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Predicting a Housing Price Index: A Two-Stage Machine Learning Approach Using Linked Micro-, Socio- and Macroeconomic Data from Frankfurt am Main

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Abstract

This study develops and evaluates a two-stage machine learning framework for forecasting the condominium price index of pre-pandemic market data of Frankfurt am Main, Germany, one quarter ahead. To the best of the author's knowledge, it is the first study to combine German micro-level transaction and listing data, socioeconomic variables and macro-financial indicators in a single residential price-forecasting framework. Furthermore, it provides the first evidence on machine learning-based transaction price index forecasting in Germany. Methodologically, the framework links disaggregated and aggregate forecasting. In stage 1, prices per square metre are estimated for four market segments using ordinary least squares, random forest, extreme gradient boosting, and a stacked ensemble in a strictly out-of-sample expanding-window design. In stage 2, these predictions are combined with lagged index values and macro-financial indicators to forecast the city-wide index. The stage 2 model achieves a relative root mean squared error of 2.25% and a mean absolute percentage error of 1.85%, outperforming a naïve persistence benchmark by reducing root mean squared error by 23%. Model interpretation indicates that price persistence dominates stage 1, reflecting market inertia, while lagged macro-financial variables and location quality composition drive index forecasts, pointing to delayed financial market transmission and heterogeneous submarket dynamics.

Keywords: housing; forecasting; index; machine learning; stacking; Frankfurt am Main; GREIX

1. Introduction

Housing markets have been demonstrated to be highly dynamic and complex systems that play a pivotal role in both the macroeconomy and private household decisions [1–3]. Observed and anticipated regional price fluctuations require local authorities to intervene through planning and regulatory instruments such as land-use controls or housing policy measures [4]. Concurrently, corporate entities must adjust their investment strategies and households make far-reaching decisions, including relocation [1,2]. This profound sensitivity to housing market movements emphasises the necessity for reliable forecasting models that possess the capacity to anticipate such dynamics in a both timely and evidence-based manner. The aforementioned complexity can be attributed, at least in part, to the high degree of geographical heterogeneity that characterises housing markets [1]. While spatial dependencies between neighbouring districts have been observed at the small-scale level [5], this effect has not been consistently proven at higher spatial levels, such as between

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cities [1]. Hence, there is a compelling body of evidence that demonstrates the importance of subnational or city-specific market analysis. Additionally, a counterintuitive finding was reported by Kaboudan and Sarkar [6], who demonstrated that such a city-related forecast worked particularly well when neighbourhood-related averages were used for determination instead of disaggregated values [1]. In the field of real estate market analysis, various methodologies can be employed in order to forecast market movements. The majority of studies concentrate on the absolute price of the property [7–19]. Others focus on predicting changes in house prices [20], long-term rental apartment locations [21,22], property values [23–26], construction costs [27] or the housing market index [28–31]. A significant benefit of forecasting indexes is that they enable the assessment of both qualitative and quantitative changes in sample distribution. This is particularly notable in the context of hedonic regression calculations [32]. Therefore, as a result of the financial crisis in 2007/2008, the EU decided to monitor the changes in the prices of residential properties using a House Price Index (HPI). The calculation of this HPI has been legally obligatory since 2013 (Commission Regulation (EU) No 93/2013). Since that time, the index has been divided into two categories: a general House Price Index and an owner-occupied housing price index (OOH). Together, these indexes play an important role in the Harmonized Indexes of Consumer Price. The EU also stipulates the mandatory use of a quality adjustment method (i.e., hedonic approach) (Commission Regulation (EU) No 2020/1148) [33]. The EU's preference for a hedonic HPI over a repeat-sales HPI is predicated on the premise that hedonic control variables have a tendency to stabilise the index, thereby engendering a less volatile measurement during periods of market volatility. However, when considered on an annual basis, both methodologies yield analogous results [34]. Aside from the issue of quality [35], data quantity (i.e., sample size) represents a further concern in the context of index forecasting, particularly with regard to the accessibility of historical data [2,36]. Hence, the market complexity, due to the real estate market's high heterogeneity, is also demonstrated in the sample composition over time [37–39]. It is conceivable that one month may witness a relatively high number of lower-priced flats being sold, attributable to a comparatively low supply of higher-priced flats. Conversely, in another month, the distribution may undergo a comprehensive shift, resulting from the finalisation of a major construction project comprising a substantial number of higher-priced flats. This would result in an immediate increase in the mean price, but would not affect the calculated index, as the quality changes are controlled by the regression coefficients [32]. The majority of data is typically collected on a monthly or quarterly basis, resulting in limited time series data [40].

Therefore, only when both the quality and quantity of data are assured can the index be widely adopted by market stakeholders [36]. However, the majority of previous studies have derived their conclusions primarily from macroeconomic indicators, despite the documented challenges associated with their accessibility and the temporal lag in data collection [2]. These challenges necessitate the development of a forecasting framework that incorporates microeconomic and socioeconomic data at the sub-city level into the broader macroeconomic context, thereby ensuring the reliability of city-wide index forecasts [41]. The majority of studies that predicted the HPI did not incorporate microeconomic variables, and those who did refused to include socioeconomic variables [1,4,5,40,42]. In Germany, the number of studies that predicted HPI remains comparatively low. Most German studies that predicted the housing market focused on absolute values, rather than indexes, to analyse price overvaluations [43] and explain relationships between influencing factors and rents [44] or prices [45]. HPI forecasting studies have been conducted with a focus on either rents [46,47] or prices [48,49] or both of these [50]. Notably, none of these studies integrated all three variable groups, namely macro-, micro- and socioeconomic variables,

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despite this being strongly recommended by Bachmann [51]. In order to ensure that the index forecast is based on the most appropriate modelling, it is suggested that a machine learning (ML) algorithm, such as random forest (RF) or extreme gradient boosting (XGB), be applied, as these often outperform traditional methodologies through the generation of fewer outlier predictions due to their ability to handle data nonlinearities [4,31,42].

Consequently, the objective of the present study is to construct an HPI forecasting framework that is based on comprehensive data from all three variable groups and employs an ML model. The city of Frankfurt am Main, Germany, was selected as the research area. The contribution of this paper is threefold. The methodological contribution of this study is a two-step forecasting approach, integrating micro- and socioeconomic data with macroeconomic data. The empirical contribution of this study lies in its analysis of the driving factors of the residential real estate market in Frankfurt am Main. Moreover, a practical contribution is demonstrated by the expanding-window design, which provides a clear indication of the when-to-model risk. This is of significance because statements for mean and median forecasts alone are not meaningful enough. As Hafemann [49] and Kholodilin and Siliverstovs [52] have demonstrated, forecasts are to be considered within a specific forecasting horizon, which should also be evaluated individually.

Moreover, in contrast to earlier German HPI forecasting studies and as can be seen in Table 1, the present paper's contribution extends beyond the mere enhancement of forecast accuracy. The study proposes a two-stage forecasting structure, in which disaggregated segment-level price signals are derived from linked transaction, listing, and socioeconomic data. These signals are transferred into a city-level index model, which incorporates macro-financial indicators. This design extends prior German forecasting work by explicitly connecting micro-level market composition with aggregate index dynamics.

Table 1. Paper's contributions to German HPI forecasting.

Prior Literature	Limitation	Contribution
Hafemann [49]	Forecasting horizon/risk focus, but less micro–socio–macro integration	Adds linked micro/listing/socio/macro framework
Kholodilin and Siliverstovs [52]	German HPI forecasting and model comparison, but not two-stage linked microdata design	Adds segment-to-index ML structure
Bachmann [51]	Recommends richer variable integration	Operationalises this recommendation empirically

The current study thus aims to investigate the following research questions:

1. How can micro-, macro- and socioeconomic factors be consolidated into one dataset?
2. Which macro-, micro- and socioeconomic factors drive the city index for condominiums in Frankfurt?
3. To which degree does the uncertainty of such a forecasting tool vary over time, and what drives this uncertainty?
4. Which residential market segment contributes most substantially to the city index, thereby exerting the strongest influence on the aggregate price level of condominiums in Frankfurt?

This paper is structured as follows. Section 1 introduces the research motivation, identifies the gap in the HPI forecasting literature and states the research questions and contributions. Section 2 provides a comprehensive review of the theoretical and empirical foundations of real estate price analysis, encompassing hedonic versus repeat-sales

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index construction, the role of aggregation, the rationale for ML methods and established determinants of real estate prices. Section 3 provides a comprehensive overview of the data, encompassing the temporal and spatial scope and the sources and construction of micro-, socio-, and macroeconomic variables. It also outlines the resulting data structure. Section 4 presents the research methodology, detailing the two-stage forecasting framework (location quality level and city index level), model selection, preprocessing, expanding-window evaluation, accuracy metrics and the explainable artificial intelligence (XAI) procedures. In Section 5, the empirical results are reported, including the relative performance of forecasts in relation to established benchmarks, the identification of error patterns over time, the analysis of key drivers in each forecasting stage and the identification of index-relevant market segments. Section 6 concludes with a summary of the findings, a discussion of the limitations and implications of the research and an outline of potential future research directions.

2. Theoretical Background

2.1. Hedonic or Repeat-Sales Approach

Forecasting property prices can be traced back to the early 20th century [42,53,54], and hedonic modelling can be described as the methodological foundation of forecasting prices and rents [55]. The methodology was initially introduced by Haas [53] and was empirically first employed by Court [56] to determine automobile prices. Years later, Lancaster [57] and Rosen [58] applied this methodology to forecast real estate prices [51,59]. In the meantime the repeat-sales approach was introduced by Bailey et al. [60] and Case and Shiller [61] and was especially used to forecast real estate indexes [5].

Both of these methods are still in use today and can be regarded as the foundation of more advanced methodologies [62]. When undertaking the task of forecasting indexes, the first decision that must be made is that of selecting a suitable methodology. Both approaches possess distinct advantages and disadvantages. Whilst the repeat-sales approach is a reliable method for comparing price changes over time for identical objects, it is subject to bias due to unmeasurable quality changes in the observed objects (i.e., renovation and modernisation). Moreover, the utilisation of this approach is restricted to properties that have undergone multiple sales, thus introducing a potential selection bias, particularly in the context of fluctuating market conditions. Consequently, the repeat-sales approach is particularly effective in contexts where it can be assumed that a significant proportion of the housing stock exhibits high ownership turnover, as is the case in liquid real estate markets, such as the United States [62], and where the number of object characteristics is limited. The hedonic approach, conversely, possesses the advantage of accounting for observed variations in quality, thereby ensuring that objects do not require multiple sales, thus utilising the full potential of both the quantity and quality of a given sample. However, this approach is predicated on the assumption of independence of space and unobservable house attributes, a premise which may, in principle, give rise to bias. Hence, the hedonic approach is particularly effective in markets where there is low ownership turnover, such as in Germany [62], and where a high proportion of object characteristics are specified [5]. As index forecasting represents the pure price change movement over time (and space), its calculation requires a static sample quality and quantity or adjustment by controlling these changes. As the real estate market is characterised by both qualitative and quantitative heterogeneity, it is considered the ideal context for the implementation of the hedonic approach. Furthermore, the low rate of ownership turnover in many markets renders direct price comparison of identical properties impractical and, at times, even impossible [33].

