What drives the real estate market? Could behavioral indicators be useful in house pricing models?

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Abstract

Purpose – The objective of this paper is to examine the determinants of the Greek house market during the period 2006–2022 using not only economic variables but also behavioral variables, taking advantage of available information on the volume of Google searches. In order to quantify the behavioral variables, we implement a Python code using the Pytrends 4.9.2 library.

Design/methodology/approach – In our study, we assert that models relying solely on economic variables, such as GDP growth, mortgage interest rates and inflation, may lack precision compared to those that integrate behavioral indicators. Recognizing the importance of behavioral insights, we incorporate Google Trends data as a key behavioral indicator, aiming to enhance our understanding of market dynamics by capturing online interest in Greek real estate through searches related to house prices, sales and related topics. To quantify our behavioral indicators, we utilize a Python code leveraging Pytrends, enabling us to extract relevant queries for global and local searches. We employ the EGARCH(1,1) model on the Greek house price index, testing several macroeconomic variables alongside our Google Trends indexes to explain housing returns.

Findings – Our findings show that in some cases the relationship between economic variables, such as inflation and mortgage rates, and house prices is not always consistent with the theory because we should highlight the special conditions of the examined country. The country of our sample, Greece, presents the special case of a country with severe sovereign debt issues, which at the same time has the privilege to have a strong currency and the support and the obligations of being an EU/EMU member.

Practical implications – The results suggest that Google Trends can be a valuable tool for academics and practitioners in order to understand what drives house prices. However, further research should be carried out on this topic, for example, causality relationships, to gain deeper insight into the possibilities and limitations of using such tools in analyzing housing market trends.

Originality/value – This is the first paper, to the best of our knowledge, that examines the benefits of Google Trends in studying the Greek house market.

Keywords Inflation, Google Trends, Real estate, Behavioral indicators

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1. Introduction

The dynamics of the real estate markets have puzzled financial economists and scholars for decades due to the substantial impact of house prices on economic activity. Previous literature has predominantly linked housing prices with traditional economic markers, such as GDP, income levels, population trends and interest rates (Bjørnland & Jacobsen, 2010; Case, Shiller, & Thompson, 2012; Gupta, Jurgilas, Miller, & Van Wyk, 2011; Plakandaras, Gupta, Katrakilidis, & Wohar, 2020; Simo-Kengne, Miller, Gupta, & Balcilar, 2016). Major economic shifts, like alterations in monetary policies or fluctuations in interest rates, have been pinpointed as significant drivers of housing prices (De Santis & Surico, 2013; Demary, 2010; Everett, de Haan, Jansen, McQuade, & Samarina, 2021; Plakandaras *et al.*, 2020; Rahal, 2016; Simo-Kengne *et al.*, 2016). Economic growth and house prices present a positive correlation (Leung, 2003; Simo-Kengne *et al.*, 2012, 2016), as economic growth raises wages and increases consumption, ultimately raising house prices as well (Kishor, 2007; Lettau & Ludvigson, 2004). A positive change in interest rates, in particular, which leads to higher mortgage rates and housing costs, has a negative impact on housing demand and exerts downward pressure on house prices (De Santis & Surico, 2013; Demary, 2010; Everett *et al.*, 2021; Rahal, 2016). Additionally, the inflation channel suggests a nuanced impact; while inflation may stimulate residential investment due to real estate's role as an inflation hedge (Fama & Schwert, 1977), it could also lead to higher interest rates, potentially suppressing real estate demand and adversely affecting house prices (Demary, 2010).

However, more recent studies show contradictory findings, highlighting the limited significance of Macroeconomic, Monetary, and Banking (MMB) fundamentals on housing prices (Alkay, Watkins, & Keskin, 2018). Hoesli, Lizieri, and MacGregor (2008) indicate that real estate offers a minimal hedge against high inflation. Additionally, other research suggests that changes in interest rates have a limited impact on housing prices (Glaeser, Gottlieb, & Gyourko, 2015; Shi, Jou, & Tripe, 2014; Taylor, 2009), implying that increases in the policy rate may not effectively depress real housing prices, particularly during periods of high inflation. Real estate can serve as a hedge against inflation (Fama & Schwert, 1977), leading to increased demand for housing to mitigate inflation risks, consequently driving up house prices (Shi *et al.*, 2014).

One potential explanation for the limited impact of MMB factors on housing prices lies in the psychological dimension of real estate investment, where consumer behavior plays a pivotal role (Beracha, Lang, & Hausler, 2019; Clayton, Ling, & Naranjo, 2009; Hausler, Ruscheinsky, & Lang, 2018). Recent studies highlight how optimistic outlooks and shifts in sentiment, detached from economic fundamentals, can instigate 'bubble-bursting' phenomena in housing markets, leading to price fluctuations (Abraham & Hendershott, 1996; Muellbauer & Murphy, 2008; Shiller, 2008). Optimistic sentiment, driven by expectations of future housing returns, tends to attract more homebuyers into the market (Dong, Hui, & Yi, 2021), boosting transaction volumes (Fischer & Stamos, 2013) and driving up housing prices (Asal, 2019; Hong, Kim, & Ahn, 2022; Tsai & Peng, 2011). Residential property's dual role as both a consumer good and an investment asset (Granziera & Kozicki, 2015; Marfatia, André, & Gupta, 2022), significantly influences demand for durable goods and shapes investors' risk perceptions toward financial assets (Fuhrer, 1993; Mishkin, Hall, Shoven, Juster, & Lovell, 1978; Throop, 1992; Van Raaij & Gianotten, 1990). Given that housing sentiment impacts housing prices, especially during periods of economic uncertainty (Anastasiou, Kapopoulos, & Zekente, 2021; De Bandt, Barhoumi, & Bruneau, 2010), it is essential to consider the behavioral effect on housing markets.

