

## Article

# The Relationship Between Economic Environment and Housing Market Dynamics

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## Abstract

The housing sector is an important pillar of the economy. Understanding the trend and factors influencing it is essential for effective policy formulation and purchasing decisions. The objectives of this study are to assess the performance trajectory of the Australian housing market and to identify key macroeconomic factors influencing it over the past two decades. The presence of structural shifts in the housing market due to changing economic conditions highlights the importance of examining both short-run adjustments and long-run equilibrium relationships; however, limited recent studies have investigated these evolving dynamics, which this study addresses by employing the cointegration and Vector Error Correction Model (VECM). Empirical findings indicated the dynamics of previous period RPPI, interest rates, population growth, COVID-19 dummy, and adjustment components (ECT) are affecting housing market dynamics but with effects varying across different lag periods. On the other hand, the long-run estimates reported variables including population growth, the COVID-19 pandemic, household income, and unemployment rate have a significant impact on RPPI at the 5% significance level. The finding of the error correction model suggests a gradual adjustment of short-term deviation with  $ECT_{t-1} = -0.078$  towards the long-term equilibrium quarterly. To further validate the robustness of the results, an Impulse Response Function (IRF) analysis was performed. The empirical findings are valuable as they provide insights that assist policymakers in formulating housing policies and support investors and purchasers in making informed decisions.

**Keywords:** housing market; economic environment; interest rates; unemployment rates; household disposable income; population growth; COVID-19; VECM; cointegration



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## 1. Introduction

The housing sector is an important economic driver for the nation; therefore, maintaining a stable and sustainable housing market is a key concern for policymakers, investors, potential homeowners, creditors, and other stakeholders in the industry. Abnormalities in housing market performance such as falling housing prices, property bubbles, or rising inventories could have far-reaching impacts on individuals, households, and the financial resilience of the nation. According to Dasey (2025) [1], the Australian housing market displayed symptoms of overheating with deteriorating affordability issues. The average house price has increased by almost fifty percent since 2020, resulting in historically low

housing affordability. A recent report by Gruber (2025) [2] stated that Australia is the second most expensive country after Hong Kong in 2024. It was twice as expensive as those in the United States and considerably higher than the UK and Canada—5.6 and 5.4 times respectively. Major cities such as Sydney, Adelaide, Brisbane, and Melbourne are “impossibly unaffordable” with multiples of 9 times or more. Recent reports also reveal that Australian house prices have outpaced income growth and the income needed to service a new mortgage has risen to 50.6 percent as of September 2024 [3,4]. A fifty-year data analysis further confirmed that median house prices in Sydney have increased from thirty-five thousand dollars in 1975 to \$1.6 million in 2024, posing significant challenges for current homebuyers. At the current rate, potential buyers would require more than a decade to save a 20 percent deposit for an average house in Australia. In Sydney, the required duration was approximately 16.7 years [1,3].

The housing sector plays a crucial role in economic stability, where price fluctuations reflect the interaction between demand pressures, access to financing, and expectations of household well-being. In Australia’s domestic sphere, the RPPI is a fundamental indicator that captures the dynamics of the property market in response to systematic shifts in macroeconomic variables [5–7]. Therefore, the significance of systematic analysis of the interaction between these variables is crucial to be understood within the framework of housing price determinants [5–8]. Accordingly, understanding the determinants of home prices is an important basis for academic and public policy analysis [5–7].

Theoretically, the relationship between macroeconomic variables and real estate values is grounded in asset market equilibrium and customer choice theories. These theories are linked to the supply and demand theorem, whereby changes in macroeconomic conditions or government intervention alter consumer preferences and market behavior, shifting housing demand and disrupting market equilibrium, thereby influencing market value of real estate [9]. Prior research contended that housing prices are affected by affordability, financing costs, and demand pressures. Disposable income and GDP strengthen household purchasing power and support rising house prices as the economy improves [5–8]. Conversely, higher interest rates increase borrowing costs and tend to depress demand for houses [10–13]. Population growth, urbanization, and household growth also increase the need for housing, especially in big cities [14–16]. Meanwhile, unemployment usually has a negative impact because it weakens income and access to financing [5,17,18]. Cross-study findings suggest that the influence of each variable can differ by region and period of observation [6–8,16].

Among all macro-determinants, interest rates emerged as the most consistent variable influencing house prices in Australia [10–13]. Studies of large cities show that rising mortgage rates or monetary policy tend to depress house prices, with responses that are not always uniform across regions [10,11,13]. The literature also shows an asymmetric response, so falling and rising interest rates do not always produce the same magnitude of effect [4]. At times when interest rates are low, house prices tend to be pushed up as financing becomes easier, while periods of tightening usually weaken price growth [10,11,13,14]. In addition to interest rates, disposable income, population growth, and unemployment play a role in shaping house prices, although the power of their influence is varied [6–9,14]. Income and economic activity are positively related to the housing market because they strengthen consumer confidence, employment opportunities, and home-buying ability [6–8]. From a demographic perspective, population growth, urbanization, and mobility increase housing demand and can strengthen price differentiation between regions [14–16]. In contrast, unemployment tends to depress the housing market because it weakens the capacity of households to buy property [8,19,20]. Recent international literature also suggests that

the influence of these variables is often heterogeneous between countries and between periods [21–23].

Recent studies suggest that housing market dynamics are becoming increasingly heterogeneous during and after the COVID-19 pandemic [21,24–30]. Pandemic studies show that monetary policy, liquidity, and financing remain the main drivers, but their influence is now moderated by changes in population mobility and location preferences [20,22,24]. Evidence from Australia shows a change in the response to internal migration, a shift in location premiums near the CBD, and an easing of speculation following interest rate hikes in 2022 [20,24,26]. Studies from Malaysia, Turkey, Europe, and the United States also confirm the existence of heterogeneous responses to macroeconomic shocks [29,31,32]. Thus, housing market analysis needs to consider policy shocks and changes in household behavior simultaneously [20,22,24].

Based on the development of the literature, there remains a need to provide a comprehensive synthesis of the relationship between RPPI and key macroeconomic factors in a more integrated framework [5–8,22]. While many studies affirm similar directional relationships, the magnitude, strength, and statistical significance exhibit considerable heterogeneity across cities, time periods, and policy context [9,10,13,33]. Therefore, research on the housing market should consider interest rates, disposable income, population growth, and unemployment as interconnected core determinants that jointly influence housing market dynamics [5–8,14]. In addition, recent evidence suggests that their relationship may have changed following the COVID-19 pandemic and monetary tightening [22,29,31]. These indications suggest the need to consider structural shifts in analyzing long-term equilibrium relationships and short-run adjustments. Nonetheless, limited studies have examined these evolving dynamics in the Australian housing market context. Therefore, to address this gap, this study applies a cointegration approach and the Vector Error Correction Model (VECM) to explore both the long-term equilibrium and short-term adjustment mechanisms driving the housing market dynamics. This study has two important implications for policymakers, home buyers, and investors. Firstly, the findings provide useful insights into housing market performance trends over the past two decades. Secondly, the identified influential factors of housing market performance can serve as important inputs for effective policy formulation and facilitate informed purchasing decisions.