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2.2. Advantage of ML Models

In general, all real estate market prediction models can be categorised into three distinct groupings: (i) time series econometric models, (ii) ML models and (iii) decomposition-ensemble models [2,63]. The advent of big data, the accessibility of computational power and the breakthrough in artificial intelligence (AI) have collectively transformed the manner in which data analysis is conducted [31]. This transformation also applies to real estate market forecasting, being particularly evident in the United States, China and India [31]. Whilst initial studies utilised econometric models, such as ordinary least squares (OLS) [58] or the autoregressive integrated moving average (ARIMA) [64], as their primary analytical framework, they are now predominantly employed as benchmarks [4] and as instruments for further interpretation [65], especially when reporting to non-academic stakeholders [42]. Bönner's [46] recent comparison of these two econometric models in Frankfurt am Main, Germany, demonstrated that, in order to forecast the office market, multivariate models (e.g., OLS) outperform univariate models (e.g., ARIMA).

The paradigm shift to ML models is due to the fact that traditional models often encounter difficulties in capturing the aforementioned complexity of real estate markets [4]. By comparison, ML models are able to manage nonlinear relationships [66,67] and outliers [42,68,69] and are less influenced by human subjectivity [68,69]. This modelling breakthrough has resulted in significant improvements in analytical results [1,70–74] and has provided more accurate and reliable predictions [75] for multiple different forecasting tasks [3]. However, this superiority is often accompanied by the often cited "black-box" nature, which describes the limitation that the effect of the independent variable on the dependent variable is "unknown" [76,77]. Moreover, ML studies, including those by Plakandaras et al. [78] and Li et al. [79], frequently encounter issues pertaining to data leakage and overfitting in bagging models, particularly RF models [2,80], which are often introduced by a high model complexity [1].

ML models have evolved significantly since the introduction of the first tree-based models by Morgan and Sonquist [81] and Quinlan's [82] decision tree (DT) model. Subsequently, issues pertaining to overfitting were addressed by the introduction of ensemble methods, such as gradient boosting by Breiman [83]. This concept has been further developed by Chen and Guestrin [84], who introduced the XGB model, an efficient variation on Breiman's [83] gradient boosting, which is the most superior tree-based ensemble method [51,85–88]. As demonstrated by [89], this dominance was also observed in the German context when this method was employed in comparison to OLS. In the field of real estate, other ML methods, including artificial neural networks (ANNs) and support vector machines (SVMs), have been frequently employed and have yielded encouraging outcomes, particularly in comparison to linear regression models [90–92]. The most common ML models employed in the real estate context are ANN, RF, SVM, and pruned model trees [51,93]. A number of studies have been conducted which compare various ML models with each other. More recently, some studies have combined ML models [3,94–96] through weighing methods such as model stacking. A key advantage of model combinations is that they enable the simultaneous utilisation of diverse model strengths, thereby enhancing overall model performance and reducing forecasting error [36]. In contrast to these findings, Kholodilin and Siliverstovs [52] demonstrated that single models have been shown to outperform model combinations when it comes to HPI forecasting in Germany with traditional methods (e.g., OLS), particularly when the forecasting window is limited. Generally, as posited by Alsawan and Alshurideh [97], in the real estate context, ML models are still underrepresented [51] and their complexity remains elementary [31].

This trend is also applicable to Germany, where only a limited number of studies have employed ML models [35,98] and fewer have applied multiple ML models, such as RF and

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XGB, to compare or combine them with each other [99]. The research domain of XAI is even less explored. In Germany, Lorenz et al. [59] implemented XAI for rent prediction in Frankfurt am Main, and Gümmer et al. [100] implemented XAI for house price predictions in Germany.

2.3. Aggregation Level

It has been demonstrated by previous studies that price indexes tend to smooth out when the geographical scale is increased, due to the heterogeneity of the data being large and varying over space [101–104]. Consequently, the utilisation of indexes for fine-scale research areas, such as city indexes, is advocated [104–106]. However, it should be noted that this approach is not without any drawbacks, as the hedonic approach necessitates a substantial sample size, especially when it is combined with ML models like ANN [107]. As the geographical granularity increases, the sample size per research area decreases. This may result in missing data, which can introduce bias to the sample affecting the validity of the results. Such a phenomenon can be explained by the infrequent dynamics of the real estate market [108] and encompasses numerous trade-offs between aggregation bias and measurement errors [109], wherein measurement error stems from statistical error arising from an insufficient sample size, and aggregation bias signifies the false assumption of geographical market homogeneity [101,110]. As was demonstrated in the early studies of Case et al. [111] and Gatzlaff and Haurin [112], less aggregated indexes are less affected by non-representative sampling and are particularly important for long-time horizon predictions [101]. Nonetheless, the aforementioned trade-offs result in an optimal granularity [101], which differs by research area. For instance, Bogin et al. [101] found that, for small US cities, a disaggregated index is least useful. Firstly, Malone and Redfearn [113] and subsequently Contat and Larson [110] modelled annual de-aggregated indexes. These indexes were based on lower fine-grained geographical units with a minimum observation count and were later aggregated to form the city-level index [5].

In German HPI studies, the aggregation level either pertained to a specific city [32,47] or encompassed the entire country [48,50]. Early studies, such as that of Kholodilin and Siliverstovs [52], had already recommended that local information and city-specific indicators should be considered. Kim and Bedorf [35] advocate for the differentiation of regional parts. Gümmer et al. [100] argue that, in order to create robust predictive models for the real estate market, it is essential to treat it as multiple diverse local markets and thus account for market granularity. Furthermore, Hafemann [49] asserts that neglecting to consider this aspect and instead focusing solely on the aggregate mean may result in an underestimation of tail risks, as the district-level risk may be underrepresented during certain periods.

2.4. Determinants of Real Estate Prices

The real estate market is influenced by a multitude of factors [3]. While there is a consensus in the literature that a wide range of factors should be considered, the characterisation of these factors varies. Dubin [114] posited that a property's price-influencing characteristics can be grouped into three categories: (i) structure (e.g., apartment size), (ii) location (e.g., distance to central business district (CBD)) and (iii) neighbourhood (e.g., crime rates) [59,115,116]. This concept is further elaborated upon by Schulten [117], who categorises the influencing site characteristics into three distinct domains: (i) quality of location and traffic, as well as transport links, (ii) socio-demographic (e.g., vacancy rates) and (iii) regional economy (e.g., purchasing power). Soot et al. [118] categorise these macro-factors as interior and exterior indicators. Interior indicators are defined as those with a direct link to the real estate industry, while exterior indicators are defined as those with an indirect link, which predominantly derive from the demand side. Rahadi et al. [119]

propose a more architecture-driven classification system comprising the following three distinct categories: (i) physical conditions, encompassing building properties, (ii) conceptual frameworks, representing design ideas for the house (e.g., minimalist architecture) and (iii) location [120]. Micheli [121] demonstrates the importance of expected consumer behaviour, such as consumption and savings, with increasing forecasting horizons, because the self-evaluated financial situation of consumers may affect the expected (housing) consumption. However, the relevance of these factors for the purpose of short-term predictions is relatively low. Therefore, they should not replace fundamental factors, which were mentioned in the previous paragraphs. Gao et al. [122] propose a classification of all factors into just two groupings. The factors under consideration may be categorised into two distinct groups: geographical (e.g., distance to CBD) and non-geographical (e.g., number of bedrooms) [120]. Similarly to Soot et al. [118], Levantesi and Piscopo [120] also distinguish macroeconomic factors, this time between the local level, defined by direct effects on the demand site (e.g., city population), and the national level (e.g., interest rates) [120]. Whilst Glaeser et al. [123] demonstrate that local factors have a significantly stronger effect on property prices, Abidoye et al. [42] demonstrate that macro-national factors, such as interest rates, also have a strong significant effect. The majority of property price predictions are predicated on either microeconomic or macroeconomic variables; however, studies rarely consider both. The majority of HPI studies concentrate on the latter [42]. Xu and Zhang [124] prefer a similar characterisation to Dubin [114], and divide all influencing factors into (i) lagged price information, (ii) property characteristics and (iii) macroeconomic and policy variables. The classification system proposed by Mohamed et al. [125] divides all factors into seven groups, namely (i) building characteristics, (ii) structural and architectural, (iii) financial, (iv) social, (v) governmental, (vi) physical and environmental and (vii) economic.

In Germany, Möbert [126] discovered that macroeconomic indicators were the primary drivers in forecasting the HPI. This finding is corroborated by Hafemann [49], who asserts that, while certain macroeconomic variables, such as interest rates and employment, play a significant role in predicting the HPI, the lagged house price growth has the most substantial impact on the lead variable. Furthermore, Kim and Bedorf [35] recommend the utilisation of locational and building-specific information, in addition to the differentiation between housing types (i.e., flats and houses). Building on these definitions and the German context, Schmid and Cheng [127] evaluated 45 price forecasting studies ranging from 2001 to 2024 and divided their independent variables into nine groups, namely: (i) location, (ii) property characteristics, (iii) environment and neighbourhood quality, (iv) microeconomic, (v) macroeconomic, (vi) accessibility and infrastructure, (vii) population, (viii) buyer/seller, and (ix) temporal.

The objective of this study is to determine the city HPI of Frankfurt am Main. To this end, a hedonic model in conjunction with ML models will be established that accesses data with the lowest possible level of aggregation. In accordance with the variable definition proposed by Schmid and Cheng [127], all variable groups should be integrated.

3. Materials

3.1. Study Period and Exclusions

Real estate markets are confronted with numerous challenges, including the threat of pandemics [31]. As Francke and Korevaar [128] demonstrated, these price developments have historically been unique events, especially in the initial stages of the pandemic in heavily affected regions. Hu and Huang [129] demonstrate how, for instance, seasonal peaks can change due to such external shocks. However, it is important to note that markets have a tendency to recuperate from such transitory shocks and revert to normal

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price developments following the pandemic [130]. Most recently, during COVID-19, this was particularly evident in vacant office buildings and apartments in large cities [130]. Such developments have the potential to distort potential forecasting models in post-pandemic times [49]. Consequently, the observation period of this study excludes the period of the pandemic and hence ends in 2019.

3.2. Study Area and Rationale

The majority of studies utilising ML models for real estate market forecasting are predominantly focused on data from China, the U.S., or India [1,31]. Only a limited number of studies have focused on the European region, including the United Kingdom [131], Spain [132], Italy [133], Turkey [95], and Russia [134]. However, Germany is disproportionately underrepresented in the extant literature, with only two studies addressing this issue. Within Germany, Frankfurt am Main holds second position in terms of city ranking, with Munich at the top. In terms of global ranking, Frankfurt am Main is positioned at number 25, and within the European context it is ranked at number nine. A comparison of prices per square metre across both global and European cities reveals no significant deviation, with the exception of recent price increases that have been shown to be adjustments to international levels, thus compensating for the initial [126]. Additionally, with a 122% increase in prices from 1984, Frankfurt has shown the second strongest price performance in Germany after Berlin and has simultaneously seen the largest drop of 12% [62]. The end of the investment cycle for Frankfurt in 2028 is expected to be one of the latest in Germany [126]. To summarise, strong long-term growth, international comparability and dynamic market movements make Frankfurt am Main an especially attractive case for investors and an exceptional study area for a city HPI forecast.

