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LONG-TERM FORECAST OF RESIDENTIAL PROPERTY PRICES IN MAJOR POLISH CITIES

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ABSTRACT

There is limited information on how residential property prices will evolve in the long term in Poland. Knowledge of this subject is crucial not only for policymakers but also for private individuals. Accordingly, this study aims to forecast long-term real residential property prices in 17 Polish provincial capitals. Using data on real housing prices in the primary and secondary markets from 2006 to 2025, four forecasting approaches were tested: ARIMA (autoregressive integrated moving average), ARIMAX (autoregressive integrated moving average with exogenous inputs), UCM (unobserved components model) and LSTM (long short-term memory). The forecast of residential property prices through the end of 2035 showed that price increases will be observed across all cities, though they will be highly heterogeneous. Significant growth is expected in large metropolitan areas, while in smaller provincial cities prices will rise only slightly due to a projected population decline. But if the demographic outlook turns negative, prices will fall across almost all the markets analysed.

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1. Introduction

Forecasting residential property prices in Poland has become challenging amid market heterogeneity and long-term demographic changes (Gong & Yao, 2022). Larger provincial capitals, such as Warsaw, Wroclaw and Krakow, attract new residents, while smaller towns are grappling with progressive depopulation. Traditional forecasts often overlook this contrast, leading to models that are ill-suited to empirical data and yield unreliable long-term predictions. The reliability of these predictions is crucial not only for assessing the functioning of the housing market but also for assessing the country's economic performance. Real estate practitioners, such as property valuers, also face the challenge of using reliable long-term property price forecasts to determine the so-called prudential value (European Valuation Standards, 2025; Crosby & Hordijk, 2025).

In light of the above, this article aims to provide a long-term forecast of residential property prices in major Polish cities using econometric and machine-learning models, while accounting for Poland's demographic trends. Demographic changes are considered a key structural factor driving long-term housing price dynamics, given their direct impact on household numbers and overall housing demand. International academic literature shows that demographic factors have a strong long-term impact on house prices, often outweighing other housing fundamentals such as income growth, interest rates or housing supply constraints (Kohlscheen, 2025).

The results indicate that real prices on the Polish housing market will rise in the long term, though this growth will vary between cities. The highest growth rates are observed in large urban centres and those with a more favourable population outlook. By the end of 2035, only in Warsaw will the real average price of residential property on both the primary and secondary markets exceed 20,000 PLN/m^2. The study did not reveal any significant differences in growth rates between the primary and secondary markets. Similarly, it is not possible to unequivocally identify a preferred forecasting method, but only to observe a tendency towards better results with approaches that include population as an additional predictor.

This study contributes to the existing literature in several ways. Firstly, it is the first analysis to attempt a long-term forecast of residential property prices in Poland. Secondly, this study juxtaposes the performance of econometric and machine learning models, a comparison rarely undertaken in the literature on housing price modelling. Thirdly, this article is the first to integrate the Central Statistical Office (CSO) demographic predictions with forecasts of residential property prices in Poland.

The following section of the article presents a literature review on methods for forecasting residential property prices and the impact of demographic factors on their dynamics. Next, the research data and methods used are described. Subsequently, the results with discussion are presented, including price forecasts and an assessment of the models' accuracy. Finally, the article summarises the key findings and suggests directions for further research.

2. Literature review

The literature on real estate price forecasting is extensive, but it largely focuses on econometric models, neglecting newly developed machine learning techniques. In the Polish context, research based on data from the National Bank of Poland (NBP) and CSO predominates, further emphasising the importance of macroeconomic factors (inflation, interest rates, real income) and market cyclicality (Bełej, 2021, 2023).

Classic approaches to modelling time series of housing prices are based on ARIMA (autoregressive integrated moving average) models and their extensions. These models perform well in short-term forecasts but often fail to account for economic changes, such as depopulation or migration (Bełej, 2021). A partial solution to this problem is the ARIMAX (autoregressive integrated moving-average with exogenous inputs) model, which allows the inclusion of exogenous variables, such as population or real income, thereby improving forecast accuracy. Another econometric approach to forecasting residential property prices is the Unobserved Components Model (UCM), which distinguishes itself by decomposing the price series into trend, seasonality, and cycle components. Like ARIMAX, the UCM model also allows for the inclusion of additional predictors related to housing supply and demand in the analysis (Huang, 2020). In the context of forecasting real estate prices using econometric modelling in the Polish market, Bełej's (2021) study is worth noting. The author attempted to forecast residential real estate prices in four major cities (Warsaw, Krakow, Poznan, and Gdansk) during the COVID-19 pandemic using an ARIMA model. The results indicated that the upward trend continued in Warsaw and Poznan, while apartment prices declined in Krakow and Gdansk during the first four months of 2021.

In the international literature, machine learning models are increasingly used to forecast housing market prices, as they allow for modelling nonlinear relationships and are robust to nonstationarity in the data. In this context, Chiu (2024), among others, applied a Long Short-Term Memory (LSTM) model to forecast residential property prices in Taiwan during the post-pandemic period. Accounting for key macroeconomic factors, the LSTM model results indicate a good fit with the empirical data and suggest that the impact of the COVID-19 pandemic on housing prices in the post-pandemic period may be negligible. Furthermore, Han & Chun (2025) applied an LSTM model enhanced with kernel density estimation to forecast housing prices in Seoul. The authors demonstrated that accounting for the local density of commercial and service facilities in the vicinity of a property significantly improves forecast accuracy, and the LSTM model achieved the highest predictive performance among all tested methods, outperforming both classical regression and other neural network architectures.

When forecasting long-term real estate prices, it is important to consider demographic changes in local housing markets. Among others, Bełej (2023) and Trojanek et al. (2023) confirm that net migration and changes in the age structure of the population have a significant, albeit delayed, impact on demand and residential real estate prices. This topic is particularly important in the context of Poland, given CSO forecasts indicating progressive demographic spatial polarisation, i.e., an increase in the number of residents in the largest cities alongside a population decline in many smaller cities (CSO, 2023).

