PACIFIC RIM PROPERTY RESEARCH JOURNAL
2024, VOL.29, No.3, 28 – 48

Dynamic relationship between investor attention and house prices: Evidence from Australian housing market

Thi Tuyet Anh Nguyen, Garrick Small, Lan Sun and Steven Boyd

School of Business and Law, Central Queensland University, Queensland, Australia

ABSTRACT

This paper examines the interrelationships between investor attention and house prices. We find that investor attention significantly influences house prices in both short term and long term. Conversely, significant changes in house prices heighten investor attention, leading to increased market activity. This reciprocal relationship between investor attention and house prices is confirmed through VAR model analysis. Granger causality tests, variance decomposition and impulse response functions were also used to investigate the dynamic of the variables in the empirical model. Our findings have several implications for policymakers, real estate investors, and market analysts. Policymakers should focus on managing short-term volatility in house prices to stabilise investor behaviour, while investors should avoid overreacting to short-term price movements. The study findings suggest that incorporating behavioural factors into economic models can enhance our understanding and improve the prediction of housing market trends.
Keywords: House price; Investor attention; Australia; VAR; Granger causality.

INTRODUCTION

Investor attention refers to the focus and interest that investors dedicate to specific information, events, or trends related to companies, investments, or markets (Gu, 2024, Chen et al., 2024). Empirical studies have shown that investor attention varies over time, significantly influencing asset prices. This variability provides valuable insights into financial market dynamics (Andrei and Hasler, 2015, Chen et al., 2022, Andrei et al., 2023). High levels of investor attention often result in upward buying pressures and responsive price reactions (Barber and Odean, 2008, Dash and Maitra, 2022). In contrary, investors are inclined to underreact to news and announcements when investor attention levels are low (DellaVigna and Pollet, 2009, Ben-Rephael et al., 2017). Previous research by Huberman and Regev (2001) and Hou et al. (2009) signify that when investors actively direct their attention towards new information, asset prices will respond accordingly.

The housing market and house prices are intertwined with broader economic activities, making them an important component of the overall economic landscape (Anari and Kolari, 2002, Bajari et al., 2005). Housing not only serves as a critical indicator of a nation's economic health but is also fundamental to maintaining financial stability and fostering economic growth (Miller et al., 2011). Like other assets, when studying house price, analysts need to pay attention to both supply and demand sides (Chow and Niu, 2015, Glaeser et al., 2005). The supply of housing depends on land availability, which is relatively fixed in the short term, while house prices are driven by demand from both investment purposes and speculation, along with the fundamental need for accommodation. As the short-term housing supply is largely inelastic, fluctuations in demand will directly impact prices. Understanding how investor attention impacts house prices is therefore critical, as housing plays a central role in economic stability and growth.

However, there is limited exploration of the reciprocal relationship between house prices and investor attention. While investor attention can influence house prices, fluctuations in house prices can also affect the levels of investor attention. When house prices rise rapidly, media coverage and public interest in the housing market typically increase. This heightened attention can attract more investors, both experienced and novice, drawn by the potential for high returns. Consequently, periods of significant price appreciation often see a surge in market participation and speculative activities (Case and Shiller, 2003). Conversely, when house prices fall, investor attention can increase as stakeholders seek to understand the causes of the decline and identify potential buying opportunities at lower costs. This phenomenon highlights that investor attention is not only a driver but also a response to housing market dynamics. Additionally, sharp increases in house prices may signal a booming market, prompting more investment and media coverage. On the other hand, significant declines can trigger panic, leading investors to pay closer attention to market signals and economic indicators. This bidirectional relationship underscores the need to consider both how investor behaviour influences house prices and how house price movements, in turn, affect investor behaviour.

This study aims to fill this gap by exploring the interrelationship between investor attention and house prices in the Australian context. Given the distinct characteristics of the Australian housing market, including high house prices and their significant impact on household wealth, it offers a unique case for examining the interplay between investor behaviour and asset prices. The findings of this research will contribute to a deeper understanding of the role of investor attention in housing price dynamics and provide valuable insights for policymakers and market participants.

Furthermore, a limited number of studies have examined the relationship between house prices and investor attention in certain countries, with a particular focus on China. However, there remains a considerable gap in understanding these dynamics within the Australian context, despite its critical relevance to policymakers. The Australian housing market is a particularly valuable case study due to its notable trends over recent decades. Australians aspire to own homes, viewing them not only as a means of shelter but also as a key pathway to wealth accumulation. According to the Australian Bureau of Statistics (2022), housing accounts for over 55% of household wealth, underscoring its central role in financial stability and economic health. Moreover, the Australian housing market faces significant affordability challenges, exacerbated by rising house prices and declining homeownership rates (Cho et al.,

2021). These challenges have driven researchers to investigate the implications of housing affordability on social equity and economic mobility, highlighting its importance for policy interventions (Burke and Hulse, 2010). In summary, the Australian housing market serves as an ideal case for analysis due to its multifaceted nature, affordability pressures, market volatility, and broader economic implications. These factors make it a compelling context for exploring the dynamic relationship between investor attention and house prices.
This paper is one of the first empirical studies to explore the linkage between the housing market and investor attention. Our findings reveal a significant interdependence between investor attention and house prices, contributing to both the finance and behavioural finance literature. Our research highlights the role of investor attention in influencing house prices and demonstrates how these behavioural aspects can lead to price deviations and increased market volatility. This study underscores the importance of integrating behavioural factors into housing price models to improve predictive accuracy and market stability.

The paper is structured as follows: Section 2 reviews relevant literature, Section 3 describes data and methodology, Section 4 presents results and discussion, and Section 5 concludes with policy recommendations.

RELATED LITERATURE

Our paper contributes to two main branches of the literature. First, the paper adds to the limited empirical research on house prices and investor attention in the finance literature. The majority of past studies focusing on housing markets explore relationships between house prices and fundamental economic indicators, such as GDP (Snieska and Burkšaitienė, 2018, Xu, 2017), unemployment rate (Liu et al., 2016), economic growth (Irandoust, 2019, Aizenman et al., 2019), inflation (Inglesi-Lotz and Gupta, 2013) and interest rates (McQuinn and O'Reilly, 2008). Meanwhile, research on the interplay between house prices and investor attention has only recently emerged. Although primary economic variables have been extensively implemented in many price forecasting models, these models still exhibit limitations in their predictive capabilities. According to Shiller (2007), psychological factors play a remarkable role in causing fluctuations in the housing market where house prices deviated from fundamental values. The biases in these models arise because people's decisions are often irrational and led by emotions rather than prudent considerations (Shiller, 2014). Put differently, real estate fundamentals alone cannot explain changes in house prices entirely; irrational factors also influence prices. However, many previous studies on the property market make the assumption that buyers and investors are rational, neglecting the importance of psychological factors such as preferences, sentiment, and attitudes (Jin et al., 2014). Hence, this paper highlights the need to incorporate psychological factors, particularly investor attention, into housing price models to improve their accuracy and explanatory power.

