67.53%
F3_L2	82.66%	YS_L7	81.55%	F4_L1	79.34%	F7_L9	67.53%	F5_L10	67.53%
F2_L1	81.92%	F3_L2	81.18%	F2_L1	77.86%	F5_L10	66.79%	**CCV10_L10**	65.68%
				h = 6					
Model 2		Model 3		Model 4		Model 5		Model 6	
F3_L1	100.00%	YS_L1	100.00%	YS_L1	100.00%	YS_L1	100.00%	YS_L1	100.00%
YS_L1	100.00%	YS_L3	100.00%	YS_L3	100.00%	YS_L3	99.63%	YS_L3	99.26%
YS_L2	100.00%	YS_L4	100.00%	F3_L1	99.63%	F3_L1	97.04%	F8	98.89%
YS_L3	100.00%	F3_L1	99.63%	YS_L4	99.63%	F2_L5	96.67%	F3_L1	98.52%
YS_L4	100.00%	F8	99.63%	F8	98.89%	F8	96.67%	F2_L5	95.93%
YS_L5	100.00%	YS_L2	98.89%	F8_L6	98.15%	F8_L1	96.30%	F3_L5	80.74%
YS_L8	100.00%	YS_L5	98.89%	F8_L1	97.41%	F3_L5	93.70%	F8_L1	76.67%
F8	99.63%	F8_L1	97.78%	F2_L5	97.04%	F3	83.33%	F8_L6	73.33%
F8_L1	98.89%	F2_L5	97.04%	F3	91.48%	F3_L4	82.59%	F2_L1	67.04%
F3_L4	97.78%	F3_L4	95.56%	F3_L4	91.48%	F8_L6	80.74%	F3	63.70%
F3_L5	97.41%	F3_L5	94.44%	YS_L5	91.11%	YS_L6	80.37%	YS_L8	61.48%
F2_L5	97.04%	F8_L6	94.44%	F8_L9	90.37%	YS_L4	79.63%	F7_L9	55.93%
F8_L6	96.30%	F3	92.96%	YS_L2	90.37%	F8_L9	72.96%	**CCV4_L5**	55.19%
F3	94.44%	F2_L1	91.11%	F3_L5	89.63%	**CC3_L9**	71.85%	F3_L4	55.19%
F7_L4	89.26%	F8_L9	88.15%	YS_L6	88.52%	F5_L10	68.52%	**CCV7_L11**	54.44%

h = 12									
Model 2		Model 3		Model 4		Model 5		Model 6	
F2	100.00%	F2	100.00%	YS_L1	100.00%	YS_L1	100.00%	YS_L1	100.00%
YS_L1	100.00%	YS_L1	100.00%	F2	99.63%	F3_L11	94.38%	F3_L11	92.88%
F2_L10	99.63%	F2_L10	98.88%	F2_L10	99.25%	F2_L10	93.26%	F3_L1	91.39%
F3_L11	99.25%	F8	98.88%	F2_L11	98.50%	F3_L1	92.51%	F3	90.64%
F8	98.88%	F3_L11	97.75%	F3_L1	95.51%	F3	89.89%	**CC5_L11**	83.52%
F3_L1	97.00%	F3_L1	96.63%	F3_L11	95.51%	**CC5_L11**	89.51%	F8	83.52%
F2_L11	95.51%	F3	94.01%	F3	94.01%	F8	85.39%	F2_L10	79.03%
F3	94.76%	F2_L11	90.26%	F8	93.63%	**CC10_L6**	78.28%	**CC10_L6**	71.16%
F5_L9	92.13%	F8_L6	80.15%	F8_L6	76.03%	**CC5**	77.53%	F2	64.04%
F8_L5	80.52%	F8_L5	76.40%	F6_L7	70.79%	F2	70.41%	F2_L11	64.04%
F8_L6	79.78%	F7	73.03%	F8_L5	70.41%	F2_L11	69.29%	NFEU1	63.30%
YS_L11	79.40%	YS_L11	72.28%	F5_L9	69.66%	NFEU1	64.79%	F5_L9	60.67%
F7	77.53%	F5_L9	70.79%	YS_L11	69.29%	F5_L9	63.67%	F6	60.67%
F3_L10	75.28%	F6_L7	70.79%	YS_L4	69.29%	F6_L9	63.30%	YS_L11	55.81%
F6_L9	74.53%	F8_L4	67.42%	F7	68.16%	**CC6_L1**	62.17%	**CC6_L1**	55.43%

