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Explorative Short-Term Predictive Models for the Belgian (Energy) Renovation Market Incorporating Macroeconomic and Sector-Specific Variables

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Abstract: Retrofitting existing buildings is a cornerstone of Europe's strategy for a sustainable built environment. Therefore, accurate short-term forecasts to evaluate policy impacts and inform future strategies are needed. This study investigates the short-term predictive modelling of renovation activity in Belgium, focusing on overall renovation activity (RA) and energy-specific renovation activity (EA). Using data from 2012 to 2023, linear modelling was employed to analyze the relationships between RA/EA and macroeconomic indicators, market confidence, building permits, and loan data, with model performance evaluated using Mean Absolute Percentage Error (MAPE). Monthly data and time lags of up to 24 months were considered. The three best-performing models for RA achieved MAPE values between 2.9% and 3.1%, with validated errors ranging from 0.1% to 4.1%. For EA, the best models yielded MAPE values between 4.4% and 4.6% and validated errors between 8.9% and 14%. Renovation loans and building permits emerged as strong predictors for RA, while building material prices and loans were more relevant for EA. The time lag analysis highlighted that renovation processes typically span 15–24 months following loan approval. However, the low accuracy observed for EA underscores the need for further refinement. This explorative effort forms a solid base, inviting additional research to enhance our predictive capabilities and improve short-term modelling of the (green) residential renovation market.

Keywords: renovation forecasting; energy retrofits; macroeconomic indicators; predictive modelling; sustainable built environment

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1. Introduction

The European Union (EU) has established ambitious objectives to attain carbon neutrality by 2050, recognizing that buildings account for approximately 40% of all energy consumption and 36% of greenhouse gas emissions [1]. Being a huge energy consumer, the building stock is an important sector for SDG 11 on sustainable cities and SDG 13 on climate action. Therefore, part of Europe's decarbonization strategy places a significant emphasis on enhancing the performance and intelligence of the building stock. However, existing dwellings exceed the number of newly built dwellings in most developed countries. Additionally, it has been suggested that, from 2020 onwards, all new constructions should be buildings that consume almost zero energy (nearly ZEBs), which has clearly improved the energy efficiency of new constructions. Therefore, aspiring to a sustainable built environment, the European Commission is particularly focused on existing buildings and their renovation rate [2]. To this end, a target annual renovation rate of 3% has been proposed (European Commission, 2023) [3]. To follow up on this target, short-term monitoring and forecasting of the renovation market is necessary. However, researching the renovation market presents notable challenges. A universally accepted method to monitor current renovation activity is lacking [4,5]. Furthermore, the diverse nature of (uncertified) renovation projects results in insufficient and often unreliable data, both for general renovations and energy-specific measures [6,7]. Data collection involves different types of sources depending on what is available, e.g., Energy Performance Certificate (EPC) databases [8], housing surveys of representative samples [9], or information derived from investments in energy-efficient renovations [10]. Nevertheless, information on the progress of the retrofitting process in the following one to two years can provide significant benefits for stakeholders. For governments, short-term data on the decarbonization progress is essential to evaluate the effectiveness and implementation of sustainability policies. Reliable short-term forecasts can facilitate the assessment of existing initiatives and support the design of future strategies [11]. Similarly, businesses in sectors such as construction, real estate, and home improvement can leverage market forecasts to optimize their operations. These forecasts can help identify growth opportunities and adapt production capacities, workforce needs, and commercial strategies to market fluctuations.

Despite these potential benefits and despite increased focus on a sustainable building stock, the short-term forecasting of renovation activity, particularly for energy-related renovations, is an underexposed theme in the literature.

Existing research primarily addresses the long-term transformation of building stock, with studies projecting trends up to 2050. These studies often rely on socio-demographic data and forecasts, including population growth, housing demand, building stock ageing, and homeowner maintenance activities [12–14]. While valuable for understanding long-term trends, such research provides limited insight into short-term dynamics in renovation rates. Filippidou et al. compare long- and short-term prediction methods for energy renovation rates in the Netherlands [11]. In their research, short-term empirical data on the social rented sector in the Netherlands are combined with a long-term dynamic stock model. However, the short-term data are used in the prediction of the long-term renovation rate but not forecasted themselves. Additionally, the database is very specific to the Netherlands and not available in full.

In the search for short-term prediction models, several studies in the literature focus on the construction industry as a whole. These studies identify macroeconomic factors such as GDP, interest rates, inflation, exchange rates, and population growth as key determinants [15–19]. Their aim is typically to predict construction demand, employment needs, material flows, and related factors. However, these studies do not specifically focus on renovation activities, and even less on energy-efficient renovations.

The added value of this paper is the exploration of short-term predictive modelling for one specific, but diverse, market segment, namely the residential renovation market. It investigates the potential of both macroeconomic variables and renovation-specific factors to predict renovation activity (overall and energy-specific) in the short term (minimum 1 year). Herein, data from consumer research among Belgian homeowners between 2012 and 2023 are being used. This study addresses the following key questions:

1. Which variables have short-term predictive value for renovation activity?

Since short-term forecasting of renovation activity is underexplored, one of the main questions is which variables are most valuable to incorporate.

2. What is the time lag between an event and its impact on renovation activity?

Given the preparatory stages involved—such as obtaining building permits, engaging architects and contractors, and procuring materials—alongside the duration of renovation activities, this study considers potential delays between influencing events and actual activity. Since these delays are not common knowledge, multiple time lags need to be surveyed.

3. Which model performs best in predicting renovation activity?

Given the exploratory nature of this study, various models have been obtained. The best-performing model has been determined, as well as the reasons for its superior performance.

4. Would a different model emerge as the best when predicting exclusively energy-efficient renovations?

Although energy renovations are often combined with structural overall renovation works, drivers differ for these types of renovations [20–22]. Therefore, separate modelling could deliver additional insights on indicators, time lags, or different mechanisms.

2. Research Concept

The objective of this paper is to explore the predictive power of a wide range of variables in terms of Belgian residential renovation activity (RA), with a particular emphasis on energy-related renovation activity (EA). Renovation or energy-related renovation activity is expressed as a percentage of homeowners performing at least one RA or EA in a given year. This study is structured as follows.

The annual trends of the variables to be predicted—renovation activity (RA) and energy-related activity (EA)—are determined using data from a yearly marketing survey spanning the period from 2012 to 2023 [23]. Potential predictors are sourced from official repositories, such as the National Bank of Belgium and the Federal Planning Bureau (FPS Economy), based on their anticipated correlation with renovation activity. To refine the selection process, overlapping variables are excluded using Pearson's correlation coefficient and R-squared analysis. The influence of temporal delays on the relationship between predictors and renovation activity is assessed by introducing time lags of 3, 6, 9, 12, 15, 18, 21, and 24 months for each variable. Subsequently, linear models (LMs) incorporating two variables are employed to evaluate the predictive power of the data for RA and EA during the period 2012–2022. The performance of these models is measured using the Mean Absolute Percentage Error (MAPE). To validate the models, predictions for 2023 are generated using the derived predictive formulas and compared with the RA and EA values obtained from the 2023 marketing survey. The overall research framework is illustrated in Figure 1 and will be further detailed in the following section.

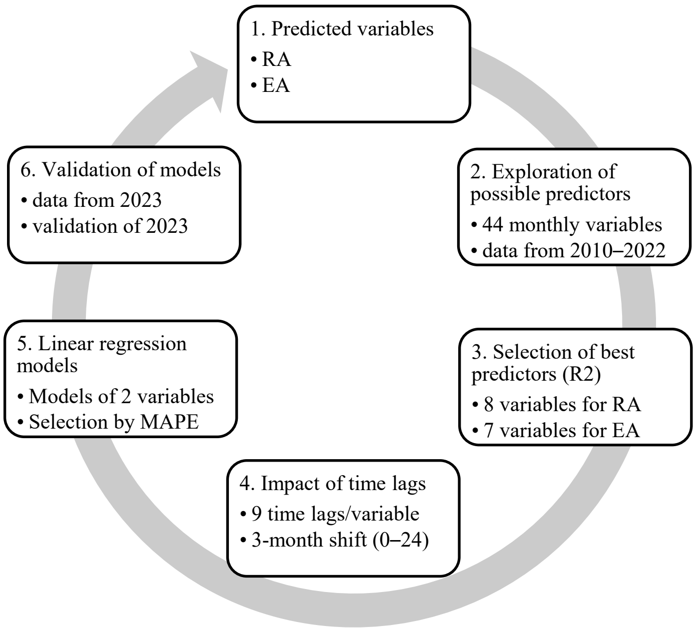

Figure 1. Research concept.