In this context, prior studies reveal that Greek homeowners perceive houses as investment assets rather than purely consumption goods (Gounopoulos, Merikas, Merika, & Triantafyllou, 2012) and view housing as a crucial investment decision for the average Greek citizen (Papageorgiou, Loulis, Efstathiades, & Ness, 2020). This stands in contrast to

the home ownership rate in the Euro area, which experienced a decline over the last decade, primarily attributed to diminishing ownership rates among young adults and low-income groups (Calabria & Calder, 2019) or escalating housing prices (Čermáková & Hromada, 2022). Furthermore, Greece has faced severe economic challenges, including a notable financial crisis (Lekkos, Staggel, Kefalas, & Vlachou, 2014), high level of debt (Leschinski & Bertram, 2017), financial instability (Anastasiou & Kapopoulos, 2023), deflation pressures (Lekkos *et al.*, 2014) and high volatility in housing prices (Gounopoulos *et al.*, 2012; Petropoulos, Liapis, & Thalassinos, 2023). These economic challenges potentially influence investor behavior, contributing to the impact on housing prices beyond market fundamentals, as noted by Marfatia *et al.* (2022). Given that the Greek housing market stands out with homeownership rates (Gounopoulos *et al.*, 2012), high impact from changes in consumer behavior (Petropoulos *et al.*, 2023) and is highly sensitive to changes in financial stress conditions (Anastasiou & Kapopoulos, 2023), it is intriguing to study how these unique characteristics interact with the dynamics of the Greek housing market, providing valuable insights for investors, policymakers and researchers alike.

In this study, we examine the influence of behavioral sentiment variables and macroeconomic fundamentals on the variability of Greek house prices. Employing EGARC(1,1) model (Nelson, 1991), we explore how behavioral and MMB fundamentals impact housing market volatility, using the House Prices Index (HPI) data spanning from 2006 to 2022. Our MMB fundamentals encompass changes in GDP, inflation and mortgage interest (MI) rates, factors known to significantly affect housing demand and prices (Bjørnland & Jacobsen, 2010; Case *et al.*, 2012; Everett *et al.*, 2021; Leung, 2003; Plakandaras *et al.*, 2020; Simo-Kengne *et al.*, 2012, 2016), especially in the Greek market (Apergis & Rezitis, 2003; Gounopoulos *et al.*, 2012).

For behavioral sentiment variables, we integrate Google search-based sentiment data from Google Trends. Notably, Google Trends has garnered attention among scholars for its reliability in measuring economic and financial uncertainty (Bilgin, Demir, Gozgor, Karabulut, & Kaya, 2019; Brodeur, Clark, Fleche, & Powdthavee, 2021; Choi & Varian, 2012; Preis, Moat, & Eugene Stanley, 2013; Vasileiou, 2021a, 2023), and is recognized as a leading sentiment indicator in financial analysis. However, while sentiment notably influences housing prices (Abildgren, Hansen, & Kuchler, 2018; Hong *et al.*, 2022; Ling, Ooi, & Le, 2015; Muellbauer & Murphy, 2008; Tsai & Peng, 2011), especially in the Greek housing market (Anastasiou *et al.*, 2021; Anastasiou & Kapopoulos, 2023), real estate research has not extensively utilized behavioral indicators based on Google Trends. The few exceptions include Dietzel (2016), who demonstrates that Google search volume data can act as a leading sentiment indicator and predict turning points in the US housing market, and Bulczak (2021), who employs Google Trends to predict the UK real estate market. While some studies on the Greek housing market utilize survey-based sentiment indexes to elucidate house price variation (Anastasiou *et al.*, 2021; Anastasiou & Kapopoulos, 2023), we find no evidence of studies utilizing Google Trends to capture behavioral sentiment.

For robustness, we introduced our sentiment measure in addition to our MMB fundamentals individually. Our main findings show that media-based information from Google Trends is highly significant in elucidating variations in Greek housing prices, beyond the traditional MMB fundamentals. Our analysis demonstrates the potency of our sentiment measure in capturing the dynamics of the Greek housing market, thereby enhancing the understanding of the interplay between consumer sentiment and traditional economic indicators. These findings underscore the pivotal role of media-based information and sentiment in shaping housing market dynamics.

Our study makes significant contributions to the existing literature in several key ways. First, we pioneer the use of Google Trends data in conjunction with macroeconomic variables to elucidate variations in house prices. By leveraging Google Trends indices, which serve as

behavioral indicators of public interest and sentiment (Vasileiou, 2021a, b), we argue that investigating media-based information and sentiment is paramount for achieving a more nuanced understanding of Greek house price volatility. This innovative approach not only enriches the current body of research but also offers a novel perspective on the drivers of housing market dynamics. Second, against the backdrop of economic uncertainty in Greece and the pronounced sensitivity of housing prices to financial instability, our study provides comprehensive insights into the impact of both behavioral patterns and economic stress conditions. By employing a novel model-based approach, we offer a detailed examination of the interplay between consumer sentiment and MMB fundaments.