Second, our paper contributes to the field of behavioural finance by investigating the impact of investor attention on housing prices. Previous studies have documented the substantial effects of investor attention in various markets, including stocks, oil, commodities, and foreign currencies. Research in behavioural finance indicates that 'investor attention' can lead asset prices to fluctuate from their fundamental values, resulting in increased volatility (Andrei and Hasler, 2015, Andrei et al., 2023, Chen et al., 2022, Vozlyublennaia, 2014). Despite its proven effect on other financial sectors, the role of investor attention in the housing market is still relatively underexplored. Traditional asset pricing models assume that investors consistently and accurately assess asset values (Da et al., 2011), with new information being immediately incorporated into prices. However, attention is a 'scarce cognitive resource' (Kahneman, 1973), and investors may have limited attention. Recent research suggests theoretical models in which investors' limited attention affects both the static and dynamic aspects of asset prices, highlighting the contrast between the enormous amount of financial information available and the limited cognitive resources of investors (Cao et al., 2021). Thus, this study underscores the significance of recognising investor attention as a key factor in housing market analysis, providing a more comprehensive insight into understanding of price dynamics and market behaviour.

In addition, our paper deepens the understanding of the Efficient Market Hypothesis (EMH) in the context of housing market. Market efficiency is a concept in financial economics that refers to the degree to which asset prices reflect all available information. In a highly efficient market, such as stock market, stock prices incorporate and quickly reflect all relevant information (Fama, 1970). However, compared to the securities market, the understanding of real estate market efficiency is limited (Gatzlaff and Tirtiroğlu, 1995). Fewer studies have examined the efficiency of the housing market compared to the extensive research on the stock market (Keogh and D'Arcy, 1999, Locke, 1986). By measuring investor attention through Google search volume, our study provides a deeper understanding of EMH in the context of house prices. While EMH suggests that asset prices reflect all available information, this paper explores whether short-term irrational behaviour, influenced by limited investor attention, causes house prices to deviate from their fundamental values, only to revert to equilibrium in the long term.

In these literatures, the linkage between investor attention and house prices has not been directly modelled. Analysing the role of investor attention in housing markets is important for several reasons. First, understanding this relationship can help improve the predictive accuracy of housing price models by incorporating behavioural factors that influence market dynamics. Second, it can provide insights into the mechanisms through which psychological factors impact market outcomes, offering a more comprehensive view of market behaviour beyond traditional economic indicators. Third, it can contribute to theory by integrating behavioural finance principles with real estate economics, thereby bridging a gap between these two fields. This integration can lead to the development of more robust theoretical models that account for the cognitive limitations of investors. Finally, this research proposes one of the earliest frameworks that connects two important areas: investor attention and housing market, within the context of Australia in the digital age.

RESEARCH METHOD

Methodology

To identify the connectedness between investor attention and house prices, our empirical models consist of two main variables: investor attention and house price indexes. Following

Petkova (2006), we control for house prices along with several primary economic variables to control for general market conditions, such as GDP, CPI, and interest rates. Prior to estimation, we perform stationarity tests on the data to avoid spurious results that can occur with non-stationary variables. If the data is non-stationary, we difference the levels and conduct stationarity tests again to confirm the data's stationarity. The Johansen and Juselius (1990) JJ cointegration test is applied to determine whether to use models such as Vector Error Correction Model (VECM), Vector Autoregression (VAR), or Autoregressive Distributed Lag (ARDL). Since our main variables are non-stationary and not cointegrated, we consider the VAR model to analyse the two variables. The VAR model, widely used in finance literature (e.g., Fiordelisi and Molyneux (2010)), allows us to test time-ordered relationships and addresses potential endogeneity issues. We determine the lag order based on criteria such as the Final Prediction Error (FPE), Akaike Information Criterion (AIC), Hannan-Quinn Information Criterion (HQ), and Schwarz Information Criterion (SC). The equations are as follows:

$$HousePrice_t = f(InvestorAttention_{t-k}, Z_t) + \varepsilon_t \quad (2)$$
$$InvestorAttention_t = f(HousePrice_{t-k}, Z_t) + \varepsilon_t \quad (3)$$

Where:

- $HousePrice_t$ is the house price index at time t.
- $HousePrice_{t-k}$ is the house price index at time $t-k$. The subscript $t-k$ indicates that house prices from a previous time period (lagged by k periods) are being used to explain investor attention at the current time t. This lag can capture the idea that changes in house prices take some time to affect investor attention.
- $InvestorAttention_t$ is the level of investor attention at time t.
- $InvestorAttention_{t-k}$ is the level of investor attention at time $t-k$. The subscript $t-k$ indicates that investor attention from a previous time period (lagged by k periods) is being used to explain house prices at the current time t. This lag captures the idea that changes in investor attention take some time to influence house prices.
- Z_t is a set of control variables including GDP, CPI and Interest rate at time t.

To study the relationship between house prices and investor attention, we perform pairwise Granger-causality tests Granger (1969). While Granger Causality tests indicate statistical causality, they do not specify the exact nature of the relationship. Furthermore, VAR models are often difficult to interpret. They suffer from interpretational challenges due to the interdependencies between the variables, which makes it hard to discern causal directions or understand the magnitude and time lags of effects. To address this, we construct impulse response functions and variance decompositions. The impulse response functions trace the response of variables to shocks in one or more variables, showing how house prices and investor attention react to sudden changes over time. Variance decomposition quantifies the proportion of forecast error variance attributable to shocks in other variables, providing insights into the dynamics of the system. These methods help us understand the magnitude and speed of the impact of shocks, thereby offering a comprehensive analysis of the interdependence between investor attention and house prices.

Data
House Price Index data was sourced from the FRED database, specifically the series ID 'QAUR628BIS' (Bank for International Settlements, 2024). This extensive dataset covers nominal residential property prices and includes over 300 data points from approximately 60 countries. The data is compiled by various public and private organisations, including national statistical offices, central banks, ministries, real estate associations, mortgage banks, and commercial data providers. The dataset exhibits significant variation across countries, particularly regarding the frequency of data collection. For the purposes of our study, the data for Australia is provided on a quarterly basis.