3. Definitions, Methods, and Means

3.1. Predicted and Target Variables

As previously discussed, the two variables to be predicted in this study are Belgian residential renovation activity (RA) and energy-related renovation activity (EA), the latter representing a subset of RA. Within the literature, the term "renovation rate" is frequently used to describe the extent of retrofitting within the building stock. However, the lack of a universally agreed-upon definition of the renovation rate has led to discrepancies in its calculation across European member states. In Belgium, the renovation rate is traditionally derived from building permit data [24]. However, this approach has notable limitations. Not all renovations require a permit; in fact, consumer research indicates that only 17% of all renovation activities are formally permitted [23]. Moreover, not all renovation activities are related to energy efficiency. For example, the installation of a new kitchen, while a renovation, does not necessarily contribute to energy-related improvements.

To address these limitations, this study utilizes renovation rate data sourced from Essencia Marketing research. Essencia Marketing, a construction-focused marketing agency, conducts annual surveys of the Belgian renovation market. These surveys are carried out online and target homeowners [23]. Since 2012, the Essencia Marketing survey has been launched every year in mid-December, questioning its respondents on their renovation activity between 1 January xxxx and 31 December xxxx. Yearly, approximately 4500 respondents—selected to be representative for the Belgian population in terms of age, region, and education—are invited to participate, sharing information on renovation activities undertaken during the preceding year. Specific groups, such as tenants, apartment owners, and owners of houses built within the last five years, are excluded to ensure the data's relevance. The Essencia Marketing survey examines 22 distinct renovation activities, classified into three categories: structural, energy-related and other. Activities related to decoration or finishing are excluded from the analysis. A detailed list of the renovation activities included in the survey is presented in Table 1.

Table 1. Overview of renovation activities.

Structural	Energy	Others
Roof	Roof insulation	Electricity
Facade	Wall insulation	Bathroom
Interior walls	Floor insulation	Kitchen
Garage	Attic insulation	Dorms
Porch	Windows and doors	Garage door
Extension	Heater	
	Solar panels	
	Heat pump	
	Ventilation	
	Solar water heater	

Since the Essencia Marketing survey questions whether the renovation work is permitted or not, a validation check is enabled. The 'official' renovation rate of 0.74% for renovations with a building permit, as outlined in the Renovation Pact, is reconstructed with the Essencia data, enhancing its reliability [24]. More information on this validation is found in [25]. Additionally, the Essencia survey provides granular data on the nature of renovation activities, facilitating a clear distinction between overall residential renovation activity (RA) and energy-related renovation activity (EA). The database specifies the annual percentage of homeowners in Belgium who undertake at least one renovation activity (RA) or at least one energy-related renovation activity (EA). The data span the years 2012 to 2023 and are illustrated graphically in Figure 2. For model development, data points from 2012 to 2022 (a total of 22 data points: 11 for RA and 11 for EA) are utilized. The 2023 data serve as an independent test case for validating the models' predictive accuracy. Although the Essencia Marketing survey provides the necessary elements, there are some limitations to be acknowledged, which are described in Section 4.4.5.

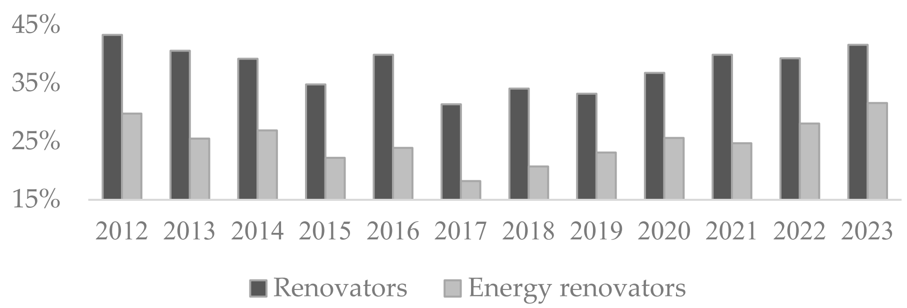

Figure 2. Evolution of RA and EA, in %, conducted by Belgian homeowners from yearly online market research.

3.2. Predictors and Predicting Variables

Forecasting models for construction output often rely on macroeconomic variables such as GDP, inflation, interest rates, exchange rates, and population growth. However, the role of these predictors remains ambiguous, as it is unclear whether these factors influence the construction sector or if the relationship operates in the opposite direction [16]. Notably, GDP growth and construction activity are strongly correlated, with the construction industry exhibiting high sensitivity to overall economic conditions [26–29]. Nonetheless, this research adopts an exploratory approach, and the analysis of causal relationships lies outside its scope.

The selection criteria for variables in this study include (1) a direct or indirect relationship to the renovation market; (2) the availability of monthly data, to facilitate the exploration of time-lagged impacts; and (3) prompt data updates, given the focus on short-term predictions. Given the importance of reliable and completely available data, only datasets from official sources such as the National Bank of Belgium and the Federal Planning Bureau (FPS Economy) were screened. Four categories were surveyed: macroeconomic indicators, confidence indicators for construction-related market players, building permits, and loans related to renovation activities. A total of 44 variables were identified (Appendix A). While taking into account the mentioned selection criteria, some plausibly valuable variables were left out due to quarterly and/or delayed reporting, e.g., "investments in dwellings", which incorporates the amount spent by household for new builds and renovation; "GDP", which is often part of other prediction models of overall construction; and "ABEX-index", an index referring to the total cost evolution of residential buildings, incorporating materials and labour. Variables often used in long-term prediction models, such as building stock information, population growth, and other demographic variables (age, household composition, etc.), were also left out as they do not meet the selection criteria.

While the obtained list of 44 variables is not exhaustive, the authors believe it captures the most critical predictors, drawing on their expertise in the Belgian renovation market, input from industry professionals, and a comprehensive literature review. This comprehensive dataset is designed to enable the modelling of predictive relationships between economic indicators, market confidence, and renovation activity while accounting for short-term dynamics and temporal lags. The categories of the selected variables are as described in the following subsections.

3.2.1. Macroeconomic Indicators

This category includes variables that reflect the broader economic evolution of a country, such as inflation, interest rates, and exchange rates. While GDP is frequently included in predictive models for total construction activity [15,16,19], its quarterly or yearly reporting intervals rendered it unsuitable for this analysis, which focuses exclusively on monthly data. Instead, two construction-specific indicators are included: the 'Added value of the construction industry to GDP' and 'A price index covering 65 building materials'.

3.2.2. Confidence Indicators for Construction-Related Market Players

The confidence levels of key players in the construction sector—such as residential contractors, building material manufacturers, and merchants—are also incorporated. Roofers, given their involvement in popular renovation activities [23], are included as well. Each confidence variable is represented by three metrics: (a) overall confidence in market conditions, (b) confidence in future market demand, and (c) evaluation of the current order book.

For each metric, both raw monthly values and levelled (smoothed) indicators are included. The levelled indicators, which are calculated using moving averages, reflect underlying economic trends with a four-month time lag, eliminating the effects of extreme fluctuations. Additionally, consumer sentiment and confidence in near-future market conditions are considered.

3.2.3. Building Permits and Renovation Loans

Data on building permits related to renovation are included as they directly pertain to construction activity. Loans for renovation are also included as a key variable. Recognizing that the purchase of an existing residence often triggers renovations [21], loans for property purchases and combined purchase–renovation loans are also analyzed.

3.2.4. Loans: Number and Amount

For loans, distinctions are made between the number of loans granted (#) and the total amount borrowed (EUR) and between demanded and delivered loans.

