ISSN 2959-6130

Assessing Early Policy Impacts of the National Housing Accord Using ARIMAX Time Series Forecasting

Gabriel Song

Sydney Grammar School, Sydney, Australia
gabrielsong1219@gmail.com

Abstract:
This paper aims to address the research gap on evaluating the National Housing Accord's effects post-implementation. It applies ARIMAX time series forecasting to the Monthly Building Approvals from the Australian Bureau of Statistics prior to the commencement of the National Housing Accord. The forecasted values are then compared to the actual values to assess the short-term impacts of the Accord to date. It was found that the actual values had an increasing trend that deviated from the flat forecasted trend, indicating a positive effect of the National Housing Accord on building approvals. However, it remained within the 80% confidence interval of the forecasting model, not allowing a definite conclusion to be drawn. The main limitations of the paper discussed included the short time frame and the selection of exogenous variables for the model. It suggested that future research should carry out a similar methodology, but at a later stage of the Accord and after revisiting the selection of exogenous variables. Overall, this paper represents an initial step toward quantitatively evaluating the effects of the NHA on housing supply.

Keywords: ARIMAX Forecasting; Housing Policy Evaluation; Housing Supply; National Housing Accord

1. Introduction

The Housing Crisis is a key issue that Australia is facing with an estimated 1.26 million low-income households spending more than 30% of their disposable income on housing in 2024-25 [1]. This can simply be explained by the insufficient supply compared to the level of demand within the Australian Housing Market which leads to higher housing costs, reducing affordability [2]. However, affordability has continued following a downward trend, with 2023 having the lowest number of houses completed in a decade (172,000) and consistently high levels of immigration causing demand-pull increases in housing prices [3, 4].

Poor housing affordability can force people to cut their spending on other essential goods such as food or medicine as well as compromise on the suitability of their housing. This means that many will be forced to settle in poor housing which will negatively impact their physical and mental health, their ability to participate in society and work as well as their connections and relationships with others [5].

The National Housing Accord (NHA) is a collaborative framework between the Australian Government, states and territories, local governments, institutional investors, and the construction sector. The Accord aims to deliver 1.2 million homes over five years from 1 July 2024 to improve housing affordability through supply-side measures, with the Commonwealth making commitments such as providing $3.5 billion to state, territory and local governments to support the delivery of new homes [6]. In addition, the states and territories have pledged, among other actions, to accelerate planning and land release to bridge the gap between supply and demand.

There have been many papers published debating the elements affecting the Australian Housing Market as well as the expected impact of policies and frameworks such as the NHA, however, there has been little research examining the short-term effects that have already occurred since NHA's implementation. This paper addresses this gap by applying ARIMAX time series forecasting to the Monthly Building Approvals dataset from the Australian Bureau of Statistics (July 2010–June 2024, prior to the commencement of the National Housing Accord). Forecasted values are then compared to actual approvals to assess the short-term impacts of the Accord to date.

2. Methodology

2.1 Dependent Variable

The seasonally adjusted monthly building approvals dataset produced by the Australian Bureau of Statistics (ABS) (Fig. 1.) was selected to be the dependent variable because it serves as a leading indication of future housing supply. Unlike other measures of new housing supply such as construction commencements or construction completions, this time series provides an early signal of how developers and households are responding to changes in policy settings and the economic environment. As a result, this makes it well-suited to assess the short-term impacts of the National Housing Accord which has only been in effect for under 10 months.