To measure investor attention related to the housing market, we utilise the Google Search Volume Index (GSVI). We chose this Google Trends index due to its widespread use in the behavioural finance literature as a proxy for measuring investor attention (Goddard et al., 2015, Da et al., 2011, Drake et al., 2012). Our dataset spans from 2004 to 2023. The selection of keywords is primarily based on studies by Nguyen et al. (2024) and several previous studies. In a study of Pham and Huynh (2020) focusing on green bonds, the authors utilised the Google Search Volume Index for the main keyword *'green bond'* to measure investor attention. For real estate, Beracha and Wintoki (2013) explored the predictive value of online search intensity using main keywords like *'real estate'* or *'rent'* in forecasting home prices. They argued that search intensity for above real estate terms within a specific city serves as a proxy for buyer sentiment for that city. In Europe, McLaren and Shanbhogue (2011) conducted research on UK house prices using country-level monthly data. They incorporated Google search data for the keyword *'estate agents'* into their autoregressive (AR) models. In a study related to Google search data and house prices, Wu and Brynjolfsson (2015) collected Internet search query volumes related to real estate from Google Trends. It allows users to obtain a query index pertaining to a specific phrase such as *'housing price'*. To capture online interests in purchasing real estate, the authors use the search index for a predefined category in Google Trends - 'Real Estate' - that contains all queries pertaining to real estate. Adopting these methods, we have incorporated three keywords: '*House price*', '*Property price*' and '*Real estate price*' to capture investor attention in the housing market. The keywords were reviewed by three experts, and their triangulation process ensured agreement on the final selection of keywords and search parameters. Furthermore, to better capture investor attention in property, we have taken further steps to refine them within the predefined 'Real Estate' category in Google Trends. This approach ensures a focus on property-related searches, based on the location, specifically Australia, with data spanning from January 2004 to December 2023. While we acknowledge the potential presence of noise in the data due to the limitations of online searches, we have made diligent efforts to minimise it to the best of our knowledge.

To synchronise the frequency of our datasets, the monthly Investor Attention data was converted to quarterly intervals. By doing this, our final dataset comprises both Investor Attention and House Price Index data on a quarterly basis, covering the period from Q1 2004 to Q4 2023.

Control variables, such as the inflation rate (CPI), are collected from the FRED database, specifically the series 'CPALTT01AUQ657N' (Organization for Economic Co-operation and

Development, 2024), which represents the percentage change from the previous period. The data on Australian GDP growth rate (GDP) are collected from the Australian Bureau of Statistics (The Australian Bureau of Statistics, 2024). The interest rate (IR) used in the main analysis is the cash rate, which is set by the Reserve Bank of Australia (The Reserve Bank of Australia, 2024). This rate is a primary monetary policy tool that reflects short-term borrowing costs in the economy.

RESULTS AND DISCUSSIONS

Descriptive Statistics

Table 1 presents some statistical figures of the data series used in this study. Each variable consists of 80 observations. The House Price Index (HPI) has an average of 104.795 with a standard deviation of 16.908, indicating moderate fluctuations. The minimum and maximum HPI values are 80.425 and 141.875, respectively, showing significant variation over the period. The Investor Attention (IA) variable, derived from the rescaling of Google Search Volume data to a range between 0 and 1, has an average value of 0.475 with a standard deviation of 0.256. The GDP (GDP growth rate) has a mean of 0.649% and a substantial standard deviation of 1.149%, indicating significant economic variability. The GDP growth rate ranges from -6.9% to 3.9%. The CPI averages 0.676% with a standard deviation of 0.572%, with values ranging from -1.887% to 2.143%. The Interest Rate (IR) has a mean of 3.220% and a standard deviation of 2.022%, showing moderate variability. The minimum IR is 0.100%, and the maximum is 7.250%, reflecting a broad spectrum of interest rates. Skewness values indicate that HPI, IA and IR are slightly positively skewed, and GDP and CPI are negatively skewed. Kurtosis values show that HPI, IA, IR and CPI have flatter distributions with fewer extreme values, while GDP has a sharp peak, indicating more extreme values.

Table 1: Summary statistics

Statistic	HPI	IA	GDP (%)	CPI (%)	IR (%)
Size	80	80	80	80	80
Mean	104.795	0.475	0.649	0.676	3.220
SD	16.908	0.256	1.149	0.572	2.022
Skewness	0.345	0.171	-2.955	-0.582	0.175
Kurtosis	-0.965	-1.025	22.581	3.950	-1.099
Min	80.425	0	-6.9	-1.887	0.1
Max	141.875	1	3.9	2.143	7.25

Stationarity Tests

The results from the stationarity tests (**Table 2**), including the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and KPSS tests, provide insights into the stationarity properties of the variables. Although CPI exhibits stationary properties without differencing, it was also differenced to maintain consistency in data transformation and ensure robust statistical properties. Differencing all variables, including control variables is essential for reliable time series analysis. Since these control variables are not of primary interest but rather serve to account for broader economic influences, differencing does not affect the interpretation of the main findings. This approach enables the analysis to focus on the relationship between investor attention and house prices while adequately controlling for economic conditions. **Figure 1** shows the plots of the differenced level data of the time series.