Despite numerous publications, there is a lack of comprehensive comparisons of different model classes (classical and machine learning) for long-term residential real estate price forecasts, particularly in Poland. This study fills this gap by testing four approaches (ARIMA, ARIMAX, UCM, LSTM) for 17 Polish provincial capitals using a standardised dataset that integrates average real estate prices with official CSO demographic forecasts.

3. Materials and methods

3.1. Data description and sources

The study is based on an analysis of quarterly time series of transaction prices per square meter for residential real estate in 17 provincial capitals in Poland. The data covers both the primary and secondary markets for the period from the third quarter of 2006 to the fourth quarter of 2025. The source of price data is the NBP databases.

To eliminate the impact of inflation, nominal prices were deflated using the Consumer Price Index (CPI) published by the CSO. The third quarter of 2006 was taken as the base period. Additionally, in models using exogenous variables (ARIMAX, UCM, LSTM), demographic data on population size were included, based on the CSO forecasts through 2060.

3.2. Data preparation

The process of preparing the research data for the modelling stage involved several steps. First, nominal prices were deflated by dividing them by the cumulative CPI index, which yielded real price series. Next, all series underwent a logarithmic transformation to stabilise the variance. The final stage of data preparation involved applying the X-13ARIMA-SEATS seasonal adjustment procedure. This effectively removed regular seasonal fluctuations from the data, which is crucial for the reliability of long-term forecasts.

The dynamics of real prices after logarithmic transformation and seasonal adjustment are presented in Figure 1. As shown, a long-term upward trend is evident in both market segments. The variation in price dynamics across cities indicates the heterogeneity of local markets and differing rates of adjustment to changes in macroeconomic and demographic conditions.

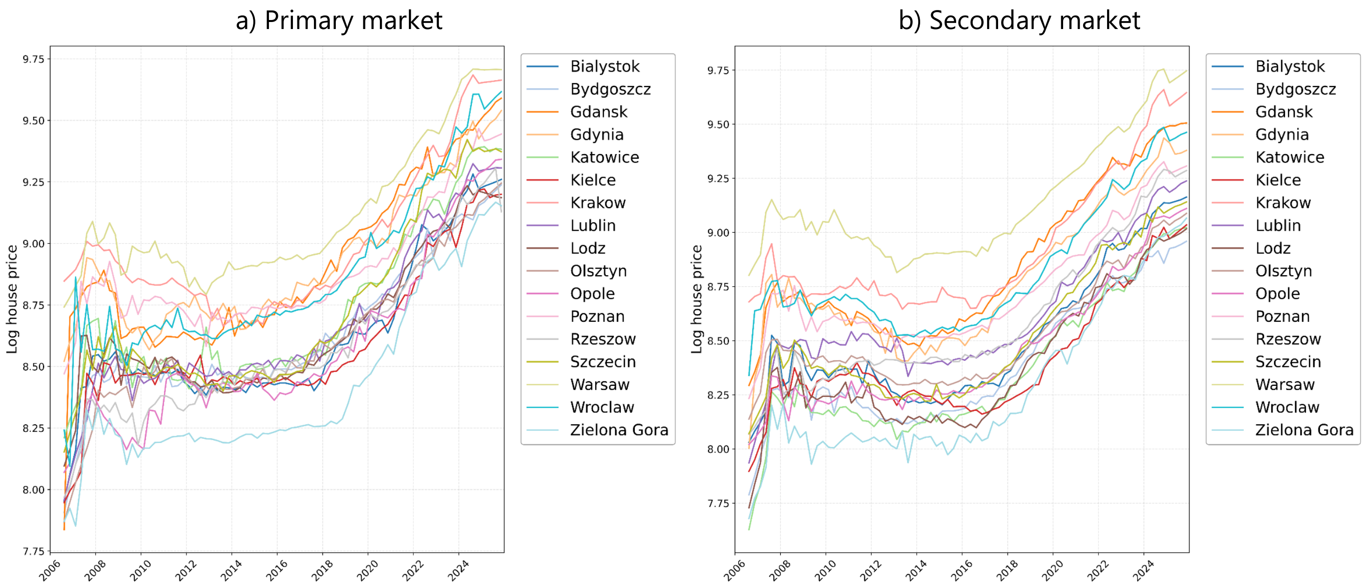

Fig. 1. The dynamics of logarithmic real transaction prices for residential real estate in Polish provincial capitals. *Source*: own study based on NBP data.

Regarding the population, prior to training the models, the variable values were logarithmized and assigned to quarters based on annual values. Furthermore, the models were trained primarily on observed population sizes for individual cities, whereas the real estate price forecast was based on the CSO population prediction. Figure 2 shows the population size along with its forecast through 2035 for the cities under study.

3.3. Methods

Four models (ARIMA, ARIMAX, UCM, and LSTM) were tested, ranging from classical econometric techniques to machine learning approaches. An additional explanatory variable (log population) was added to most models, which should significantly improve forecast accuracy. Unfortunately, due to the lack of long-term city-level forecasts for other housing fundamentals, such as wage levels, it was not possible to increase the number of exogenous variables.

ARIMA is a classical time series model whose parameters (p, d, q) were selected individually for each series – that is, separately for each city—by minimizing the AIC criterion within the range of 0 to 4 for p and q, and 1 to 2 for d. When $d = 0$, the ARIMA model can be written as:

$$y_t = \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{j=1}^{q} \theta_i \varepsilon_{t-j} + \varepsilon_t, \quad (1)$$