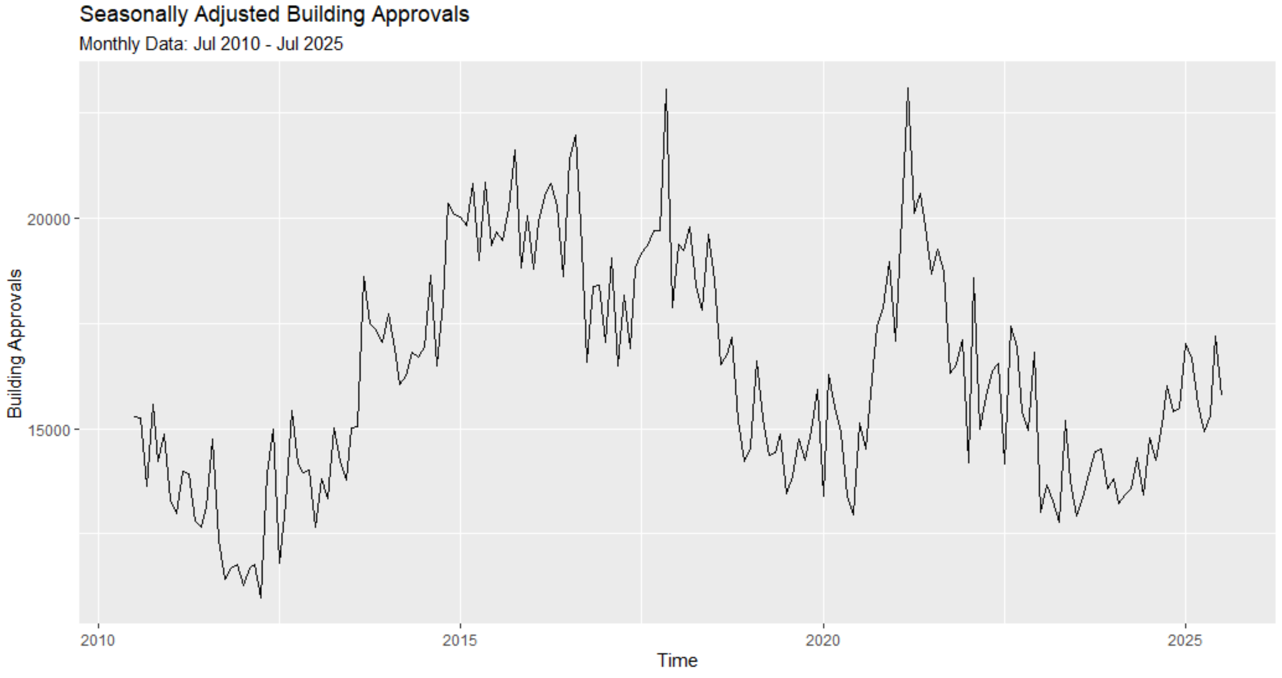

Fig. 1 Autoplot of Monthly Seasonally Adjusted Building Approvals from the ABS in R

To align with the other data discussed later in the paper, this monthly time series was converted to a quarterly series by summing the three months in each quarter and omitting the July and August 2025 values, as these quarters are not yet complete. This new time series can be seen in Fig. 2.

ISSN 2959-6130

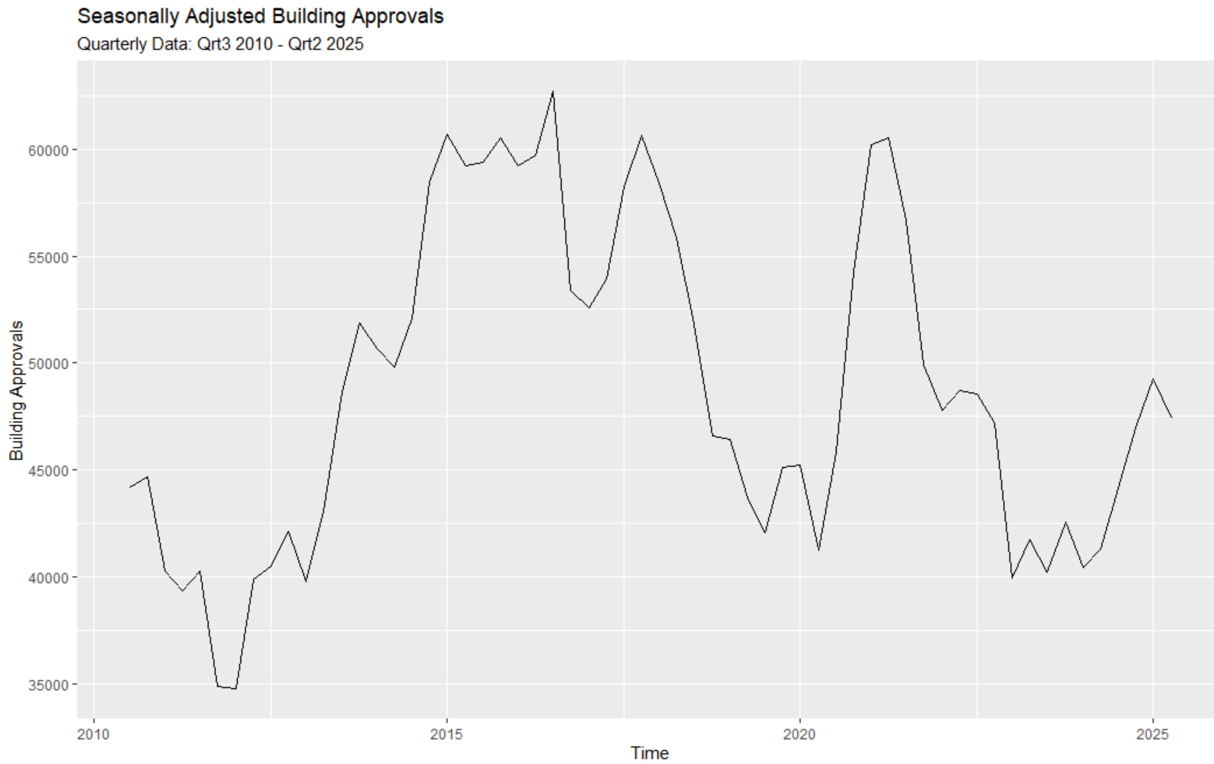

Fig. 2 Autoplot of Quarterly Seasonally Adjusted Building Approvals from the ABS in R

2.2 Time Series Forecasting Model

ARIMA (Autoregressive Integrated Moving Average) is one of the most frequently used time series forecasting method. It involves an autoregressive (AR) component with order p that uses a linear combination of past values to forecast future values as well as a moving average (MA) component with order q that uses a linear combination of past errors to forecast future errors [7]. Finally, d orders of differencing (I) (subtracting a value from its previous value d times) are also applied to the original time series to ensure that it is stationary, or in other words, ensure that its statistical properties like mean and variance remain constant over time. Combining all these elements, we get a powerful ARIMA model which is not only simple but also captures crucial trends and autocorrelation [8]. Its formula is given by:

$$\varphi(B)(1-B)^d Z_t = \theta(B)a_t \tag{1}$$

where B is the backshift notation and $(1-B)^d$ represents differencing of order d, $\varphi(B)$ is the AR component of order p with formula (2), $\theta(B)$ is the MA component of order q with formula (3), Z_t is the value at time t, and a_t is the white noise [9].