Our findings not only enhance the understanding of the Greek housing market dynamics but also serve as a valuable template for policymakers, regulators and researchers grappling with economic challenges elsewhere. By adapting our methodology, policymakers and regulators can gain deeper insights into the factors shaping housing markets and develop more effective strategies to mitigate risks and promote stability in housing sectors across various economic contexts. Thus, our study not only advances economic literature but also holds significant implications for policymakers and stakeholders seeking to navigate turbulent economic landscapes and foster sustainable housing markets.

The rest of this paper goes as following: Section 2 presents the variables and the preliminary data of our study. Section 3 analyses the econometric model and presents the empirical results, and Section 4 concludes the study, discusses the findings and suggests some ideas for further research.

2. Data and variables

In this paper, we use data from the Bank of Greece for the HPI and the MI, and we gather the GDP year on year change (GDP_yoy) and Inflation (I) from the Hellenic Statistical Authority. These variables will be the MMB variables that are usually used in similar studies (Apergis & Rezitis, 2003).

From behavioral standpoint, the easy part is that if somebody is interested in buying a house, he/she searches the internet for properties and prices. Internet searches are a very useful tool for scholars because they enable us to incorporate what people are interested in and this may be an indication for their actions (Vasileiou, 2021b). The difficult part is to find which are the most representative terms taking into consideration specific factors that could influence each market. For example, during the last decade, there has been considerable discussion in Greece about the interest of foreigners in buying Greek properties, as well as the impact of such transactions on the domestic real estate market and the economy as a whole [1]. Foreign buyers are looking to purchase vacation homes or searching for investment opportunities, whereby they buy houses to convert them into Airbnb units. Non-EU nationals are also seeking to obtain a Golden Visa, which they can do by buying property (Lekkos *et al.*, 2014; Papageorgiou *et al.*, 2020).

The challenging aspect of the behavioral analysis lies in the identification and quantification of pertinent behavioral indices. Pytrends facilitates the creation of behavioral indicators by leveraging its functionalities for extracting related topics, queries and suggestions. To construct these indicators, we explore various search terms, as Pytrends allows the use of up to five terms simultaneously. The efficacy of different term combinations is tested to ascertain which combination best encapsulates the sought-after interest.

The results are not presented in raw volumes; rather, they are normalized and indexed on a scale from 0 to 100. To gauge international interest, English terms such as "Greece Golden Visa," "House Sales in Greece," etc., are employed. In contrast, for domestic interest originating from Greek users, terms like «Πωλήσεις Σπιτιών» and «Ενοικιάσεις Σπιτιών» (translated as "House Sales" and "Homes to Rent" in Greek, respectively) are tested.

Additionally, the act of visiting real estate websites, spanning from real estate agents to platforms for house rentals and sales, serves as an indicator of a prospective willingness to purchase property.

Given the abundance of suggested and related terms, and the myriad possible combinations, a new code is implemented to determine the most representative term combination for the specified objective. Consequently, a Local Search (LS) index is introduced to encapsulate the intention of Greek individuals to acquire a property. World Searches Index is devised to quantify global interest in Greek real estate.

Figure 1 visually represents the relationship between each variable, including MMB and the behavioral indices, with the Housing Price Index (HPI). This graphical representation aids in comprehending the interplay between these variables.

We should note that house prices in Greece decreased from the end of 2008 up until the end of 2017, which closely coincides with the Greek sovereign debt crisis and GDP decline that lasted from 2009 to 2017. These years constitute a large period of our sample, but since 2017 house prices have risen. We present the relationship of the explanatory MMB variables (MI, I, GDP_yoy) and the behavioral indices (World_Searches, LSs) with the dependent variable (HPI) in Figure 1, and we clarify the following points:

(1) Inflation presents a negative relationship to the HPI, which means that investments in house property were not a way to hedge against inflation during the entire examined period. This runs counter to what international theory suggests in the case of a small, emerging and open economies that do not have a very strong currency (Assibey-Yeboah & Mohsin, 2014; Thornton & Vasilakis, 2016). A possible explanation for these preliminary results could be that Greece may be a small and open economy, but it belongs to the European Union (EU) and the European Monetary Union (EMU), and it has strong currency. If Greece weren't a member of the EU/EMU, its currency would have probably depreciated during the sovereign crisis and inflation issues would have emerged (e.g., cost inflation due to price increases in oil, imported goods, etc.). In such a case, house prices in a soft currency would be higher. The fact that Greek house prices decreased during the debt crisis, and inflation was not so high due to EU/EMU and to the Euro.