3.3. Data Sources

As mentioned before, to build a good HPI forecasting model, both good quality and quantity in data are needed. Hence, all variable groups, as proposed by the definition of Schmid and Cheng [127], should be integrated: (i) location, (ii) property characteristics, (iii) environment and neighbourhood quality, (iv) microeconomic, (v) macroeconomic, (vi) accessibility and infrastructure, (vii) population, (viii) buyer/seller, and (ix) temporal. These variable groups are represented by the following datasets:

- Microeconomic data: building-specific–RWI–Leibniz Institute for Economic Research (RWI), Essen, Germany & Expert Committee Frankfurt am Main, Frankfurt, Germany (groups i, ii, viii, ix);
- Listing data–RWI, Essen, Germany;
- Transaction data–Expert Committee Frankfurt am Main, Frankfurt, Germany;
- Microeconomic data: socioeconomic–RWI, Essen, Germany (groups iii, iv, vi, ix);
- Macroeconomic data (groups v, vii, ix);
    - Construction cost index for residential buildings–German Federal Statistical Office (DESTATIS), Wiesbaden, Germany (quarterly);
    - Population size of Frankfurt–DESTATIS, Wiesbaden, Germany (annual);
    - Consumer price index–Organisation for Economic Co-operation and Development (OECD), Paris, France (quarterly);
    - Interest rates for long-term government bond yields–OECD, Paris, France (quarterly);
    - Registered unemployment–OECD, Paris, France (quarterly);
    - Dax–Kiel Institute for the World Economy (IfW), Kiel, Germany (monthly);
    - Land price index–IfW, Kiel, Germany (annual).

The descriptive statistics of all used variables can be seen in Table A1 in Appendix A.

3.3.1. Microeconomic Data: Building-Specific

All data sources impose a trade-off between data quality and quantity. While the quality of the data should meet a minimum standard to be considered reliable, the quantity of data is of equal importance, as a reduced sample size has the potential to engender an inaccuracy in the reflection of market conditions [135]. The existing literature about market coverage for Germany's leading online real estate listing platform, Immobilienscout24, presents a range of figures. The diversity of these statements is notable, with Georgi and Barkow [136] citing a market coverage of 50 percent, Germany's Federal Cartel Office determining a market share of 70 percent [137] and Henger and Voigtländer [138] indicating a figure as high as 90 percent. In light of the comprehensive market coverage, the dataset of ImmobilienScout24 is considered the most suitable source for determining listing prices. According to Brenning and Henn [139], listing data from online real estate listing platforms can be extracted from the websites in real time via web scraping [44,140], or alternatively it can be provided directly via cooperation agreements with the providers. In the present study, option two was selected, whereby a cooperation agreement was initiated with the RWI [141].

As with listing data, there are a variety of options by which transaction data can be acquired. In accordance with the legislations stipulated by the German Civil Code (BGB 2024 §311b) and the Federal Building Code (BauGB 2023 §195), the notarisation of purchase contracts for real estate of any kind in Germany is mandatory, and notaries are obligated to transmit the relevant data to the expert committee. Consequently, the collection of transaction prices by the designated expert committee ensures comprehensive market coverage within the area of its responsibility. Only in a limited number of cases, such as share deals, are properties excluded from the expert committee's dataset. However, due to the high sensitivity of the data, strict data protection regulations under state law are in place to ensure their protection, which limits their availability to special cases (BauGB 2023, §193). As with the prior agreement for access to the listing data, the agreement with the expert committee also covers the essential aspects of data protection, aggregation and anonymisation.

By combining the listing and the transaction data, it is possible to generate a building-specific dataset of both high quality and quantity, thereby meeting the concerns of previous studies regarding data for forecasting challenges [35]. As no specific address is available for direct object merging, the merge has been facilitated by Schmid's [142] methodology for threshold optimisation with real estate data.

3.3.2. Microeconomic Data: Socioeconomic

The socioeconomic data were provided by the RWI, which is collaborating with Micromarketing-Systeme und Consult GmbH. As with the RWI listings, the dataset is aggregated on the grid level (i.e., 1×1 km raster cells). This grid-level projection is based on the EU directive standardised European projection system, INSPIRE (Infrastructure for Spatial Information in Europe). The dataset contains variables from multiple domains, including building structure, economic indicators, household structure, demographics, mobility, and, in addition to the grid information, further regional classifications for federal states, districts, municipalities, and postcodes [143]. As the dataset is only available for scientific research, a cooperation contract was signed with the RWI.

3.3.3. Macroeconomic Data

In addition to the microeconomic data acquired under contract, additional macroeconomic data that are publicly available were also utilised. The following datasets were compiled for analysis:

- Quarterly construction cost index for residential buildings;
- Annual population size of Frankfurt;
- Quarterly consumer price index;
- Quarterly interest rates for long-term government bond yields;
- Quarterly registered unemployment;
- Monthly German stock index (DAX);
- Annual land price index;
- Quarterly German Real Estate Index (GREIX).

Apart from the real estate index, there are few differences between the various providers of the macroeconomic datasets. However, it should be noted that there are several providers who utilise a variety of methods for constructing the real estate index. In the present study, GREIX (IfW, Kiel, Germany) was selected. The GREIX is a transaction-based real estate price index, with its base year set to 2000. It is constructed from expert committee transaction data [62]. In this study, the quarterly GREIX condominium price index for Frankfurt am Main is used as the dependent city-level index variable. The reason for selecting the GREIX as the dependent variable is twofold. Firstly, in contrast to the indexes of certain other providers, GREIX is based on actual transaction data from expert committees. Secondly, the methodology employed in the collection and construction of the GREIX is transparent. This ensures that the index does not demonstrate arbitrary fluctuations over time attributable to methodological changes [62].

4. Methods

4.1. Overview

Figure 1 illustrates the methodological workflow of this paper. For all steps, the software Rstudio (v2025.05.0+496) was used. First, the microeconomic variables were merged at object level and aggregated at the grid level. Socioeconomic variables were then added to the grid-level data structure. The choice of forecasting algorithm was driven by an RF-based selection process. After comprehensive preprocessing, the forecasting exercise employed a two-stage ML approach (location quality and city levels). Before the second forecasting stage, macroeconomic data were added at the city level. Throughout this whole process, the data structure shifted from (i) pooled cross-sectional to (ii) panel, and finally to (iii) time series. Each of these steps is described in detail below.

4.2. Data Structure and Aggregation

The analytical process initiated with a pooled cross-sectional data structure at the transaction level, wherein individual property transactions were designated as the unit of observation. At this stage, two primary data sources, namely transaction and listing records, were merged with a threshold analysis based on Schmid [142]. Detailed information pertaining to this linkage procedure can be found in Table A2 in Appendix A. The transaction data include realised sale prices and structural property characteristics, while listing data provide pre-sale information such as list prices and exposure duration. Prior to aggregation, non-market transactions (e.g., forced sales) were eliminated to ensure that observed prices reflect market-based valuation processes. Transaction prices were then standardised by apartment size to obtain prices per square metre, which formed the basis for all subsequent aggregation and forecasting steps.

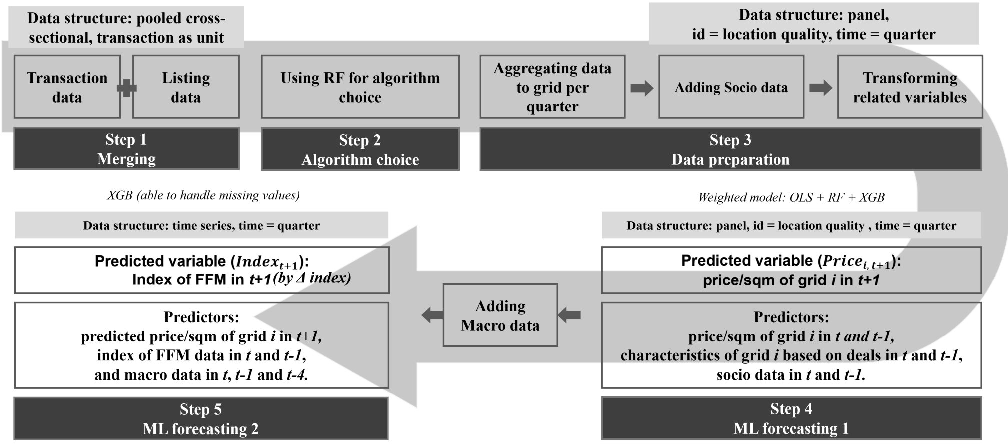

Figure 1. Methodology workflow (source: author's own work). Notes: Frankfurt am Main (FFM) is the study's research area. The models ordinary least squares (OLS), random forest (RF) and extreme gradient boosting (XGB) were used for analysis.

4.3. Algorithm Choice and Model Class Justification

Due to the heterogeneity of property markets and the existence of nonlinear relationships between prices, location and structural characteristics, an RF classifier was employed as a diagnostic tool, to find out which ML models should be utilised as tools for the predictive analysis. This methodology has been demonstrated to be effective to select the most suitable algorithm family for a given dataset [127]. The RF model yielded an area under the curve (AUC) of 0.85 and an accuracy of 0.88. The utilisation of the RF model with the data from this study demonstrated that ensemble algorithms are the optimal solution for the given data. This may be attributable to the presence of highly complex variables, such as locational variables, and the extensive observation period.

Generally, the capacity to discern nonlinearities, threshold effects and higher-order interactions is a compelling rationale for the employment of ensemble learning methods in conjunction with linear benchmarks. The diagnostic led to the development of a framework that combines OLS with RF and XGB models. The final model set was selected in order to combine interpretability, nonlinear predictive capacity, and ensemble robustness. The OLS model was incorporated into the study as a transparent linear benchmark [4], serving as a reference point for the assessment of whether more flexible ML models offer enhanced predictive value [144,145]. The inclusion of RF was motivated by the potential of tree-based bagging models to capture nonlinearities and interaction effects while exhibiting relative robustness to outliers [146]. The XGB model was selected due to its capacity to handle heterogeneous predictor spaces, its ability to model nonlinear dependencies, and its capability to manage missing values internally [84]. The rationale behind the implementation of the stacked model was to combine the complementary strengths of the individual learners [147]. At the city level, XGB was favoured due to its robustness to missing values and its suitability for high-dimensional predictor spaces [84]. Additional city-level benchmarks, including OLS and ARIMA specifications, were considered but not implemented as primary benchmarks. The city-level forecasting task contains a limited number of quarterly observations and several predictors with missing values. In this setting, OLS and ARIMA would require additional imputation, listwise deletion, or strong assumptions regarding the missing observations. Such procedures would either further reduce the effective sample size or introduce additional uncertainty unrelated to the proposed two-stage design. XGB is therefore used as the direct ML benchmark because it can handle missing values internally and is better suited to heterogeneous predictor structures in small-sample forecasting settings.

In order to assess whether the two-stage framework improves on standard alternatives, a comparison is made between the proposed model and two benchmark classes: a naïve persistence benchmark and a single-stage XGB benchmark. The naïve benchmark evaluates whether the framework improves on simple index persistence, while the single-stage XGB benchmark forecasts the city-level index directly without using segment-level first-stage predictions. This second benchmark directly tests whether the proposed two-stage structure adds predictive value beyond a direct ML specification.