$$\varphi(B) = 1 - \varphi_1 B - \varphi_2 B^2 - \cdots - \varphi_p B^p \tag{2}$$

$$\theta(B) = 1 + \theta_1 B + \theta_2 B^2 + \cdots + \theta_q B^q \tag{3}$$

As mentioned, ARIMA is a very reliable, yet simple model for temporal data, making it attractive for any sort of time series forecasting such as this one. However, it must be noted that the volume of building approvals is heavily dependent on external economic conditions and sudden policy changes which may not be captured well by a standard ARIMA model. Therefore, the ARIMA model used should be extended to include these exogenous variables, or the ARIMAX model. Its formula is given by:

$$\varphi(B)(1-B)^d Z_t = \theta(B)a_t + \beta X_t \tag{4}$$

where β is a vector of coefficients β_1, β_2, $\cdots$, β_k, X_t is a vector of exogenous regressors $x_{1,t}$, $x_{2,t}$, $\cdots$, $x_{k,t}$ at time t and βX_t with expanded formula (5) represents the effect of the exogenous regressors.

$$\beta X_t = \beta_1 x_{1,t} + \beta_2 x_{2,t} + \cdots + \beta_k x_{k,t} \tag{5}$$

2.3 Exogenous Variables

Building approvals are influenced by both demand-side and supply-side factors. In theory, higher demand for housing can increase market prices, providing incentives for developers and households to construct new housing or improve existing properties, while lower demand tends to reduce these activities. However, housing supply in

Australia is highly inelastic [10]. This means that the demand-driven effects on building approvals are relatively limited. Consequently, this paper will focus on supply-side factors (which may also have some demand-driven effects) as the chosen exogenous variables in the ARIMAX model. In addition, a dummy variable will be included to account for a policy shock that is not captured by the selected exogenous variables.

2.3.1 Producer Price Index (PPI) for Input to the House Construction Industry

The Australian Producer Price Indexes (PPIs) are a set of indexes that measure price changes of products (goods and services) either as they leave the place of production or as they enter the production process [11]. For example, the quarterly PPI for inputs to house construction prices, published by the ABS, tracks changes in the prices of building materials used in residential construction. Rising construction costs have been identified as a key factor behind increases in housing prices [12]. This is likely due to how increases in construction costs will reduce the overall supply of new housing as developers are less incentivised to develop [13, 14]. Therefore, the PPI for inputs to house construction serves as an important exogenous variable in modelling new housing supply and, consequently, building approvals. The time-series can be seen in Fig. 3.

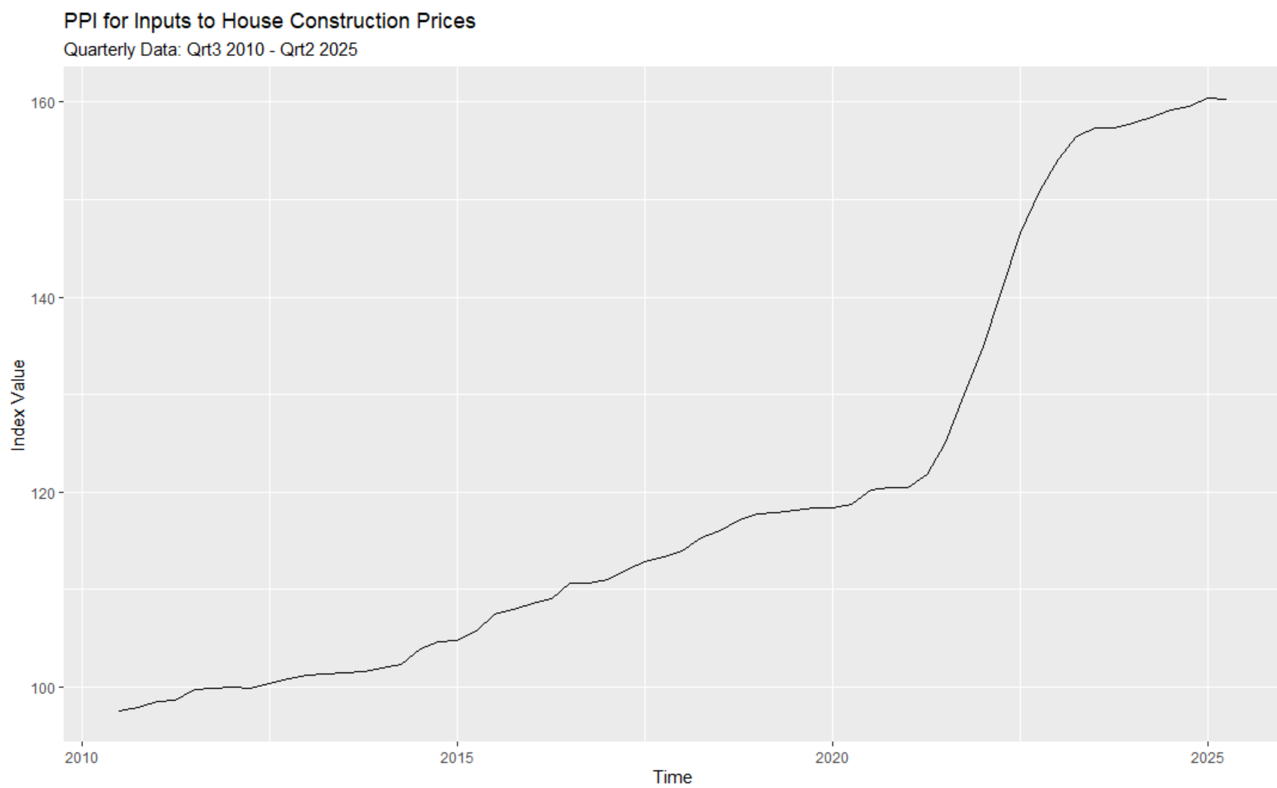

Fig. 3 Autoplot of quarterly PPI for inputs to house construction prices from the ABS in R

Although one quarter's index value may be higher than another's, this does not necessarily imply lower building approvals. What influences approvals is not the absolute level of the index, but the change in the index from one period to the next. For this reason, it is more appropriate to use quarter-to-quarter changes (i.e., the relative differences) in the index as the exogenous variable, rather than the raw index values. The new time-series can be seen in Fig. 4.