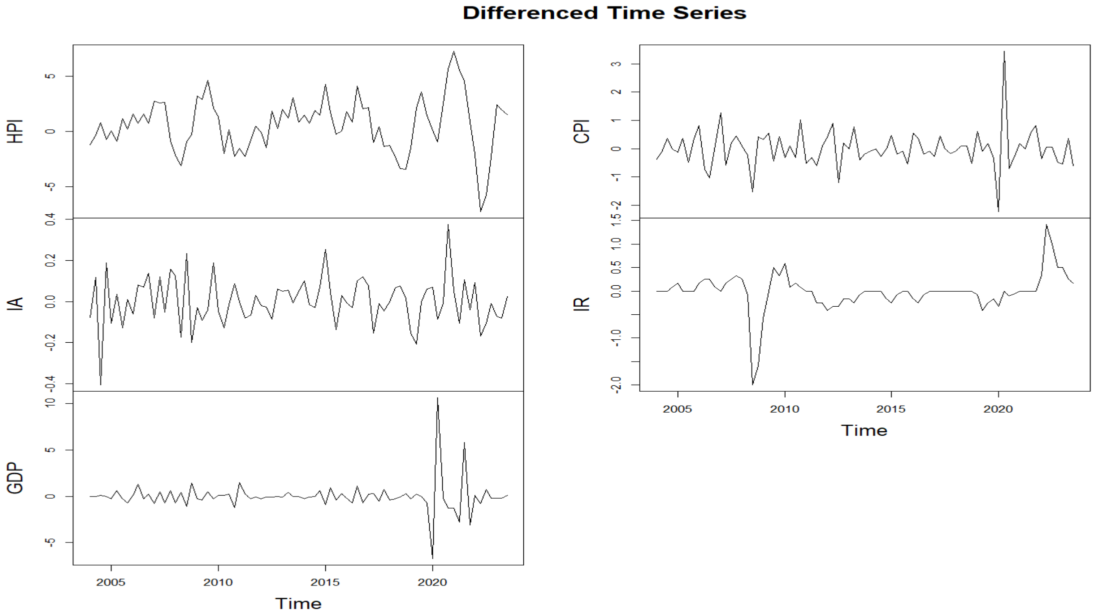

Figure 1: Plots of differenced level data for time series variables

Table 2: Stationary test

Null hypothesis: the variables are non-stationary in the tested form				
	Levels	**Results**	**First differences**	**Results**
Panel A: Augmented Dickey-Fuller (ADF) test				
HPI	-4.4987*	Stationary	-6.7056*	Stationary
IA	-3.2352	Non-stationary	-6.2047*	Stationary
GDP	-7.2983*	Stationary	-9.5943*	Stationary
CPI	-3.9383*	Stationary	-8.5248*	Stationary
IR	-1.65	Non-stationary	-4.4668*	Stationary
Panel B: Phillip-Perron (PP) test				
HPI	-17.093	Non-stationary	-30.781*	Stationary
IA	-20.396*	Stationary	-89.253*	Stationary
GDP	-74.256*	Stationary	-93.272*	Stationary
CPI	-55.86*	Stationary	-87.182*	Stationary
IR	-5.475	Non-stationary	-29.159*	Stationary
Null hypothesis: the variables are stationary in the tested form				
Panel C: KPSS (Kwiatkowski-Phillips-Schmidt-Shin) test				
HPI	1.9001*	Non-stationary	0.036145	Stationary
IA	1.4323*	Non-stationary	0.070155	Stationary
GDP	0.0657	Non-stationary	0.026411	Stationary
CPI	0.20672	Stationary	0.032438	Stationary
IR	1.5811*	Non-stationary	0.18948	Stationary

*Significance level: 0.05. Note: *p<0.05*

Correlation

The correlation matrix **(Table 3)** provides initial insights into the relationships of the chosen variables for VAR models. In this study, the House Price Index (HPI) is the dependent variable, while Investor Attention (IA) is the primary independent variable. The control variables include GDP, CPI, and IR. The positive correlation between HPI and IA at 5% significance level suggests a moderate relationship between them, implying that as investor attention increases, house prices tend to rise, or vice versa. A more in-depth analysis using VAR could explore whether changes in investor attention lead to future movements in house prices or if the reverse is true.

Table 3: Correlation after investigation the stationary of the data

	HPI	**IA**	**GDP**	**CPI**	**IR**
HPI	1				
IA	0.2331**	1			
GDP	-0.635	-0.0882	1		
CPI	-0.0126	-0.1730	-0.5423***	1	
IR	-0.2027	-0.0971	0.0465	0.0772	1

Note: ∗∗∗, ∗∗ and ∗ denote significance at the 1%, 5% and 10% levels, respectively.

Co-integration Test

To assess the long-term equilibrium relationships between the variables in our study, we conducted Johansen cointegration tests. These tests help determine whether a set of non-stationary series are cointegrated, indicating that they share a common stochastic drift.

Table 4: Co-integration test

Hypothesis	**Test Statistic**	**10% Critical Value**	**5% Critical Value**	**1% Critical Value**
Trace Statistic Test				
$r \leq 1$	5.56	7.52	9.24	12.97
$r = 0$	14.51	17.85	19.96	24.6
Maximum Eigenvalue Statistic Test				
$r \leq 1$	5.56	7.52	9.24	12.97
$r = 0$	8.95	13.75	15.67	20.2

Table 4 presents the results of both the trace and maximal eigenvalue tests, which consistently indicate that there is no cointegration between the variables at the specified significance levels. This lack of cointegration suggests that the variables do not share a long-term equilibrium relationship and therefore should be analysed using models that do not assume cointegration, in this study - VAR model.

Vector Autoregression (VAR) model

We estimate the VAR model where the lag order is based on the Final prediction error (FPE), the Akaike information Sustainability criterion (AIC), the Hannan–Quinn information criterion (HQ), and the Schwarz information criterion (SC), most criteria suggest that lag order is 6.

Table 5: VAR model

VAR Estimation Results		
Sample size	73	
Log Likelihood	-42.43	
Roots of the characteristic polynomial	0.9181; 0.9181; 0.9127; 0.8312; 0.8312; 0.8044; 0.8044; 0.7977; 0.7977; 0.7639; 0.7639; 0.2752.	
	Dependent variable	
	HPI	**IA**
HPI(-1)	0.975***	0.021**
IA(-1)	-1.374	-0.233*
HPI(-2)	0.038	-0.001
IA(-2)	0.206	-0.355***
HPI(-3)	-0.637***	0.020*
IA(-3)	3.098	-0.361***
HPI(-4)	0.351**	-0.001
IA(-4)	0.677	-0.131
HPI(-5)	-0.217	-0.003
IA(-5)	-2.196	-0.113
HPI(-6)	0.185	0.025**
IA(-6)	-3.667**	-0.301**
Const	0.196	-0.026*
GDP	0.134	0.011
CPI	-0.516	-0.050**
IR	-0.41	-0.071**
Multiple R^2	0.754	0.369
Adjusted R^2	0.689	0.203

Note: ∗∗∗, ∗∗ and ∗ denote significance at the 1%, 5% and 10% levels, respectively.

Based on the results (Table 5), no root lies outside the unit circle, indicating that the VAR model satisfies the stability condition. Although VAR estimation results are often difficult to interpret, these results reveal a dynamic interplay between the House Price Index (HPI) and Investor Attention (IA).