After gathering the timeseries, all data were set at a similar scale. We distinguished between data points for which the theoretical upper and lower boundaries are known (%) and the variables for which they are unknown (indices, EUR, #). For this last group, the data are standardized. Standardization is performed by applying the formula from Equation (1) to each variable, in which μx represents the mean value and σx represents the standard deviation. Missing values should be set to 0 after standardization. This is equivalent to using the average for missing values. However, in the current analysis there are no missing values. As the predicted parameters have a yearly frequency, an average of the last 12 months is used to synchronize the observations (Figure 3).

$$Z = (X - \mu x)/\sigma x \tag{1}$$

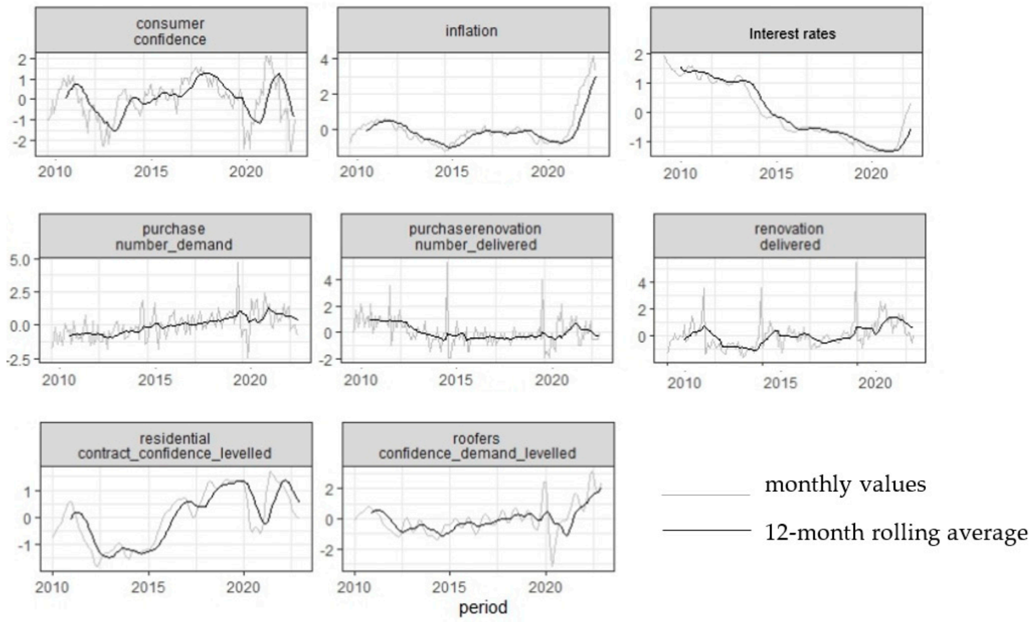

Figure 3. Actual monthly values and 12-month rolling average of some variables.

3.3. Elimination of Redundant Variables

This study explores the predictive power of a broad set of underlying indicators. However, the inclusion of a large number of variables increases the risk of overfitting, which can be addressed by retaining only the most valuable predictors [30,31]. Firstly, the relationships between variables were analyzed using Pearson's correlation test. In the literature, indicators with a correlation coefficient greater than 0.70 are flagged as strongly correlated [32,33]. Therefore, this threshold was applied in this study to identify correlated variables. Secondly, for each correlated pair, their individual contributions to predicting renovation activity (RA) and energy-related renovation activity (EA) were evaluated through univariate regression. Among other methods, the linear regression model is a proven method and is most widely used for (short-term) forecasting [34–37] because regression models are better at describing the influence of individual factors and are easy to understand [38,39]. Only the variables with the higher R-squared (R^2) value, indicating a stronger explanatory power, were retained.

According to Palmer et al., model efficiency is obtained by minimizing the number of predictors which account for the maximum variance in the criterion [34]. Following the described elimination process, our large number of variables was reduced to eight for modelling the percentage of overall renovators (RA) and seven for modelling the percentage of energy renovators (EA), as summarized in Table 2.

Table 2. Selected variables after elimination procedure.

Target Variable	Predicting Variables	Category	R^2
Renovators	Manufacturers_demand_gross	Confidence	0.55
	Purchaserenovation_#_delivered	Loans	0.36
	Building permits_houses	Permits	0.35
	Residential contractor_levelled	Confidence	0.27
	Exchange rate EUR–USD	Macroeconomic	0.24
	Consumer_outlook	Confidence	0.08
	Inflation	Macroeconomic	0.05
	Renovation_EUR_delivered	Loans	0.02
Energy renovators	Consumer	Confidence	0.64
	Purchaserenovation_#_delivered	Loans	0.41
	Residential contractor_demand_levelled	Confidence	0.29
	Interest rate	Macroeconomic	0.20
	Building permits_houses	Permits	0.18
	Price index of building materials	Macroeconomic	0.13
	Inflation	Macroeconomic	0.12

The gross confidence of manufacturers in future market demand (manufacturers_demand_gross) emerges as the strongest predictor for RA, achieving an R^2 of 0.55. This indicates that over half of the variation in RA can be explained by this variable. Delivered loans for a purchase and renovation and the delivered number of building permits for a renovation are also retained, attaining an R^2 of 0.36 and 0.35. Additionally, the confidence of residential contractors and the consumer outlook are also selected for modelling RA. As not highly correlated macroeconomic indicators ($p = -0.44$), the exchange rate and inflation are both retained. Finally, the total amount lent for renovations is also taken into account, although the predicted value of this variable in terms of RA is low ($R^2 = 0.02$).

For EA, the highest R^2 was found for the overall confidence of consumers (consumer), with an R^2 value of 0.64. This suggests that consumer confidence is a highly influential factor in predicting energy-related renovation activities. The four variables which were retained for predicting RA were also retained for predicting EA, namely the number of loans delivered for a purchase or renovation, the confidence of the residential contractor, the delivered number of building permits for renovations, and inflation. Mark the difference in the predicted values for RA and EA, considering the same variable. These differences could suggest a different outcome as prediction model for RA and EA. Furthermore, two new variables are selected: the interest rate and the price index of building materials.

This process ensures the development of models that are both robust and generalizable by minimizing the risk of overfitting while retaining the most impactful indicators for analysis. However, choosing this approach also implies the omission of variables with an inherent predictive value for RA or EA; e.g., consumer confidence obtains an R^2 of 0.35 for RA. But, due its high correlation with the gross confidence of manufacturers, which scores an even higher R^2, consumer confidence is not retained for further modelling. Similarly, the gross confidence of manufacturers seems very valuable in predicting EA ($R^2 = 0.6354$). However, considering its high correlation with consumer confidence, which has an R^2 that is slightly higher than that of the gross confidence of manufacturers ($R^2 = 0.6393$), it is omitted.

3.4. Time Lags

Each selected variable provides monthly observations, with the recorded date corresponding to the month the data reflect. However, the publication timing varies among variables. For instance, confidence indicators are typically available at the start of the subsequent month, whereas building permits are published approximately four months after their issuance.

Using monthly indicators enables the exploration of potential time lags in terms of their effects on renovation activities. For example, a decline in interest rates may encourage consumers to invest in property, but the impact is not immediate due to the time required for processes such as obtaining permits, applying for loans, or hiring contractors. Since the exact lead time between an event and its impact on renovation activity is uncertain, a systematic approach was taken: each monthly variable was shifted in three-month increments, from 0 months (no lag) to 24 months (maximum lag). This results in nine lagged versions for each variable. As an example, Figure 4 plots four different time lags for the interest rate, where the effect of the shift in time on the data are visualized. After introducing these time lags, the monthly observations are averaged over the previous 12 months to align with the annual frequency of the predicted variables (RA and EA). This synchronization ensures that the time-lagged effects are aggregated appropriately to reflect their influence on yearly renovation activity, which always reflects the works performed between January and December of a given year. To incorporate events with up to a 24-month lag while modelling renovation activities starting in 2012, data from January 2010 to December 2022 are utilized. This ensures that all lagged observations up to 24 months are accounted for in the analysis. This methodology allows for a detailed exploration of temporal relationships and provides insight into how delayed effects of economic and market conditions influence renovation activities over time.

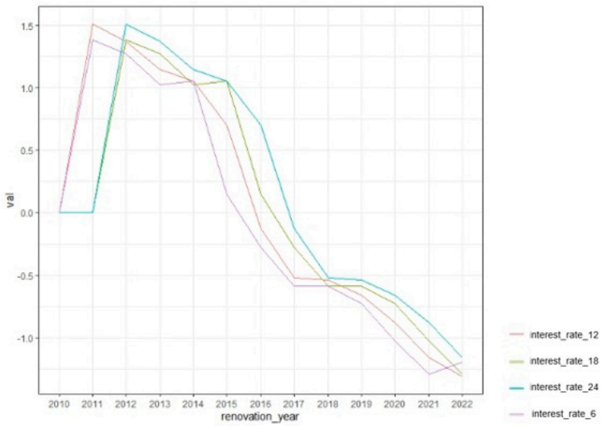

Figure 4. Example of interest rate time lags of 6, 12, 18, and 24 months.