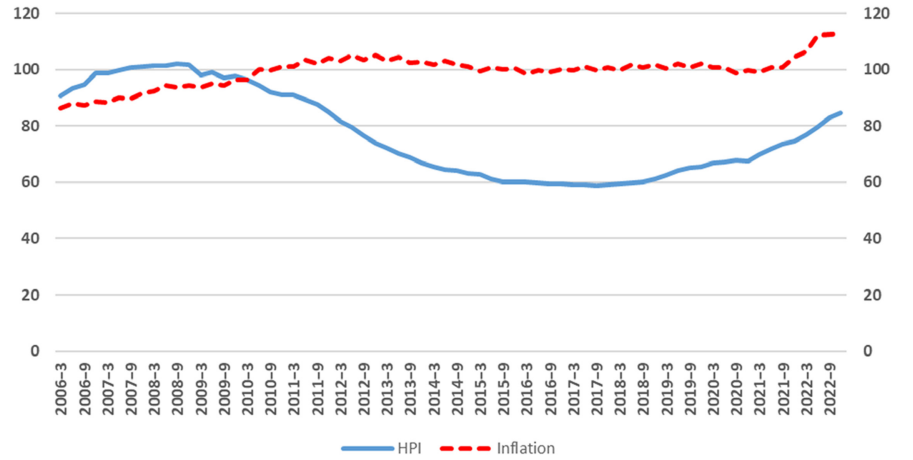
(2) GDP has positive behavior to the house prices, as the theory suggests. One easily observed exception is during the COVID-19 period when the GDP falls, but the house prices remain almost the same. This can be attributed to the stimulus packages that gave liquidity and income during the isolation and not very productive years (Vasileiou, 2023).

(3) MI rates seem to be higher when the house prices were higher and lower when the prices declined. This positive relationship could be explained by the fact that bank interests followed the European rates when Greece suffered from its sovereign crisis (2009–2017), due to its strong currency (Euro) and the assistance of EU/EMU. When house prices fell, MI rates were as low as those in the Euro area. Low interests reduce the cost of a house and make the investment case more tantalizing, and usually the lead to an increase of the demand and of the prices. However, in Greece, local and foreign interest in buying property in the country increased when prices and mortgage rates increased.

(4) World interest in Greek properties seems to have a positive relationship with house prices in the last HPI rise period, but it has a seasonality [2].

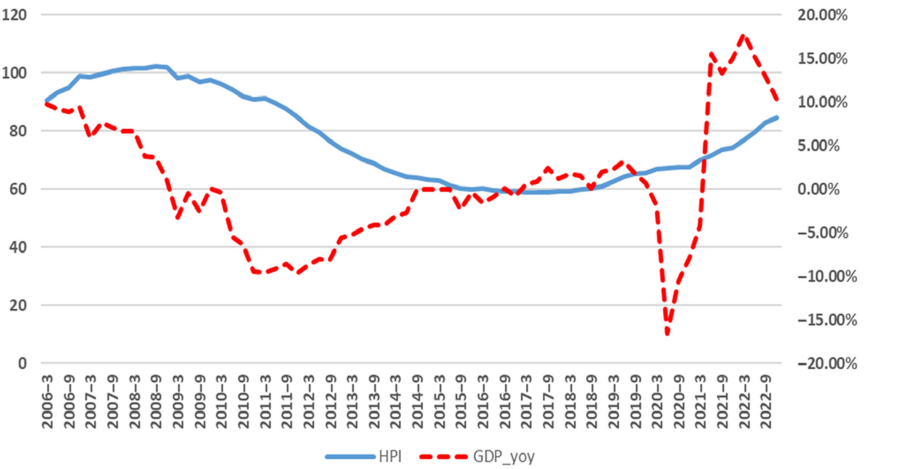
(5) The LSs for Greek property seem to have a smoother time series (without seasonality) and a positive relationship with the HPI.

Table 1 depicts the correlation matrix, revealing pivotal insights into the intricate relationships among key variables within our dataset. Notably, the HPI exhibits a robust positive correlation with interest rates (MI) (0.881), underscoring the significant influence of interest rates on housing prices. Conversely, the HPI demonstrates a moderate negative correlation with inflation (I) (−0.504), suggesting a potential inverse relationship between inflation and housing prices. Inflation also manifests strong negative correlations with MI (−0.566) and LSs (−0.744), hinting at the potential impact of inflation on mortgage rates and



House Price index and Inflation

(a)

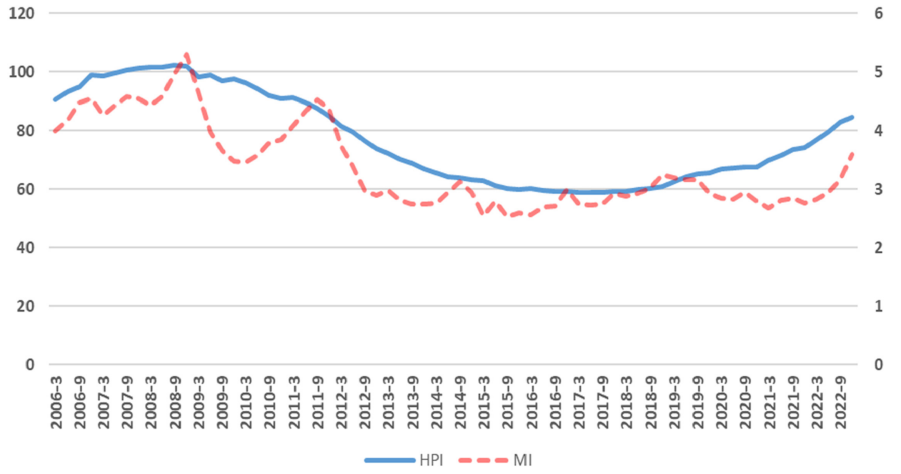


House Price index and GDP_yoy

(b)