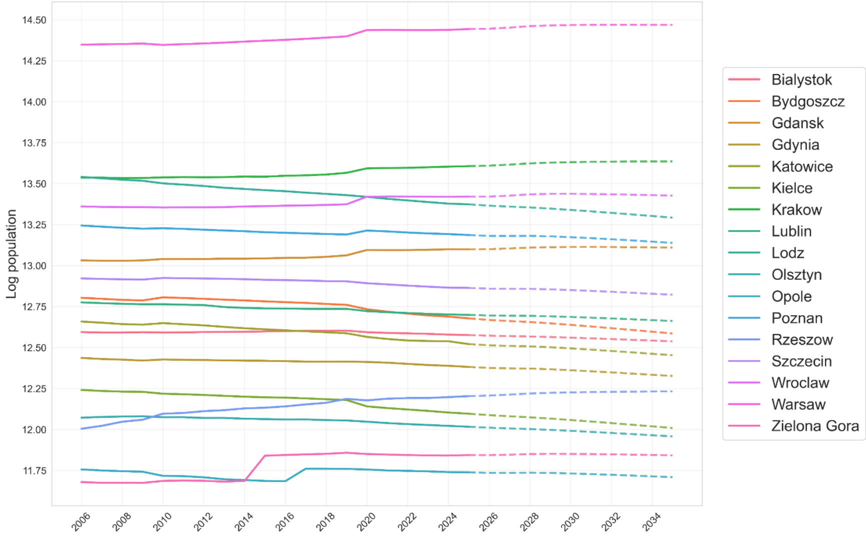

Fig. 2. Population growth trends in Polish provincial capitals, along with a forecast through 2035. *Source*: own study based on CSO data.

where: t is the time index, i is the autoregressive index, j is the moving-average index, y_t is the dependent variable (the real housing price), ϕ_i, θ_i are the model's parameters, ε_t is the error term, p is the order of delays of the autoregressive process, q is the order of delays of the moving-average process. When $d > 0$, we first differentiate y_t and then apply the appropriate ARMA model.

An extension of the ARIMA model is the ARIMAX model, which includes population as an exogenous variable (x_t) and is defined by the following formula:

$$y_t = \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{j=1}^{q} \theta_i \varepsilon_{t-j} + \sigma x_t + \varepsilon_t. \quad (2)$$

For the ARIMAX model, the procedure for selecting the (p, d, q) order was performed anew, independently of the optimal parameters obtained for the ARIMA model without exogenous variables. For each city, taking into account the explanatory variable (population), the same grid of values was searched: $p = [0; 4]$, $d = [1; 2]$, $q = [0; 4]$. The selection criterion was the minimum AIC, and the ARIMAX model parameters were estimated using maximum likelihood. This approach ensures an optimal fit while accounting for the additional exogenous variable.

The UCM model decomposes a time series into components that cannot be directly observed—namely, the trend, seasonality, cycle, and random component—using the following formula:

$$y_t = t_t + c_t + s_t + \sigma x_t + \varepsilon_t, \quad (3)$$

where: t_t denotes the trend component, c_t denotes the cyclical component, s_t denotes the seasonal component, and ε_t denotes the random component. The components (trend, cycle, and seasonality) were selected individually for each city using the AIC information criterion. The model was estimated using the maximum likelihood method. As in the ARIMAX case, the UCM model included population as an additional predictor.

LSTM is a type of recurrent neural network designed to analyse sequential data, such as time series, and its key feature is the so-called memory cell, which allows the model to decide which past information to retain and which to discard. The logarithmic and seasonally adjusted data were rescaled to the range $[0, 1]$, and population was added as an explanatory variable. The data was transformed into sequences with a time window of 4 (for each time series, optimisation was performed within the range of 2–11, and ultimately the median of the optimal values was adopted to ensure comparability of results). The model architecture consists of two LSTM layers (50 units each), two dropout layers ($p = 0.2$), and one output layer (1 neuron). The model was trained using the Adam optimiser ($learning\ rate = 0.001$), the MSE loss function, a batch size of 8, and a maximum of 200 epochs, with early stopping. Multi-year forecasts were generated using an iterative (recursive) method. Dropout and early stopping mitigate the risk of overfitting.

When modelling residential property prices over time, the issue of non-stationarity often arises.

However, this does not pose an obstacle in the present study. This is because UCM and LSTM models are also suitable for non-stationary data. In contrast, for ARIMA and ARIMAX models, stationarity is achieved by differentiating the dependent variable ($d > 0$).

The fourth quarter of 2035, i.e., 10 years ahead, was set as the horizon for the long-term forecast, a typical timeframe for analysing economic indicators (Clark & Davig, 2013). Although it was not possible to assess the accuracy of the realised forecast, an evaluation of price predictions based on observed data was conducted to select the best model from the four proposed. Specifically, the dataset was divided into training and test sets in proportions that allowed for a 10-year forecast. The best model was selected based on the minimum mean absolute percentage error (MAPE). Subsequently, the final forecast was generated using the model selected in the previous step, by repeating the training procedure on the full dataset and integrating demographic forecasts from the CSO.

4. Results

4.1. Model selection

The first stage of the study involved selecting the optimal model class for each city and market type based on the MAPE metric calculated using a 10-year ex post forecast. The results of the model selection and the accuracy achieved (MAPE on the test set) are presented in Table 1.

The results indicate that the UCM model is the best, as it accounts for typical phenomena in the housing market price-formation process, such as trends and cyclicality (Harvey & Koopman, 2009). The LSTM model also performs well in ex post forecasting of housing prices, suggesting the presence of nonlinear relationships in the data, particularly between population and prices. Classical forecasting methods, i.e., ARIMA and ARIMAX, proved to be the best in ten cases. In general, contrary to previous studies (e.g., Siami-Namini et al., 2018), the LSTM machine learning model is not superior to econometric methods, which confirms their usefulness for forecasting prices in the real estate market.

It should also be noted that the ARIMA model—i.e., the model without an additional explanatory variable—performed best in only 5 cases, underscoring the importance of including additional predictors that influence housing supply and demand in the modelling process (Trojanek et al., 2023).

Regarding ex-post prediction error, the lowest values were recorded, among others, in Katowice (secondary market: 2.5%), Lublin (secondary market: 2.7%), and Gdansk (secondary market: 2.9%). In contrast, the highest MAPE values occurred primarily in smaller cities in the primary market (Opole, Rzeszow, Zielona Gora), which may result from greater volatility and weaker predictability in these markets.

Table 1

Model selection and forecast accuracy for individual cities.