4.4. Data Preparation and Panel Construction

At the grid level, socio-demographic indicators such as purchasing power, household structure, residential building stock and age composition were included. This introduced spatial bias, as the allocation of socio-demographic indicators might be affected by flexible grid definitions, also known as Openshaw's [148] modifiable area unit problem (MAUP). The MAUP affects results when point-based measures of spatial phenomena are aggregated into spatial partitions or areal units (such as regions or districts), as in, for example, population density or illness rates. The resulting summary values (e.g., totals, rates, proportions, densities) are influenced by both the shape and scale of the aggregation unit [148]. However, given that this grid definition is the only one available, it was not possible to merge the datasets in any other way. As these variables are typically only available on an annual basis, they were interpolated to produce quarterly observations using a rule-based procedure. The conversion of the data to a quarterly format was achieved through the implementation of linear interpolation. In instances where a single valid value was available, it was maintained as is. However, in scenarios where no value was present, the yearly average was employed as a fallback value. Consequently, grid-level information was given priority, and where unavailable, grid-average values were used as a fallback to preserve sample completeness. The management of missing values was achieved through the implementation of a data processing strategy that entailed the following steps: the recording of invalid or designated "Other missing" entries as "NA", the verification of merge consistency, and the application of complete-case deletion prior to the modelling stage. Transactions and observations that exhibited indications of buyer-subjective bias, such as those involving forced auctions, were excluded from the analysis. The impact of price on the decision-making process was mitigated by the utilisation of median prices per square metre within each location quality quarter. Subsequently, with a view to minimising spatial noise and density differences, individual properties were aggregated. It was not possible to assign a regular spatial grid (i.e., 1 × 1 km grid cell) based on geographic coordinates due to a paucity of data. Consequently, the aggregation was executed on the location quality (Lagequalität), reported by the official expert committee, which is determined on the basis of official land values and expert validations [149]. Because of data limitations, the levels had to be adjusted to four clusters (see Table 2). This approach is advantageous in terms of spatial convenience, as it serves to mitigate the impact of MAUP, as the aggregation of the grid cells into grid blocks (e.g., 4 × 4) would have resulted in spatial randomness.

Table 2. Distribution of location qualities.

Location Quality	N	Min	Q1	Median	Q3	Max
Very low and low	664	562	1837	3122	3934	8666
Medium	3029	570	2738	3778	5496	15,641
High	1125	828	3046	4346	5764	11,666
Very high	354	1236	3358	4782	6775	14,706

Subsequently, for each quarter, the median for the target variable and the mean for predictors within each location quality group were calculated. This step involves outlier and NA row exclusions, as well as data transformation from a pooled cross-sectional (object-level) structure to a panel structure (location quality level). In this new structure, the cross-sectional unit is the location quality and the temporal dimension is the calendar quarter. Subsequently, several transformations (i.e., Yeo-Johnson, and Log) were applied to ensure statistical comparability. By the end of Step 3, the dataset constitutes a balanced panel, with the location quality acting as the cross-sectional identifier and the quarter acting as the time index. All subsequent forecasting steps use an expanding-window evaluation framework. The selection of an expanding-window evaluation design is predicated on its alignment with the stipulated real-time forecasting framework. At each forecast origin, the model is estimated using all information that would have been available historically, while observations beyond the cut-off quarter are excluded. Such an approach is especially suitable for the present application, given that the second-stage index model is estimated on a limited quarterly time series. A rolling-window design would discard the already scarce historical observations and would require the arbitrary selection of a window length. The presence of lagged macro-financial variables, including four-quarter lags, would present a significant challenge in this regard. Hence, the utilisation of short rolling windows could potentially lead to unstable results influenced by window-length artefacts. The expanding-window design is thus the most transparent and data-efficient ex ante evaluation framework for the available sample. Repeating this procedure for the period from 2017Q1 to 2018Q4 ensures a strict out-of-sample (i.e., outer backtest) evaluation. To evaluate the models, the data must be split into training and testing data. As there are no rules regarding the splitting ratio in the literature [66], researchers must determine this ratio themselves [150]. The sample was therefore split into 80% training (split into 80% time-aware cross-validation (CV) training and 20% CV validation) and 20% testing data [151].

4.5. Stage 1 Model Setup: Location Quality-Level Price Prediction

In the first forecasting stage, prices per square metre at the aggregated location quality level were predicted one quarter ahead. The predicted variable is defined as follows:

Price(i,t + 1), where i denotes the location quality group and t denotes the current quarter. Predictors include contemporaneous and lagged prices; structural and locational characteristics derived from transactions in quarters (t) and (t − 1); and socio-demographic variables in quarters (t) and (t − 1).

This forecasting step operates on a panel data structure (location quality × quarter). Models were estimated using OLS as a linear benchmark, as well as RF and XGB to capture nonlinear dynamics, and a weighted model (stacked model) integrating forecasts from all of the above. The stacked model was optimised using the inner CV's prediction accuracy, the root mean squared error (RMSE). Forecast evaluation used an expanding-window design to ensure strict out-of-sample prediction.

4.6. Stage 2 Model Setup: Index-Level Prediction

The second forecasting stage used the predicted values on the aggregated location quality as inputs to forecast a city-level real estate price index for Frankfurt am Main. During this process, the data structure shifts from a panel to a time series, with the quarter acting as the temporal index.

The predicted variable is defined as Index(t + 1), representing the condominium price index at the city level in the subsequent quarter. The model forecasts the one-step change in the index,

$$\Delta\text{Index}(t + 1) = \text{Index}(t + 1) - \text{Index}(t), \tag{1}$$

then reconstructs

$$\text{Index}(t + 1) = \text{Index}(t) + \Delta \tag{2}$$

Predictors include predicted location quality-level prices at (t + 1); values of the city-level index at (t) and (t − 1); and macroeconomic variables at (t), (t − 1), and (t − 4).

The macroeconomic variables were given multiple lags, as past studies have demonstrated that this is beneficial for this type of variable [42]. A pivotal methodological consideration concerns the publication timing of macroeconomic indicators. In real-time forecasting environments, macroeconomic variables are typically released with reporting delays. The introduction of look-ahead bias would therefore result in an artificial inflation of predictive performance. In order to guarantee strict ex ante forecast validity, contemporaneous macroeconomic observations at time t were to be excluded from the estimation procedure. This design ensures that, at each forecasting origin, the model exclusively utilises information that would have been observable at the time of prediction. The adjustment of publication lag is of particular importance for variables such as construction costs, consumer prices, interest rates, unemployment, land prices and population figures. The only macroeconomic information that is incorporated at time t is the stock market index. The current and lagged index values are included as persistence signals. As such, the location quality prices for the next quarter are not observed values but predictions generated in stage 1, and are therefore available internally to the forecasting framework. An overview of the lagging of variables can be seen in Table 3.

Table 3. Lagging of variables (source: author's own work).

Predictor Group	Used Timing	Reason
Index	t, t − 1	Available at forecast origin
Stage 1 segment prices	Predicted t + 1	generated internally
DAX	t or lagged	High-frequency/available earlier
Macroeconomic variables	t − 1, t − 4	Publication lags
Annual variables	Lagged/interpolated	Slow-moving controls

XGB is crucial in this last forecasting step, as it can integrate heterogeneous inputs [1] and handle missing values [84], and the superiority of XGB in analysing German real estate markets has already been proven [89].

4.7. Evaluation and Explainability

Across both forecasting stages, models are evaluated based on RMSE, relative root mean squared error (RRMSE) and adjusted R^2. As the first forecasting step is operating on the transformed scale, mean absolute error (MAE) and mean absolute percentage error (MAPE) were only reported for the second forecasting step. These model metrics are widely adopted in the literature [42,91,152], are proven to be good indicators of a model's predictive accuracy [153], and are easy to interpret. Due to the black-box nature of ML algorithms, there is a lack of transparency with regard to the variables' correlations [59].

Therefore, XAI was used to determine which features contribute to the predictions and to what extent [51]. The variable interactions were measured by means of a feature importance (FI) plot, which illustrates the relevance of single features. This is achieved by measuring the change in prediction error caused by permuting the observed values of a single feature while keeping all other features unchanged [59]. In addition to variable importance, SHapley Additive exPlanations (SHAP) values are utilised to examine the direction and relative magnitude of key predictors in all ML models in both stages. The utilisation of SHAP values provides a more detailed decomposition of individual predictions, thereby facilitating the interpretation of the nonlinear contributions of macro-financial and segment-level variables [154,155].

4.8. Robustness and Sensitivity Testing

In order to assess the impact of first-stage forecast errors on the second-stage index forecast, an error propagation sensitivity analysis is conducted. The baseline specification employs location quality prices that have been predicted in stage 1. In this study, the current specification is compared with an oracle specification. The oracle specification is derived from observed segment-level prices [156–158]. In addition, a reduced specification is also considered. This reduced specification excludes segment-level price predictions. The employment of a comparative analysis facilitates the explicit evaluation of the contribution and potential instability of first-stage predictions.

Furthermore, in order to assess the sensitivity of the macro-financial lag structure, an alternative lag specification is compared, including one-quarter, two-quarter, and four-quarter lag structures. The purpose of this robustness check is to ascertain whether the reported driver structure is specific to the selected lag length or remains stable across plausible short-horizon macro-transmission windows.

5. Results and Discussion

5.1. Stage 1 Model Performance: Location Quality-Level Price Prediction

The stage-1 forecast performance for all of the eight one-step-ahead forecasts (2017 Q1–2018 Q4) can be seen in Figures 2 and 3. As the R^2 value cannot be interpreted for the test data, here only the training evaluation is of interest. The evaluation shows clearly that all R^2 values are robust over time and vary between 0.80 and 0.93. For the RRMSE value, the test results are more of interest, as they are the key metric for the first forecasting step. It can be seen that, for the stacked model, a fair RRMSE between 0.35 and 0.21 was achieved. Furthermore, in accordance with the extant literature [40], the linear model (i.e., OLS) demonstrates a satisfactory degree of compatibility for the prediction of the subsequent quarter. However, in accordance with literature [51,85–89], the ML models outperform the OLS in most cases, and, in line with Glynn [36] but contrasting with Kholodilin and Siliverstovs [52], the stacked model shows an overall superior performance. As the RRMSE values in Figure 3 are calculated on the transformed scale, they cannot be interpreted as absolute errors. The back-transformed values are lower and show RRMSEs between 0.16 and 0.26 (exemplary for round 9).

The relatively noisy predictive performance of the first stage is consistent with the extant literature, as price predictions tend to exhibit such characteristics and index predictions typically smoothen out variation [5]. When interpreting the two-stage results in terms of the aggregation strategy, it can be seen that the noisy first-stage forecasts are consistent with residual micro-volatility at the segment level. Conversely, the second-stage index forecast benefits from the smoothing inherent in aggregation. However, it remains vulnerable when shocks are distributed unevenly across segments. Moreover, this approach is consistent with established evaluation practices in Germany. Within the framework of German law (§194 BauGB), the term “normal circumstances” emerges as a pivotal concept in the evaluation of real estate transactions. This concept is characterised by uncertainty ranges of up to 20 to 30 percent [159].