Source: own elaboration

Table 8 - Step-wise boosting variable selection rate for the real housing returns - West (YW)

				h = 1					
Model 2		Model 3		Model 4		Model 5		Model 6	
F2	100.00%	F2	100.00%	F2	100.00%	F2	100.00%	F2	100.00%
F2_L3	100.00%	F3	100.00%	F3	100.00%	F3	100.00%	F3	100.00%
F3	100.00%	F3_L1	100.00%	F4_L1	100.00%	F4_L1	100.00%	YW_L1	100.00%
F3_L1	100.00%	F4_L1	100.00%	F6_L11	100.00%	YW_L1	100.00%	YW_L2	100.00%
F3_L2	100.00%	F6_L11	100.00%	YW_L1	100.00%	YW_L2	100.00%	YW_L3	100.00%
F4_L1	100.00%	YW_L1	100.00%	YW_L2	100.00%	YW_L3	100.00%	YW_L4	100.00%
F6_L11	100.00%	YW_L2	100.00%	YW_L3	100.00%	YW_L4	100.00%	F3_L1	95.59%
F7_L5	100.00%	YW_L3	100.00%	YW_L4	100.00%	F2_L3	99.63%	F2_L3	92.28%
YW_L1	100.00%	YW_L4	100.00%	F2_L3	99.63%	F6_L11	97.79%	F4_L1	91.91%
YW_L2	100.00%	F2_L3	99.63%	F3_L1	99.63%	F3_L1	97.43%	F7_L5	88.97%
YW_L3	100.00%	F7_L5	99.63%	F7_L5	99.63%	F3_L4	93.01%	**CCV2_L8**	75.37%
YW_L4	100.00%	F3_L2	99.26%	F8_L2	99.63%	F8_L2	93.01%	F6_L5	74.26%
F8_L2	99.63%	F8_L2	98.53%	F3_L2	97.79%	F3_L2	91.54%	F7_L7	72.79%
F6_L5	95.22%	F6_L5	97.06%	F6_L5	94.12%	F7_L5	91.54%	F6_L11	71.32%
F2_L2	94.49%	F2_L2	94.12%	F2_L2	92.65%	F6_L5	86.40%	YW_L6	69.85%
				h = 3					
Model 2		Model 3		Model 4		Model 5		Model 6	
F2	100.00%	F2	100.00%	F2_L1	100.00%	F2_L1	100.00%	F2_L1	100.00%
F2_L1	100.00%	F2_L1	100.00%	F3_L1	100.00%	F3_L1	100.00%	F3_L1	100.00%
F3	100.00%	F3	100.00%	F3_L2	100.00%	F3_L2	100.00%	F3_L2	100.00%
F3_L1	100.00%	F3_L1	100.00%	YW_L1	100.00%	YW_L1	100.00%	YW_L1	100.00%
F3_L2	100.00%	F3_L2	100.00%	YW_L2	100.00%	YW_L4	100.00%	YW_L4	100.00%
YW_L1	100.00%	YW_L1	100.00%	YW_L3	100.00%	F3	98.52%	F2_L2	96.31%
YW_L2	100.00%	YW_L2	100.00%	YW_L4	100.00%	YW_L2	97.42%	**CCV2_L9**	84.50%