An overview of the procedure for the interest rate is listed in Appendix B. First, the actual values are standardized according to Equation (1). An average of the last 12 months is calculated for modelling RA and EA. Even so, the standardized values are shifted by 3 months and 24 months, for example. Again, the average of the last 12 months is obtained.

3.5. Modelling

Given the small dataset of 11 results for the percentage of renovators and percentage of energy renovators completing work from 2012 to 2022, there is a genuine risk of overfitting. Using too many variables can lead to overfitting, where the model becomes too complex and captures noise rather than the actual signal [40,41]. Overfitted models seem to work exceptionally well on the data that are used during training, but they fall apart if predictions need to be made for new observations. Therefore, each model will only consist of two independent predictors.

To estimate the (energy) renovator percentage for the following year, simple linear models (LMs) are created, taking into account only the variables selected after elimination (see Table 2) and 9 time lags. For each model, a comparison is made of the Mean Absolute Percentage Error (MAPE). The MAPE is a commonly used metric that defines the accuracy of a forecasting model and is calculated as in Equation (2), in which Ai represents the actual percentage of (energy) renovators and Fi represents the predicted percentage of (energy) renovations [42–44]. The lower the MAPE, the more accurate the model is, since the obtained percentage errors are smaller.

$$\mathrm{MAPE} = \frac{1}{\mathrm{n}} \sum_{\mathrm{i}=1}^{\mathrm{n}} \frac{|\mathrm{Ai} - \mathrm{Fi}|}{\mathrm{Ai}} \quad (2)$$

Ai = actual value;
Fi = forecast value;
n is total number of observations (11).

Each model consists of 2 different variables with a specific time lag, e.g., variable 1 in time lag 1 in combination with variable 2 in time lag 1. Each model results in a MAPE consisting of the mean of 11 percentage errors between the forecasted renovator percentage and the actual renovator percentage (for 2012 until 2022). Since every variable consists of 9 time lags ($8 \times 9 = 72$) and every time lag is combined with 9 time lags of 7 other variables ($9 \times 7 = 63$), a total of 2.268 models were explored ($72 \times 63/2 = 2.268$) for the prediction of RA.

4. Results and Discussion

4.1. Best Linear Models Based on MAPEs

Figure 5 presents boxplots illustrating the distribution of the MAPE for the eight selected variables used to predict residential renovation activity (RA). Each boxplot contains 567 MAPE values, corresponding to the combinations of the nine time lags for each variable and the nine time lags of the other seven variables ($9 \times 9 \times 7 = 567$). Each individual dot within the boxplot represents the mean of the 11 annual error percentages for the period 2012–2022. The variable "purchaserenovation_number_delivered" exhibits the lowest median MAPE, suggesting it is the strongest individual predictor of RA. Furthermore, the combination of building_permits_houses and purchaserenovation_number_delivered produces the smallest MAPE among all variable pairings, indicating strong predictive synergy between these two variables. The pairing of building_permits _houses with manufacturers_demand_gross demonstrates the second lowest MAPE. Notably, manufacturers_demand_gross was identified as the strongest predictor in the univariate analysis based on its R^2 value. However, when combined with other variables, its predictive accuracy diminishes, leading to higher overall percentage errors and, consequently, a higher MAPE.

Figure 6 depicts the MAPE distribution for predicting energy-related renovation activity (EA). Similarly to RA, the variable "purchaserenovation_number_delivered" achieves the lowest median MAPE, confirming its significance in predicting EA. The most accurate prediction (lowest MAPE) is obtained with the combination of purchaserenovation_number_delivered and price_index_of_building_materials. The second best performance is observed with the combination of purchaserenovation_number_delivered and consumer_confidence, the latter of which demonstrated the highest R^2 value in the univariate analysis for predicting EA. However, the MAPE for models predicting EA is consistently higher than those for RA. Although the use of the MAPE for evaluating the accuracy of predictive models is broadly discussed in the literature [42–44], there are no specific thresholds for its interpretation. It varies depending on the context and industry standards. In other papers discussing short-term models for energy load predictions, the best-performing models obtained a MAPE of around 3 to 4% [37,45]. Considering the renovation context, the MAPE indicates that forecasting EA is more challenging and less precise than predicting RA.

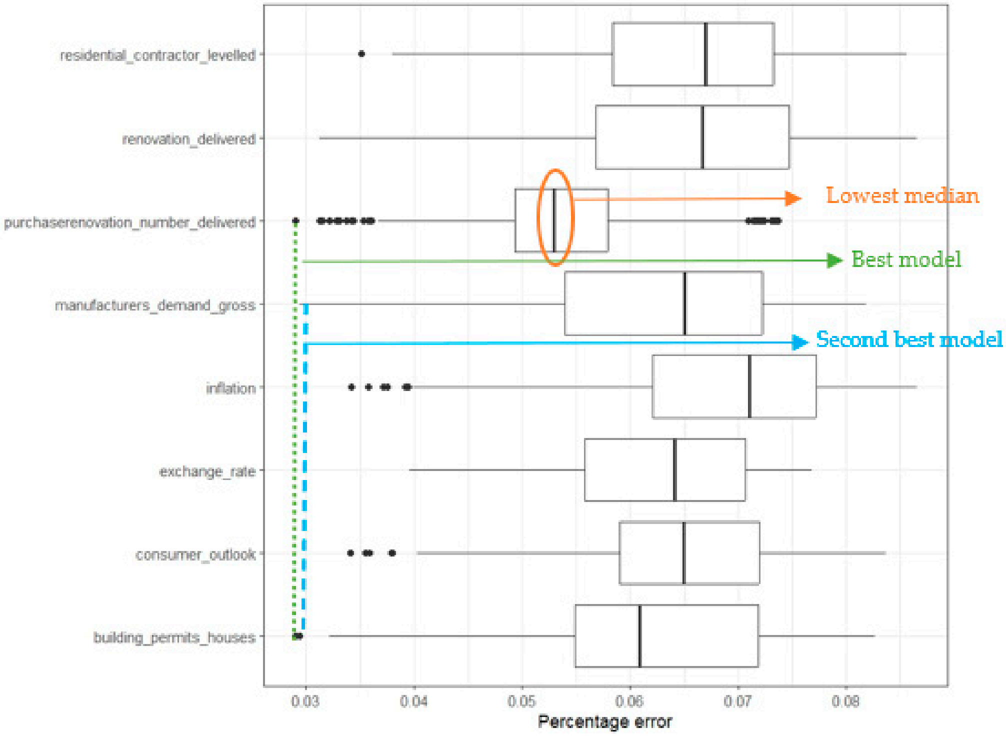

Figure 5. Boxplots for RA, showing the lowest median, the best, and second best linear models based on MAPE. Each individual dot within the boxplot represents the mean of the 11 annual error percentages for the period 2012–2022.