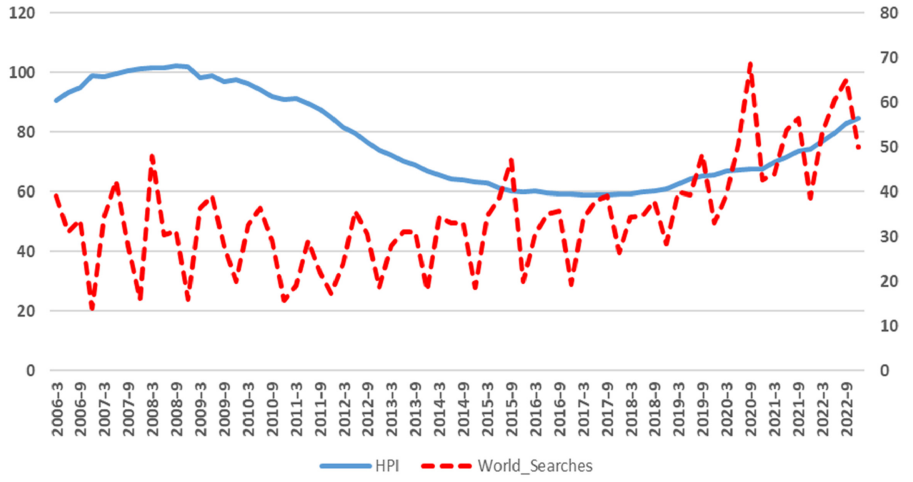
Figure 1.
House Price index and the Explanatory Variables

(*continued*)



House Price index and Mortgage interest

(c)

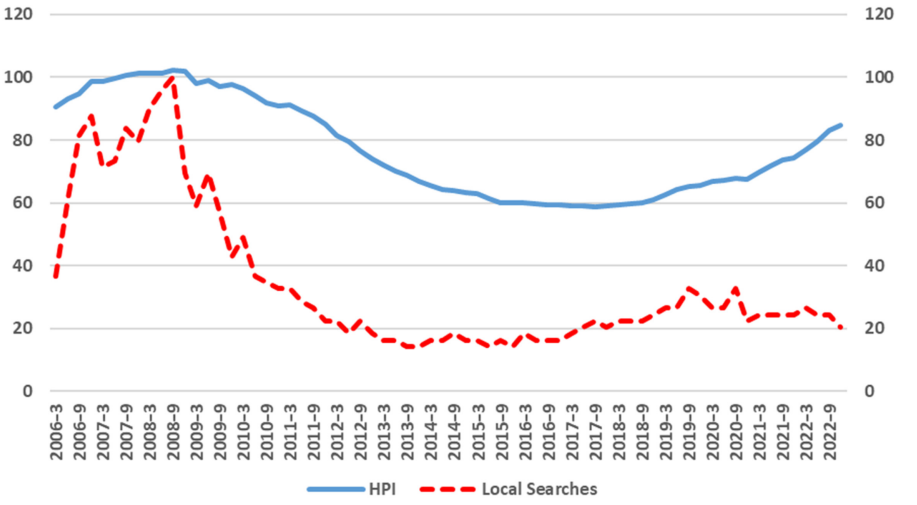


House Price index and World Searches

(d)

(*continued*)

Figure 1.



House Price index and Local Searches

(e)

Source(s): Figure by authors

Figure 1.

	HPI	I	GDP_yoy	MI	World_Searches	Local_Searches
HPI	1.000	−0.504	0.156	0.881	−0.189	0.818
I	−0.504	1.000	−0.145	−0.566	0.256	−0.744
GDP_yoy	0.156	−0.145	1.000	0.081	0.352	0.302
MI	0.881	−0.566	0.081	1.000	−0.328	0.823
World_Searches	−0.189	0.256	0.352	−0.328	1.000	−0.126
Local_Searches	0.818	−0.744	0.302	0.823	−0.126	1.000

Source(s): Table by authors

Table 1.
Correlation matrix of our variables

local interest in housing. Considering the behavioral variables, Google Trends Worldwide Searches (World_Searches) demonstrate a weak positive correlation with HPI; however, the LSs (Local_Searches) exhibit strong positive correlations with HPI (0.818) and MI (0.823), highlighting the substantial influence of local sentiment and interest on housing market dynamics. These correlations underscore the complex interplay between macroeconomic factors, consumer sentiment and housing market trends.

Lastly, Table 2 presents the descriptive statistics of our study. We use the first differences of these variables because many of them are not stationary when we test them at level [3]. Notable observations include marginal decreases in HPI returns, juxtaposed with moderately positive inflation rates, hinting at potential shifts in market dynamics. However, the high standard deviations of these variables indicate significant variations in housing prices and inflation, possibly attributed to recent economic challenges faced by Greece. The GDP change hovers marginally above 0.00, indicating stable economic growth over the period, albeit with potential outliers that underscore economic resilience. The negative mean of MI signifies a

	dr_HPI	d_I	GDP_yoy	d_MI	d_World_ Searches	d_Local_ Searches
Mean	−0.090	0.400	0.000	−0.006	0.164	0.003247
Median	0.000	0.453	0.000	0.017	2.667	0.000000
Maximum	4.000	5.742	0.198	0.433	32.000	0.666667
Minimum	−3.700	−2.160	−0.146	−0.667	−27.000	−0.312500
Std. Dev	1.630	1.553	0.036	0.232	12.132	0.160336
Skewness	0.062	0.596	1.511	−0.837	−0.096	0.972760
Kurtosis	2.801	3.580	18.475	3.722	2.621	6.033527
Jarque-Bera	0.153	4.902*	694.021***	9.268***	0.505	36.256***
ADF	−6.501***	−3.017**	−5.631***	−5.273***	−5.848***	−9.564***
Observations	67	67	67	67	67	67