ISSN 2959-6130

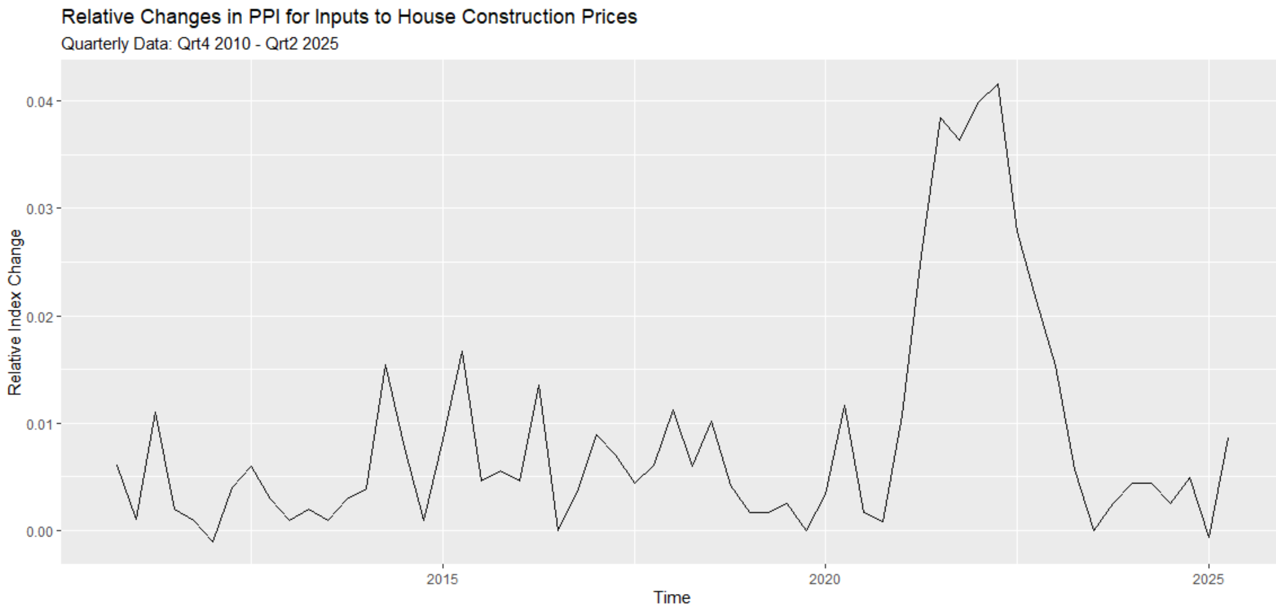

Fig. 4 Autoplot of relative changes in PPI for inputs to house construction prices from ABS in R

As changes in input costs require time to influence building approvals, a one-quarter lag is to be included to account for this delay. In addition, this lag will help mitigate potential endogeneity. Input costs and the volume of new supply are heavily related as increases in building approvals will lead to a greater demand for materials, driving up these prices and therefore, the input costs. By doing so, the lagged PPI values, which are unaffected by present building approvals, will affect the current level of building approvals, reducing the potential effects of endogeneity.

2.3.2 Target Cash Rate

The target cash rate set by the Reserve Bank of Australia (RBA) eight times a year, significantly affects the overall rate of borrowing within the Australian economy. Therefore, in periods of higher cash rates, financing construction and developing operations will generally become more expensive. As many developers utilise loans to fund large-scale operations, the overall construction costs will increase, resulting in the reduction of the overall supply of new housing [13, 14]. Additionally, increases in the cash rate will also decrease the demand for housing as mortgage costs increase, further having a (although weak) contractionary effect on the supply of housing. Therefore, for all these reasons, the cash rate was also selected as another exogenous variable in modelling building approvals. It should be noted that unlike PPI, the target cash rate is set in response to broad macroeconomic conditions rather than building approvals specifically, so the risk of endogeneity with approvals is low.

To ensure consistency with the quarterly PPI data, the target cash rate series was also converted to quarterly frequency by taking the average monthly target cash rate values provided by the RBA within each quarter. This time-series can be seen in Fig. 5.