City	Market type	Best model	MAPE (%)	RMSE	MAE
Bialystok	Primary	ARIMA	3.8	0.062	0.048
Bialystok	Secondary	ARIMAX	3.2	0.055	0.042
Bydgoszcz	Primary	LSTM	5.1	0.078	0.061
Bydgoszcz	Secondary	LSTM	4.4	0.071	0.055
Gdansk	Primary	ARIMAX	6.7	0.095	0.074
Gdansk	Secondary	UCM	2.9	0.048	0.037
Gdynia	Primary	UCM	4.6	0.072	0.056
Gdynia	Secondary	LSTM	5.3	0.081	0.063
Katowice	Primary	LSTM	2.8	0.045	0.035
Katowice	Secondary	UCM	2.5	0.041	0.032
Kielce	Primary	LSTM	4.2	0.068	0.053
Kielce	Secondary	LSTM	3.6	0.059	0.046
Krakow	Primary	ARIMA	3.1	0.052	0.040
Krakow	Secondary	UCM	5.9	0.088	0.068
Lublin	Primary	LSTM	3.4	0.057	0.044
Lublin	Secondary	UCM	2.7	0.044	0.034
Lodz	Primary	LSTM	4.8	0.075	0.058
Lodz	Secondary	UCM	4.1	0.066	0.051
Olsztyn	Primary	ARIMA	5.5	0.082	0.064
Olsztyn	Secondary	ARIMA	3.5	0.058	0.045
Opole	Primary	UCM	6.2	0.092	0.071
Opole	Secondary	UCM	3.8	0.061	0.047
Poznan	Primary	LSTM	5.0	0.077	0.060

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Poznan	Secondary	LSTM	4.7	0.074	0.057
Rzeszow	Primary	ARIMAX	5.8	0.085	0.066
Rzeszow	Secondary	LSTM	3.3	0.054	0.042
Szczecin	Primary	UCM	5.4	0.079	0.061
Szczecin	Secondary	UCM	4.3	0.068	0.053
Warsaw	Primary	UCM	4.9	0.071	0.055
Warsaw	Secondary	ARIMAX	5.6	0.082	0.064
Wroclaw	Primary	UCM	4.5	0.069	0.053
Wroclaw	Secondary	UCM	6.4	0.091	0.070
Zielona Gora	Primary	ARIMAX	6.1	0.088	0.068
Zielona Gora	Secondary	ARIMA	5.7	0.084	0.065

Source: own study.

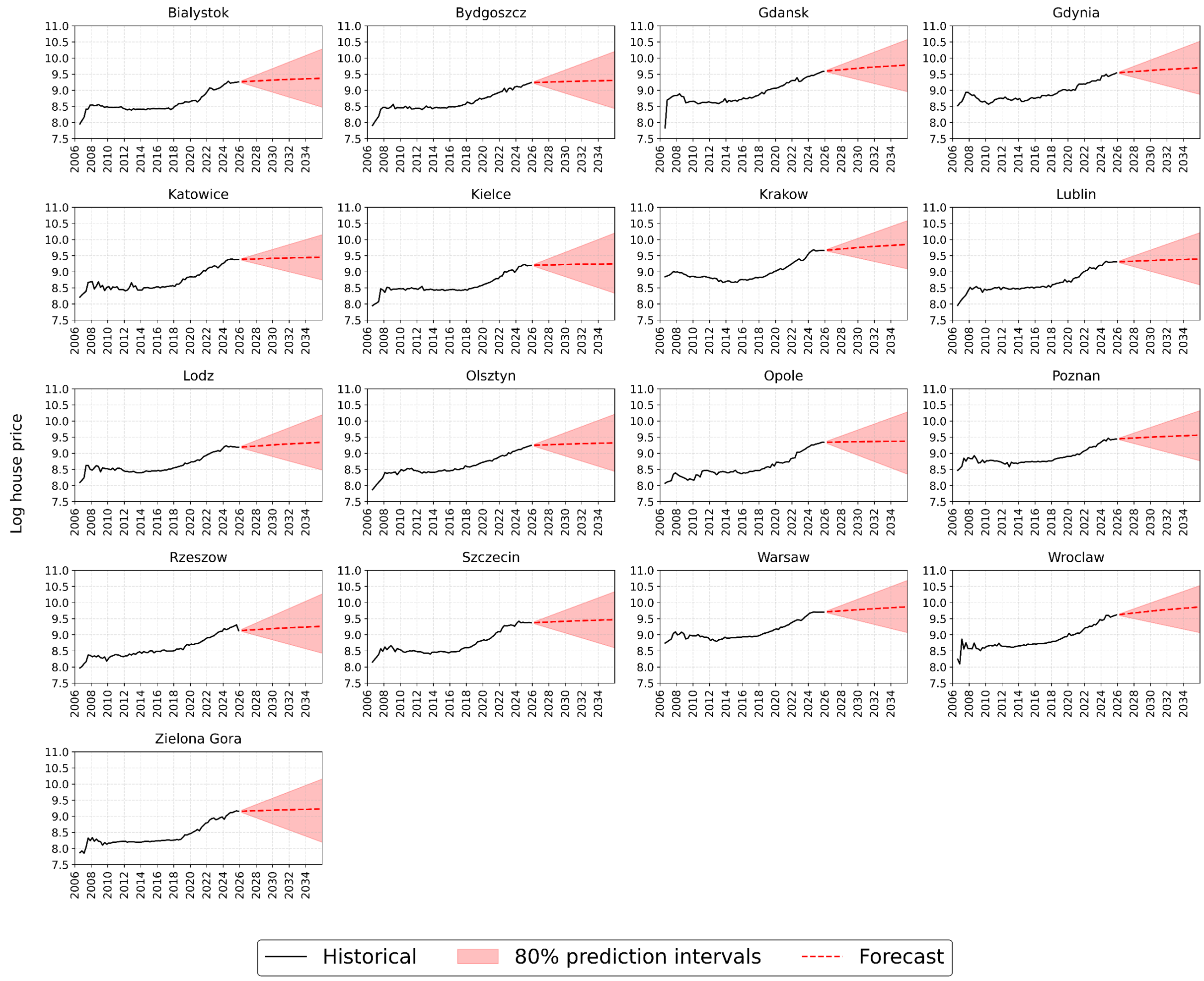

Fig. 3. Forecasted logarithmic real transaction prices for residential real estate in the primary market. *Source*: own study.