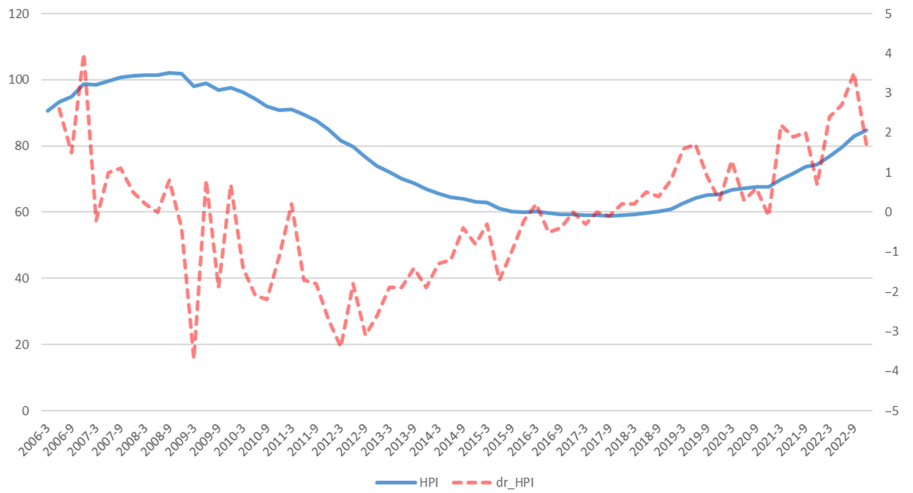
Note(s): ***,** and * indicate statistical significance at the 1%, 5% and 10% level respectively
Source(s): Table by authors

Table 2.
Descriptive statistics of our variables

slight decrease in interest rates, potentially impacting housing affordability. Examining our Google trend indicators, the table reveals a negative average for world searches, suggesting waning global interest in the Greek housing market. Conversely, a positive value for LSs indicates a surge in the online interest, emphasizing the significance of digital indicators in deciphering local consumer behavior. While all variables are stationary, it's noteworthy that d_HPI and d_World_Searches do not follow the normal distribution.

3. Econometric methodology

To ensure appropriate modeling for our dataset, we conducted empirical tests initially. Figure 2 presents the HPI and the year-on-year changes of the index. The figure demonstrates clustered volatility in the returns, indicative of volatility clustering patterns. Additionally, Figure 3 displays the autocorrelation of the first differences of HPI (dr_HPI) raised to the power of two, offering further quantitative evidence of volatility clustering.



Source(s): Figure by authors

Figure 2.
The Greek House Prices Index and its percentage change during the period 2006–2022

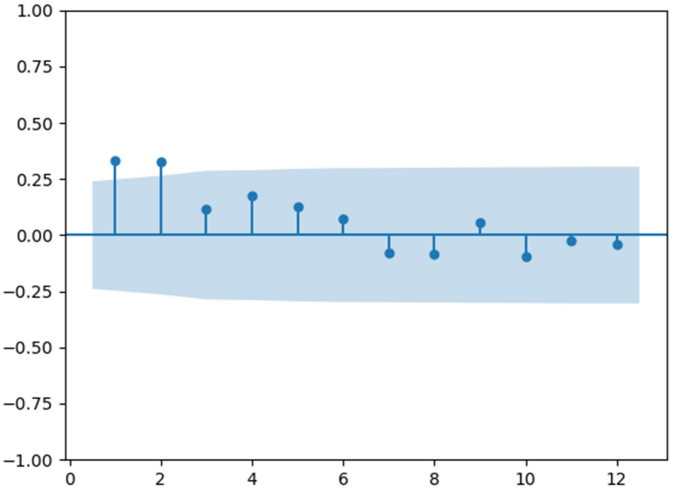


Figure 3.
Volatility clustering of the HPI index, autocorrelation of HPI returns in the power of 2

Source(s): Figure by authors

These results indicate than an Ordinary Least Squares (OLS) model may not be appropriate for our dataset due to the volatility clustering issue, suggesting that Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) volatility models are more appropriate to resolve autocorrelation and Autoregressive Conditional Heteroskedasticity (ARCH) issues of the OLS.

To explore the dynamic volatility of real estate price changes in relation to our MMB fundamentals and market sentiment proxies, we adopted GARCH modeling techniques. We utilize the quasi-maximum likelihood estimator (QMLE) for parameter estimation to ensure robustness, as it maintains consistency and asymptotically valid standard errors even in the presence of non-normality (Bollerslev & Zhou, 2006; Chang & McAleer, 2017). We employed the Broyden-Fletcher-Goldfarb-Shanno (BFGS) optimization algorithm, as it optimizes the likelihood function (Mahmood & Khan, 2020), enhancing the efficiency of our modeling approach.