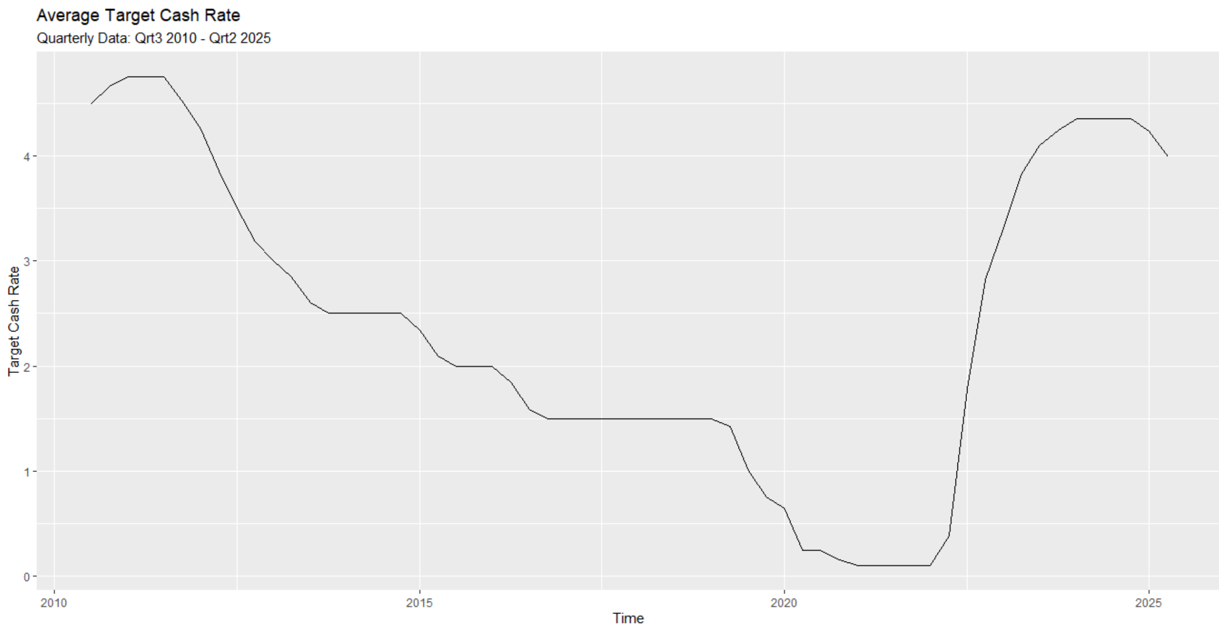

Fig. 5 Auto plot of average quarterly target cash rate from the RBA in R

Like the scenario with the PPI, it will take time for changes in the target cash rate to be reflected in the interest rates on business loans for developers and mortgages for individuals. It will also take time for these changes in interest rates to influence the level of building approvals. Therefore, a two-quarter lag has been selected to account for this delay.

2.3.3 Dummy Variables

Dummy variables (or binary variables) are used to capture a structural change or policy shock in data that cannot be explained by other continuous regressors. Incorporating a dummy variable that captures the effect of an event into our ARIMAX model gives us the following formula:

$$\varphi(B)(1-B)^d Z_t = \theta(B)a_t + \beta X_t + \gamma D_t \quad (6)$$

where γ is the coefficient of the dummy variable, measuring the magnitude of the effect of the event and D_t is defined as 1 if the event occurs at time t, and 0 otherwise.
One main policy shock that occurred was the introduction of HomeBuilder in 2020. This was an Australian government scheme that provided a $25,000 grant for new home contracts and substantial renovations signed between 4 June 2020 and 31 December 2020. This was later extended to provide a $15,000 grant for eligible contracts between 1 January 2021 and 31 March 2021 [15]. The policy incentivised individuals and developers to improve the standard of their own housing as well as constructing new housing, resulting in the massive surge in building approvals which peaked in Q1 2021 evident in Fig.1. Therefore, to improve the accuracy of this ARIMAX model by accounting for this temporary structural shift, a pulse dummy variable will be used for the period between Q3 2020 and Q1 2021 inclusive.

2.4 Forecasting Data Time Frame

To lag the exogenous variables appropriately, only the building approvals values from Q1 2011 to Q2 2025 are considered. In addition, the quarterly average cash rate is only considered from Q3 2010 to Q4 2024, and the PPI is only considered from Q4 2010 to Q1 2025.
A suitable ARIMAX model will be selected based on the building approvals time series from Q1 2011 to Q2 2024. The period from Q1 2011 to Q1 2022 will serve as the training set, while Q2 2022 to Q2 2024 will be reserved for testing. This split provides 45 quarters of training data and 9 quarters of testing data, aligning with the standard 80-20 train-test ratio.

2.5 Diagnostic Checks

The validity of the ARIMAX model will be assessed through a series of statistical tests and analyses, comparing its fit against the actual data from both the training and test sets.
On the training set, the objective is to ensure that residuals of the training data are consistent white noise, indicating that the model has adequately captured the dynamics of the series. This is done by analysing the residual plot, the residual histogram, its autocorrelation plot, and using the Ljung-Box test, a portmanteau test for the randomness of residuals. The Ljung-Box test statistic is given by the formula:

$$Q^* = T(T+2)\sum_{k=1}^{\ell}(T-k)^{-1}r_k^2 \quad (7)$$

ISSN 2959-6130

where ℓ is the maximum lag being considered, T is the number of observations, r_k is the autocorrelation for lag k and the test statistic Q^* follows a χ2 (chi-square) distribution with ℓ degrees of freedom [7]. If the p-value of this test statistic is less than the significance level of $\alpha = 0.05$, the null hypothesis of uncorrelated residuals is rejected, indicating that the residuals do not behave like white noise and that the model has not fully captured the time series structure.

On the test set, the objective is to evaluate the model's predictive accuracy. The MAE (Mean Absolute Error) and RMSE (Root Mean Squared Error) are both scale-dependent measures of the error between forecasted values and actual values in the test set. They are given by the following formulas:

$$MAE = mean\left(\left|e_t\right|\right) \tag{8}$$

$$RMSE = \sqrt{mean\left(e_t^2\right)} \tag{9}$$

where $e^t = y^t - ?^t$ such that y^t is the observed value at time t and $?^t$ is the forecasted value at time t. While MAE measures the average size of the errors, RMSE penalises large errors more heavily. Together, these metrics will provide insights into the accuracy of the model in forecasting future values.