4.2. House price forecasting

After selecting the best models and re-estimating them on the full dataset, final forecasts of real transaction prices per square meter for residential properties in Poland's major cities were generated for the period up to the fourth quarter of 2035. The results of this analysis are presented in Figures 3 and 4.

In the primary market for the years 2026–2035, forecast prices show significant polarisation, i.e., the fastest growth is observed in the largest provincial capitals (Warsaw, Krakow, Wroclaw, Gdansk), while in smaller centres (including Kielce, Opole, and Zielona Gora), real residential property prices are expected to stabilise. These findings are consistent with research conducted by Gyourko et al. (2013), who indicate that in so-called "superstar cities," high price increases result from high household incomes and limited supply. These results also align with the CSO's population dynamics projections. In particular, higher price growth is evident in cities with a more favourable demographic outlook, consistent with the research by Gong and Yao

(2022). In contrast, in smaller cities experiencing depopulation, forecasts indicate a risk of long-term house price stabilisation. The heterogeneity of long-term price forecasts is also evident between the primary and secondary markets. In particular, price increases appear more stable and pronounced in the secondary market over the long term. To formally verify the above hypothesis, we regress price growth for the period 2025–2035 on market type, city size, and population predictions:

$$hpg_i = \alpha_{0i} + \alpha_{1i} m_i + \alpha_{2i} p_i + \alpha_{3i} pg_i + \varepsilon_i, \quad (4)$$

where: hpg_i is the percentage change in residential property prices over the period 2025Q4–2035Q4, m_i is a binary variable taking the value 1 if the secondary market, p_i is the log population in 2025, approximating the current size of the city, pg_i is the projected change in population between 2025 and 2035. The estimation results are presented in Table 2, which confirms that price increases are evident in large urban centres and in locations with optimistic demographic projections. In contrast, the model rejected the hypothesis of different price-growth rates between the primary and secondary markets.

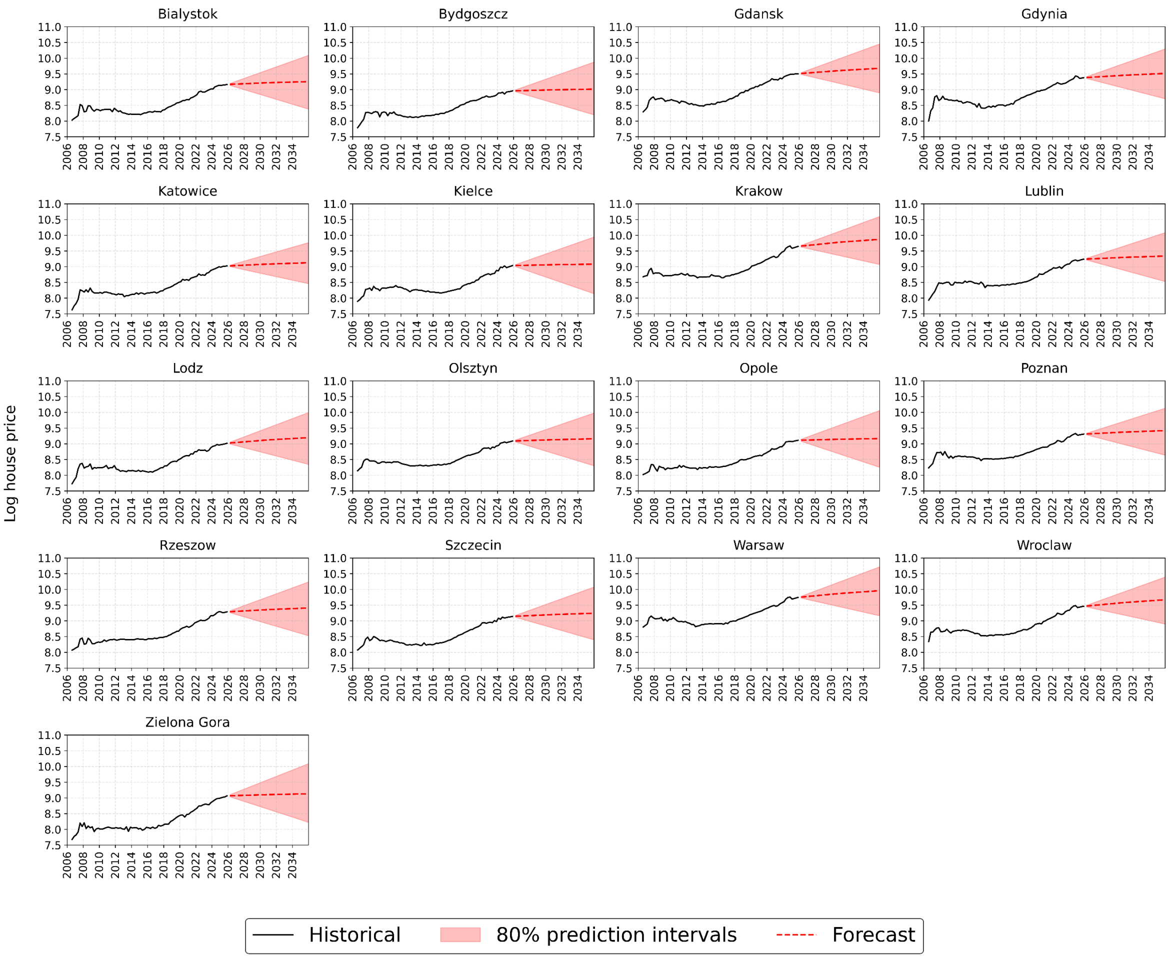

Fig. 4. Forecasted logarithmic real transaction prices for residential properties in the secondary market. *Source*: own study.