## 2. Literature Review

The influence of macroeconomic variables on the housing market has been studied in many countries. Among others, interest rates, household income, employment rates, and demographic changes are some of the determining factors identified by researchers [4,34]. In Malaysia, housing price movement was found to be influenced by macroeconomic variables in the long run, with different variables exerting varying degrees of impact [35]. The study found that increase in interest rates, inflation, and housing supply are inversely related to housing prices, whereas domestic currency movements are positively associated with housing prices. Wang et al. (2018) [36] explored the presence of a housing bubble in Australia using data from 1995Q4 to 2015Q4. They posit that employment rates, mortgage interest rates, consumer sentiment and the stock market performance are the key drivers of the Australian housing prices. Additionally, the market was not in a bubble state during the study period as there was evidence of long-term equilibrium in housing prices. In Western Europe, rising house prices exerted a significant influence on wealth-to-income ratios, which led to the perception that investment in the housing market offers a lucrative avenue for wealth accumulation [37]. A similar study investigates the macro-determinants of the Lithuanian market, which provided evidence that interest rates, inflation, and employment rates are influencing the performance of its national housing price index [38].

Indeed, the relationship between macroeconomic aggregates and asset prices like residential housing is rooted in asset market equilibrium theory and consumer choice theory. Changes in macroeconomic factors, specifically monetary policy and interest rate fluctuations, can alter the capitalization rate in the asset market. Notably, previous studies indicated that the RPPI or house prices in Australia are influenced by a combination of fundamental economic factors and credit market conditions, rather than random movements [5–8]. Based on the preceding summary and broader evidence, house prices can be viewed as the outcome of the interaction among financing, household purchasing power, and demand pressures [7,8]. As such, home price movements reflect changes in the broader economic environment [1,3]. Thus, RPPI is often used to see how the market responds to changes in interest rates, income, and demographic conditions [6,7]. However, the influence of RPPI is not always the same across cities and periods, as market responses can differ between Sydney, Melbourne, and other regions [10,13,22]. Previous evidence also emphasized that the COVID-19 pandemic period introduced an unprecedented shock that generated heterogeneous responses in housing price dynamics [22,24,26].

Within the framework of asset market equilibrium theory, prior studies attributed housing price elasticity to the demand and supply theorem. Credit expansion and contraction driven by changes in interest rates play key role in shaping housing market cycles. Nonetheless, there is no consensus on this view. For instance, studies such as Favilukis et al. (2017) [39] and Greenwald and Guren (2025) [17] found that credit conditions were closely associated with housing market dynamics in the 2000s, while Kaplan et al. (2020) [40] presented an opposing finding. In general, in an environment of relaxed borrowing constraints, such as during periods of lower interest rates, housing demand will increase. This will exert upward pressure on housing prices [11,40]. Lekhuleni and Ndlovu (2023) [34] examine the relationship between South African real house prices and microeconomic variables from 2000 to 2019. The results suggested a significant association between housing prices and mortgage rates, unemployment rates, gross domestic product, and exchange rates. In contrast, Kartal et al. [31] investigated the housing demand of Turkey between 1970 and 2011 and discovered that housing prices were not affected by interest rates.

Prior studies in the Australian context provided evidence that interest rates are the most consistent and significant variable in explaining home price movements [10,12,13]. Rising mortgage rates or tighter monetary policy generally suppress housing demand by increasing borrowing costs [10,12]. Previous studies also indicated that the effect of interest rates is evident in the housing markets of major cities such as Sydney and Melbourne [8,10,13]. This highlights that changes in financing costs influence mortgage affordability and housing demand [4,7]. Recent studies further indicated that the impact of interest rates may be asymmetric and varies across regions [9,12]. This suggests that the transmission of interest rate changes to housing prices varies across cities, particularly during periods of policy shifts and structural market changes [21,25].

Within the asset market equilibrium framework, household disposable income represents a demand-side determinant that influences consumer behavior. Variations in income affect purchasing power, shaping housing demand and equilibrium price dynamics [5–7]. Numerous studies reported disposable income affecting house prices positively and was considered a significant long-term determinant [7,8]. Higher household income implies greater affordability, a stronger capability to absorb elevated prices, an increased ability to secure mortgage financing, and improved capability to meet down payment requirements, thereby influencing demand and prices [5,7,41]. This variable is often used to explain the demand-side dynamics of the Australian housing market [6,8]. However, the relationship between household income and housing prices is inclusive. For instance, Yildirim and Yildirim (2025) [42] contended that there is a positive relationship between household

income and housing affordability. However, rising rental and house prices can offset this effect by reducing affordability, especially among low-income households, hence influencing housing demand and price levels. This finding was supported by Yahaya and Farhana (2026) [43] in a later study. Nonetheless, using data collected from 2007 to 2024 for three of the major cities in China, Yu (2024) [44] revealed that there is no significant relationship between the two variables. In more recent studies, disposable income remains an important determinant but is often examined alongside issues of affordability, prosperity, and inequality [45–47]. Thus, its influence does not stand alone, but interacts with interest rates, credit conditions, and local market dynamics [7,8].

In addition, population growth, migration, and urbanization have consistently strengthened the demand for housing, particularly in Australia's major cities [14,16,27]. Prior studies reported that population and migration are related to rising house prices as well as housing financing activities [15,16]. This demographic pressure increases the need for housing and increases competition in the property market [14,27]. Therefore, population variables are often used to explain changes in housing demand in the medium and long term [5–7]. In recent periods, the impact has been increasingly visible as mobility and urbanization have changed demand patterns, especially after the COVID-19 pandemic [20,22,24]. Thus, population not only explains price levels, but also shifts in location and housing preferences [15,16].

On the other hand, unemployment negatively impacts housing prices as rising unemployment lowers incomes and weakens households' ability to buy property [5–7]. It was positioned as one of the long-term determinants of the Australian housing market [7,8]. When the labor market weakens, demand for housing tends to slow down as purchasing power declines [5,6]. Consequently, unemployment rate is often used as an indicator of household economic health and financial capability [7,8]. Although important, the influence of unemployment is often considered less dominant than interest rates and housing financing [7,9,12]. This implies that unemployment rate remains a relevant determinant for housing market dynamics; however, its influence may be overshadowed by monetary policy and credit conditions [13,22].