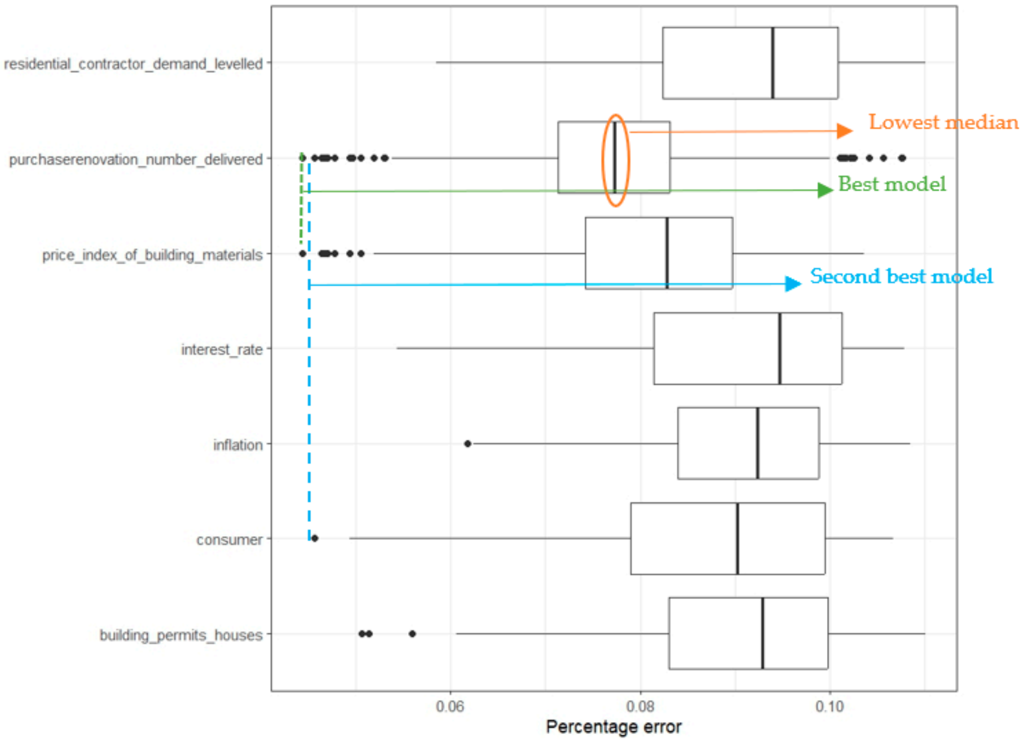

Figure 6. Boxplots for EA, showing the lowest median, the best, and second best linear models based on MAPE. Each individual dot within the boxplot represents the mean of the 11 annual error percentages for the period 2012–2022.

4.2. Impact of Time Lags

To analyze the impact of time lags more in detail, Figures 7 and 8 show boxplots of the MAPEs for each parameter across different time lags and for RA and for EA. The most favourable median MAPE is observed for the variable "purchaserenovation_number_delivered_24" for RA and for "consumer_0" for EA. The top-performing models, according their MAPEs, are summarized in Table 3.

Table 3. Best-performing models based on MAPE.

Target Variable	Model	Predicting Variables	MAPE
Renovators	M1-RA	building_permits_houses_0xpurchaserenovation_number_delivered_18	2.9%
	M2-RA	building_permits_houses_0xmanufacturers_demand_gross_0	2.9%
	M3-RA	renovation_delivered_15xpurchaserenovation_number_delivered_24	3.1%
Energy Renovators	M1-EA	price_index_of_building_materials_15xpurchaserenovation_number_delivered_24	4.4%
	M2-EA	consumer_0xpurchaserenovation_number_delivered_0	4.6%
	M3-EA	price_index_of_building_materials_12xpurchaserenovation_number_delivered_24	4.6%

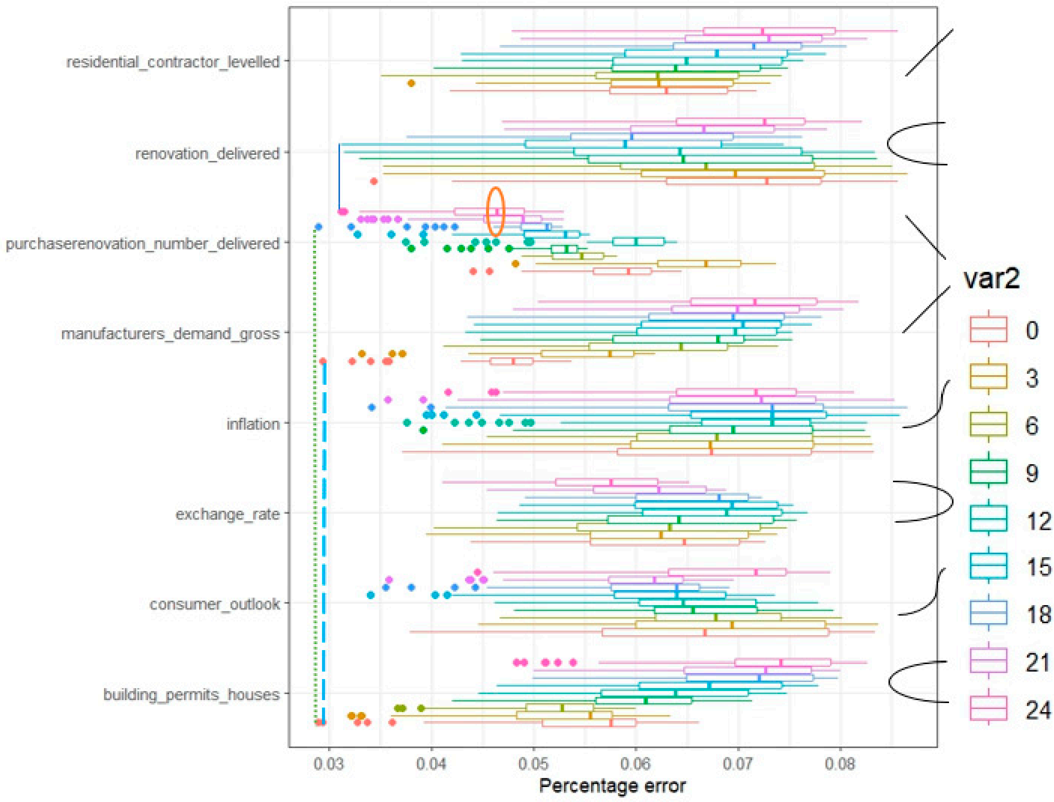

Figure 7. Boxplot of MAPE within each time lag for the RA indicating the lowest MAPE; the three best-performing models and a shape (at the right) indicate the trend of the boxplots per variable. An increasing trend means that the lower the time lag, the better the model performs, e.g., residential_contractor_levelled. A decreasing trend refers to the opposite, namely higher time lags will result in better predictions, e.g., purchaserenovation_number_delivered. In a parabolic trend, a central time lag provides the best or worst MAPE, depending on the direction of the parabola, e.g., renovation_delivered and exchange_rate. For inflation and consumer_outlook no clear trend was found. The graph shows the lowest median, the best, second best and third best linear models based on MAPE. Each individual dot within the boxplot represents the mean of the 11 annual error percentages for the period 2012–2022.

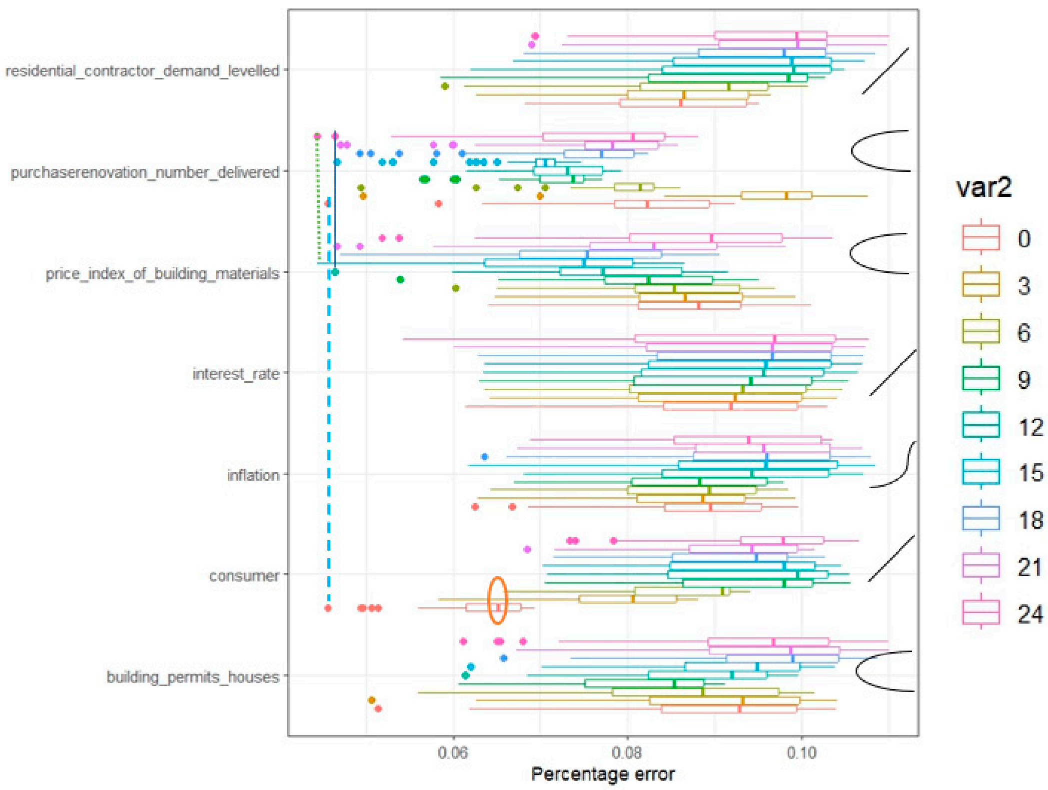

Figure 8. Boxplot of the MAPE in each time lag for the EA indicating the lowest MAPE; the three best-performing models and a shape (at the right) indicate the trend of the boxplots per variable. The graph shows the lowest median, the best, second best and third best linear models based on MAPE. Each individual dot within the boxplot represents the mean of the 11 annual error percentages for the period 2012–2022.