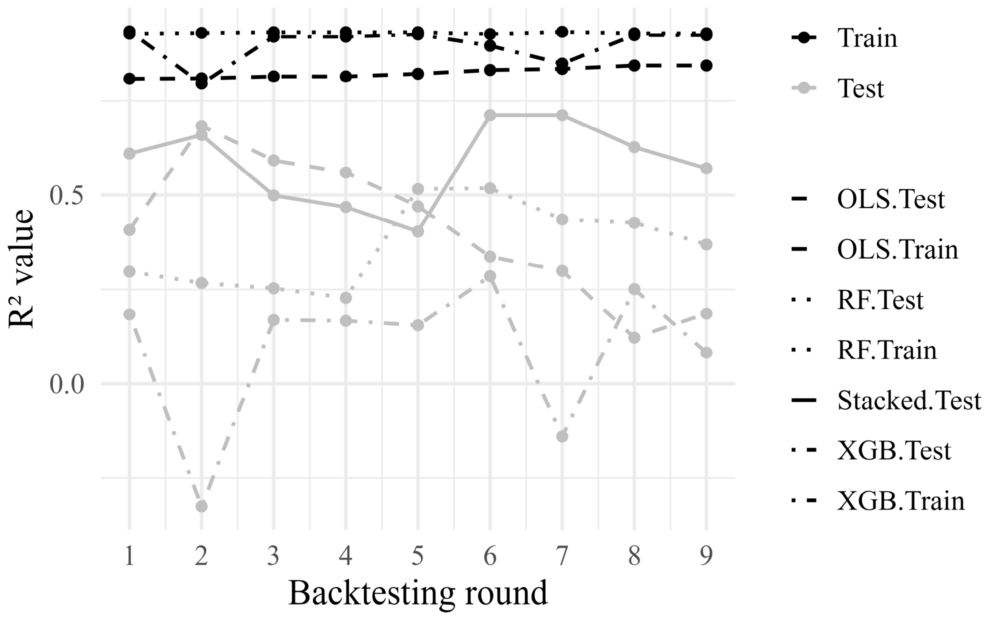

Figure 2. Evaluation of R^2 per round (source: author's own work).

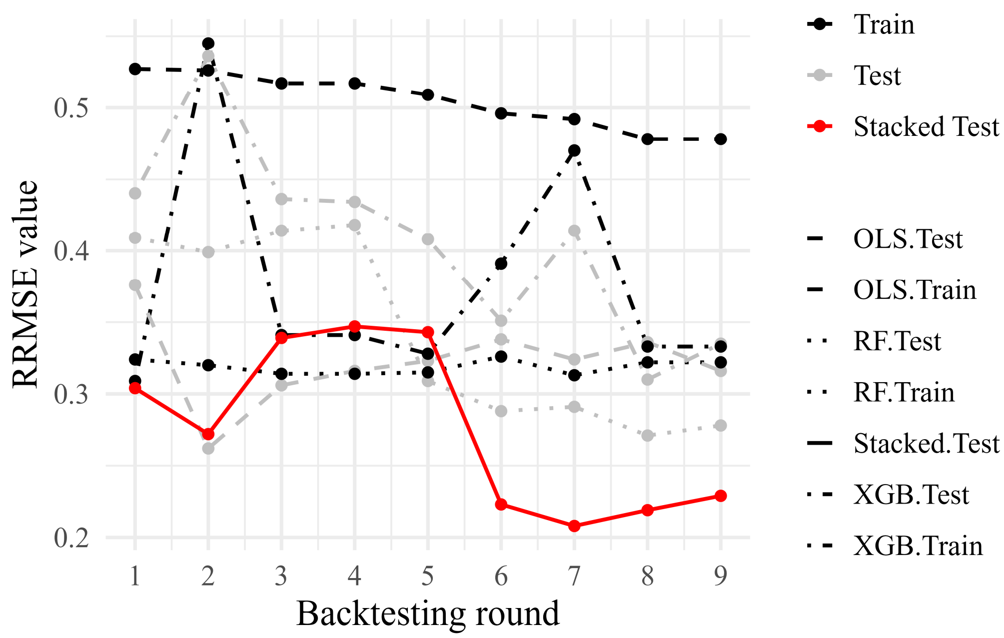

Figure 3. Evaluation of RRMSE per round (source: author's own work).

5.2. Stage 2 Performance: Index-Level Prediction

Across all eight one-step-ahead forecasts, the model achieves an MAE = 3.88 index points, RMSE = 4.67, and R^2 = 0.89. In relative terms, the RRMSE is equivalent to 2.25% of the mean index level and the MAPE is 1.85%. The RRMSE ratio in comparison to the naïve benchmark is 0.776, indicating that the model reduces RMSE by approximately 23% relative to the naïve forecast. A comparison of the Diebold–Mariano (DM) model with squared error loss yielded a result of DM = -2.53 (p = 0.039), indicating that the model's loss is significantly lower than the naïve baseline over this backtest window. However, given the relatively small research period, it does not establish general superiority across market regimes.

A wide range of ML algorithms has been applied in the real estate forecasting literature, often yielding encouraging predictive accuracy. In their review, Jin and Xu [1] report that empirical studies have documented MAPE values spanning a broad range, including

- 8% to 9% [160];
- 7% to 8% [160,161];
- 6% to 7% [160,162];
- 5% to 6% [79,160,162];
- 4% to 5% [160,163];
- 3% to 4% [162,164];
- 2% to 3% [161,165];
- 1% to 2% [132,161,162,164];
- Less than 1% [161,162,164–166].

The comparability of modelling outcomes is not straightforward, as data structures and variable metric scales are different. A good evaluation metric used in many previous studies before is RRMSE [1,167–170]. This metric is, for instance, better than MAPE, as it is not dependent on the metric scale of the dependent variable. This allows prediction accuracy to be classified according to the following grading system, as defined by Jin and Xu [1]:

- Excellent accuracy for RRMSE < 10%;
- Good accuracy for 10% < RRMSE < 20%;
- Fair accuracy for 20% < RRMSE < 30%;
- Poor accuracy for RRMSE $\geq$ 30%.

When evaluated in comparison to the studies referenced, the MAPE achieved is positioned at the upper end of the international spectrum. A comparison of the RRMSE also demonstrates that the model has excellent accuracy. As identified by Jin and Xu [1], under certain circumstances, a model that exhibits poor performance in terms of mean accuracy may still generate accurate predictions. This is due to the fact that time series encompass a broad spectrum of characteristics, with some being more readily identifiable than others [1]. Consequently, the model's performance variance is also in line with the literature.

5.3. Quarter-to-Quarter Error Diagnostics

The quarter-level error patterns, seen in Table 4 and Figure 4, demonstrate that the model achieves a clear victory in five out of eight rounds (62.5% success rate), suffers a defeat in two rounds, and achieves a draw in one round. The enhancements are observed to occur during periods where the index demonstrates a sustained trend, particularly during periods of upward movement. In these instances, the model performs a correction of the naïve lag, thereby reducing the magnitude of error. However, the naïve model remains competitive in specific contexts, and its most significant underperformance occurs at the end of the sample. The model displays a reasonable degree of proficiency in capturing the direction of quarterly changes, with an accuracy of 0.714 signifying the correctness of five out of seven directional alterations.

The fundamental weakness is not direction but magnitude at turning points: The most significant discrepancy was observed in Q4 2018, where the model overpredicted the index, with a predicted value of 231 versus the actual figure of 223 (an error of +8.04% and an APE of 3.60%). In comparison, the naïve forecast exhibited a closer alignment with 225 (an error of +2.18% and an APE of 0.98%). Another significant discrepancy was observed in Q1 2017 (error +6.92; APE 3.70%), where the naïve approach exhibited a higher degree of proximity.

Table 4. Index backtest of model's prediction vs. naïve's prediction.

#	Year	Quarter	Actual	Pred Model	Error Model	APE Model	Pred Naïve	Error Naïve	APE Naïve
1	2017	1	187	194	6.92	0.0370	189	1.82	0.00972
2	2017	2	193	191	−2.64	0.0137	187	−6.02	0.0312
3	2017	3	198	197	−0.336	0.00170	193	−4.58	0.0232
4	2017	4	204	202	−1.48	0.00726	198	−5.88	0.0289
5	2018	1	211	209	−2.26	0.0107	204	−7.18	0.0341
6	2018	2	222	216	−6.07	0.0273	211	−11.3	0.0509
7	2018	3	225	229	3.31	0.0147	222	−3.27	0.0145
8	2018	4	223	231	8.04	0.0360	225	2.18	0.00976

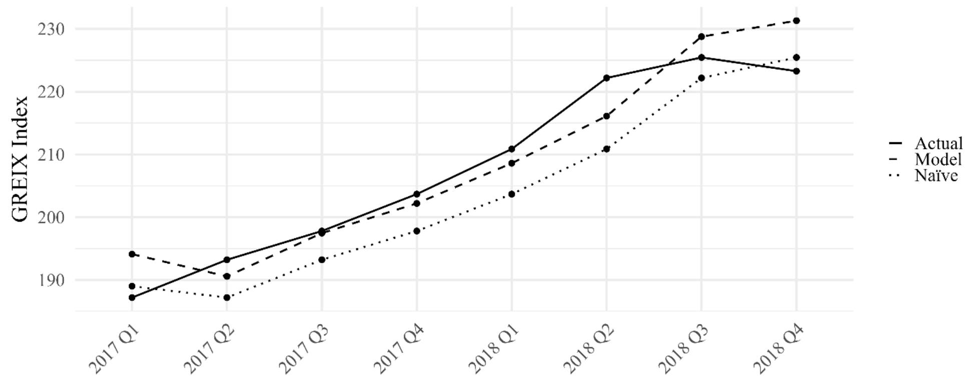

Figure 4. Trend line of model vs. naïve (source: author's own work).

The cumulative loss differential plot (see Figure 5) demonstrates a predominantly negative trend over the backtest period, aligning with the overall DM test outcome. The curve demonstrates a marked increase in the final quarter, indicating that a single error in identifying a turning point can result in the loss of a significant proportion of the accumulated advantage, despite overall superior average performance.

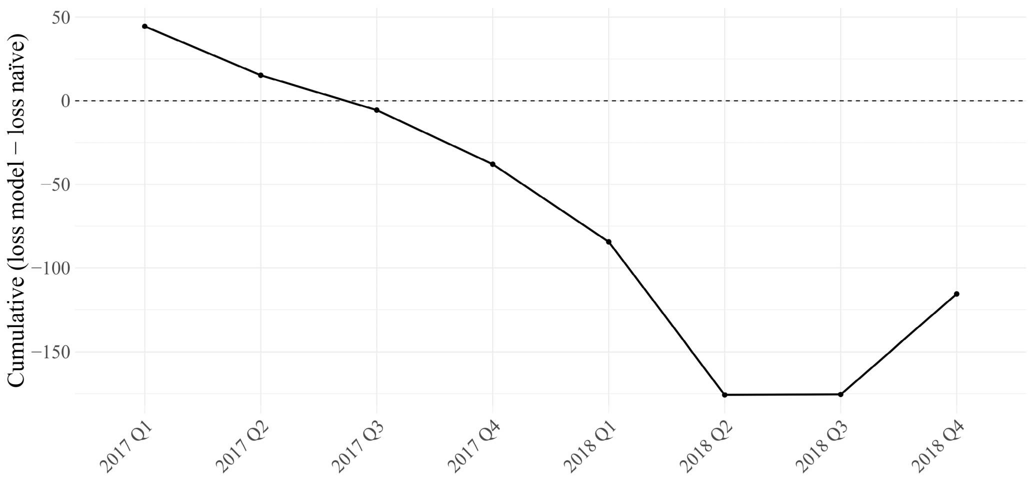

Figure 5. Cumulative loss differential plot (source: author's own work).