Finally, COVID-19, an international health crisis, prompted the Australian government to implement border closures and city lockdowns between March 2020 and February 2022. This resulted in widespread adverse economic consequences including declines in productivity and consumption. Giudice et al. (2020) [48] examined the impact of the COVID-19 pandemic on the housing prices in the Campania region of Italy. The study posits that the pandemic depressed housing consumption by 4.16 percent in the short run and 6.49 percent in the medium run. Similarly, a study conducted in China postulates that communities affected by the COVID-19 pandemic experienced a 2.47 percent decline in housing prices [49].

In terms of research methodologies used in analyzing the housing market pricing dynamics, recently, in addition to traditional econometric methods, researchers have adopted machine learning approaches in housing market studies. The choice of methodology depends on the research objectives and the desired level of interpretability. As the primary objective of this study is to explain the relationship between variables and test economic theories, rather than to solely optimize predictive accuracy, traditional econometric methods are more suitable. Furthermore, these methods offer strong interpretability with estimated coefficients that allow researchers to examine the direction, magnitude, and statistical significance of individual factors influencing housing market performance. In comparison, many machine learning methods are often perceived as “black box” models due to their limited ability in explaining the underlying mechanisms driving predictions. Moreover, traditional econometric models are superior in explaining mechanisms and evaluating policy

implications while machine learning methods are stronger for forecasting and identifying predictive patterns [50].

### 3. Data and Methodology

Sections 3.1 and 3.2 discuss the data, econometric model, and statistical tests used in this study.

#### 3.1. Data

This study utilized quarterly macroeconomics and housing index data spanning from 2005:Q3 to 2024:Q4 for analysis. Presented below is the mathematic model used in this study.

$$RPPI = f(R, income, pop, unem, COVID-19) \quad (1)$$

where RPPI is the Real Residential Property Price Index; R is the interest rates; income is the household disposable income; pop is the population; and unem is the unemployment rates and in the study, a dummy variable is applied for COVID-19. RPPI, unem and pop were obtained from the Australian Bureau of Statistics; household income was gathered from the Bank of International Settlements (BIS) database.

The set of conditioning variables include interest rates, household disposable income, population, and unemployment rate. Interest rate is expected to have an inverse relationship with the real residential property index as a lower interest rate would encourage property investment activities and vice versa [12,41]. On the other hand, population size, household disposable income, and real residential property dynamics are expected to be positively related as the demand of residential property will increase with the rise in disposable income population. Additionally, a higher unemployment rate is predicted to be negatively related to the residential property index.

Following similar research conducted to examine the relationship of macroeconomic variables and housing market [18,51], the following econometric approaches were used for analysis: (i) Augmented Dickey–Fuller test to assess variables' order of integration, (ii) Johansen and Juselius' (1990) [52] cointegration test to investigate the long-run relationship between variables, and (iii) the Vector Error Correction Model (VECM) to examine the short-run and long-run dynamics of the variables in the model.

#### 3.2. Econometric Model

The application of the Vector Error Correction Model (VECM) has an advantage in housing market analysis as it is able to capture short-term relationships as well as adjustment mechanisms towards long-term equilibrium. The housing market is generally characterized by non-stationary economic variables, such as house prices, income, and interest rates, but these variables can have a stable long-term relationship [53]. Under these conditions, VECM becomes an appropriate model as it not only explains short-term fluctuations but also shows how quickly deviations from the long-term equilibrium are corrected over time [54]. Thus, VECM allows researchers to understand how home prices respond to changes in macroeconomic variables in the short term, as well as how the RPPI moves back towards long-term equilibrium after economic shocks. In the context of this study, the regression equation used is as follows:

$$LnRPPI_t = \alpha_0 + \beta_1 LnR_t + \beta_2 LnIncome_t + \beta_3 LnPop_t + \beta_4 LnUnem_t + \beta_5 dCOVID_t + \varepsilon_t \quad (2)$$

where  $dCOVID_t = 1$  is the pandemic period of COVID-19 and  $dCOVID_t = 0$  is a normal period;  $\alpha_0$  is the value of a constant;  $\beta_1 - \beta_5$  is the value of the coefficient of an independent variable; and  $\varepsilon_t$  is an error term. Error Correction Term (ECT) is an important component of the VECM as it shows the mechanism of housing price adjustment towards long-term

equilibrium after an economic shock. In the context of the housing market, house prices can deviate from the long-term balance due to changes in interest rates, household income, unemployment rates, population, and external shocks such as the COVID-19 pandemic. Through ECT, the model can measure how much the deviation is corrected in the following period. Thus, ECT not only shows the existence of a long-term relationship between variables but also explains the speed at which the housing market adjusts after an imbalance occurs. According to [55], the application of ECT in the VECM is relevant because the housing market generally does not immediately return to stability after experiencing changes in economic conditions. For example, rising interest rates can suppress the demand for homes, but price adjustments do not occur instantly due to credit conditions, market participants' expectations, rigidity of property prices, and the transaction process that takes time. If the ECT coefficient is negative and significant, then it indicates that when housing prices deviate from the long-term equilibrium, some of the deviation will be corrected in the following period. The ECT equation in the model is as follows:

$$ECT_{t-1} = LnRPPI_{t-1} - \alpha_0 - \beta_1 LnR_{t-1} - \beta_2 LnIncome_{t-1} - \beta_3 LnPop_{t-1} - \beta_4 LnUnem_{t-1} \quad (3)$$

COVID-19 *dummy* variables are generally stationary, so they can be treated as exogenous variables in the VECM, rather than as part of a cointegration relationship. The VECM equations used in the research model are:

$$\begin{aligned} \Delta LnRPPI_t = & \alpha_0 + \lambda ECT_{t-1} \\ & + \sum_{i=1}^{p-1} \gamma_{1i} \Delta LnRPPI_{t-i} + \sum_{i=1}^{p-1} \gamma_{2i} \Delta LnR_{t-i} + \sum_{i=1}^{p-1} \gamma_{3i} \Delta LnIncome_{t-i} + \sum_{i=1}^{p-1} \gamma_{4i} \Delta LnPop_{t-i} \\ & + \sum_{i=1}^{p-1} \gamma_{5i} \Delta LnUnem_{t-i} + \theta dCOVID_t \end{aligned} \quad (4)$$