In addition to identifying the lowest median MAPE and best-performing models, the distribution of MAPE values across time lags provides crucial insights into variable-specific trends, as evident from the boxplot shapes:

- The median MAPE for confidence indicators among market players shows an increasing trend as time lags grow. This suggests that recent data for these indicators improve the reliability of the predictive models. This is logical, as market confidence reflects short-term sentiment, making it a strong immediate predictor but less relevant over extended time lags.
- The lowest median MAPE for EA is found in "consumer confidence_0". Indeed, previous studies state that higher consumer confidence leads to higher household consumption and, in certain circumstances, higher investment spending [46,47]. When combined with purchaserenovation_number_delivered_0 the second lowest MAPE is seen. Additionally, the boxplots demonstrate the short-term effect of consumer confidence, since the MAPE increases considerably when the time lag increases.
- "Purchaserenovation_number_delivered" data from 24 months prior yield lower MAPE values than more recent data when predicting overall renovation activity (RA). This aligns with the understanding that significant lead time—up to two years—is required for the processes of property acquisition, building permit or loan applications, and the initiation of construction following a house purchase.
- The boxplot for building permits exhibits a parabolic trend, with MAPE values suggesting that a time lag of approximately 6 months is optimal for predicting RA, whereas a lag of 9 months is most effective for predicting EA. These findings reflect the average

delay between the approval of a building permit and the commencement of renovation work, as inferred from the MAPE values. The extended delay observed for EA appears unusual. However, this may be explained by considering renovation as a sequential process in which structural and energy-related activities are performed in stages [9]. For instance, energy measures such as wall insulation may be implemented following wall construction, or solar panels may be installed after roof renewal. Additionally, when building permits are combined with other variables, the best predictive performance is achieved with no delay (RA) or a three-month delay (EA).

For EA, M1-EA achieves the best results, though its increased MAPE reflects the complexity of predicting energy-specific renovations compared to overall renovation activity. These findings underscore the need to balance accuracy, time lag considerations, and the practical requirements of stakeholders when selecting predictive models.

4.3. Validation of Best-Performing Models

The outcome of the Essencia Marketing renovation research in 2023, which was not incorporated into the initial modelling, serves as an independent validation dataset. Focusing on the three best models for RA and EA, the standardized values for 2023 were calculated for the included variables. Subsequently, the prediction formulas from these six models were applied. By comparing the computed outcomes for 2023 with the actual results from the Essencia Marketing renovation research, the percentage error for each model was determined for the year 2023 (Table 4). Since the validation is set up for one year (2023), a single percentage error is obtained and not a MAPE, which takes into account several years.

Table 4. Obtained percentage error from validation using 2023 data.

Target Variable	Model	Predicting Variables	Percentage Error
Renovators	M1-RA	building_permits_houses_0xpurchaserenovation_number_delivered_18	4.1%
	M2-RA	building_permits_houses_0xmanufacturers_demand_gross_0	2.6%
	M3-RA	renovation_delivered_15xpurchaserenovation_number_delivered_24	0.1%
Energy Renovators	M1-EA	price_index_of_building_materials_15xpurchaserenovation_number_delivered_24	14%
	M2-EA	consumer_0xpurchaserenovation_number_delivered_0	8.9%
	M3-EA	price_index_of_building_materials_12xpurchaserenovation_number_delivered_24	12%

The predictions from the three models aimed at forecasting overall renovation activity exhibited discrepancies of less than 4.1% compared to the marketing survey results. This validation suggests that the model incorporating historical data on delivered loans provides the most accurate approximation. However, predicting energy renovation activity proved more challenging. The differences between the model predictions and the marketing survey results ranged from nearly 9% to 14%. Furthermore, the model yielding the closest prediction was based on present values.

4.4. Discussion

4.4.1. Preferred Prediction Model for RA

Forecasting renovation activity poses significant challenges in terms of identifying a single optimal predictive model. Based on MAPEs, the M1-RA model incorporates current data on building permits and loans for property purchase and renovation, adjusted for an 18-month lag. Model validation, however, indicates that the most reliable model is M3-RA, which utilizes the number of loans for property purchase and renovation dating back two years and the amount lent for renovation with a 15-month lag. These considerations highlight the distinction between the two models.

The MAPE for both models does not exceed 3.1%, with validation revealing a maximum error of 4.1%. Since no similar study on predicting the residential renovation market in the short term was found, a comparison of the attained error percentage is not possible. Looking at industry standards, references are found at around a 3 to 4% error percentage [37,45]. Nevertheless, as this study's primary aim is to forecast renovation activity, preference could be given to the model with longer time lags, as it facilitates predictions extending further into the future.

Figure 9 illustrates a timeline commencing from a specific reference point (e.g., 31 October 2024). For M1-RA, the most recent data on building permits date to 30 June 2024, while data on the number of purchase–renovation loans delivered are available up to 30 September 2024. Accounting for the time lags, building permit data remain tied to 30 June 2024, while purchase–renovation loan data can be projected 18 months forward to 31 March 2025. However, when the two variables are combined in the M1-RA prediction formula, the most recent building permit data (30 June 2024) limits the prediction, resulting in an estimated renovation activity rate as of 30 June 2024, reflecting the previous 12 months. In contrast, M3-RA utilizes the data available for both variables as of 30 September 2024. After applying their respective time lags (15 months for loan amounts and 24 months for the number of loans), the model can produce predictions for 31 December 2025. Consequently, as of October 2024, M3-RA can provide estimates for renovation activity covering the 12 months leading up to 31 December 2025. Given these attributes, the elevated time lags of the M3-RA model enable forecasts that align more closely with this study's objective of providing long-term projections.

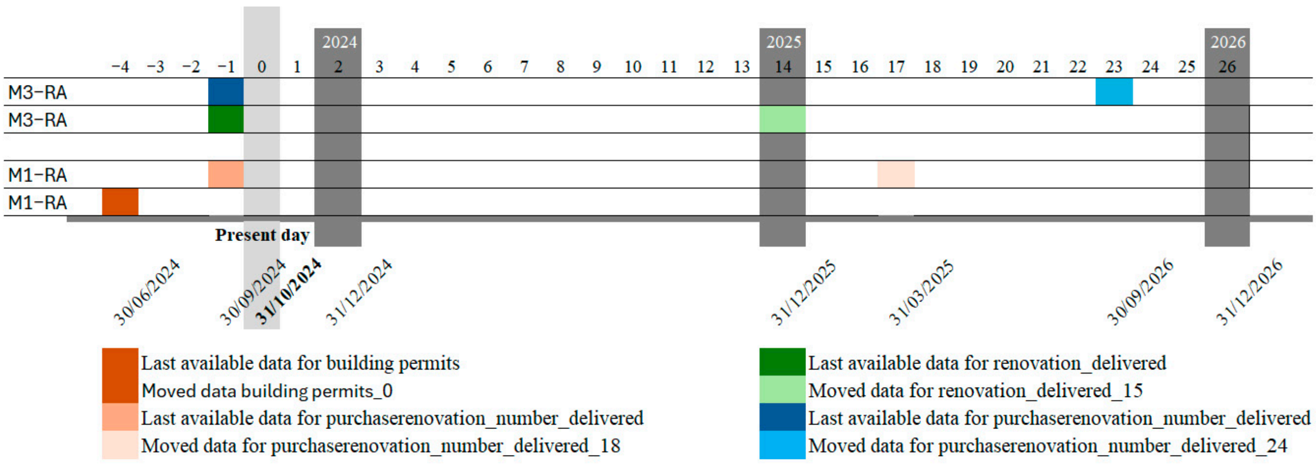

Figure 9. Timeline example for M1-RA and M3-RA predicting RA at a given moment (31 October 2024), where the M1−RA prediction holds until 30 June 2024 and M3-RA predicts until 31 December 2025.