Notably, lagged HPI variables exhibit a significant positive impact on current HPI values, particularly evident in the first lag (HPI(-1)) and the fourth lag (HPI(-4)), indicating a persistent trend in house price movements over time. However, the third lag (HPI(-3)) shows a significant negative impact. Autocorrelation appears to be the finding here, along with perhaps a cycle existing in HPI. Conversely, IA's lagged variables present a nuanced picture, with the first lag (IA(-1)), second lag (IA(-2)), and third lag (IA(-3)) showing a significant negative effect on IA itself, suggesting potential mean reversion in investor attention, or perhaps a cyclical trend in IA. The interaction between HPI and IA across different lags highlights the complexity of their relationship. For instance, the sixth lag (IA(-6)) has a significant negative impact on both HPI and IA, while the first lag (HPI(-1)), the third lag (HPI(-3)), and sixth lag (HPI(-6)) show significant positive effects on IA. These findings suggest that while past house prices can influence current investor attention, the relationships are nuanced and may vary over different periods. However, interpreting these results is challenging due to the dynamic nature of the interactions. To better understand the underlying mechanisms, the impulse response functions and variance decomposition results are presented in the next section.

To test the stability for the VAR model, serial correlation, heteroscedasticity and normality of residuals test are presented in **Table 6**. Based on these results, we fail to find significant evidence to suggest the presence of serial correlation in the residuals of the VAR model. We do not find significant evidence to suggest the presence of conditional heteroscedasticity (ARCH effects) in the residuals of the VAR model. None of the tests, JB test, skewness test, and kurtosis test, provide significant evidence to reject the null hypothesis of normal distribution at conventional significance levels.

Table 6: Serial correlation, heteroscedasticity and normality of residuals test results

Test Type	Test Statistic	p-value	Null Hypothesis	Results
Serial Correlation			No serial correlation	
Edgerton-Shukur F test	1.1219	0.3421	Fail to reject null hypothesis	No serial correlation
Heteroscedasticity			No heteroscedasticity	
ARCH	42.202	0.878	Fail to reject null hypothesis	No heteroscedasticity
Normality of Residuals			Residuals follow a normal distribution	
JB-Test	3.9991	0.4061	Fail to reject null hypothesis	Normal distribution
Skewness	2.4613	0.2921	Fail to reject null hypothesis	No skewness
Kurtosis	1.5379	0.4635	Fail to reject null hypothesis	No excess kurtosis

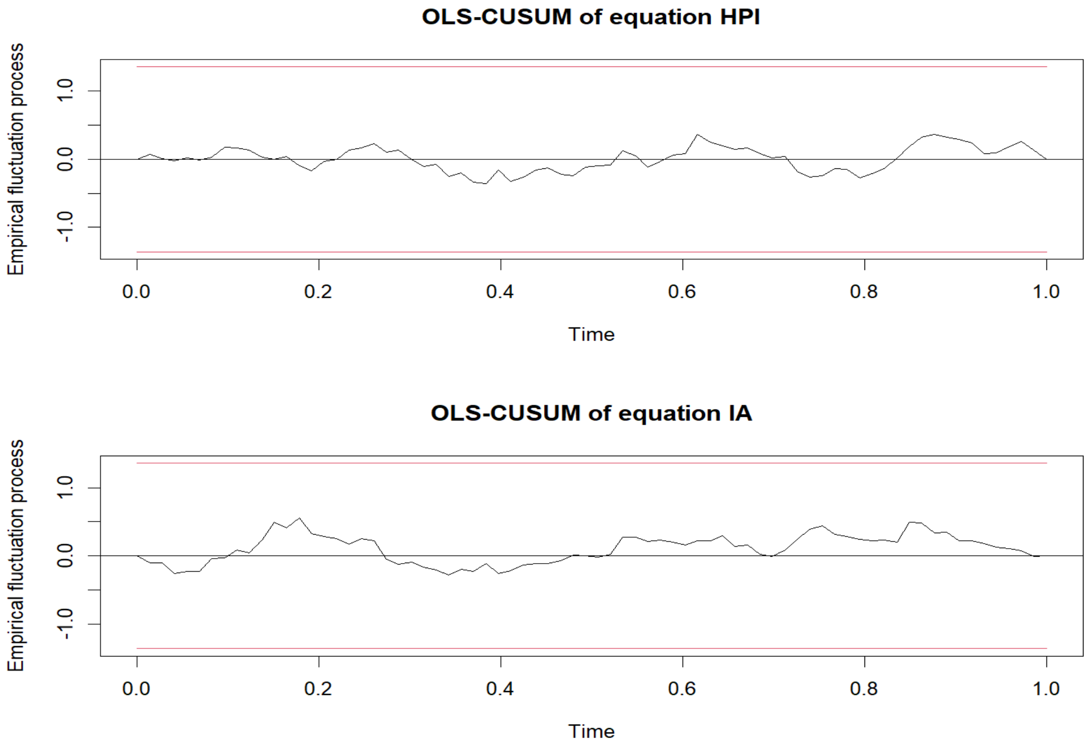

Figure 2: Testing for structural breaks in the residuals

Furthermore, based on **Figure 2**, the OLS-CUSUM test results indicate that the coefficients of both the HPI and IA equations in the VAR model are stable over time. This stability is crucial for the reliability of the model's forecasts and for making inferences about the dynamic relationship between HPI and IA. The absence of structural breaks implies that the relationships captured by the model remain consistent throughout the sample period, supporting the validity of the FEVD analysis and other inferences drawn from the VAR model. As a result, VAR model is reliable and stable for further analysis.

Granger Causality

Table 7 presents the Granger Causality tests for both variables HPI and IA. The p-value for the hypothesis 'HPI does not Granger-cause IA' is significantly smaller than the significance level, providing strong evidence to reject the null hypothesis. Therefore, there is Granger causality from HPI to IA. Similarly, the p-value for the hypothesis 'IA does not Granger-cause HPI' is smaller than the significance level, suggesting evidence to reject the null hypothesis. Thus, there is Granger causality from IA to HPI.

This analysis indicates bidirectional Granger causality between HPI and IA. These findings are consistent with existing theories on market dynamics and investor behaviour. According to the Efficient Market Hypothesis, asset prices reflect all available information. However, the observed Granger causality implies that investors may react to changes in house prices by increasing their attention, possibly seeking to capitalize on new information or trends. This aligns with behavioural finance theories which suggest that investor behaviour is often influenced by recent market movements and sentiments, resulting in a succession of factors leading from one cause to another, where rising prices attract more attention and participation, which in turn can drive prices further up.

