Forecasting real housing price returns of the USA using machine learning: the role of climate risks

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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 complex relationship between climate change and real housing price returns in the USA, leveraging a comprehensive dataset and advanced machine learning technique – the stepwise boosting method. This ensemble learning technique significantly enhances our analysis. Our findings suggest that climate change variables can influence real housing price returns, particularly in the short term, but the relationship is complex and varies by region. The adaptive learning capability of step-wise boosting has been crucial in uncovering these insights. This methodological approach not only underscores the importance of employing advanced predictive models in analysing the effects of climate change on urban development but also highlights the potential for informed decision-making, sustainable urban planning, and climate risk mitigation.

Keywords: climate finance; housing market; machine learning; predictive modelling; step-wise boosting.

JEL codes: C22; C53; Q54; R31.

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1 Introduction

Climate change has deep and widespread ramifications across various aspects of our daily lives. The economic implications of climate change are substantial, impacting infrastructure, violent crime, agriculture, and energy demand (Hsiang et al., 2017). Among its multiples consequences, climate change extends its reach to the housing sector, an important part of the economy, serving both as a fundamental human need and a significant financial asset for many. It affects housing and house prices in several connected ways. Home buyers increasingly consider climate risks when choosing where to live, potentially boosting demand and property prices in less susceptible areas while reducing demand and lowering prices in high-risk regions (Heinen et al., 2019; Kim et al., 2022).

Intensifying climate change is anticipated to amplify the frequency and severity of severe weather events such as hurricanes, floods, and wildfires (Emanuel, 2017; IPCC, 2021), leading to increased property damage and devaluation. The escalation of climate-related risks has translated into higher homeowner insurance premiums, particularly in high-risk regions, rendering home-ownership less affordable and impacting house prices in disaster-prone areas (Kousky, 2014). Indeed, Tucker (1997), utilising an options model, concluded that the heightened variability in climate is reflected in the expected damages to insured assets, imposing a substantial economic burden.

The relevance of this field of study is further underscored by the growing importance of environmental, social, and governance (ESG) criteria in the investment world. Concerns about climate change and its potential impacts on investments have made it imperative to consider assets in relation to sustainability and the real estate market constitutes a substantial part of the financial world. Globally, the residential real estate market was valued at approximately $326.7 trillion in 2020 (Savills World Research, 2020). Institutional investors, including real estate investment trusts (REITs), have allocated significant resources to real estate assets. In the USA, the market capitalisation of REITs exceeded $1 trillion in 2021 (NAREIT, 2021). Moreover, mortgage-backed securities (MBS) play an integral role, with outstanding agency MBS in the US surpassing $9 trillion in 2020 (Federal Reserve, 2020).

Furthermore, the housing market serves as an economic indicator. Residential investment contributed approximately 4.1% to the US GDP in 2020, highlighting its significance in reflecting broader economic conditions (US Bureau of Economic Analysis, 2021). A robust housing market often signals economic growth and consumer confidence, whereas a downturn can indicate economic challenges (Case and Shiller, 2003).

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

This study incorporates decades of climate data, including temperature, precipitation, and drought. Additionally, it considers 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 potential to inform policymakers, real estate professionals, and the public about the economic implications of climate change on housing markets. As the trajectory of climate change unfolds, understanding how housing prices respond to climate variables becomes crucial for informed decision making, sustainable urban development, and risk mitigation in the face of a changing climate. Subsequent sections of this paper delve deeper into our methodology and present our findings regarding the US housing market amid the challenges of climate change.

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 stepwise boosting algorithm. The forecasting procedures and model performance metrics employed are presented in Section 3.3. Sections 3.4 and 3.5 analyse 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 relationship between climate change factors and the economy have been the subject of extensive research and policy discussions. Numerous studies have highlighted vulnerabilities and potential consequences associated with a changing climate to the housing sector. Around the world, early inquiries in Italy (Maddison and Bigano, 2003) and in Germany (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 exert a considerable influence on housing markets. The European housing sector also encounters climate-related challenges, as demonstrated by Domínguez-Amarillo 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. 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 highlights the challenge of incorporating climate change adaptation and mitigation strategies into coastal housing policies while simultaneously aligning with the imperative of affordable housing goals.