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Figure 6 demonstrates a consistent narrative: the model RMSE remains below the naïve RMSE for most of the period but increases at the conclusion of the period due to the underperformance in Q4 2018. Consequently, it can be argued that forecasting risk is dominated by regime shifts, rather than by typical quarters.

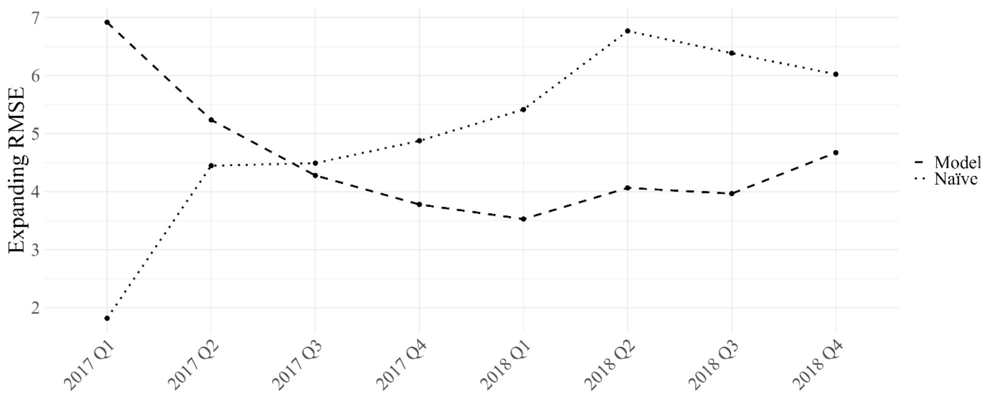

Figure 6. Expanding root mean squared error (RMSE) of model vs. naïve (source: author's own work).

The extent of forecast uncertainty is indicated by the absolute forecast error, as presented in Table 2, and the expanding RMSE, as demonstrated in Figure 6, over the backtest window. The findings suggest that uncertainty is not constant over time, but rather increases around turning-point quarters, particularly when the lagged macro-financial structure persists in reflecting the preceding trend regime.

5.4. Model Interpretability: Key Drivers in Stage 1 and Stage 2

In the OLS variable importance plot (VIP) in Figure 7, price information (i.e., price and price_lag), socioeconomic neighbourhood information (i.e., unemployment and foreigner), and demand proxies (i.e., seller_private and hits) are identified as the primary variables. The VIPs of the ML models XGB (see Figure 8) and RF (see Figure 9) show that these models have a corresponding dominance of price information (i.e., price and price_lag). This is consistent with a nonlinear model that places significant reliance on persistence, complemented by a select number of high-signal variables [171]. Socioeconomic neighbourhood information and demand proxies, on the other hand, play only a minor role. This observation indicates that the majority of the incremental predictive power is derived from a restricted subset of covariates, which is in line with the literature [51].

Figure 7. VIP OLS (source: author's own work).

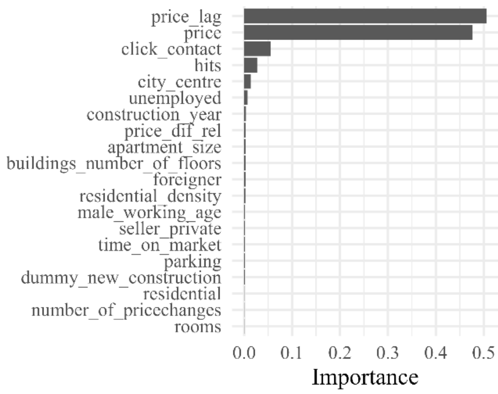

Figure 8. VIP XGB (source: author's own work).

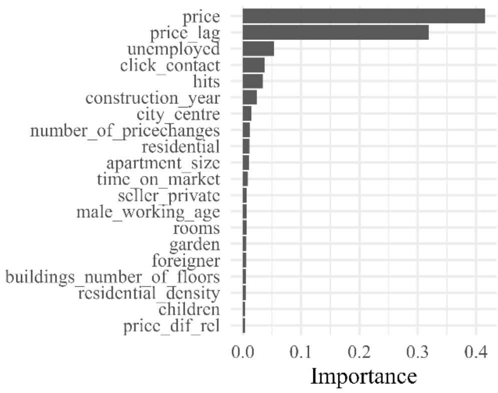

Figure 9. VIP RF (source: author's own work).

On the transformed target scale, the stacked ensemble weights (10% Intercept/6% OLS/84% XGB) suggest that performance is predominantly driven by XGB members, with a minor contribution from OLS. Hence, for the final model, (i) the nonlinear structure is significant, yet (ii) the linear signal continues to offer complementary value. This finding is consistent with the groupings of determinants that have been previously reported in the extant literature. Empirical evidence consistently highlights lagged price information as a predominant short-horizon predictor, with German findings underlining the significance of lagged house price growth as the most robust lead signal [49].

Lastly, the VIP of the index-stage XGB in Figure 10 and beeswarm SHAP values in Figure 11 demonstrate the primary drivers of the forecast, which are predominantly lagged macro-financial variables, particularly DAX_lag4 (dominant), followed by construction_costs_lag4, and finally a combination of location quality dummies, thereby underscoring the importance of segment composition in shaping aggregate dynamics. Furthermore, it can be observed that location quality 2 (i.e., medium) has a comparatively low importance. This phenomenon could be attributed to the high variation in prices, as evidenced in Table 2. Moreover, this class exhibits the maximum price of the entire dataset, with only a slight deviation from the absolute minimum price. A comparatively low gain is exhibited by the index_t in the displayed top features, consistent with the model utilising it primarily as a secondary adjustment once macro dynamics and location structure have been accounted for.

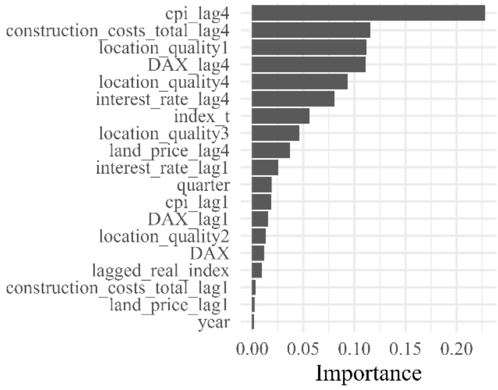

Figure 10. VIP XGB index (source: author's own work).

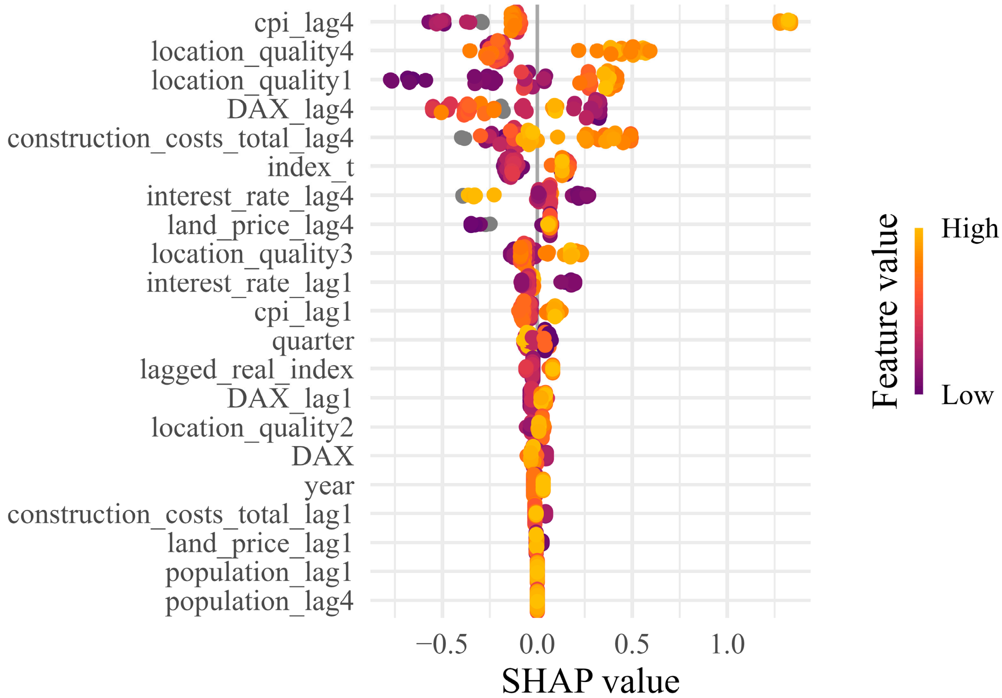

Figure 11. Beeswarm of SHAP values for XGB index.

This structure indicates that, within the backtest window, the model predominantly interprets Frankfurt's quarterly index movements as (i) a lagged reflection of broader financial conditions and associated cost pressures and (ii) fluctuations in the effective composition of location quality segments that collectively contribute to the city index. Substantively, these location quality dummies imply that short-term index changes are not only "macro-driven" but are also sensitive to which segments are most influential in a given quarter. Hence, composition effects matter for the aggregate trajectory even when forecasting a hedonic-style index. The lagged index information primarily functions as a secondary correction rather than the predominant signal. The direct reliance on macro-financial variables aligns with German findings that macroeconomic indicators can function as primary drivers in HPI forecasting [126]. In accordance with the findings of Kim and Bedorf [35], locational information appears to be important, although building-specific information cannot be confirmed as equally important. This driver structure further facilitates interpretation of the error pattern: when the index follows a sustained trend, macro-lag and composition signals assist the model in correcting the naïve persistence. Conversely, when the market encounters a turning point, reliance on lagged macro information can result in magnitude errors, as evidenced by the most significant discrepancy in 2018Q4 despite the generally robust average performance across the eight forecasts.

The extant literature distinguishes between local drivers (e.g., city- or neighbourhood-specific demand/supply conditions) and national drivers (e.g., financing conditions and macro policy variables) and argues that their relative importance can differ across spatial scales. Within this context, the index-stage dominance of lagged macro-financial variables in this study's model can be interpreted as indicative of Frankfurt's city index being predominantly influenced by national and capital market conditions, with local heterogeneity primarily impacting through the segmentation channel (location quality dummies). This interpretation aligns with research suggesting that local market structure exerts influence on aggregation. However, short-horizon turning points and trend strength have been found to be significantly influenced by broader macro regimes rather than purely local fundamentals. The following subsection thus translates these predictive patterns into economic mechanisms, distinguishing between persistence-driven market inertia, macro-financial transmission and heterogeneous submarket dynamics.