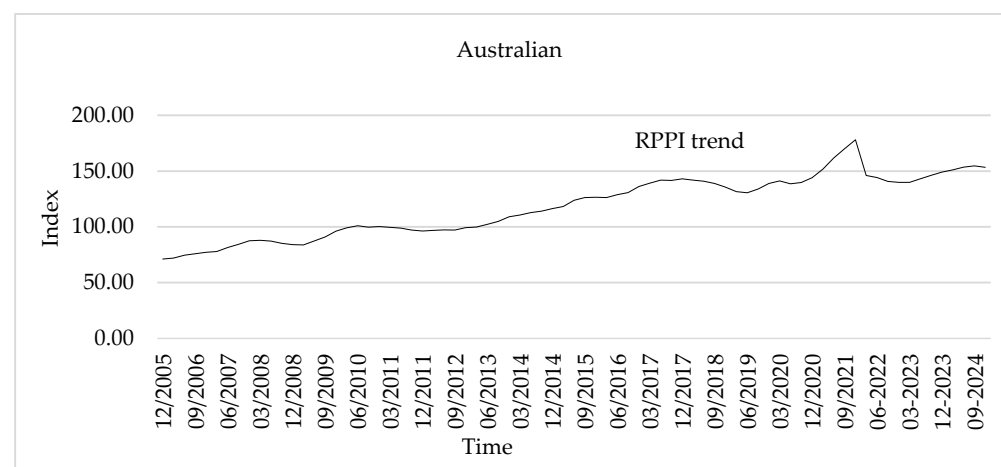
where  $\Delta RPPI_t$  is the change in the housing price index in Australia;  $ECT_{t-1}$  is an Error Correction Term that describes adjustments to regain balance in the long run;  $\lambda$  is the expected coefficient value on  $-1 < \lambda < 0$ . The application of matrix equations in the VECM is important as it clarifies the structure of the multivariate relationships between the cointegrated variables [47,56]. In this analysis, variables such as house prices, interest rates, income, population, unemployment, and other market factors do not move in isolation, but can affect each other simultaneously. Using the form of a matrix is able to show how each variable responds to changes in other variables, both in the short term and in the process of adjustment towards long-term equilibrium. This is a central aspect in housing market research because housing prices are often influenced by a combination of macroeconomic factors, financing conditions, and market demand dynamics. In addition, according to [57], matrix equations help explain that VECM is not just a one-way model that looks at the influence of independent variables on home prices but is a system of equations that treats key variables as part of an interrelated mechanism. In the context of the housing market, changes in interest rates can affect home prices, but changes in home prices can also relate to market expectations, investment decisions, and policy responses. Therefore, the use of matrix equations makes the model specification more comprehensive, as it is able to describe the dynamic relationships between variables together. Thus, the matrix equation in VECM strengthens the methodological basis of the research because it shows the cointegration structure, error correction mechanism, and short-term interaction between variables in one complete analysis framework. The matrix equation in the study is as follows:

$$\begin{bmatrix} \Delta \text{LnRPPI}_t \\ \Delta \text{LR}_t \\ \Delta \text{LnIncome}_t \\ \Delta \text{LnPop}_t \\ \Delta \text{LnUnem}_t \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \mu_3 \\ \mu_4 \\ \mu_5 \end{bmatrix} + \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \alpha_4 \\ \alpha_5 \end{bmatrix} \text{ECT}_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \begin{bmatrix} \Delta \text{LnRPPI}_{t-i} \\ \Delta \text{LR}_{t-i} \\ \Delta \text{LnIncome}_{t-i} \\ \Delta \text{LnPop}_{t-i} \\ \Delta \text{LnUnem}_{t-i} \end{bmatrix} + \begin{bmatrix} \theta_1 \\ \theta_2 \\ \theta_3 \\ \theta_4 \\ \theta_5 \end{bmatrix} d\text{COVID}_t + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \\ \varepsilon_{5t} \end{bmatrix} \quad (5)$$

The application of matrix forms in the VECM provides the advantage of being able to group various economic variables into one interconnected system, rather than analyzing them through a single separate equation model. In the context of the housing market, variables such as house prices, interest rates, income, population, and unemployment rates can dynamically influence each other, so the matrix approach helps to describe these relationships more comprehensively. In addition, the shape of the matrix makes the cointegration structure explicitly visible, which is a key aspect in the use of VECM to explain the long-term relationships between variables. Through the Error Correction Term (ECT) component displayed in the matrix system, the model can also show how each variable readjusts to equilibrium after a shock [54,57].

#### 4. Analysis and Empirical Findings

The performance of the RPPI of Australia over the past two decades is depicted in Figure 1. From the line graph, we can see that the RPPI grew steadily and peaked before the COVID-19 pandemic. This demonstrates that the Australian housing market has a strong price appreciation trend over the long term.



**Figure 1.** Residential price performance index Australia from Q42005 to Q42024 (source: author).

The 2020–2021 period represents a significant phrase in the housing market, which increased sharply to reach its peak. Economically, this condition can indicate changes in market behavior during the COVID-19 pandemic, such as changes in housing preferences, policy stimulus, low interest rates, and increased demand for housing amid changes in work patterns and mobility [12]. Following the pandemic, between 2022 and mid-2024, similar to many other countries, the Reserve Bank increased interest rates numerous times to ease rising inflation rates. This monetary policy raised mortgage borrowing costs, contributing to a decline in housing prices. As interest rates began to stabilize in 2024, housing prices gradually recovered.

Table 1 shows descriptive statistics of the variables included in the model for analysis. Prior to advancing to further analysis, all variables included in the model were standardized by transforming them into logarithmic format to improve comparability and reduce potential heteroscedasticity. The descriptive statistics indicate that all variables have rel-

atively adjacent mean and median values, suggesting that the distribution of the data is fairly balanced and does not show extreme differences between the average and middle values. This is confirmed by the Jarque–Berra test that data matches normal distribution.  $\Delta$ RPPI,  $\Delta$ Pop,  $\Delta$ Income,  $\Delta$ Unem, and  $\Delta$ R reported a mean of 4.661, 9.437, 6.952, 1.636, and 1.183, respectively. With regard to the standard deviation,  $\Delta$ RPPI,  $\Delta$ Pop,  $\Delta$ Income,  $\Delta$ Unem, and  $\Delta$ R reported a value of 0.137, 0.098, 0.156, 0.135, and 0.120, respectively.