Turning our attention to the USA, the Global Change Research Program published a comprehensive assessment by Melillo et al (2014) outlining the impact of climate change on infrastructure in the USA. Key findings from this report emphasised 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. 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. On the other hand, climate risks can negatively impact housing prices. Kahn's (2009) influential study scrutinised climate amenity values by assessing home prices in major US metropolitan areas. His research showed that anticipated shifts in temperature and precipitation could adversely affect housing prices, with certain cities experiencing declines exceeding 50%. 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. These findings underscore the complex ways in which climate change variables impact housing costs, encompassing both direct and indirect consequences. Additionally, climate change has significant implications for housing conditions and health outcomes, with a pronounced effect on marginalised 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 USA, 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 21st century.

The intricacy of the relationship between climate and housing prices has spurred a variety of analytical approaches. As a result, numerous statistical models and methodologies have been employed in the USA. 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). One frequently utilised 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 considered spatial econometric models, such as the spatial autoregressive model and geographically weighted regression (Zou et al., 2022). These models offer a more accurate 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 USA (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 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 addition to the advances made by the current literature, this research contributes to the understanding of the complex interplay between climate change and real state markets by investigating weather climate-related variables such as anomalies in temperature, precipitation, and drought can impact or help predict housing market returns. Ultimately, the insights derived from this research can help policymakers and economic agents to make informed decisions in a world increasingly shaped by the 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 analyses data spanning several decades, incorporating climate-related variables such as anomalies in temperature, precipitation, and drought. To model housing returns, the paper utilises 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 modelling, particularly by analysing their selection rates within the boosting algorithm.

The modelling for this study was executed using R and R Studio. For the specific task of applying stepwise boosting, the mboost package was employed, adhering to the methodologies outlined by Hofner et al. (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.

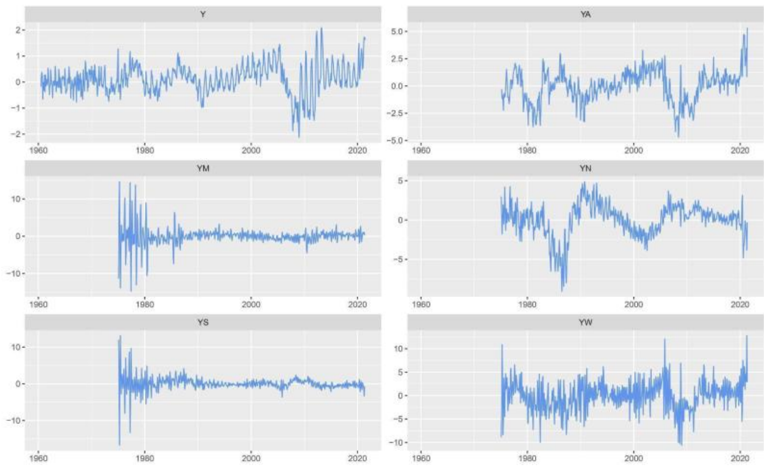
2.1 Data

In this study, we employed a comprehensive array of six distinct dependent variables, each serving as a measure of real housing log-returns. The first of these variables encapsulated the entirety of real housing returns within the USA, spanning the temporal range from July 1960 to June 2021, and shall be denoted as 'Y'. The real housing price data was obtained from the online data segment of Professor Robert J. Shiller. Additionally, four other dependent variables were established to scrutinise housing returns within distinct regions of the USA: 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. Note that these regional and national real housing returns factors are based on decomposition from a Bayesian dynamic factor model (DFM) applied to data on all the 50 US states plus District of Columbia (DC), as outlined in Del Negro and Otrok (2007) and Sheng et al. (2021), to account for regional heterogeneities and segmented nature of the US housing market. The nominal house price data was derived from Freddie Mac and then deflated by the aggregate US Consumer Price Index (CPI), obtained from the FRED database of the Federal Reserve Bank of St. Louis, to get to real values.

The independent variables utilised in this study can be categorised 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, and MEU12, i.e., macroeconomic uncertainties at horizons of one-, three- and 12-month-ahead; FEU1, FEU3, and FEU12, i.e., financial uncertainties at horizons of one-, three- and 12-month-ahead while the third set was characterised by NMEU1, NMEU3, NMEU12, NFEU1, NFEU3, and NFEU12, which are corresponding macroeconomic and financial uncertainties respectively, due to outbreaks of infectious diseases, like the COVID-19 pandemic. The choices of these predictors are in line with the housing market forecasting literature [see, for example, Gupta et al. (2022) and Bouras et al. (2023) for detailed reviews].