5.5. Model Robustness and Sensitivity

In order to undertake a robustness check for error propagation, the predicted segment-level prices were replaced with observed segment-level prices in an oracle specification.

As can be seen in Table 5 (or in more detail in Table A3 in Appendix A), the oracle specification does not enhance the precision of forecasts in comparison to the primary specification. The RRMSE fluctuated marginally from 2.25% to 2.27%, and the MAPE varied slightly from 1.85% to 1.90%. The oracle specification directly tests error propagation from stage 1 to stage 2 by replacing predicted segment-level prices with observed segment-level prices. Because the oracle specification does not improve performance relative to the baseline, the results suggest that the main forecast errors are not primarily caused by stage 1 prediction noise, but rather by stage 2 turning-point risk and lagged macro-financial adjustment. Furthermore, the lag sensitivity analysis showed that the results remained stable over different specifications (see Table A3 in Appendix A). The RRMSE fluctuated between 2.18% and 2.33%, and the MAPE varied between 1.85% and 1.89%.

Table 5. Model performance across specifications.

Model Specification	Design	RRMSE	MAPE	Interpretation
Naïve persistence	Index(t + 1) = Index(t)	2.896	2.527	Simple baseline
Single-stage XGB	Direct city index forecast without stage 1 segment prices	2.334	1.947	Tests whether the two-stage design adds value
Two-stage XGB/stacked framework	Stage 1 segment prices + stage 2 city index forecast	2.247	1.854	Main specification
Oracle specification	Observed segment prices instead of predicted stage 1 prices	2.269	1.895	Tests stage 1 error propagation

A final analysis, comparing the model specification without microeconomic information (utilising a one-stage XGB model without location quality prices) with the main model (incorporating location quality), demonstrates that the incorporation of location quality enhances the model's performance. As demonstrated in Figure 12, the two-stage model exhibited equivalent or superior performance, yet never inferior. This finding suggests that the segment-level component contributes predictive information beyond a direct city-level ML forecast, even though the magnitude of the improvement should be interpreted cautiously given the short backtest window.

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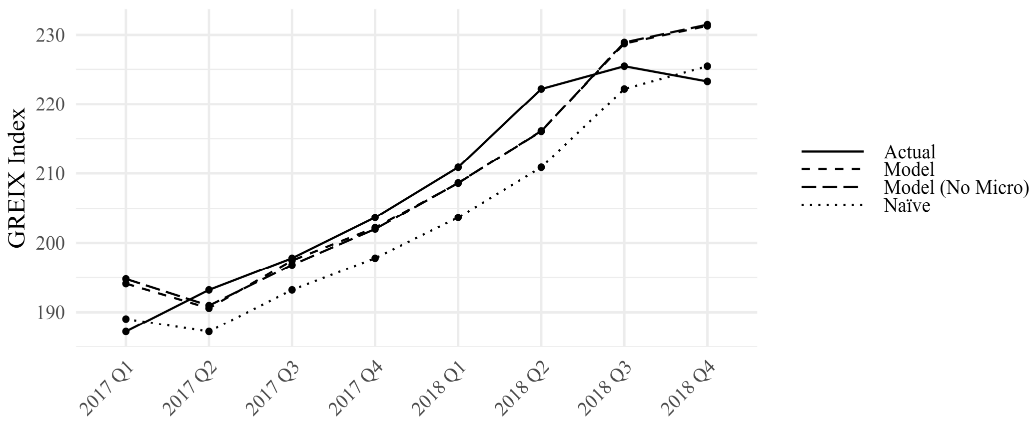

Figure 12. Model performance: main vs. naïve vs. single-stage XGB.

5.6. Economic Interpretation of Predictive Drivers

The XAI results suggest that the model exploits information channels consistent with three economic mechanisms that shape short-term condominium price index dynamics in Frankfurt am Main. Firstly, the dominance of current and lagged price information in the initial forecasting stage is indicative of market inertia. Residential real estate markets adjust slowly due to a number of factors. Firstly, transactions are infrequent, which slows the market down. Secondly, the search and matching processes take time, which hinders the market's dynamism. Thirdly, prices are partly shaped by seller expectations, which can create a bias in the market. Finally, comparable past transactions influence both valuation and negotiation behaviour, creating a feedback loop that can affect market efficiency. Consequently, recent segment-level prices contain substantial information about the next-quarter price level. This finding is consistent with the short-horizon nature of the forecasting task: over one quarter, the market is less likely to be driven by abrupt changes in fundamentals than by gradual adjustment processes and persistence in local valuation expectations.

Secondly, the significance of lagged macro-financial indicators in the index-stage model signifies the presence of a financial and capital market transmission channel. The relevance of DAX_lag4 indicates a correlation between the Frankfurt condominium market and broader financial conditions, wealth effects, investor sentiment and portfolio-allocation dynamics. This interpretation is substantiated by Frankfurt's status as a financial centre and its internationally connected housing market. In a similar fashion, the significance of lagged construction costs signals a supply-side cost channel: rising construction costs impact replacement values, new-build feasibility and developer pricing strategies, yet these consequences materialise with a delay. The utilisation of lagged macro-financial variables functions not only as a technical device to circumvent look-ahead bias, but also as a manifestation of economic significance, given that real estate markets characteristically exhibit delayed responses to macroeconomic shocks.

Thirdly, the role of location quality variables reflects heterogeneous submarket dynamics. The city-wide index does not emerge from a homogeneous market, but rather from the interaction of different location quality segments. Alterations in the relative influence of these segments have the capacity to exert an effect on the aggregate index, even in circumstances where the overall city market appears stable. The two-stage design captures an important economic mechanism: segment-level price formation occurs upstream, while the city-level index reflects both macro-financial conditions and the composition of transactions across submarkets. In the context of the medium-location segment, its comparatively weak importance may be indicative of internal heterogeneity, which could result in diminished informativeness as a distinct aggregate signal. This is further illustrated in Figure 13, which shows how the SHAP effect of the high-quality segment changes when the low-quality segment is high/low. Consequently, the findings demonstrate that the predicted segment-level price signals are not arbitrary noise, but rather that the model employs them in a structured manner. The contrast between location_quality1 and location_quality4 indicates that segment-level price signals from varying market quality segments are incorporated into the index forecast in different ways.

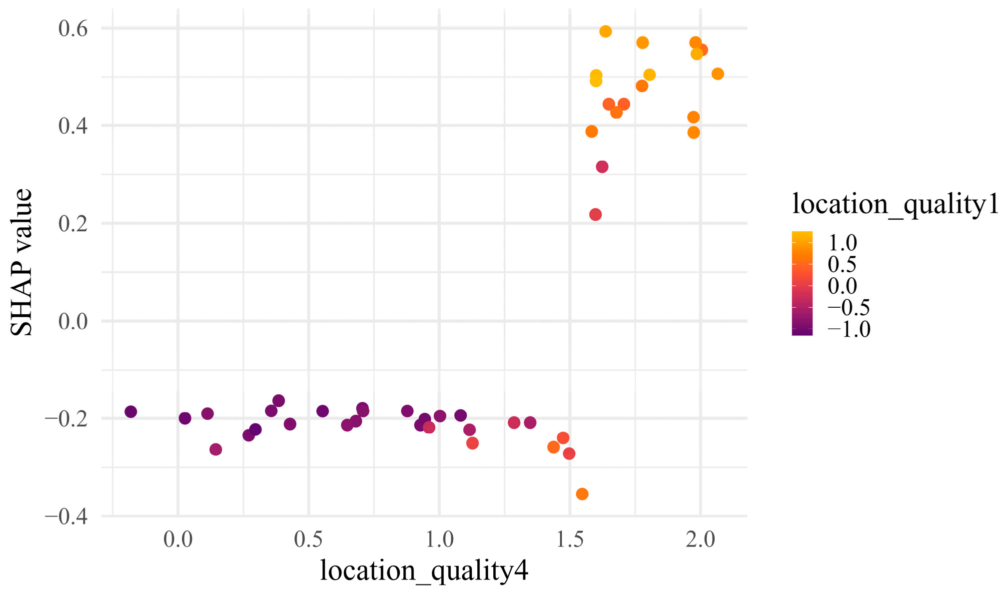

Figure 13. SHAP dependence plot of location quality 4 by location quality 1.

These mechanisms also facilitate comprehension of the observed error structure. In periods of sustained upward movement, market inertia, lagged macro-financial signals and segment composition enable the model to outperform the naïve and single-stage benchmark. However, at such critical junctures, the prevailing structural framework can result in delayed adjustment or overshooting, given that lagged indicators continue to reflect the preceding regime. Therefore, the model's weaker performance in Q4 2018 should not be interpreted solely as a technical forecast error, but rather as evidence that short-term index forecasting is particularly vulnerable to changes in market regimes.

6. Conclusions

6.1. Summary

The central motivation for this study is the uncertainty surrounding previous market forecasts. Utilising a stacked algorithm based on ML algorithms XGB and RF, supplemented by an OLS, and employing multiple levels of data ranging from object to location quality and city level, a one-quarter-ahead forecast was developed that exhibits significantly superior performance in comparison to the random walk within the examined pre-pandemic backtest window. With MAPE set at 1.85% and, at an index level of approximately 220, an APE around 4 index points, this approach represents a significant enhancement over the naïve persistence approach in most cases. The analysis revealed the factors that are most significant for such a city index forecast, and it highlighted data availability issues. The study also demonstrates the correlation between data availability and forecasting reliability. This multi-level approach contrasts with more traditional, coarse regional- or city-level analyses and provides a more comprehensive view of the factors that influence housing prices beyond just local market data, reflecting the broader economic context of the market. The findings of the present study serve to bring the two forecasting perspectives (i.e., price and index) into alignment by demonstrating that factors such as persistence and local market proxies (e.g., unemployment and seller type) act upstream, thereby shaping the predicted price inputs. Conversely, macro-financial variables predominate at the index stage when forecasting aggregate quarterly movements.

Moreover, the model is characterised by its adaptability and scalability, which facilitate enhanced decision-making at the micro level and informed policy development at the macro level. The primary practical constraint pertains to regime dependence (i.e., the model's reliability during stable or expanding phases), indicating that segment-level signals and macro-financial lags may not fully capture the abrupt reversals observed in the relatively limited sample of negative-growth episodes. The most significant discrepancy occurs in Q4 2018, with a further noteworthy error evident in Q1 2017. This pattern is consistent with the driver structure: a forecasting rule that is strongly anchored in lagged macro-financial variables and market segment dummies may adjust well in trend regimes but respond too slowly (or overshoot) when the market shifts abruptly. In such instances, attaining a random-walk baseline can prove challenging.

To make explicit how the empirical findings address the four research questions, Table 6 summarises the corresponding evidence and manuscript sections.

Table 6. Study's research questions and main findings.

Research Question	Main Finding
RQ1: How can micro-, macro- and socioeconomic factors be consolidated into one dataset?	The study links transaction data, listing data, socioeconomic grid-level data, and macro-financial indicators through a staged aggregation procedure from object level to location quality level and finally to city index level.
RQ2: Which macro-, micro- and socioeconomic factors drive the city index?	Stage 1 is mainly driven by price persistence and selected local variables, while stage 2 is mainly driven by lagged macro-financial variables and location quality composition.
RQ3: To which degree does forecast uncertainty vary over time, and what drives it?	Forecast uncertainty is not constant; errors increase particularly around turning points, especially in Q1 2017 and Q4 2018.
RQ4: Which residential market segment contributes most substantially to the city index?	Location quality composition matters for the aggregate index, with higher-quality and lower-quality segment signals contributing differently to the city-level forecast.