Table 7: Granger Causality tests

Null Hypothesis	**F-Test**	**p-value**
HPI does not Granger-cause IA	3.8732	0.0015
IA does not Granger-cause HPI	1.9681	0.0759

Impulse Response Functions

The impulse response functions analysis, visualised in **Figure 3**, reveals that a positive shock to HPI initially spikes IA significantly, peaking around 3 units in a few quarters. This indicates that rising house prices quickly capture investor attention, aligning with behavioural finance theories on attention allocation. Medium-term data shows IA declining back to near zero by the 10th quarter, suggesting short-lived investor focus due to efficient market hypothesis principles. Long-term IA stabilizes near zero, indicating transient effects on investor behaviour. Conversely, a positive IA shock prompts a smaller, but notable, immediate HPI rise, echoing adaptive market hypothesis concepts. Over 30 quarters, this influence fades, affirming Efficient Market Hypothesis with long-term market efficiency.

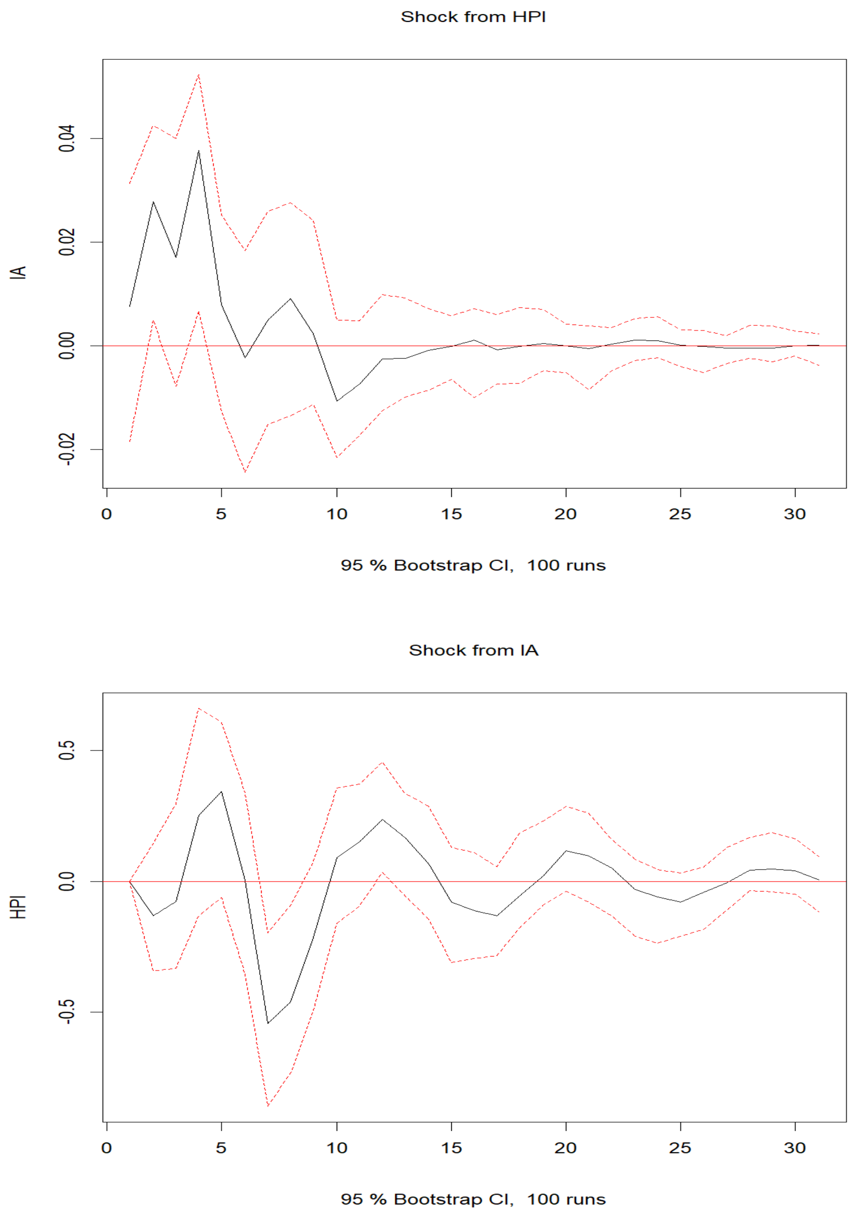

Figure 3: Impulse Response Functions

Variance Decomposition

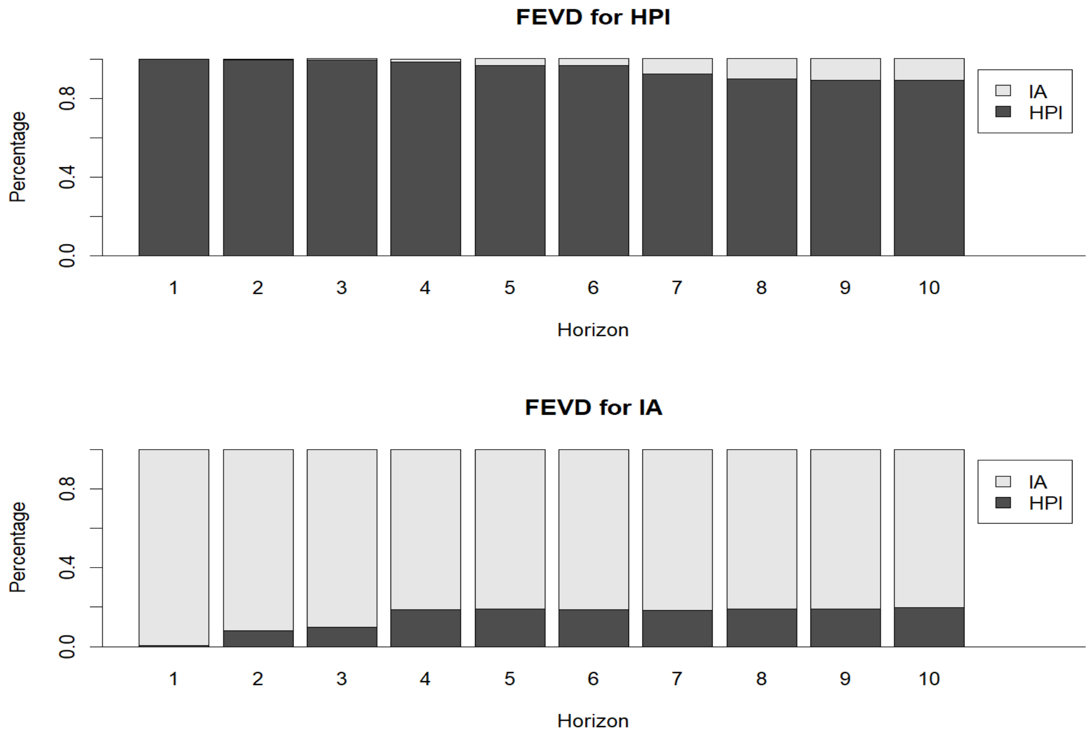

Figure 4: Forecast Error Variance Decomposition

The Forecast Error Variance Decomposition (FEVD) plots, presented in **Figure 4**, for HPI and IA provide critical insights into the dynamic relationship between these two variables over a forecast horizon of 10 quarters. The FEVD suggests that IA has predictive ability regarding HPI, where changes in investor attention can provide insights into future movements in house prices. The influence of HPI on IA also suggests that fluctuations in house prices can capture investor attention and influence their behaviour, contributing to a succession of factors leading from one cause to another between market prices and investor sentiment.