Among the several GARCH models tested, empirical evidence emphasizes the superiority of the EGARCH(1,1) model with a normal error distribution (Nelson, 1991). Estimation results indicate that the EGARCH(1,1) model achieved minimized values for both Akaike (AIC) and Schwarz information criteria (SIC), making it optimal choice for scrutinizing sentiment impacts on Greek housing prices. Furthermore, the Exponential Generalized AutoRegressive Conditional Heteroskedasticity (EGARCH) model's ability to represent variance in logarithmic form facilitates flexible coefficient adjustments without imposing constraints (López-Cabarcos, Pérez-Pico, Piñeiro-Chousa, & Šević, 2021), thereby enabling us to capture asymmetric volatility responses to positive and negative housing market shifts more efficiently.

The mean equation of our EGARCH(1,1) model specification is:

$$dr_{HPIt} = a_0 + a_1 * d\_I_t + a_2 * GDP\_yoy_t + a_3 * D\_MI_t + a_4 * d\_World\_Searches_t\, a_5 * d\_Local\_Searches_t + \varepsilon_t \quad (1)$$

where μ is the mean of the returns, and ε_t is the error term $\varepsilon_t \sim N(0,\sigma\_t)$.

The conditional variance for our EGARCH(1,1,1) model is:

$$\log(\sigma_t^2) = c_0 + c_1 \times \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + c_2 \times \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + c_3 \times \log(\sigma_{t-1}^2) \quad (2)$$

Where the log guarantees the non-negativity of the σ_t^2 even when the parameters c_0, c_1, c_2 and c_3 are negative. c_1 is the ARCH, capturing the short-term volatility clustering and the symmetric effect of the autoregressive model. c_3 is the GARCH term, measuring persistency in the conditional volatility. The c_2 coefficient captures the leverage effect, i.e., if $c_2 < 0$ and statistically significant, it implies that negative innovations exert greater impact on volatility compared to similar-sized positive innovations. This underscores inherent asymmetry in the response of real estate price volatility to shifts in market sentiment.

Lastly, for robustness, we incorporate Google Trends behavioral indicators alongside our MMB fundamentals individually. This approach allows us to discern the behavioral consumer effect on housing prices beyond the macroeconomic fundamentals. Our findings are consolidated into three distinct models, each shedding light on the intricate interplay between market sentiment and traditional economic factors in influencing housing prices.

4. Results

Table 3 presents the results of the EGARCH(1,1) model for all MMB fundamentals and Google Trends sentiment indicators. Model (1) includes all macroeconomic fundamentals in the mean equation; Model (2) adds the world search Google Trends index, while Model (3) incorporates all MMB fundamentals alongside both world and LS Google Trends indexes.

In Model (1), where only the MMB fundamentals are considered in the mean equation, notable patterns emerge from the coefficient estimates. The negative coefficient for α_1 suggests

Mean equation	Model 1	Model 2	Model 3
α_0	0.002740*** (0.000146)	0.002623*** (0.001018)	0.002158 (0.001552)
α_1	−0.002344*** (0.000560)	−0.002187*** (0.000564)	−0.001439** (0.000733)
α_2	0.095737*** (0.025843)	0.098265*** (0.024795)	0.084174** (0.038312)
α_3	0.011897** (0.006008)	0.012960** (0.006185)	0.013989** (0.007071)
α_4		5.09E−05 (8.52E−05)	−4.53E−05 (0.000147)
α_5			0.003643*** (0.001264)
Conditional variance			
c_0	−6.235933** (3.152252)	−6.389334* (3.277138)	−4.650906 (4.560370)
c_1	1.406826** (0.583822)	1.501897** (0.624552)	0.636721 (0.448490)
c_2	−0.105347 (0.308109)	−0.109840 (0.314787)	−0.131822 (0.301321)
c_3	0.461861 (0.461861)	0.455663 (0.355387)	0.555462 (0.478686)
Residuals Q-tests			
Q1	0.027	0.039	1.023
Q2	0.835	0.869	1.269
Q3	1.073	1.194	1.273
ARCH LM – F-statistic			
LM1	0.017	0.088	5.61E−05
LM2	0.019	0.045	0.019
LM3	0.035	0.037	0.036

Note(s): Significance levels are denoted as ***, **, and * for statistical significance at the 1%, 5%, and 10% level, respectively. Standard deviations of the estimated parameters are presented in parentheses
Source(s): Table by authors

Table 3.
GARCH models

an intriguing relationship between inflation and housing price returns, aligning with the traditional understanding that higher inflation erodes purchasing power and diminishes housing demand. This finding, consistent with Hoesli *et al.* (2008), implies that Greek real estate may not serve as an effective hedge against inflationary pressures. Conversely, the positive coefficients for α_2 and α_3 indicate that increases in GDP and MI rates correspond to higher housing price returns, reflecting the positive influence of economic growth and financing conditions on housing demand. This affirms the common understanding that economic expansion tends to drive up house prices due to increased consumer spending (Kishor, 2007; Leung, 2003; Simo-Kengne *et al.*, 2016). However, the findings also suggest a nuanced relationship with interest rates, where higher rates typically constrain housing affordability but may paradoxically stimulate demand during periods of financial uncertainty, as noted by Shi *et al.* (2014). This result indicates that increases in the policy rate may not effectively depress real housing prices, especially during economic turmoil, as investors consider real estate assets as a good investment during turbulent times, thereby increasing demand for housing.