Nonetheless, M1-RA and M2-RA remain viable alternatives. Firstly, the MAPE obtained for these two models during development was lower than that for M3-RA, although the difference is small. Secondly, the validation of the models was only performed for one year. Further validation of the three models in time will provide more insights. Finally, in scenarios requiring shorter forecasting horizons or where data availability constrains the application of M3-RA, the use of the other models could be preferred.

4.4.2. Added Value of Predicting Residential Renovation

Forecasting renovation activities provides significant value for stakeholders in the renovation sector, given the substantial size of the market, the intricate decision-making processes involved, and the wide range of associated activities. Accurate predictions allow companies to optimize the allocation of resources, personnel, and logistics. For instance, in recent years, a decline has been observed in residential markets. Consequently, manufacturers have adjusted their production volumes and inventory levels. It would be advantageous to have prior knowledge of anticipated market shifts to effectively align with demand fluctuations. Moreover, such forecasts benefit governments by facilitating the evaluation of existing policies, the assessment of past initiatives, and the design of future strategies. E.g., in Flanders (Belgium), since 2023, new owners of energy-devouring residential buildings (with an energy label E or F) are required, within five years of purchase, to carry out deep energy renovations to achieve a minimum energy label of D. In January 2025, the government extended the period from five to six years, to provide homeowners more time for renovation activities. However, the impact of this adapted legislation is unknown. By means of a predictive model, renovation activity can be estimated based on the evolution of the selected predictors (e.g., consumer confidence and the number of loans for a purchase with renovation, as with M2-EA).

As previously mentioned, European countries approach data collection and analysis of their building stock in a decentralized and inconsistent manner. Replicating predictive methodologies across different countries and validating the outcomes could establish a standardized framework for estimating renovation rates. This framework would enable consistent and scalable analyses of building stocks across various regions.

Additionally, this study contributes valuable insights for researchers by identifying the most relevant predictors of renovation activity. For instance, boxplot analyses of different time lags (Figures 7 and 8) highlight realistic lead times, such as the time between obtaining a building permit and initiating renovation work, or the interval between securing a loan and beginning renovation activities. These findings may inform the development of other predictive models.

4.4.3. Energy-Related Renovation Activity Versus Overall Renovation Activity

The models' predictive accuracy for energy-related renovation activity is significantly lower than for overall renovation activity, as evidenced by higher MAPE values and validation results.

Due to these elevated percentage errors, current models for energy-related renovations lack the reliability required for precise forecasting. However, given the critical importance of retrofitting existing buildings to improve energy efficiency, further research in this area is essential. In the literature, differing drivers underlying energy-related and general renovation activities have been identified. While the adoption of energy-related renovation activities tends to be linked to overall renovation works, this association is not universally observed [48,49]. General renovations are often prompted by preventive or essential maintenance requirements [50,51]. In contrast, a review conducted by Kastner and Stern found that "energy-relevant investment decisions were often associated with beliefs about consequences for and beyond the household and with receiving energy consulting and financial incentives. Associations between energy relevant investments and several other explanatory variable categories were rare or ambiguous" [52]. Additionally, Szymańska et al. identified rising energy prices as the most critical factor driving households to invest in renewable energy sources [53]. This trend was also evident in the current study, where (1) an energy crisis (2022) led to a significant increase in energy prices and (2) changes were made in subsidy policies (2023) for solar panels in Flanders (Belgium), thereby boosting the popularity of energy efficiency measures (see Figure 2). Although these exceptional events may account for the observed high variability in our models' predictive accuracy, energy prices we not detected to be a good predictor of energy renovation in this study.

Additionally, subsidy schemes were not incorporated due to the absence of monthly data. Furthermore, the niche nature of energy renovations, which involve a smaller participant base, exacerbates the sampling error, contributing to the unreliability of our predictions. Therefore, revisiting these analyses is strongly recommended. Firstly, the inclusion of additional data points in future analyses will enhance and refine our insights. Secondly, the scope of this study could be expanded by incorporating additional variables, such as financial incentives or energy-related metrics, including energy consumption. Finally, revisiting this research with an annual rather than a monthly perspective on the variables may yield more robust and meaningful results. Despite the high accuracy of our models for overall renovation activity, caution is warranted when interpreting their results. The limited dataset used necessitated model simplification, restricting the analysis to only two variables, which may reduce the models' generalizability to other contexts or future timeframes. To improve their robustness, future research should aim to enhance the size of the dataset and explore more complex models, incorporating additional predictors.

4.4.4. Prediction of Total Construction Activity by Means of Construction Indicators

The most effective models for predicting renovation activity focus on variables directly related to renovations rather than broader economic indicators, such as interest rates, inflation, or exchange rates, which are commonly used in models forecasting total construction activity. Future research could explore whether disaggregating total construction activity into specific market segments, each modelled with segment-relevant variables, would yield more accurate predictions. For instance, using building permits for new housing developments in models focused on the residential new construction market might improve precision.

By incorporating directly relevant variables for each segment, this approach could provide a more detailed and accurate framework for forecasting total construction activity while addressing the unique characteristics of each market segment. However, segmented forecasting presents additional challenges and does not guarantee improved model performance. For instance, in Belgium, limited data are available regarding the non-residential renovation market. Moreover, a more granular approach could result in a higher margin of error. The only means to evaluate the efficacy of this new approach is through empirical testing.

4.4.5. The Use of Data of the Essencia Marketing Survey, a Form of Online Consumer Research

The Essencia Marketing survey relies on data obtained from an online consumer survey conducted between 2012 and 2023, providing detailed insights into renovation activity (RA) and energy-related activity (EA), which is therefore suitable for modelling renovation forecasts. However, several limitations to the methodology must be acknowledged. The Essencia marketing database is known to underestimate the representation of lower socio-economic households. Since renovation activities are likely constrained by budget limitations, this underrepresentation may lead to an overestimation of this group's renovation activity compared to higher-income groups. Furthermore, the survey is restricted to homeowners, and excludes tenants and apartment owners. As a result, the findings do not reflect renovation trends within the rental and apartment sectors. Additionally, renovation activity is calculated as a percentage of homeowners, as the dataset does not include information on square metres of renovation or energy usage. Also, the data were collected through an online survey. Although homeowners generally possess knowledge about the renovation activities they have undertaken, variations in interpretation are inevitable. For example, a porch renovation might be classified as a structural improvement, but it could also involve replacing windows and doors, which would qualify as an energy-related measure. Finally, while the size of the database enables a comprehensive analysis of the evolution of RA and EA, the predictive modelling we performed was based on only 11 data points, corresponding to 11 years of data. For validation, one single year (2023) was utilized. Therefore, the authors aim to continually test the outcomes of the three best-performing models and evaluate their robustness over time.

4.4.6. Need for Further Research on Short-Term Prediction Models for RA and EA

As outlined, this study investigates the short-term forecasting of the residential renovation market. The results indicate acceptable models for RA but non-acceptable models for EA, based on MAPEs. Furthermore, the robustness of the models could not be assessed due to the lack of supplementary data. Nonetheless, since the obtained models will ultimately be utilized and evaluated by Essencia Marketing, their level of robustness will become evident through their practical application.

However, further research in this area is essential. First, the obtained models could be simulated with data from other countries. Secondly, other regions or countries may possess additional valuable data that could enhance their forecasting accuracy. Additionally, the use of monthly frequency has excluded certain relevant variables (e.g., GDP, housing investments). Testing variables at a lower frequency, such as quarterly or yearly, could yield meaningful insights. Furthermore, employing alternative modelling techniques (e.g., Support Vector Machine, Neural Networks) or evaluation metrics (Cumulative Variation of Root Mean Square Error, Cross-validation, etc.) may produce different results. Finally, the non-acceptable models for EA raise critical questions. Additional research on specific energy renovations is necessary to determine whether short-term forecasting within this niche segment is feasible.

It is evident that this study, as an explorative effort into short-term prediction of the residential renovation market, requires further refinement. Researchers active in the domain of building stock retrofitting are encouraged to advance the process of variable selection, modelling technique choice, and evaluation metric selection to improve the predictive capabilities and reliability of future models.

5. Conclusions

This study sought to develop models for forecasting renovation activity in the Belgian market by examining the influence of macroeconomic and confidence-based variables. The findings underscore the significant predictive power of key indicators, such as delivered renovation loans and building permits, in estimating renovation activity, both broadly and in the specific context of energy efficiency. However, predicting energy-related renovations proved more challenging, highlighting the complexity and variability of this niche market segment.