YW_L3	100.00%	YW_L4	100.00%	F2	99.63%	F2_L2	96.68%	YW_L2	81.55%
YW_L4	100.00%	YW_L3	99.63%	F3	99.63%	**CC6**	95.20%	F3	78.23%
YW_L5	100.00%	F7_L5	98.52%	F7_L5	99.63%	F2_L11	91.88%	**CC6**	77.86%
F7_L5	98.15%	YW_L5	97.42%	F2_L2	96.68%	F7_L5	86.72%	**CCV10_L9**	77.12%
F2_L2	96.31%	F8_L3	97.05%	F2_L4	95.57%	F2	83.03%	**CC5_L6**	70.85%
F6_L5	95.94%	F2_L2	96.68%	F2_L5	95.57%	F4_L3	79.34%	**CCV10_L10**	70.11%
F8_L3	95.57%	F2_L11	95.57%	YW_L5	93.73%	F8_L3	73.43%	F6	66.42%
F8_L7	93.36%	F2_L5	94.83%	F2_L11	91.88%	**CC5_L6**	71.96%	**CCV8_L5**	64.21%
h = 6									
Model 2		Model 3		Model 4		Model 5		Model 6	
F2	100.00%	F2	100.00%	F2	100.00%	F2_L1	100.00%	F2_L4	100.00%
F2_L1	100.00%	F2_L1	100.00%	F2_L1	100.00%	F2_L4	100.00%	F3_L1	100.00%
F2_L4	100.00%	F2_L4	100.00%	F2_L4	100.00%	F3	100.00%	F3_L5	100.00%
F3	100.00%	F3	100.00%	F2_L5	100.00%	F3_L1	100.00%	YW_L1	100.00%
F3_L1	100.00%	F3_L1	100.00%	F3	100.00%	F3_L5	100.00%	YW_L3	100.00%
F3_L2	100.00%	F3_L2	100.00%	F3_L1	100.00%	YW_L1	100.00%	F2_L5	98.52%
F3_L5	100.00%	F3_L5	100.00%	F3_L2	100.00%	YW_L3	100.00%	F2_L1	95.56%
F8_L3	100.00%	F8_L3	100.00%	F3_L5	100.00%	F2_L5	99.63%	F3	95.19%
YW_L1	100.00%	YW_L1	100.00%	F8_L3	100.00%	F8_L3	97.04%	F3_L4	92.22%
YW_L3	100.00%	YW_L3	100.00%	YW_L1	100.00%	F2	96.30%	F3_L11	77.41%
YW_L5	100.00%	YW_L5	100.00%	YW_L3	100.00%	F2_L7	96.30%	**CCV2_L6**	74.81%
YW_L2	98.89%	YW_L2	98.52%	YW_L5	99.26%	F3_L4	91.85%	F2_L7	74.81%
F6_L5	98.52%	F2_L5	98.15%	YW_L2	96.67%	F3_L11	89.63%	F8_L3	72.22%
F2_L5	97.78%	F8_L10	96.30%	F3_L11	94.44%	F3_L2	86.67%	F2	71.11%
F4_L1	96.67%	F3_L11	94.81%	F2_L7	92.22%	YW_L4	80.74%	F7_L9	65.93%
h = 12									

Model 2		Model 3		Model 4		Model 5		Model 6	
F2	100.00%	F2	100.00%	F2	100.00%	F2	100.00%	F2	100.00%
F2_L10	100.00%	F2_L10	100.00%	F2_L10	100.00%	F2_L10	100.00%	F2_L10	100.00%
F2_L11	100.00%	F2_L11	100.00%	F2_L11	100.00%	F3	100.00%	F3	100.00%
F3	100.00%	F3	100.00%	F3	100.00%	F3_L1	100.00%	F3_L1	100.00%
F3_L1	100.00%	F3_L1	100.00%	F3_L1	100.00%	F3_L11	100.00%	F3_L11	100.00%
F3_L11	100.00%	F3_L11	100.00%	F3_L11	100.00%	YW_L1	100.00%	YW_L1	100.00%
F8_L3	100.00%	YW_L1	100.00%	YW_L1	100.00%	YW_L3	100.00%	YW_L3	100.00%
YW_L1	100.00%	YW_L3	100.00%	YW_L3	100.00%	F3_L10	89.14%	F3_L10	90.64%
YW_L3	100.00%	F8_L3	99.25%	F8_L3	95.51%	F8_L3	84.64%	F2_L9	88.76%
F6_L9	98.88%	F2_L1	97.00%	F2_L1	94.76%	**CC5_L4**	84.27%	F8_L3	83.90%
YW_L11	97.38%	YW_L11	96.63%	F3_L9	90.64%	F2_L1	83.15%	**CC6_L1**	81.65%
F2_L1	96.25%	F6_L9	95.88%	YW_L11	88.01%	F2_L11	81.65%	F6_L7	75.28%
F7_L1	92.88%	F3_L9	89.89%	F6_L9	86.14%	**CC6_L1**	80.90%	F3_L7	74.91%
F8_L8	88.39%	F4_L10	88.01%	F4_L10	85.02%	F2_L9	78.65%	F2_L11	72.66%
F3_L7	87.27%	F3_L7	85.02%	F2_L9	83.52%	F6_L9	77.90%	**CCV8_L5**	71.54%

Source: own elaboration