**Table 1.** Descriptive statistics.

|                | LnRPPI | LnR    | LnIncome | LnPop | LnUnem |
|----------------|--------|--------|----------|-------|--------|
| Mean           | 4.661  | 1.183  | 6.952    | 9.437 | 1.636  |
| Median         | 4.694  | 1.278  | 6.969    | 9.433 | 1.647  |
| Maximum        | 4.949  | 1.852  | 7.193    | 9.624 | 1.950  |
| Minimum        | 4.402  | −0.117 | 6.607    | 9.258 | 1.364  |
| Std. Dev.      | 0.137  | 0.120  | 0.156    | 0.098 | 0.135  |
| Skewness       | −0.109 | −0.624 | −0.465   | 0.038 | −0.004 |
| Jarque–Bera    | 4.078  | 1.362  | 4.033    | 2.878 | 1.374  |
| JB-probability | 0.130  | 0.510  | 0.133    | 0.237 | 0.503  |

Note: All variables are transformed into log format.

Table 2 exhibits the results of the stationarity tests. It is a critical preliminary step in time series analysis as it determines the order of integration of variables and guides the selection of econometric techniques [58]. If a data series is non-stationary, then the estimated relationship can be unstable [59]. The Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests are both capable of detecting presence of unit roots, but with different correction approaches. The ADF test addresses the autocorrelation problem by adding a lagged difference component to the model, making the test results more reliable when the data has serial correlation [60–62]. Meanwhile, the PP test makes nonparametric adjustments to autocorrelation and heteroscedasticity without having to explicitly determine the lag length [63]. Using both tests together enhances the robustness of the stationarity analysis as the results of the ADF test can be compared with those from the PP test to confirm the consistency of the variables’ order of integration. The results presented in Table 2 suggest that all variables used in this study become stationary after first differencing, indicating that they are integrated of order one,  $I(1)$ , under both the ADF and PP approaches. This consistency confirms that all variables have constant mean and variance properties after first differencing, supporting the validity of the subsequent econometric analysis, namely cointegration analysis and VECM estimation.

**Table 2.** Augmented Dickey–Fuller and Phillips–Perron (PP) unit root test results.

| Variables | ADF Test     |                   | PP Test      |                   |
|-----------|--------------|-------------------|--------------|-------------------|
|           | Level $I(0)$ | First Diff $I(1)$ | Level $I(0)$ | First Diff $I(1)$ |
| LnRPPI    | −2.053       | −6.080 ***        | −2.452       | −4.289 ***        |
| LnR       | −1.317       | −6.649 ***        | −1.193       | −6.649 ***        |
| LnIncome  | −2.999       | −11.318 ***       | −2.910       | −11.291 ***       |
| LnPop     | −2.949       | −9.793 ***        | −2.887       | −11.137 ***       |
| LnUnem    | −2.352       | −6.377 ***        | −2.113       | −6.377 ***        |

Notes: The reported numbers are  $t$ -statistics with  $p$ -values in the brackets. Asterisks (\*\*\*) indicate significant at the 1% level of significance.

The Johansen Cointegration test results are reported in Table 3. This technique has an advantage in multivariate series analysis as it is able to identify more than one cointegration vector simultaneously, making it more suitable than the single-equation approach when it involves multiple variables interacting with each other [64]. Through statistical Trace

tests and maximum eigenvalue tests, this method can determine the cointegration matrix rank that indicates the number of long-term equilibrium relationships among the variables in the model [65]. Moreover, according to [66], this estimation is based on the transformation of the Vector Autoregressive (VAR) model into the Vector Error Correction Model (VECM), so that the long-term relationship and the dynamics of short-term adjustment can be estimated integrally within a single analytical framework. Therefore, the Johansen Cointegration technique is ideally applied prior to the VECM estimation, as it not only verifies the existence of a long-term equilibrium relationship but also provides a solid basis for developing a valid VECM. Furthermore, it enables the model to capture the adjustment dynamics through which variables respond and gradually converge back to equilibrium.

**Table 3.** Johansen Cointegration test results.

| Hypothesized Number of CE(s) | Max-Eigen Statistics | Trace Statistic | Critical Value | Prob  |
|------------------------------|----------------------|-----------------|----------------|-------|
| None *                       | 0.521                | 137.546 ***     | 95.754         | 0.000 |
| At most 1 *                  | 0.424                | 84.611 ***      | 69.819         | 0.002 |
| At most 2                    | 0.286                | 44.880 *        | 47.856         | 0.093 |
| At most 3                    | 0.149                | 20.656          | 29.797         | 0.379 |
| At most 4                    | 0.118                | 9.068           | 15.495         | 0.359 |
| At most 5                    | 0.0001               | 0.009           | 3.841          | 0.923 |
| Maximum Eigenvalue           |                      |                 |                |       |
| None *                       | 0.521                | 52.935 ***      | 40.078         | 0.001 |
| At most 1 *                  | 0.424                | 39.731 ***      | 33.877         | 0.009 |
| At most 2                    | 0.286                | 24.224          | 27.584         | 0.127 |
| At most 3                    | 0.149                | 11.588          | 21.132         | 0.589 |
| At most 4                    | 0.118                | 9.058           | 14.264         | 0.281 |
| At most 5                    | 0.0001               | 0.009           | 3.841          | 0.923 |

Notes: Both the Max-Eigen test and Trace test indicate two cointegrating equations at the 1% level. The asterisks (\*\*\*) and (\*) denote rejection of the null hypothesis at the 1%, and 10% significance level, respectively.

The results suggest that the null hypothesis of no cointegration for  $r = 0$  and  $r = 1$  are rejected by both the Trace and Max-Eigen tests. Therefore, there are at least two significant cointegrating relationships in the system. This also confirms the existence of long-run relationships between RPPI and independent variables including interest rates, income, population, unemployment rate, and COVID-19. After verifying the presence of cointegrating relationships in the model, this study continues to investigate the interaction among the variables in the model using VECM. Table 4 reports empirical results of the VECM analysis performed in this study.

**Table 4.** VECM results for the model.

| Variables | Coefficients | t-Statistics |
|-----------|--------------|--------------|
| Constant  | 29.025       |              |
| LnRPPI    | 1.000        |              |
| LnR       | −0.109       | −1.758       |
| LnIncome  | 2.886 ***    | 3.210        |
| LnPop     | −5.423 ***   | −3.852       |
| LnUnem    | −1.476 ***   | −6.149       |
| dCOVID    | −0.376 ***   | −3.375       |

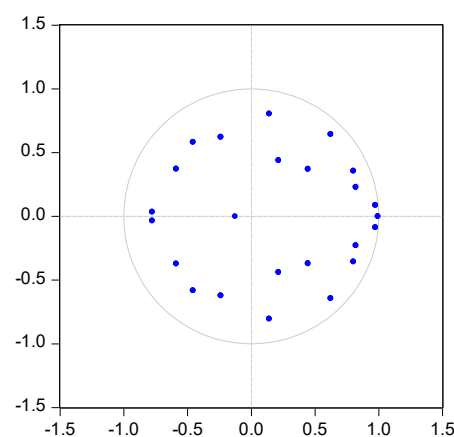
Note: Asterisks (\*\*\*) indicate significant at the 1% level of significance.