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.

Figure 1 Real housing returns (see online version for colours)



Source: Own elaboration based on data from the Freddie Mac House Price Indexes (1960–2021)

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 and 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

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)

Table 1 Descriptive statistics for the dependent and independent variables (continued)

Variables	*Mean*	*St. Dev.*	*Min*	*Max*
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

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)

Table 1 Descriptive statistics for the dependent and independent variables (continued)

Variables	*Mean*	*St. Dev.*	*Min*	*Max*
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)

2.2 Methodology

In the subsequent section, we explain the partitioning scheme of the dataset into training and testing sets for the out-of-sample forecasting method, in order to assess the predictive performance of our model. However, a challenge arises when implementing this procedure within the context of our study. Namely, the resulting datasets exhibit more variables than observations. This issue precludes the straightforward application of conventional linear regression, as it would arise in inconsistency due to the absence of a unique solution.

In response to this, we turn to the methodology of stepwise boosting, an ensemble learning technique that enhances model performance by iteratively correcting errors made by previous models. This method belongs to the family of boosting algorithms, which fundamentally aim to convert a series of weak learners into a strong collective model. Unlike other machine learning approaches that rely on a single hypothesis, stepwise boosting strategically builds its predictive strength by focusing on the data points that previous iterations have misclassified. This adaptive learning capability significantly sets it apart from other ensemble methods like bagging or random forests. While methods like random forests build decision trees in parallel without considering the performance of individual trees, stepwise boosting meticulously adjusts the weights of incorrectly classified instances, thus ensuring that subsequent models focus more on difficult cases. This adaptability not only improves model accuracy but also enhances learning efficiency, as each step in the sequence directly addresses the shortcomings of the previous model.

One clear advantage of the stepwise boosting, as delineated by the work of Zhang and Haghani (2015), is that the algorithm not only captures the complex interplay between input variables and response variables but also offers insights into the relative significance of individual input variables. This desirable characteristic emerges through the iterative nature of the boosting procedure. The outcome is a function that aptly balances predictive accuracy and model simplicity.

In more formal terms this stepwise boosting methodology can be described as follows. Let y_t be a time series of interest and x_t a vector of regressor variables. The $\hat{y}_t$ boosting estimation is the result of a sum of M distinct parts plus a constant, having the following form:

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

where $f^{(0)}$ is a constant, v is shrinkage parameter that ranges from 0 to 1 and $g^{(m)}$ is the learner estimated at iteration m. The total number of iterations, M, represents the trade-off between model fitness and complexity. Numerous metrics are available for quantifying this trade-off, including the Akaike information criterion (AIC), Bayesian information criterion (BIC), and cross-validation (CV). The main function of this parameter is to prevent overfitting of an excessive number of iterations. In this study, we opted for the corrected AIC (AICC) proposed by Hurvich et al. (1998), which avoids the large variability and tendency to undersmooth of the AIC or CV.

Also pivotal for the boosting algorithm quality, is the parameter v, commonly referred to as the *step size*. 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 regularisation that gives a controlled bias to the model while simultaneously reducing its variance. This ensures that our model remains resilient against overfitting, making it a valuable 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 $v = 0.1$.

The iterative nature of the boosting algorithm can be described by the following steps:

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

b obtain the residuals from such model $u_t = y_t - f_t^{(m-1)}$

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 $g^{(m)} = \beta_{(i)}x_{(i)}$

g set the new model as $f^{(m)} = f^{(m-1)} + vg^{(m)}$

h repeat the steps b through g for m iterations.

3.3 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 endeavour 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 the lags of the dependent variable at its disposal but also the entirety of the five sets of variables enumerated in Section 3.1. This progression was designed to systematically probe the incremental value of each variable set. In more details, the group of regressor variables for each model may be summarised as:

model 1 lags of real housing returns

model 2 same as model 1 + macro and financial factors

model 3 same as model 2 + macro and financial uncertainties

model 4 same as model 3 + non-macro and non-financial uncertainties

model 5 same as model 4 + climate change

model 6 same as model 5 + climate change volatility.

Furthermore, a pivotal aspect of our methodology involved the normalisation 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 standardisation of variables using mean and standard deviation, this normalisation process ensured that our models operated untainted by data leakage from the test set.

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 datasets are a result of the division of the original data into training set and test set in a 1:2 ratio.