The theoretical implications of these findings underscore the importance of both historical house prices and investor attention in determining future house prices. The contribution of IA to the variance in HPI highlights the role of investor attention in driving market trends, supporting behavioural finance theories that market psychology and attention can impact price dynamics. The predictive power of IA over HPI suggests that monitoring investor attention can provide valuable insights for forecasting house price movements.

Conclusions

The dynamic relationship between house prices and investor attention is complex and bidirectional. Investor attention can drive short-term fluctuations and long-term trends in house prices, while significant changes in house prices can heighten investor attention, leading to increased market activity. This empirical study confirms the reciprocal relationship between investor attention and house prices. Understanding this bidirectional relationship is essential for a more comprehensive analysis of housing market dynamics.

The VAR model captures the intricate dynamic interactions among HPI, IA, and control variables, revealing significant lagged effects and providing a robust framework for understanding these relationships. Stability tests confirm the model's reliability, with no evidence of serial correlation, heteroscedasticity, or structural breaks, ensuring the validity of our findings.

Granger causality tests show bidirectional causality between HPI and IA, suggesting that not only does investor attention affect housing prices, but changes in housing prices also influence investor behaviour. Impulse response functions further elucidate this relationship, showing an immediate but short-lived impact of HPI shocks on IA and vice versa, consistent with market efficiency and behavioural finance theories. Finally, the impulse response functions analysis reveals that shocks in investor attention have a significant but temporary and fluctuating impact on the House Price Index. The initial response is positive and volatile, reflecting increased attention and demand for housing. The forecast error variance decomposition highlights the substantial role of IA in explaining HPI variations, reinforcing the importance of investor sentiment in housing market dynamics.

These findings may have significant implications for policymakers, real estate investors, and market analysts. Monitoring investor attention, such as through sentiment indices derived from online search trends, news analytics, or social media activity, can provide possible insights for forecasting housing price movements and pre-empting speculative activity. To mitigate short-term market volatility and stabilise speculative behaviour during periods of heightened activity, a combination of policy interventions, regulatory measures, and market controls may be triggered by observations of investor interest such as assessed in this study.

Furthermore, the transient nature of the impact implies that, while house price changes initially draw significant attention from investors, this effect does not persist in the long term. Policymakers could focus on improving access to real-time market data to foster greater transparency and better decision-making. Additionally, they could invest in educating market participants about common behavioural biases, helping them to make more informed, rational choices in a rapidly evolving market environment. Similarly, investors should adopt data-driven strategies to assess market conditions, recognising that short-term shocks do not lead to sustained changes or long-term trends in housing markets.

In conclusion, this study sheds light on the interaction between housing prices and investor behaviour, emphasising the need for incorporating behavioural factors into traditional economic models to better understand and predict housing market trends.

This study, while providing significant insights into the dynamic relationship between house prices and investor attention, has certain limitations. Firstly, the analysis is constrained by the availability and scope of the data, focusing primarily on aggregate national-level indicators. This may overlook regional variations and local market dynamics that could offer a more detailed understanding of the relationship. Secondly, the study employs traditional econometric tools which, while robust, may not fully capture the complexity and non-linearity of investor behaviour and housing market interactions. The reliance on historical data also means that the models may not adequately account for recent changes in usage patterns on digital platforms. Additionally, the study's findings are context-specific and may not be generalizable to other countries or different economic environments without further validation. The regression analysis is limited by the sample size, which may affect the statistical power and robustness of the results. Additionally, the quarterly frequency of the sample could hinder the detection of subtle changes in the relationship. Future research should address these limitations by incorporating longer time series and more frequent observations, exploring regional and local market data, utilising advanced econometric techniques, and considering the impact of new technologies and investor demographics on market dynamics.

Disclosure Statements

No potential conflict of interest was reported by the authors.

REFERENCES

Aizenman, J., Jinjarak, Y. & Zheng, H. 2019. Housing Bubbles, Economic Growth, And Institutions. Open Economies Review, 30, 655-674.
Anari, A. & Kolari, J. 2002. House Prices And Inflation. Real Estate Economics, 30, 67-84.
Andrei, D., Friedman, H. & Ozel, N. B. 2023. Economic Uncertainty And Investor Attention. Journal Of Financial Economics, 149, 179-217.
Andrei, D. & Hasler, M. 2015. Investor Attention And Stock Market Volatility. The Review Of Financial Studies, 28, 33-72.
Bajari, P., Benkard, C. L. & Krainer, J. 2005. House Prices And Consumer Welfare. Journal Of Urban Economics, 58, 474-487.
Bank For International Settlements. 2024. Real Residential Property Prices For Australia [Qaur368bis] Retrieved From Fred, Federal Reserve Bank Of St. Louis. Available: https://fred.stlouisfed.org/series/qaur368bis
Barber, B. M. & Odean, T. 2008. All That Glitters: The Effect Of Attention And News On The Buying Behavior Of Individual And Institutional Investors. The Review Of Financial Studies, 21, 785-818.
Ben-Rephael, A., Da, Z. & Israelsen, R. D. 2017. It Depends On Where You Search: Institutional Investor Attention And Underreaction To News. The Review Of Financial Studies, 30, 3009-3047.
Beracha, E. & Wintoki, M. B. 2013. Forecasting Residential Real Estate Price Changes From Online Search Activity. Journal Of Real Estate Research, 35, 283-312.
Burke, T. & Hulse, K. 2010. The Institutional Structure Of Housing And The Sub-Prime Crisis: An Australian Case Study. Housing Studies, 25, 821-838.
Cao, Z., Kilic, O. & Wang, X. 2021. Investor Attention, Divergence Of Opinions, And Stock Returns. Journal Of Behavioral Finance, 22, 265-279.
Case, K. E. & Shiller, R. J. 2003. Is There A Bubble In The Housing Market? Brookings Papers On Economic Activity, 2003, 299-362.
Chen, J., Tang, G., Yao, J. & Zhou, G. 2022. Investor Attention And Stock Returns. Journal Of Financial And Quantitative Analysis, 57, 455-484.
Chen, Y., Masron, T. A. & Mai, W. 2024. Role Of Investor Attention And Executive Green Awareness On Environmental Information Disclosure Of Chinese High-Tech Listed Companies. Journal Of Environmental Management, 365, 121552.
Cho, Y., Li, S. M. & Uren, L. 2021. Understanding Housing Affordability In Australia. Australian Economic Review, 54, 375-386.
Chow, G. C. & Niu, L. 2015. Housing Prices In Urban China As Determined By Demand And Supply. Pacific Economic Review, 20, 1-16.
Da, Z., Engelberg, J. & Gao, P. 2011. In Search Of Attention. The Journal Of Finance, 66, 1461-1499.
Dash, S. R. & Maitra, D. 2022. The Covid-19 Pandemic Uncertainty, Investor Sentiment, And Global Equity Markets: Evidence From The Time-Frequency Co-Movements. The North American Journal Of Economics And Finance, 62, 101712.
Dellavigna, S. & Pollet, J. M. 2009. Investor Inattention And Friday Earnings Announcements. The Journal Of Finance, 64, 709-749.