2.6 Forecast Analysis/Comparison

Once the model is fitted, it will be used to generate forecasts for Q3 2024 – Q2 2025, the period during which the National Housing Accord has been in effect. These forecasts for quarterly building approvals will then be qualitatively compared with the actual observed values. This will provide evidence for the assessment of the early policy impacts of the NHA on building approvals and by extension, on future housing supply in Australia.

3. Results

The ARIMAX model received from the training set has parameters (p, d, q) to be (1, 0, 1). In addition, its specific coefficients are shown in Table. 1.

Table. 1 Coefficients used in the final ARIMAX model

Coefficient	AR1	MA1	Intercept	PPI Change	Cash Rate	Dummy
Value	0.7449	0.5216	55226.273	48721.32	-2773.479	-1686.862

Recall that the general formula of an ARIMAX model with exogenous variables and a dummy variable is given by (6). Therefore, the specific formula of this model is given by:

$$\begin{aligned}&\left(1-0.7449B\right)Z_t = \left(1+0.5216B\right)a_t + 48721.32P_t - \\ &2773.479C_t - 1686.86D_t + 55226.273\end{aligned} \tag{10}$$

Or after simplification:

$$\begin{aligned}&Z_t = 55226.273 + 0.7449Z_{t-1} + 48721.32P_t - \\ &2773.479C_t - 1686.86D_t + a_t + 0.5216a_{t-1}\end{aligned} \tag{11}$$

In addition, performing residual diagnostics yields the results seen in Fig. 6, Table. 2, Fig.7 and Fig. 8.

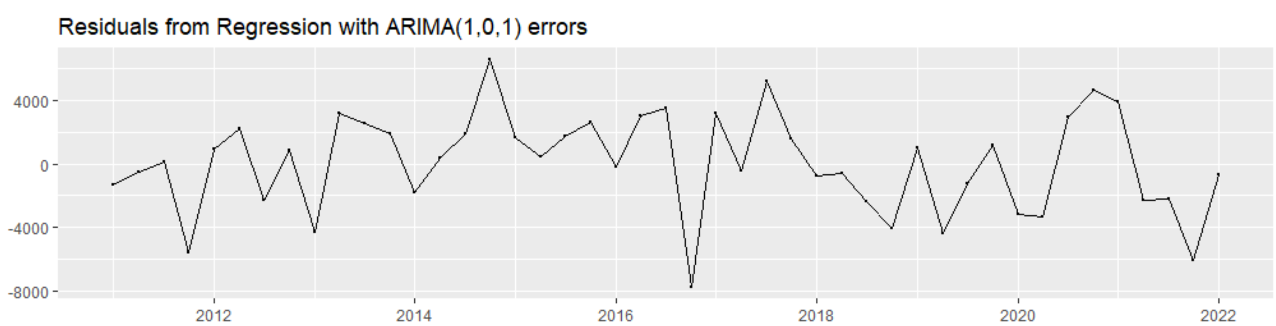

Fig. 6. Autoplot of residuals from ARIMAX model

In Fig. 6, the residuals do behave consistently with white noise, fluctuating randomly around a mean of approximately 0.

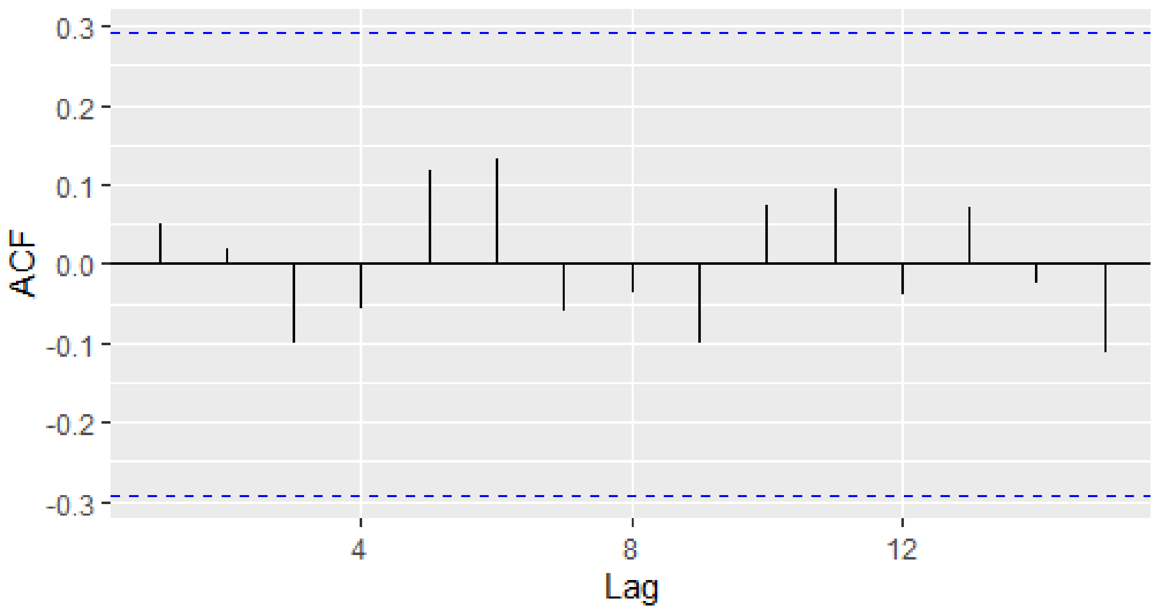

Fig. 7 ACF Plot of residuals from ARIMAX model

Fig. 7 shows all autocorrelation values are very close to 0 and fall within the 95% confidence interval that are 1.96 standard deviations away from the centre of 0. This aligns with the expectation that if the residuals are random and normally distributed, then only 5% of all autocorrelation values should lie outside these bounds.