In a nutshell, the long-term equations in the VECM can be written as:

$$LnRPPI = 29.025 - 0.109LnR + 2.886LnIncome - 5.423LnPop - 1.476LnUnem - 0.376dCOVID$$

The income variable had a positive and significant effect on the RPPI with a coefficient of 2.886. This means that in the long run, the increase in household disposable income is likely to increase housing prices. These results are in line with the theory that higher household incomes will increase purchasing power, ability to pay mortgages, and demand for housing. The interest rate variable ( $R$ ) has a negative coefficient of  $-0.109$ , which means that rising interest rates tend to lower housing prices in the long run. However, a  $t$ -statistical value of  $-1.758$  suggests that the effect is not significant. The population variable ( $pop$ ) has a negative and significant coefficient of  $-5.423$ . These findings suggest that after controlling for other determinants, population growth is negatively associated with housing prices in the long run. The negative coefficient does not necessarily imply that population growth directly reduces housing prices; rather, it may reflect the influence of underlying factors such as declining housing affordability, supply pressure, and changes in population composition (demographic shifts or migration patterns). For example, as housing becomes less affordable, more individuals may choose to delay home purchases and immigrants may choose to share rental accommodation, thereby reducing the effective housing demand for homes [67,68]. The unemployment rate ( $unem$ ) exhibits a significant negative long-term relationship with the RPPI, with a coefficient of  $-1.476$ . This result aligns with the housing market theory, as higher unemployment weakens household incomes, lowers the ability to pay mortgage installments, increases economic uncertainty, and reduces demand for housing. The COVID-19 dummy variable presents a negative and significant effect with a coefficient of  $-0.376$ . This suggests that the COVID-19 pandemic period is putting downward pressure on the RPPI in the long run. This finding supports the view that the COVID-19 pandemic represents an external shock to the housing market, affecting price dynamics and changes in household decision-making regarding housing demand.

Following the selection of a lag order of four based on the Akaike Information Criterion, the dynamic stability of the estimated system is verified through the inverse roots of the AR characteristic polynomial (see Figure 2).



**Figure 2.** Inverse roots of AR characteristic polynomial (source: authors).

As reported in Figure 2, all twenty-four roots of the companion matrix lie strictly within the unit circle, with the largest modulus equal to 0.9928 and the smallest equal to 0.1265, confirming that no root exceeds unity and that the system satisfies the stability condition. The presence of a dominant root close to, but below, one (0.9928) is consistent with the highly persistent, cointegrated  $I(1)$  behavior of the underlying series rather than explosive dynamics, and it corroborates the cointegration structure imposed in the VECM. The satisfaction of the stability condition ensures that the impulse responses converge and that the estimated short-run adjustment parameters, including the error-correction

term, are well defined, thereby validating the adequacy of the selected lag structure for subsequent inference.

The results of the short-term VECM estimate are presented in Table 5. Empirical findings show that the change in the RPPI is influenced by several variables in the short term, particularly by the dynamics of the previous period RPPI, interest rates, population, COVID-19 dummy, and adjustment components (ECT). The  $\Delta RPPI_{t-1}$  coefficient has a positive and significant value of 0.545, which indicates the persistence effect of housing prices in the short term, suggesting that the increase in RPPI in the previous period tends to encourage an increase in RPPI in the current period. However,  $\Delta RPPI_{t-3}$  has a negative and significant value of  $-0.538$ , which indicates a correction or reversal effect after several periods. In other words, housing price increases are not necessarily persistent overtime; rather, they may undergo a readjustment after a few lags. The interest rate variable at the first lag ( $\Delta R_{t-1}$ ) had a negative and significant effect on the RPPI with a coefficient of  $-0.038$ . This shows that interest rate hikes in the short term tend to depress housing prices. Economically, these results are consistent with the housing market theory as rising interest rates increase mortgage costs, lower the ability to buy homes, and consequently, weaken housing demand. However, the effect of interest rates from the second to fourth lag are insignificant, implying that the impact of interest rate changes is concentrated in the initial period with the impact weakening as the housing market gradually adjusts towards equilibrium. The response pattern of housing prices to interest rate changes also explains why the Reserve Bank typically adjusts interest rates through a series of incremental changes.

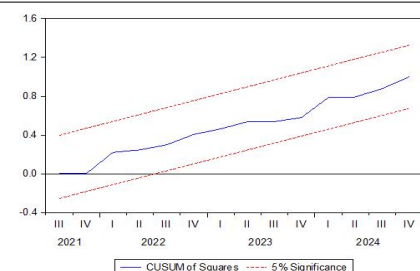
The income variable does not have a significant effect on the RPPI in the short run, implying that changes in household income level do not immediately translate into changes in housing prices. The impact of income on the housing market is likely to be more visible in the long term because the decision to buy a home takes time, financial planning, and the financing process. Meanwhile, the population variable at the second lag ( $\Delta pop_{t-2}$ ) had a positive and significant effect of 0.977, suggesting that the increase in population may drive housing demand after a certain time gap. The unemployment variable does not have a strong short-term influence on the RPPI; this suggests that the effect of labor market conditions may occur with a delay. On the other hand, the COVID-19 dummy at the first lag is negative and statistically significant at  $-0.042$  at the 5% level, indicating that the pandemic shocks are putting negative pressure on housing prices in the short run. This result indicates that the COVID-19 pandemic created immediate disruption, associated with increased uncertainty, restrictions on economic activity, and changes in housing market behavior. The  $ECT(-1)$  coefficient is negative and significant at  $-0.078$ , which means that there is an adjustment mechanism towards long-term equilibrium, whereby about 7.8% of deviation from the long-term equilibrium is corrected in each period.

To improve robustness of the analysis, an Impulse Response Function (IRF) measures from the VECM is illustrated in Figure 3. It shows how each variable responds to the shock of one standard deviation from the other in the next several periods. For RPPIs, the shock to the RPPI itself produces a positive response in the initial period, then weakens and moves back towards the equilibrium point. This is in line with the results of short-term estimates which showed a significant influence of  $\Delta RPPI_{t-1}$  and  $\Delta RPPI_{t-3}$ , suggesting the presence of price persistence in the housing market. This reflects the gradual adjustment process of the housing price dynamics whereby market expectations and supply rigidities take time to realign. However, this effect does not last indefinitely as the error correction mechanism facilitates gradual adjustment towards the long-run equilibrium [69]. In addition, according to [70], housing prices return to their fundamental value over a longer period of time, often through a fault correction mechanism or a market adjustment mechanism.