Drake, M. S., Roulstone, D. T. & Thornock, J. R. 2012. Investor Information Demand: Evidence From Google Searches Around Earnings Announcements. Journal Of Accounting Research, 50, 1001-1040.
Fama, E. F. 1970. Efficient Capital Markets. Journal Of Finance, 25, 383-417.
Gatzlaff, D. & Tirtiroğlu, D. 1995. Real Estate Market Efficiency: Issues And Evidence. Journal Of Real Estate Literature, 3, 157-189.
Glaeser, E. L., Gyourko, J. & Saks, R. E. 2005. Why Have Housing Prices Gone Up? American Economic Review, 95, 329-333.
Goddard, J., Kita, A. & Wang, Q. 2015. Investor Attention And Fx Market Volatility. Journal Of International Financial Markets, Institutions And Money, 38, 79-96.
Gu, J. 2024. Investor Attention And Esg Performance: Lessons From China's Manufacturing Industry. Journal Of Environmental Management, 355, 120483.
Hou, K., Xiong, W. & Peng, L. 2009. A Tale Of Two Anomalies: The Implications Of Investor Attention For Price And Earnings Momentum. Available At Ssrn 976394.
Huberman, G. & Regev, T. 2001. Contagious Speculation And A Cure For Cancer: A Nonevent That Made Stock Prices Soar. The Journal Of Finance, 56, 387-396.
Inglesi-Lotz, R. & Gupta, R. 2013. The Long-Run Relationship Between House Prices And Inflation In South Africa: An Ardl Approach. International Journal Of Strategic Property Management, 17, 188-198.
Irandoust, M. 2019. House Prices And Unemployment: An Empirical Analysis Of Causality. International Journal Of Housing Markets And Analysis, 12, 148-164.
Jin, C., Soydemir, G. & Tidwell, A. 2014. The Us Housing Market And The Pricing Of Risk: Fundamental Analysis And Market Sentiment. Journal Of Real Estate Research, 36, 187-220.
Kahneman, D. 1973. Attention And Effort, Englewood Cliffs, Nj: Prentice-Hall.
Keogh, G. & D'arcy, E. 1999. Property Market Efficiency: An Institutional Economics Perspective. Urban Studies, 36, 2401-2414.
Liu, Z., Miao, J. & Zha, T. 2016. Land Prices And Unemployment. Journal Of Monetary Economics, 80, 86-105.
Locke, S. M. 1986. Real Estate Market Efficiency. Land Development Studies, 3, 171-178.
Mclaren, N. & Shanbhogue, R. 2011. Using Internet Search Data As Economic Indicators. Bank Of England Quarterly Bulletin, Q2.
Mcquinn, K. & O'reilly, G. 2008. Assessing The Role Of Income And Interest Rates In Determining House Prices. Economic Modelling, 25, 377-390.
Miller, N., Peng, L. & Sklarz, M. 2011. House Prices And Economic Growth. The Journal Of Real Estate Finance And Economics, 42, 522-541.
Nguyen, T. T. A., Small, G., Sun, L. & Boyd, S. Investigating The Relationship Between Investor Attention And House Prices: A Case Study Of Australia. In: Susilawati, C., Ed. 30th Annual Pacific Rim Real Estate Society Conference, 2024 Goad Coast, Queensland, Australia.
Organization For Economic Co-Operation And Development. 2024. Consumer Price Index: All Items: Total For Australia [Cpaltt01auq657n]. Retrieved From Fred, Federal Reserve Bank Of St. Louis. Available: https://fred.stlouisfed.org/series/cpaltt01auq657n
Pham, L. & Huynh, T. L. D. 2020. How Does Investor Attention Influence The Green Bond Market? Finance Research Letters, 35, 101533.
Shiller, R. J. 2007. Understanding Recent Trends In House Prices And Home Ownership. National Bureau Of Economic Research Cambridge, Mass., Usa.
Shiller, R. J. 2014. Speculative Asset Prices. American Economic Review, 104, 1486-1517.

Snieska, V. & Burkšaitienė, D. 2018. Panel Data Analysis Of Public And Private Debt And House Price Influence On Gdp In The European Union Countries. Inžinerinė Ekonomika, 29, 197-204.
The Australian Bureau Of Statistics. 2022. Household Income And Wealth, Australia [Online]. Available: https://www.abs.gov.au/statistics/economy/finance/household-income-and-wealth-australia/latest-release [accessed 09 december 2024].
The Australian Bureau Of Statistics. 2024. Australian National Accounts: National Income, Expenditure And Product. Available: https://www.abs.gov.au/statistics/economy/national-accounts/australian-national-accounts-national-income-expenditure-and-product/latest-release
The Reserve Bank Of Australia. 2024. Interest Rates. Available: https://www.rba.gov.au/statistics/tables/#interest-rates
Vozlyublennaia, N. 2014. Investor Attention, Index Performance, And Return Predictability. Journal Of Banking & Finance, 41, 17-35.
Wu, L. & Brynjolfsson, E. 2015. The Future Of Prediction: How Google Searches Foreshadow Housing Prices And Sales. Economic Analysis Of The Digital Economy. University Of Chicago Press.
Xu, T. 2017. The Relationship Between Interest Rates, Income, Gdp Growth And House Prices. Research In Economics And Management, 2, 30-37.