While no single model emerged as definitively superior for predicting overall renovation activity, the preferred linear model utilized the number of loans delivered for property purchase and renovation, with a 24-month lag, combined with the amount of loans for renovation, with a 15-month lag. This model achieved a MAPE of 3.1% and a validated percentage error of 0.1%. The analysis of time lags further illuminated the temporal dynamics of renovation activity, revealing that predictive variables, such as building permits and loan delivery, exhibited significant forecasting potential with lags ranging from 6 to 24 months. For example, loans granted 15 to 24 months prior were found to strongly predict current renovation activity, reflecting the extended timelines required for planning, financing, and executing renovation projects.

Future research should prioritize refining these models by incorporating additional data and addressing the unique challenges associated with the energy renovation sector.

Enhancing these models would support Europe's strategy for a sustainable built environment and would enable policymakers, businesses, and other stakeholders to more effectively make decisions related to retrofitting the existing building stock and better anticipate market trends.

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Appendix A

Table A1. List of predicting variables tested in this study.

Category	Variable	Source	Unit
Macroeconomic	Inflation	NBB	%
	Interest rate	NBB	%
	Exchange rate EUR–USD	NBB	%
	Value-added construction industry	NBB	EUR
	Price index of building materials	NBB	index
Confidence	Residential contractor_gross	NBB	index
	Residential contractor_levelled	NBB	index
	Residential contractor_demand_gross	NBB	index
	Residential contractor_demand_levelled	NBB	index
	Residential contractor_orders_gross	NBB	index
	Residential contractor_orders_levelled	NBB	index
	Roofers_gross	NBB	index
	Roofers_levelled	NBB	index
	Roofers_demand_gross	NBB	index
	Roofers_demand_levelled	NBB	index
	Roofers_orders_gross	NBB	index
	Roofers_orders_levelled	NBB	index
	Manufacturers_gross	NBB	index
	Manufacturers_levelled	NBB	index
	Manufacturers_demand_gross	NBB	index
	Manufacturers_demand_levelled	NBB	index
	Merchants_gross	NBB	index
	Merchants_levelled	NBB	index
	Merchants_demand_gross	NBB	index
	Merchants_demand_levelled	NBB	index
	Merchant_orders_gross	NBB	index
	Merchant_orders_levelled	NBB	index
	Merchant_turnover_gross	NBB	index
	Merchant_turnover_levelled	NBB	index
	Consumer	NBB	index
	Consumer_outlook	NBB	index

Table A1. *Cont.*

Category	Variable	Source	Unit
Permits	Building permits_houses	FPS Econ	#
Loans	Purchase_#_demand	NBB	#
	Purchase_€_demand	NBB	EUR
	Purchase_#_delivered	NBB	#
	Purchase_€_delivered	NBB	EUR
	Renovation_#_demand	NBB	#
	Renovation_€_demand	NBB	EUR
	Renovation_#_delivered	NBB	#
	Renovation_€_delivered	NBB	EUR
	Purchaserenovation_#_demand	NBB	#
	Purchaserenovation_€_demand	NBB	EUR
	Purchaserenovation_#_delivered	NBB	#
	Purchaserenovation_€_delivered	NBB	EUR

Appendix B

	Result of Essencia Marketing survey	Actual values	formula Avg (2010–2022): 2.63 σ (2010–2022): 0.97	Avg 12 months	Time lag 3 months	Avg 12 months	Time lag 24 months	Avg 12 months
Date	**RA**	**interest rate**	**Standardization**	**interest rate_0**		**interest rate_3**		**interest rate_24**
31/01/2010		4.45	1.89					
28/02/2010		4.41	1.85					
31/03/2010		4.32	1.76					
30/04/2010		4.24	1.67		1.89			
31/05/2010		4.16	1.59		1.85			
30/06/2010		4.03	1.45		1.76			
31/07/2010		4.03	1.45		1.67			
31/08/2010		4.00	1.42		1.59			
30/09/2010		3.90	1.32		1.45			
31/10/2010		3.86	1.28		1.45			
30/11/2010		3.83	1.25		1.42			
31/12/2010		3.82	1.24	1.51	1.32			
31/01/2011		3.88	1.30	1.47	1.28			
28/02/2011		3.92	1.34	1.42	1.25			
31/03/2011		3.98	1.40	1.39	1.24	1.51		
30/04/2011		4.09	1.52	1.38	1.30	1.47		
31/05/2011		4.13	1.56	1.38	1.34	1.42		
30/06/2011		4.12	1.55	1.39	1.40	1.39		
31/07/2011		4.13	1.56	1.39	1.52	1.38		
31/08/2011		4.05	1.48	1.40	1.56	1.38		
30/09/2011		3.93	1.35	1.40	1.55	1.39		
31/10/2011		3.79	1.21	1.40	1.56	1.39		
30/11/2011		3.72	1.13	1.39	1.48	1.40		
31/12/2011		3.69	1.10	1.37	1.35	1.40		
31/01/2012		3.87	1.29	1.37	1.21	1.40	1.89	
29/02/2012		3.90	1.32	1.37	1.13	1.39	1.85	
31/03/2012		3.90	1.32	1.36	1.10	1.37	1.76	
30/04/2012		3.85	1.27	1.34	1.29	1.37	1.67	
31/05/2012		3.81	1.23	1.32	1.32	1.37	1.59	
30/06/2012		3.67	1.08	1.28	1.32	1.36	1.45	
31/07/2012		3.58	0.99	1.23	1.27	1.34	1.45	
31/08/2012		3.59	1.00	1.19	1.23	1.32	1.42	
30/09/2012		3.59	1.00	1.16	1.08	1.28	1.32	
31/10/2012		3.64	1.05	1.15	0.99	1.23	1.28	
30/11/2012		3.70	1.11	1.15	1.00	1.19	1.25	
31/12/2012	**43%**	3.69	1.10	**1.15**	1.00	**1.16**	1.24	**1.51**
31/01/2013		3.65	1.06	1.13	1.05	1.15	1.30	1.47
28/02/2013		3.68	1.09	1.11	1.11	1.15	1.34	1.42
31/03/2013		3.64	1.05	1.09	1.10	1.15	1.40	1.39
30/04/2013		3.60	1.01	1.06	1.06	1.13	1.52	1.38
31/05/2013		3.55	0.96	1.04	1.09	1.11	1.56	1.38
30/06/2013		3.50	0.91	1.03	1.05	1.09	1.55	1.39
31/07/2013		3.53	0.94	1.02	1.01	1.06	1.56	1.39
31/08/2013		3.56	0.97	1.02	0.96	1.04	1.48	1.40
30/09/2013		3.62	1.03	1.02	0.91	1.03	1.35	1.40
31/10/2013		3.75	1.16	1.03	0.94	1.02	1.21	1.40
30/11/2013		3.83	1.25	1.04	0.97	1.02	1.13	1.39
31/12/2013	**41%**	3.84	1.26	**1.06**	1.03	**1.02**	1.10	**1.37**
31/01/2014		3.82	1.24	1.07	1.16	1.03	1.29	1.37
28/02/2014		3.76	1.18	1.08	1.25	1.04	1.32	1.37
31/03/2014		3.66	1.07	1.08	1.26	1.06	1.32	1.36
30/04/2014		3.56	0.97	1.08	1.24	1.07	1.27	1.34
31/05/2014		3.46	0.86	1.07	1.18	1.08	1.23	1.32
30/06/2014		3.35	0.75	1.06	1.07	1.08	1.08	1.28
31/07/2014		3.23	0.63	1.03	0.97	1.08	0.99	1.23
31/08/2014		3.12	0.51	0.99	0.86	1.07	1.00	1.19
30/09/2014		3.04	0.43	0.94	0.75	1.06	1.00	1.16
31/10/2014		2.97	0.36	0.87	0.63	1.03	1.05	1.15
30/11/2014		2.91	0.29	0.80	0.51	0.99	1.11	1.15
31/12/2014	**39%**	2.79	0.17	**0.70**	0.43	**0.94**	1.10	**1.15**
31/01/2015		2.7	0.08	0.61	0.36	0.87	1.06	1.13

Figure A1. Example of the synchronization procedure of the monthly variable 'interest rate' with annual predictions (RA), including time lags of 0, 3 and 24 months.

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