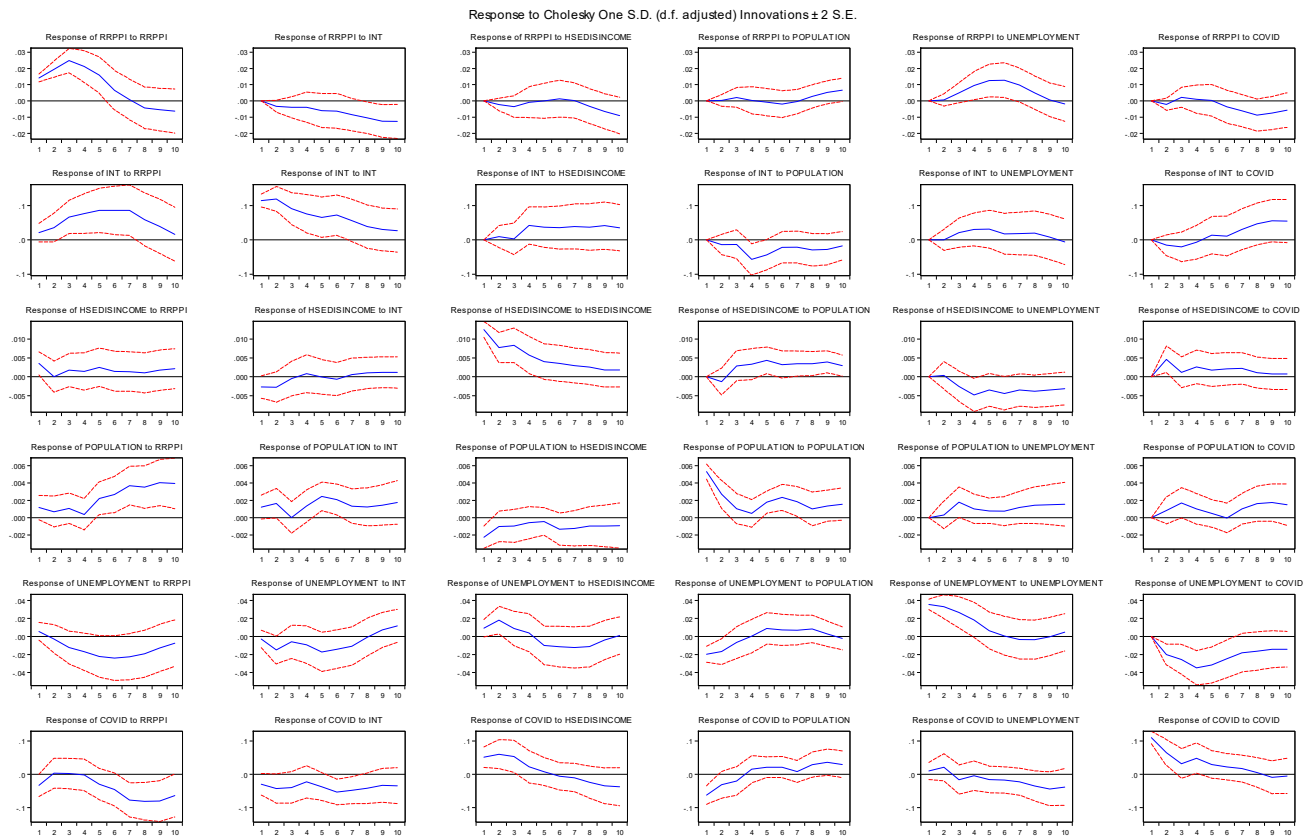
**Table 5.** Estimate of error correction model results.

| Variable                        | Coefficient             | <i>t</i> -Statistics |
|---------------------------------|-------------------------|----------------------|
| $\Delta \text{LnRPPI}_{t-1}$    | 0.545 ***               | 3.435                |
| $\Delta \text{LnRPPI}_{t-2}$    | 0.296                   | 1.667                |
| $\Delta \text{LnRPPI}_{t-3}$    | −0.538 ***              | −3.476               |
| $\Delta \text{LnRPPI}_{t-4}$    | 0.109                   | 0.721                |
| $\Delta \text{LnR}_{t-1}$       | −0.038 **               | −2.291               |
| $\Delta \text{LnR}_{t-2}$       | 0.008                   | 0.467                |
| $\Delta \text{LnR}_{t-3}$       | 0.015                   | 0.899                |
| $\Delta \text{LnR}_{t-4}$       | −0.009                  | −0.467               |
| $\Delta \text{LnIncome}_{t-1}$  | −0.033                  | −0.184               |
| $\Delta \text{LnIncome}_{t-2}$  | −0.076                  | −0.444               |
| $\Delta \text{LnIncome}_{t-3}$  | 0.113                   | 0.704                |
| $\Delta \text{LnIncome}_{t-4}$  | 0.076                   | 0.528                |
| $\Delta \text{LnPop}_{t-1}$     | −0.379                  | −0.885               |
| $\Delta \text{LnPop}_{t-2}$     | 0.977 **                | 2.266                |
| $\Delta \text{LnPop}_{t-3}$     | −0.060                  | −0.141               |
| $\Delta \text{LnPop}_{t-4}$     | 0.119                   | 0.303                |
| $\Delta \text{LnUnem}_{t-1}$    | −0.034                  | −0.643               |
| $\Delta \text{LnUnem}_{t-2}$    | 0.045                   | 0.840                |
| $\Delta \text{LnUnem}_{t-3}$    | −0.016                  | −0.285               |
| $\Delta \text{LnUnem}_{t-4}$    | 0.064                   | −1.244               |
| $\Delta \text{dCOVID-19}_{t-1}$ | 0.042 **                | −2.118               |
| $\Delta \text{dCOVID-19}_{t-2}$ | 0.031                   | 1.435                |
| $\Delta \text{dCOVID-19}_{t-3}$ | −0.014                  | −0.661               |
| $\Delta \text{dCOVID-19}_{t-4}$ | 0.001                   | 0.032                |
| ECT(−1)                         | −0.078 **               | −2.702               |
| Adj R-squared                   | 0.639                   |                      |
| F-Stat                          | 6.025 ***               |                      |
| S.E. equation                   | 0.014                   |                      |
| Serial correlation LM test      | $p > 0.05$ (lag 1 to 5) |                      |
| Heteroskedasticity test         | 1052.483, $p = 0.4726$  |                      |
| Normality test (Jarque–Bera)    | 3.7083, $p = 0.156585$  |                      |

Stability test



Note: Asterisks (\*\*\*) and (\*\*) indicate significant at the 1% and 5% level of significance, respectively.