Table 2

Factors influencing long-term trends in residential property prices

Variable	Parameter
Constant	–0.75***
m_i	–0.01
p_i	0.07***
pg_i	0.78***
R^2	0.69
N	34

Notes: ***$p < 0.01$. *Source*: own study.

Finally, Figure 5 shows price levels in the fourth quarter of 2035 for each city analysed. As can be seen, in the primary market, the 20,000 PLN/m² level will be reached only in Warsaw, while slightly lower values will be observed in Krakow, Wroclaw, and Gdansk. Prices in the remaining provincial capitals will hover below PLN 15,000/m². Similar trends can be observed in the secondary market, though here two cities dominate: Warsaw and Krakow. These results are consistent with other studies of the Polish housing market, indicating strong growth dynamics in the local housing markets of Krakow, Warsaw, Gdansk, and Wroclaw (Tomal, 2019, 2020).

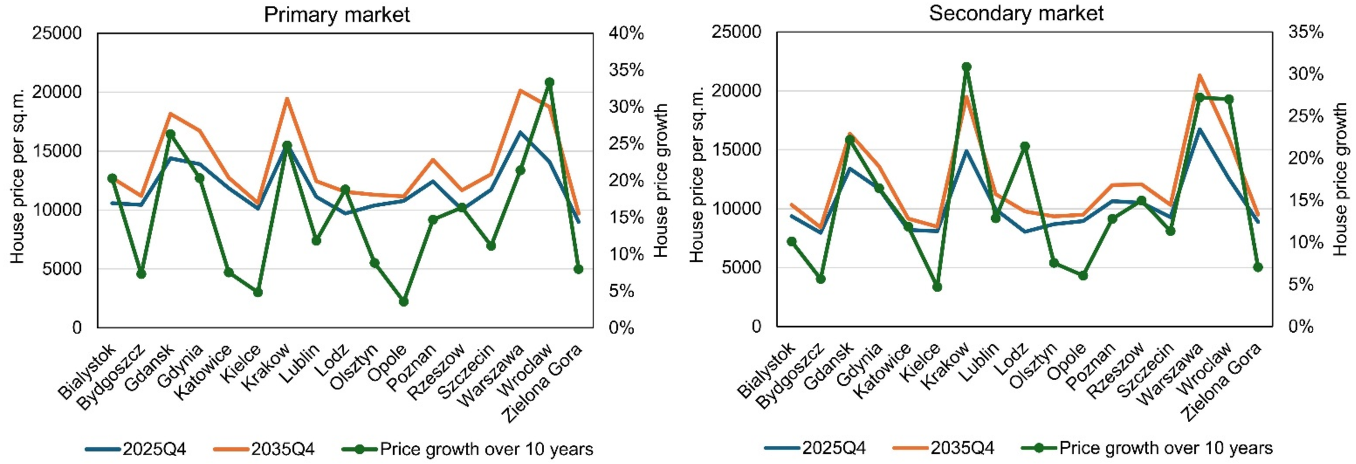

Fig. 5. Changes in residential property prices between 2025 and 2035. *Source*: own study.

4.3. Robustness tests

As noted in previous studies, the impact of demographic changes on residential property prices may be delayed. Therefore, we examined whether lagging the population predictor by 1 year ($t-4$) and 2 years ($t-8$) would change the selection of the best model for future residential price forecasts. Furthermore, housing prices depend on other fundamental factors, such as wage levels and unemployment rates. Consequently, as an additional robustness test, we examined how the model selection results would change if an employment rate variable were included. However, the results of this analysis should be treated with caution, as there are no long-term forecasts for this predictor at the city level; they are available only at the national level.

Based on the baseline and lagged-population models, it can be concluded that there was no difference in selecting the optimal model class for real estate price forecasting (see Table 3). In terms of ex post forecast accuracy, the baseline approach also exhibits lower MAPE values in most cases. Finally, in the model that accounts for the employment rate, changes in model selection are evident in five cases. MAPE values are also generally lower, by an average of 0.36, suggesting scope to improve long-term price forecasts as data availability improves.

Table 3

Robustness test.

City	Market type	Baseline scenario		Log population (t-4)		Log population (t-8)		Baseline scenario and employment rate	
		Best model	MAPE (%)	Best model	MAPE (%)	Best model	MAPE (%)	Best model	MAPE (%)
Bialystok	Primary	ARIMA	3.8	ARIMA	8.8	ARIMA	7.8	ARIMAX	3.5
Bialystok	Secondary	ARIMAX	3.2	ARIMAX	2.1	ARIMAX	2.2	ARIMAX	2.9
Bydgoszcz	Primary	LSTM	5.1	LSTM	3.9	LSTM	4.3	LSTM	4.7
Bydgoszcz	Secondary	LSTM	4.4	LSTM	2.1	LSTM	4.5	LSTM	4.1
Gdansk	Primary	ARIMAX	6.7	ARIMAX	2.9	ARIMAX	3.2	ARIMAX	6.1
Gdansk	Secondary	UCM	2.9	UCM	14.1	UCM	3.3	UCM	2.6
Gdynia	Primary	UCM	4.6	UCM	6.4	UCM	7.5	UCM	4.3
Gdynia	Secondary	LSTM	5.3	LSTM	4.0	LSTM	4.0	LSTM	4.9
Katowice	Primary	LSTM	2.8	LSTM	21.1	LSTM	21.2	LSTM	2.6
Katowice	Secondary	UCM	2.5	UCM	3.6	UCM	3.5	UCM	2.3
Kielce	Primary	LSTM	4.2	LSTM	3.9	LSTM	4.0	LSTM	3.9
Kielce	Secondary	LSTM	3.6	LSTM	6.7	LSTM	7.1	LSTM	3.4
Krakow	Primary	ARIMA	3.1	ARIMA	6.6	ARIMA	4.3	ARIMAX	2.8
Krakow	Secondary	UCM	5.9	UCM	3.9	UCM	3.9	UCM	5.4
Lublin	Primary	LSTM	3.4	LSTM	10.4	LSTM	10.2	LSTM	3.1
Lublin	Secondary	UCM	2.7	UCM	3.8	UCM	3.6	UCM	2.5
Lodz	Primary	LSTM	4.8	LSTM	4.1	LSTM	5.5	LSTM	4.4
Lodz	Secondary	UCM	4.1	UCM	4.5	UCM	4.5	UCM	3.8
Olsztyn	Primary	ARIMA	5.5	ARIMA	5.7	ARIMA	5.4	ARIMAX	5.1