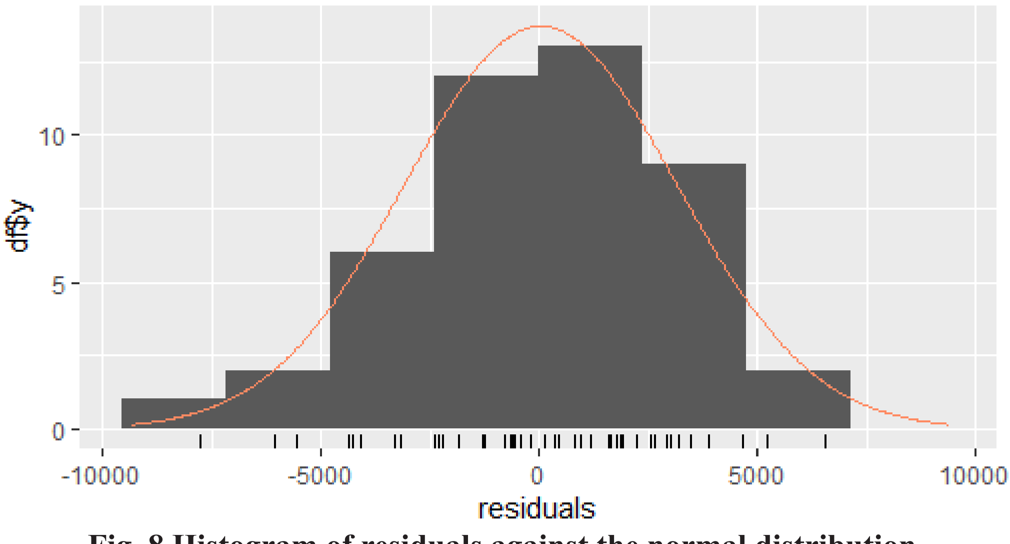

Fig. 8 Histogram of residuals against the normal distribution

In Fig. 8, although the histogram of residuals does show a slightly left skew, it still closely resembles a normal distribution. Finally, the Ljung-Box Test (Table. 2), yields a p-value of 0.8364. This is a very large p-value that is well above the significance value of $\alpha = 0.05$, further indicating the randomness of the residuals. Therefore, all this analysis demonstrates that the residuals from this ARIMAX model is consistent with white noise, passing our diagnostic check for the training set.

Table. 2 Results from the Ljung-Box Test

	Q* Statistic	Degrees of Freedom	P-Value
Value	2.7762	6	0.8364

ISSN 2959-6130

The measures of error received from testing the ARIMAX model's accuracy is seen in Table. 3.

Table. 3 Error Metrics from the ARIMAX Model in the test set

Metric	MAE	RMSE
Value	3475.226	4117.103

The mean of the quarterly building approvals is given by the intercept of the ARIMAX model which is 55226.273 (Table. 3) because no differencing is applied to our quarterly building approvals time series. Therefore, this means that both the MAE and RMSE values are both well-below 10% of the mean, which demonstrates that the error of the model is low and that it provides accurate forecasts into the future, passing our diagnostic check for the testing check.

Hence, these diagnostic checks on both the training and testing sets indicate that the ARIMAX model fits the data well and produces accurate, reliable forecasts. See Appendix C for more on how the model was trained and tested.

4. Analysis

Forecasting the future values of building approvals from the start of the testing set in Q2 2022 to Q2 2025 using this ARIMAX model yields Fig. 9.

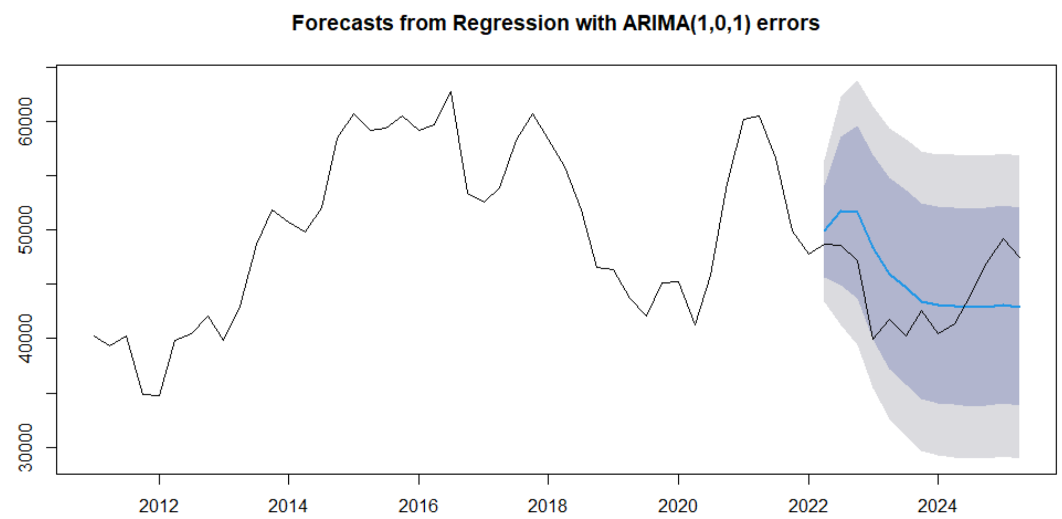

Fig. 9 ARIMAX model forecasts from Q2 2022 to Q2 2025

If attention is focused on the forecasts from Q2 2024 onwards, when the National Housing Accord has been in effect, the model predicts that building approvals would remain relatively flat. In contrast, the actual values from this period show a clear upwards trend, suggesting that the NHA may have contributed to an increase in quarterly building approvals and hence, the supply of new housing. However, all observed values from Q2 2024 onwards remain within the 80% confidence interval shown by the dark-blue shaded region. This is an indication that a definitive conclusion cannot be drawn as it is still statistically plausible that these outcomes could still plausibly occur by chance.