**Figure 3.** Impulse Response Function (IRF) of VECM (source: authors).

The RPPI's response to interest rate shocks tends to be negative, especially after the initial period, this suggests that rising interest rates increase the cost of mortgage financing [71], lowering the affordability of homes [72], and weakening housing demand [73]. In the long run, the interest rate coefficient is also negative despite its weaker significance. Hence, the IRF result reinforces the argument that interest rates are one of the important transmission channels in the Australian housing market. Given that the effects of interest rate changes are observed in the short run, policymakers should adopt gradual rate adjustment to achieve the desired monetary policy outcomes while allowing time for market responses to materialize. The RPPI's response to the household income shock does not appear to be strong in the short term, which is consistent with the short-term VECM estimates. However, in the long-term estimation, income presents a positive and statistically significant effect on the RPPI. These contrasting results imply that changes in household income take time to translate into the housing price dynamics. White (2015) [74] contends that household income is the main driver of housing demand and house prices, but the response depends on credit conditions and market liquidity. Moreover, while income shocks can shift demand, adjustment costs and barriers in lending can slow down household responses [75].

The response of RPPI to population change emerges after several periods in the IRF analysis. This is in accordance with short-term results, where  $\Delta \text{pop}_{t-2}$  has a positive and significant effect on RPPI. It shows that population growth has a positive effect on RPPI in the short run, but this initial demand effect may be reversed due to other structural factors such as sharing accommodations, delays in home purchases, and changes in population distribution (for example, government policies that encourage immigrants to settle in regional areas can ease pressure on housing demand and thus moderate housing prices in major cities) [76,77]. The impulse response of the RPPI to changes in unemployment implies a limited short-run effect, consistent with the short-run estimation. Nevertheless, the long-run

estimates reveal a significant negative relationship that indicates that unemployment does not generate an immediate adjustment in housing prices but can weaken housing demand and exert downward pressure on prices in the long run. Structural unemployment has more substantial long-term effects as it reduces income security, increases credit risk, and reduces market confidence in purchasing a house. Sarmiento (2012) [78] posits that higher unemployment rates increase the risk of mortgage installment default and foreclosure. Furthermore, job losses can have a substantial impact not only on default risk but also on housing prices [79].

Meanwhile, IRF results on the RPPI response to the COVID-19 pandemic shock was consistent with the results of both the short-term (where  $\Delta \text{COVID-19}_{t-1}$  is negative and significant) and long-term estimations. This indicates that the COVID-19 pandemic emerged as an external shock, placing downward pressure on the housing market through escalated economic uncertainty, mobility restrictions, changes in market behavior, and disruptions to housing transaction activities (such as auctions). The relationship between IRF and VECM estimation can be seen in a negative and significant  $\text{ECT}(-1)$  value of  $-0.078$ . Essentially, the IRF portrays that shocks to the RPPI due to changes in macroeconomic variables are not permanent but are gradually absorbed by the system, allowing the housing market to converge towards its long-term equilibrium.

## 5. Conclusions

The objectives of this study were to examine the performance trends of the Australian housing market and identify key economic factors influencing it over the past two decades. The presence of structural shifts in an asset market due to changing economic conditions highlights the importance of analyzing both short-run adjustments and long-run equilibrium relationships. However, limited recent studies have examined these evolving relationships within the Australian housing market context. To address this gap, this study employed the cointegration approach and the Vector Error Correction Model (VECM) to investigate these relationships. The results indicate that Australia housing prices were on an upward trajectory during the study period. Empirical results indicated that at least two significant cointegrating relationships exist in the model. Furthermore, VECM results indicated that household income, population growth, unemployment rate, and the COVID-19 pandemic influence RPPI dynamics. Meanwhile, the results of the short-term VECM estimate show that the change in the RPPI is influenced by several variables in the short term, particularly by the dynamics of the previous period RPPI, interest rate changes, population growth, COVID-19 dummy, and adjustment components (ECT) with effects varying across different lag periods. This empirical finding provides important implications for policy development and implementation. For example, since the effects of interest rates changes are observed in the short run, it remains an effective tool for short-term market intervention. To achieve a more sustained effects, policymakers should adopt gradual rate adjustment over a period of time to achieve the desired monetary policy outcomes. In addition, the presence of price persistence suggests that the housing market adjusts gradually, requiring buyers to include this in decision-making and policymakers to take this into consideration before introducing policy intervention. In addition, results also reported that the economic variables included in the model were able to explain 63.9% of the variations in the Australian housing market dynamics. On the other hand, the long-run estimates reported that variables including population growth, the COVID-19 pandemic, household income, and unemployment rate are found to have a significant impact on RPPI at the 5% significance level. The finding of the error correction model suggests a gradual adjustment of short-term deviation with  $\text{ECT}_{t-1} = -0.078$  towards the long-term equilibrium quarterly. To further validate the robustness of the results, an Impulse Response Function

(IRF) analysis was performed. The IRF results confirm the validity of the VECM findings, demonstrating that the dynamic responses of housing prices to economic shocks align with the short-run and long-run estimations.

## 6. Limitations

While this study contributes to the theoretical and empirical understanding of housing market dynamics, it has several limitations that can serve as potential area for future research. Firstly, even though Transit-Oriented Development (TOD) has an influence on the housing market, this study did not focus on this area as it does not represent a nationally applicable determinant of housing prices. In geographically large countries like Australia, given that TOD is primarily an urban development strategy which is largely absent in regional and remote areas (which nevertheless contribute substantially to the national housing price performance), including TOD would potentially introduce geographic bias and reduce the generalizability of the model. Furthermore, previous studies provided inconsistent findings regarding the impact of TOD on housing values. Even though improving accessibility may increase demand and prices, negative externalities such as traffic congestion, noise, and overcrowding due to TOD may offset this benefit. Nonetheless, future research can include TOD in urban area studies, especially in city-level studies in Australia where its impacts is more pronounced.

Secondly, while machine learning approaches are increasingly used in housing market research, the selection of methodology relies heavily on research objectives and the desired level of interpretability. As the primary objective of this study is to explain the relationship between variables and test economic theories, rather than optimize predictive accuracy, traditional econometric methods are more suitable. Furthermore, these methods offer strong interpretability with estimated coefficients, allowing researchers to examine the direction, magnitude, and statistical significance of individual factors influencing housing market dynamics. In comparison, many machine learning methods are often perceived as “black box” models due to their limited ability in explaining the underlying mechanisms driving predictions. Moreover, traditional econometric models are superior in explaining mechanisms and evaluating policy implications. Nonetheless, for future studies adopting a data-driven approach with a primary focus on providing strong forecasting and identifying predictive patterns, machine learning approaches would be a suitable option.

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