From an economic perspective, the observed short-term fluctuations in the Frankfurt condominium index can be attributed to three interrelated mechanisms: price formation inertia at the segment level, delayed transmission of macro-financial conditions into the housing market and shifts in composition across heterogeneous location quality submarkets. Consequently, the model enhances not only the precision of forecasts but also offers a systematic explanation of the interplay between local and aggregate dynamics within a housing market at the city level.

6.2. Limitations and Future Research Directions

One potential shortcoming of the study is the relatively modest sample size of the index forecasts. Consequently, the interpretation of the Diebold–Mariano test should be executed with caution. The result provides indicative evidence of lower squared error loss relative to the naïve benchmark within this specific backtest window. However, it does not establish general superiority across market regimes. Moreover, while the expanding-window design guarantees stringent out-of-sample evaluation, the test period encompasses only a restricted pre-pandemic market environment, excluding subsequent regime shifts such as the impact of the pandemic, the ECB interest rate hiking cycle, or the subsequent downturn in the

German residential market. Consequently, the results should not be interpreted as evidence of universal model superiority across all market regimes. In contrast, the findings illustrate that the proposed two-stage framework has the potential to surpass a simplistic persistence benchmark within the confines of the pre-pandemic short-horizon backtest window. The out-of-sample window could not be extended without substantially reducing the training window. Given the limited quarterly structure of the second-stage index forecasting task, a larger test window would leave too few observations for reliable model estimation and would increase the risk of overfitting. The study therefore applies an 80/20 percent split, with 80 percent of the observations used for training and 20 percent for testing. Within the training sample, a further time-aware cross-validation split of 80 percent training and 20 percent validation is applied. This design preserves a sufficiently large training window while still allowing a strict out-of-sample evaluation for 2017Q1–2018Q4. The limited test window nevertheless remains an important constraint, and the findings are therefore interpreted only for the examined pre-pandemic backtest period. It is recommended that future research extend the framework to more recent market regimes once comparable transaction, listing, and socioeconomic microdata become available. Future research with longer post-2019 index histories should also compare expanding- and rolling-window schemes to assess model stability across different market regimes.

Furthermore, this can be attributed to the panel structure, which stipulates that the sample size is contingent on the number of quarters contained within the training and test datasets [42]. However, given that the ML algorithm XGB was utilised for this analysis, and this algorithm has been demonstrated to be effective in handling low sample sizes [84], the limitation is deemed to be negligible, though it cannot be disregarded because, as described by Schmid [142], listing and transaction market data are different in their distributions. One reason for this is the lack of data for the more expensive cases, which leads to sample bias [172]. Hence, even though XGB handles the low sample size of the second forecasting stage, the results might be slightly biased due to distributional biases of the microeconomic data in the first forecasting stage. Furthermore, it is important to note that, although the results apply to Frankfurt, it is difficult to generalise them, which can be attributed to the differential importance attributed to factors in different German cities [52]. Finally, the model must be noted as being designed for prediction rather than causal identification. The utilisation of lagged macro-financial variables is employed to ensure real-time availability and to mitigate concerns pertaining to simultaneity. However, this approach does not entirely eliminate all forms of endogeneity. Consequently, the XAI analyses and economic interpretations must be interpreted as predictive relevance rather than causal effects. Future research should (i) broaden the evaluation period to encompass further market conditions and additional turning points, (ii) assess regime-aware variants (e.g., change-point detection or regime-switching features) to mitigate turning-point magnitude risk and (iii) expand the information set with policy and institutional variables as outlined in the limitations, whilst ensuring strict real-time availability.

6.3. Practical Implications

In addition to the technical findings, this study also offers practical implications for stakeholders in the residential real estate market. The motivations of both the public and private sector in this regard are twofold: firstly, to obtain an assessment of the future development of the real estate market and, secondly, to understand the drivers of such an outcome. For instance, the findings of this study have the potential to inform the development of targeted housing market policy, thereby mitigating the risk of market overheating. Simultaneously, the findings can be utilised to inform risk management in portfolio composition. Hence, as Abidoye et al. [42] already proposed, such a forecasting

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instrument could be used as a decision support tool. However, stakeholders are advised to treat point forecasts as regime-dependent and to complement them with tail-aware monitoring (e.g., scenario or stress interpretations) in circumstances where macro conditions suggest a turning-point environment.

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Abbreviations

The following abbreviations are used in this manuscript:

ANN	Artificial Neural Network
APE	Absolute Percentage Error
ARIMA	Autoregressive Integrated Moving Average
AUC	Area Under the Curve
BauGB	Baugesetzbuch/Federal Building Code
BGB	Bürgerliches Gesetzbuch/German Civil Code
CBD	Central Business District
CV	Cross-Validation
DAX	German Stock Index
DESTATIS	German Federal Statistical Office
DM	Diebold–Mariano (test/statistic)
DT	Decision Tree
EU	European Union
FI	Feature Importance
GREIX	German Real Estate Index
HPI	House Price Index
INSPIRE	Infrastructure for Spatial Information in Europe
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MAUP	Modifiable Area Unit Problem
ML	Machine Learning
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary Least Squares
RF	Random Forest
RMSE	Root Mean Squared Error
RRMSE	Relative Root Mean Squared Error
RWI	RWI–Leibniz-Institut für Wirtschaftsforschung
SHAP	SHapley Additive exPlanations
SVM	Support Vector Machine
VIP	Variable Importance Plot
XAI	Explainable Artificial Intelligence
XGB	Extreme Gradient Boosting

Appendix A

Table A1. Descriptive statistics of key variables.

Category	Label	N	Mean	Sd	Min	Median	Max
Listing data	Contact clicks	187	11.306	7.734	1.000	10.444	44.000
Listing data	Listing hits	187	1734	953	225	1636	5228
Listing data	Time on market	187	59.372	30.334	8.400	54.444	232.000
Listing data	Number of price changes	187	1.235	0.202	1.000	1.200	1.900
Location segment	Location quality segment	187	2.492	1.119	1.000	2.000	4.000
Microeconomic data: building-specific	Number of building floors	187	5.578	2.606	2.250	5.136	24.200
Microeconomic data: building-specific	Construction year	187	1987	14.094	1937	1988	2017
Microeconomic data: building-specific	New construction	187	0.314	0.215	0.000	0.326	1.000
Microeconomic data: building-specific	Floor	187	3.412	1.162	1.000	3.250	11.929
Microeconomic data: building-specific	Number of rooms	187	2.951	0.374	2.000	2.957	4.667
Microeconomic data: building-specific	Apartment size	187	86.65	16.71	54.74	84.17	161.30
Microeconomic data: building/location-specific	Distance/city-centre area	187	0.531	0.325	0.000	0.500	1.000
Microeconomic data: socioeconomic	Socioeconomic unemployment	187	6.890	2.254	1.637	6.463	12.311
Microeconomic data: socioeconomic	Foreign population share	187	24.911	5.626	14.312	24.826	42.852
Microeconomic data: socioeconomic	Children	187	0.251	0.030	0.183	0.248	0.356
Microeconomic data: socioeconomic	Male working-age population	187	20.911	0.454	19.496	20.932	22.043
Microeconomic data: socioeconomic	Residential buildings	187	780.170	165.835	371.550	755.155	1213.000
Microeconomic data: socioeconomic	Residential density	187	0.623	0.080	0.403	0.626	0.845
Transaction data	Relative price difference	187	0.590	1.807	−5.400	0.457	7.000
Transaction data	Median transaction price per sqm	187	3434	1508	1160	3216	8411
Transaction data	Lagged segment price	187	3353	1477	1160	3140	8411
Transaction data	Lead segment price	187	3502	1539	1160	3332	8411
Index data	Quarterly GREIX change	47	2.915	3.408	−3.960	2.550	12.730
Index data	Lagged GREIX	47	137.591	37.441	96.270	128.170	225.450
Index data	Current GREIX	47	140.293	38.946	96.670	131.750	225.450

Table A1. *Cont.*

Category	Label	N	Mean	Sd	Min	Median	Max
Macroeconomic data: lagged	DAX, lag 1	47	189,726	55,622	97,131	174,097	296,195
Macroeconomic data: lagged	DAX, lag 4	45	182,069	50,673	97,131	168,240	296,195
Macroeconomic data: lagged	Construction cost index, lag 1	47	82.940	3.817	75.200	83.500	90.200
Macroeconomic data: lagged	Construction cost index, lag 4	45	82.304	3.652	74.500	82.800	88.000
Macroeconomic data: lagged	Consumer price index, lag 1	47	96.830	4.264	88.659	97.739	104.551
Macroeconomic data: lagged	Consumer price index, lag 4	45	96.184	4.154	87.912	96.868	102.617
Macroeconomic data: lagged	Long-term government bond yield, lag 1	47	1.892	1.432	−0.123	1.608	4.343
Macroeconomic data: lagged	Long-term government bond yield, lag 4	45	2.031	1.434	−0.123	1.746	4.343
Macroeconomic data: lagged	Land price index, lag 1	47	990.856	143.380	844.000	931.000	1312.500
Macroeconomic data: lagged	Land price index, lag 4	45	967.728	118.702	844.000	917.500	1285.500
Macroeconomic data: lagged	Population size Frankfurt, lag 1	47	695,906	31,122	652,610	684,949	749,942
Macroeconomic data: lagged	Population size Frankfurt, lag 4	45	691,440	29,105	652,431	679,664	744,240
Stage 1 segment price forecast	Predicted segment price: low/very low location quality	47	−0.072	0.833	−1.154	−0.237	1.279
Stage 1 segment price forecast	Predicted segment price: medium location quality	47	0.494	0.672	−0.790	0.687	1.585
Stage 1 segment price forecast	Predicted segment price: high location quality	47	0.723	0.687	−0.489	0.935	1.721
Stage 1 segment price forecast	Predicted segment price: very high location quality	46	1.169	0.631	−0.181	1.317	2.066

Table A2. Sample sizes of listings and merged dataset.

Step	Rule	Remaining Observations
Initial listing observations	All condominium transactions	135,522
Exclude non-market transactions	Duplicates, etc.	62,187
Match with transactions	Threshold optimisation	5193
Matching rate	Merged listings	8%

Table A3. Robustness test results (lag sensitivity and error propagation).

Macro_spec	N Forecasts	MAPE	RRMSE	MAPE Naive	RRMSE Naive	Win Rate vs. Naive
main_lag1 + lag4	8	1.854	2.247	2.527	2.896	0.625
main lag 1 + lag4_oracle	8	1.895	2.269	2.527	2.896	0.625
main_lag1 + lag4_without_location quality	8	1.947	2.334	2.527	2.896	0.625
lag1_only	8	1.852	2.181	2.527	2.896	0.750
lag4_only	8	1.891	2.276	2.527	2.896	0.625
all_lags_1–4	8	1.876	2.274	2.527	2.896	0.625

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