To highlight the efficacy of each model and understand the impact of different variable sets on predictive power, we employed four 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 statistics are described, respectively, as:

$$RMSE = \sqrt{\sum \frac{\left(\hat{y}_i - y_i\right)^2}{n}} \tag{2}$$

and

$$MAE = \frac{1}{n}\sum\left(\hat{y}_i - y_i\right) \tag{3}$$

where 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 GW test can handle forecasts based on both nested and non-nested models, which is an advantage over the test proposed by Diebold and Mariano (1995). The GW 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 judgements about model superiority when statistically significant differences emerged.

Additionally, we incorporated the model confidence set (MCS) (Hansen et al., 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.

3.4 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 complex 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 outperform the benchmark. These findings emphasise the particular nature of predictive modelling, where certain variables can exert 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)

Model	*RMSE*	*MAE*	*GW test MSE*	*GW test Mae*	*MCS rank M*	*MCS rank R*
			h = 1			
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 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 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 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

Note: *Statistical difference at 5%.

Source: Own elaboration

In the analysis of forecasting performance across these different models, no significant differences were observed for the aggregate variable encompassing data from all four regions (YA), with the MCS ranks consistently favouring models 2, 3, and 4 over model 1 across various forecast horizons. Similarly, at the regional level, models incorporating climate change variables failed to outperform the benchmark model. This performance is in line with the conclusions of Sussman et al. (2014), who documented varied impacts of climate change variables on housing prices across different US regions. In their work, despite these regional disparities, a consistent effect on the mean change in housing prices was observed, aligning with our short-term findings on overall housing returns. For a more exhaustive presentation of the statistical results pertaining to the forecasting performance of the evaluated models, interested parties are directed to the Appendix.

3.5 Variable selection

As the selection of variables is an important aspect in the context of stepwise boosting, this section seeks to evaluate the relevance of climate change variables in the modelling 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 3, 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 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) emphasised 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 observations underscore the potential influence of climate change variables on our modelling efforts, particularly in scenarios where specific lagged values manifest recurrently.

Table 3 Stepwise 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%

Source: Own elaboration

Table 3 Stepwise boosting variable selection rate for the overall real housing returns (Y) (continued)

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%

Source: Own elaboration

Table 3 Stepwise boosting variable selection rate for the overall real housing returns (Y) (continued)

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%

Source: Own elaboration

Table 3 Stepwise boosting variable selection rate for the overall real housing returns (Y) (continued)

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

Our study analysed the impact of climate change variables on aggregate and regional housing returns. While climate change variables were less dominant in the aggregate housing returns (YA), particularly noticeable at h = 6 with only one variable selected, they remain significant in our selection process. In regional housing returns, the importance of climate change variables varies, with some significance noted in the Midwest and Northeast regions at various time horizons. Despite not always enhancing forecasting accuracy, the consistent selection of certain climate change factors, with frequencies over 80%, underscores their potential importance.

The consistent selection of certain climate change factors, even without a clear enhancement in forecasting accuracy, underscores their potential importance in the housing market, resonating with the findings on climate impact by Sussman et al. (2014) in which there is a varying influence of climate change variables on housing prices depending on assumptions and regional contexts. For more detailed insights into the variable selection for the evaluated models, please refer to the Appendix.

4 Conclusions

This paper intended to shed light on the relationship between climate change and housing prices within the USA. The study underscores the influence of climate change factors on housing prices, revealing specific 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 the understanding of the complex interplay between climate change and housing markets, emphasising the need for policymakers, real estate professionals, and urban planners to consider climate-related factors when making informed decisions about land use, transportation, and climate mitigation strategies. As the world continues to grapple with the challenges of climate change, understanding its impact on housing prices becomes increasingly important for sustainable urban development and risk mitigation.

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 analysing 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. At the same time, as we are dealing with climate risks, from a technical perspective, one can resort to the analysis of second-moment effects, i.e., volatility of housing returns, using a host of machine-learning approach beyond stepwise boosting. We must point out that, one limitation of our work is that here, we only consider physical aspect of climate risks and not the transition component involving the move to a low-carbon economy, which can also play a major role. Also, given that all our current conclusions are based on the analysis of an advanced economy only, contingent on data availability, a similar analysis for an emerging economy or economies, highly vulnerable to climate risks (say like, China and India), can help us generalise our findings.

Appendices/Supplementary materials are available on request by emailing the corresponding author or can be obtained under https://www.xxx.xxx.

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