Olsztyn	Secondary	ARIMA	3.5	ARIMA	2.9	ARIMA	2.6	ARIMAX	3.2
Opole	Primary	UCM	6.2	UCM	19.0	UCM	15.3	UCM	5.7
Opole	Secondary	UCM	3.8	UCM	7.9	UCM	3.6	UCM	3.5
Poznan	Primary	LSTM	5.0	LSTM	18.0	LSTM	4.7	LSTM	4.6
Poznan	Secondary	LSTM	4.7	LSTM	4.4	LSTM	9.9	LSTM	4.3
Rzeszow	Primary	ARIMAX	5.8	ARIMAX	10.7	ARIMAX	6.0	ARIMAX	5.3
Rzeszow	Secondary	LSTM	3.3	LSTM	3.5	LSTM	4.3	LSTM	3.0
Szczecin	Primary	UCM	5.4	UCM	8.0	UCM	6.3	UCM	5.0
Szczecin	Secondary	UCM	4.3	UCM	6.7	UCM	5.2	UCM	4.0
Warsaw	Primary	UCM	4.9	UCM	5.0	UCM	4.9	UCM	4.5
Warsaw	Secondary	ARIMAX	5.6	ARIMAX	3.2	ARIMAX	3.3	ARIMAX	5.1
Wroclaw	Primary	UCM	4.5	UCM	13.3	UCM	16.2	UCM	4.2
Wroclaw	Secondary	UCM	6.4	UCM	5.9	UCM	6.0	UCM	5.9
Zielona Gora	Primary	ARIMAX	6.1	ARIMAX	16.9	ARIMAX	4.4	ARIMAX	5.6
Zielona Gora	Secondary	ARIMA	5.7	ARIMA	4.9	ARIMA	4.9	ARIMAX	5.2

Source: own study.

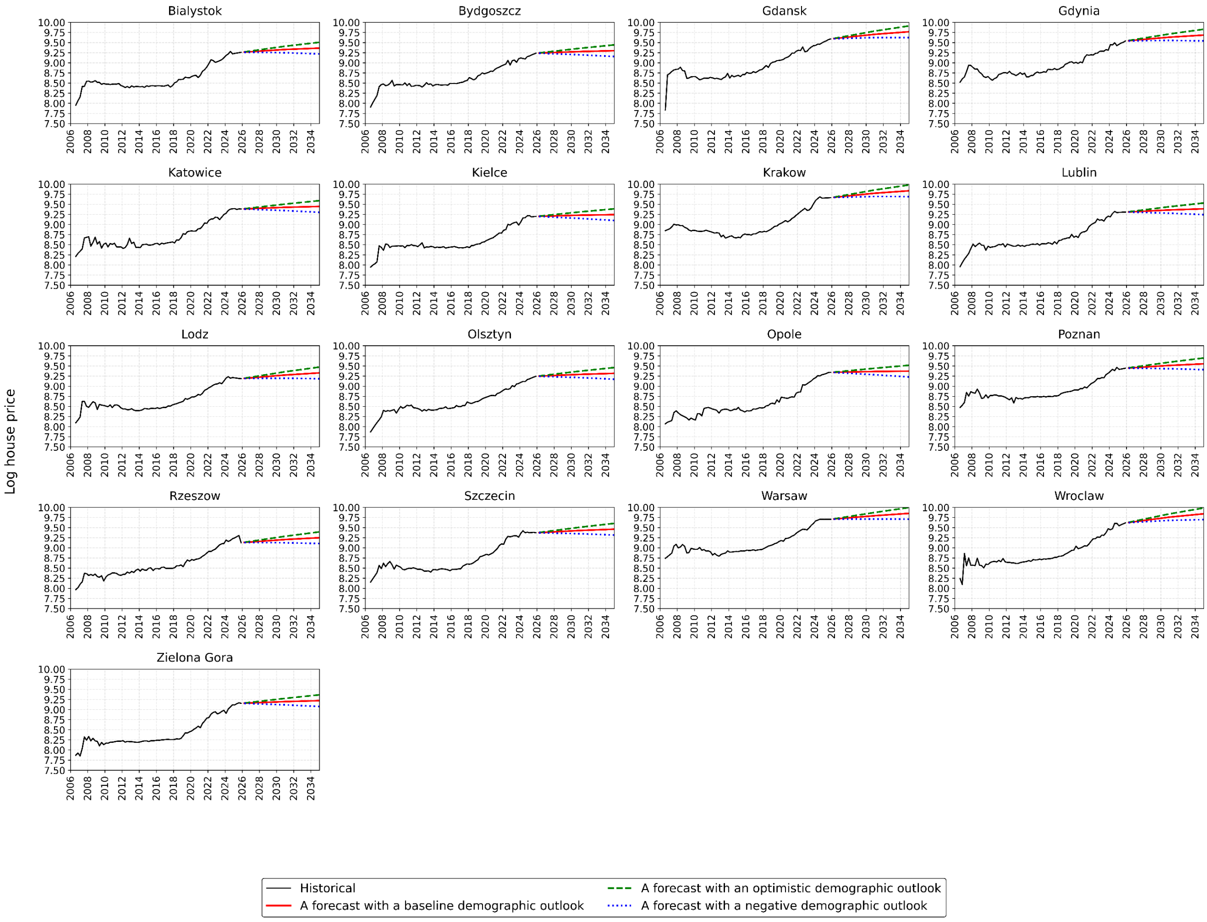

Fig. 6. Forecasted logarithmic real transaction prices for residential real estate in the primary market with alternative demographic outlooks.
Source: own study.