There are many potential limitations to this paper. First, it has been under 10 months since the NHA was implemented. This means that a lot of this policy's effects are still unable to be properly assessed which gives a potential justification for why a definitive conclusion is unable to be drawn. Furthermore, as the time frame is so short, most of the effect can only be reflected by the number of building approvals, which is may not be a clear reflection of future increases in housing supply. This is because a lot of projects are never started, and even more stall due to a variety of reasons such as supply bottlenecks. It is estimated that approximately 17% of approvals will fail to translate into completions [16].

Another limitation would be the core limitations with the ARIMAX method. The complexity of the ARIMAX model means that overfitting is a significant risk [17]. This can occur when too many exogenous regressors are used, meaning that only a few of the most impactful variables should be selected. Therefore, not all potential drivers can be included. As a result, some future variations in the dependent variable may remain unexplained, potentially harming the performance of ARIMAX models. Specifically, in this paper, the PPI for inputs to house construction prices, cash rate and one dummy variable were selected as exogenous variables out of many other different choices such as labour costs and labour supply.

In addition, a key assumption in ARIMAX models is that the exogenous regressors have weak. Weak exogeneity is when the error term is uncorrelated with current and past regressors, while still allowing correlation with future values [18]. This means that although lagging the exogenous variables did help reduce simultaneity bias, it does not guarantee weak exogeneity as past regressors may be correlated with the current error term. This means that our forecasts may have been negatively impacted by such biases, making it another limitation of this model.

5. Conclusion

This paper assessed the short-term impacts of the National Housing Accord using ARIMAX time-series forecasting. The results suggest that building approvals have shown an upward trend since the Accord's implementation, compared with the flat trend forecasted by the ARIMAX model. However, this positive effect remains within the model's 80% confidence interval, meaning it is not yet statistically significant, and no definitive conclusion can be drawn. A key limitation is the short timeframe, as the Accord has only been in effect for 10 months. This means that all the effects of this policy are not exactly clear yet. In addition, it also restricts the analysis to building approvals, which, while a useful leading indicator, do not directly measure increases in housing supply. Further limitations stem from the ARIMAX model itself and from the choice and treatment of exogenous variables, which may have reduced forecast accuracy. It is recommended that this methodology be reapplied once the Accord has been in place longer, allowing clearer effects to emerge and enabling analysis of dependent variables such as housing completions and commencements. Future research should also revisit the choice of exogenous variables, testing alternative specifications to improve model accuracy. Overall, this paper provides an early assessment of the National Housing Accord's short-term impacts using ARIMAX time-series forecasting. It represents a first step in addressing the research gap on evaluating the Accord's effects post-implementation. While no statistically significant impacts were observed in the first 10 months, the observed differences in trends suggest that the NHA may positively influence future housing supply, with effects likely becoming more pronounced over time.

References

[1] ANU CSPR (Australian National University Centre for Social Policy Research). Trends and projections for housing costs and housing stress in Australia, 2025.

[2] Department of the Treasury. Supporting social and affordable housing under the Housing Australia Future Fund and the National Housing Accord: Impact Analysis. Canberra: Office of Impact Analysis; 2024.

[3] National Housing Supply and Affordability Council. State of the housing system 2024. 2024.

[4] Moallemi M, Melser D. The impact of immigration on housing prices in Australia. Papers in Regional Science. 2020;99(3):773–786.

[5] Productivity Commission. In need of repair: The National Housing and Homelessness Agreement. Canberra: Productivity Commission; 2022.

[6] Australian Government Department of the Treasury. Delivering the National Housing Accord. Canberra: Treasury; 2023.

[7] Hyndman R. J., Athanasopoulos G. *Forecasting: Principles and Practice* (3rd ed.). OTexts, 2021

[8] Lennert F. Time series modeling: Why ARIMA models beat linear regression for temporal data. Statistical Horizons; 2025.

[9] Hyndman, R. J., & Athanasopoulos, G. Forecasting: Principles and Practice (3rd ed.). OTexts, 2021.

[10] Saunders C., Tulip P. A model of the Australian housing market. RBA Research Discussion Paper, 2019.

[11] Australian Bureau of Statistics. Producer Price Indexes, Australia. Canberra: ABS; 2025.

[12] Mansur S. A., Abdul Hamid A. R., Yusof N. A. Rising trend in construction cost and housing price. Journal of Advanced Research in Business and Management Studies. 2020 Oct 23;3(1):94–104.

[13] Housing prices and rents in Australia 1980–2023: Facts, explanations, and implications. Applied Economics Working Paper. 2023

[14] Ong V., Leishman C. The economics of housing supply: Key concepts and issues. NSW research report, 2024.

[15] NSW Government. HomeBuilder. Revenue NSW, 2025.

[16] Devine G. Why rising apartment approvals are not Australia's housing crisis saviour. API Magazine, 2025.

[17] Majka M. ARIMAX: Time series forecasting with external variables. LinkedIn. 2024.

[18] Mikusheva A., Sølvsten M. Linear regression with weak exogeneity. Quantitative Economics. 2025;16(2):367–403.