4.4. Alternative demographic scenarios

The forecasts presented in the previous sections were based on population projections that assumed an average increase in Poland's fertility rate. The CSO also provides two alternative population predictions for high and low fertility rates, respectively. Consequently, taking this into account, additional forecasts for residential property prices were produced and are presented in Figures 6 and 7. The results indicate that, generally speaking, with a high fertility rate, significantly higher price increases can be expected than those predicted in the baseline scenario. Conversely, a negative demographic situation would lead to a price decline in almost all cities, across both the primary and secondary markets. These results indicate that residential property prices in Poland are highly sensitive to demographic factors.

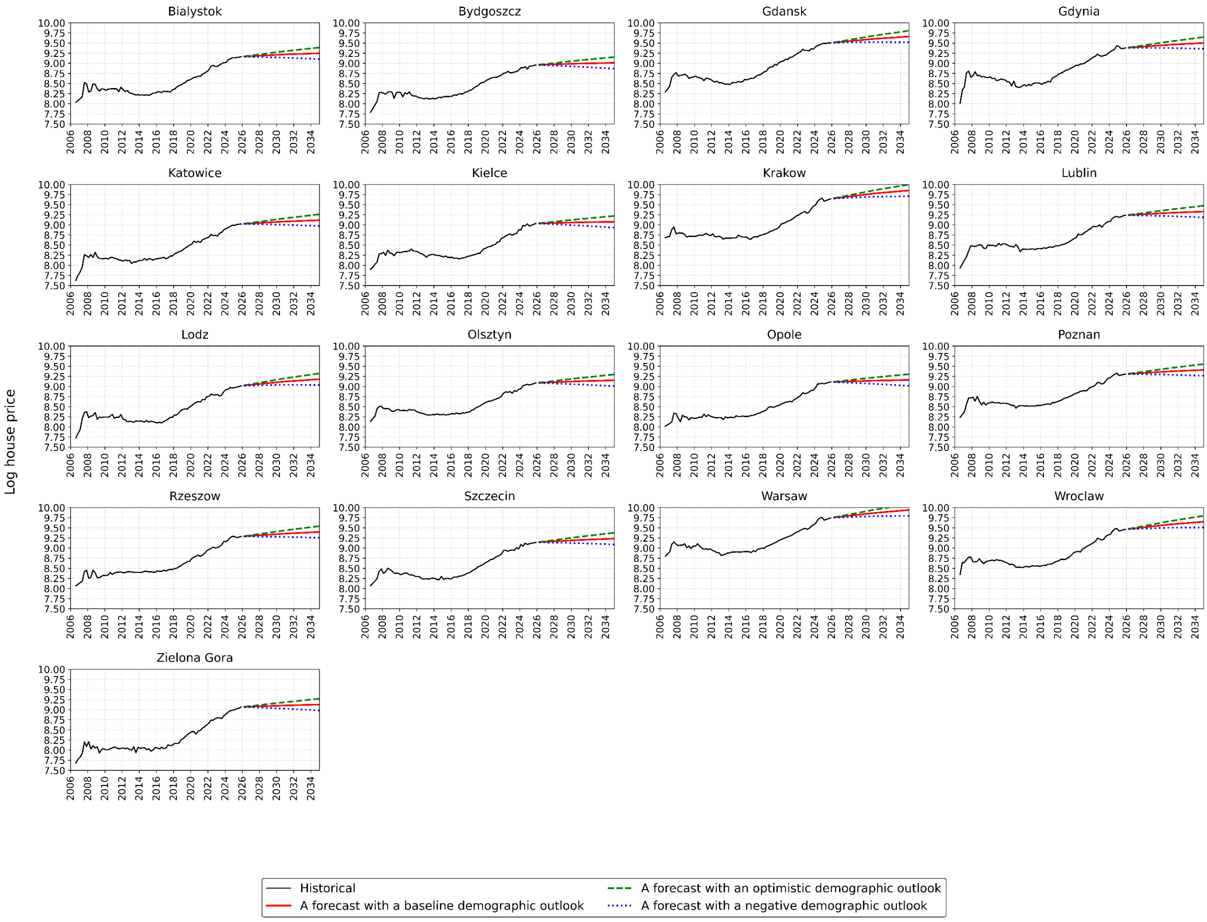

Fig. 7. Forecasted logarithmic real transaction prices for residential real estate in the secondary market with alternative demographic outlooks. *Source*: own study.

5. Conclusions

This article attempts to provide a long-term forecast of real residential property prices in the primary and secondary markets of Polish provincial capitals. The results indicate that, in general, real residential property prices are expected to rise through the end of 2035, though this trend varies across cities. Dynamic growth is expected in large metropolitan areas and those with positive demographic forecasts. But if the demographic outlook turns negative, prices will fall across almost all the markets analysed.

The main strength of this study is that it is the first in the literature to address long-term housing price forecasts in the Polish market. Second, there has been a lack of studies analysing such a wide range of forecasting approaches, from the standard ARIMA model to LSTM-based machine learning. This study also has its limitations. First, the accuracy of the forecasts cannot be precisely assessed, so the results should be treated only as probable. In particular, the price forecasts received are subject to uncertainty, which increases as the forecast horizon extends. Second, housing market prices depend on many macro-level factors, yet city-specific long-term predictions are available only in the context of demographic changes. Consequently, the projections presented in this study depend largely on the demographic channel. Finally, our projections do not account for the possibility of structural breaks.

Future studies should address these limitations. Furthermore, it would be valuable to prepare forecasts for nominal prices and for a larger number of cities in Poland, especially those at the county and municipal levels, where depopulation processes may intensify significantly over the long term, leading to a major demand shock in local housing markets.

This study is of significant importance to policymakers and private individuals. They can incorporate long-term residential property price forecasts into public policy development, particularly housing-related policies. On the other hand, real estate professionals, such as appraisers, have a key indicator of the potential for property values to hold over the long term, which will significantly facilitate the determination of a prudential value. In turn, developers and investors, based on the forecasts, have a reference point for future housing projects and achievable price ceilings.

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Conflict of interest

The Author is a section editor of Real Estate Management and Valuation but took no part in the peer review and decision-making processes for this article.

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