When the additional world search Google Trends index is incorporated in Model (2), the results provide further insights. Interestingly, the introduction of the World search Google Trends index ($\alpha 4$) shows that online search behavior globally might not significantly affect housing price returns in the Greek market, as evidenced by the non-significant coefficient. This could suggest that increases in global online interest in the Greek housing market may not consistently correlate with housing price returns. This finding aligns with Papageorgiou *et al.* (2020), which emphasizes that investment decisions regarding holiday homes in Greece are primarily driven by factors such as property value, characteristics, hidden costs and the broader economic environment. Given the recent market changes in Greece, including economic fluctuations and policy reforms, the insignificant impact of global online search behavior on housing price movements suggests that other factors may play a more dominant role in shaping the Greek real estate market dynamics. Overall, the positive (insignificant) coefficient suggests that increases in global online interest in the Greek housing market may be associated with higher housing price returns, indicating that global sentiment impacts Greek housing market dynamics.

Lastly, the results from Model (3) shed light on the complex dynamics influencing Greek housing price volatility. While the traditional economic indicators remain influential, the incorporation of Google Trends data reveals the growing importance of online sentiment and behavior. The inclusion of the LS Google Trends index ($\alpha 5$) provides valuable insights into domestic online search patterns and their impact on housing price returns. The positive coefficient (0.003643) suggests that heightened local online interest corresponds with increased housing price returns, emphasizing the pivotal role of local sentiment and preferences in shaping housing market dynamics. This observation aligns with established theories linking local house price beliefs to housing search behavior (Ben-David, Fermand, Kuhnen, & Li, 2018; Gargano, Giacoletti, & Jarnecic, 2023; Piazzesi, Schneider, & Stroebel, 2020), emphasizing the impact of uncertainties regarding house price fluctuations on investment decisions (Ben-David *et al.*, 2018). In line with previous studies by Anastasiou *et al.* (2021) and Anastasiou and Kapopoulos (2023), our findings underscore the significance of local housing sentiment in influencing Greek housing prices. However, mirroring the outcomes from Model (2), the world search index remains insignificant, emphasizing that the Greek housing market is mainly affected by local sentiment rather than global sentiment.

Interestingly, the magnitude of the coefficient for local sentiment surpasses that of inflation ($\alpha 1$), suggesting that changes in local sentiment may have a more pronounced effect on housing prices than fluctuations in inflation rates. However, when compared to the impact of GDP and interest rates, the influence of local sentiment appears relatively modest. Nonetheless, these findings emphasize the importance of considering both traditional

economic metrics and emerging digital data sources in understanding and forecasting trends in the Greek real estate market, enriching our understanding of housing market dynamics.

Overall, the results across the three models underscore the multifaceted nature of the factors influencing Greek housing price volatility. While macroeconomic fundamentals play a significant role in shaping housing market dynamics, the inclusion of Google Trends indicators reveals the growing influence of online sentiment and behavior. By acknowledging the role of local sentiment alongside macroeconomic fundamentals, these findings provide deeper insights into the housing market dynamics.

5. Discussion, conclusions and further research

To the best of our knowledge, this is the first paper on the Greek real estate market that tries to incorporate behavioral indicators based on people's searches on the internet. We construct a house pricing model that combines MMB variables that are usually applied, with behavioral indicators compiled from Google Trends.

We find that inflation has a negative and statistically significant impact on the house prices, which could be explained by the fact that Greece, a country with long-term sovereign issues (2008–2017) which led to a marked decline in its GDP, did not suffer from inflation. This is largely due to its adoption of the Euro and EU/EMU support, so inflation remained low and the HPI in Euro values declined. In an alternative scenario, recession and a soft/weak individual currency would drive inflation up and house prices in local currency's value would be higher. In such a case, the relationship could be positive and the house values could be a hedge against inflation.

Similar explanation holds for the MI: the relationship is positive because when Greece suffered from the sovereign crisis (2008–2017) and house prices fell, the MI also fell because of the EMU and EU support. Without the EU/EMU and the Euro (ceteris paribus regarding other MMB variables), when the MI decline it is more tantalizing to buy a house, thus, the demand increases and the prices also. After 2017, when the prices increased, inflation and the MI also increased, following the Euro area. Consistent with the theory relating economic growth and real estate prices (Leung, 2003; Simo-Kengne *et al.*, 2012, 2016), we find that the GDP_yoy growth presents positive and statistically significant correlation with the HPI returns. The positive relationship between the HPI and MI adds new empirical evidence and explanations on this controversial relationship. In this pair of variables, we should note again that Greece had crucial sovereign issues for many of the years included in our sample and the empirical results would have been different if Greece was not a member of the EU and the EMU [4].

The worldwide interest for buying a property in Greece for any reason (investment, retirement and Golden Visa) does not have any statistically significant influence on house prices. This result though may require reexamination because of several reasons as the following:

(1) We may not have included the appropriate terms in our search index

(2) We may not have written them in the correct language and/or Google is not the most popular search engine in some countries, for example, many Greek Golden visas were given to Chinese citizens [5]

(3) We may need to adopt another way to add this indicator to an econometric model, such as dummy variables

Moreover, the house market is not as liquid as the stock market. Possibly, the intention from abroad does not have instant impact on house prices and local interest [6]. This could be an issue for further research.

The positive and statistically significant impact of LSs on the HPI reflects the digital age we live in. Nowadays, when individuals seek to purchase a house, they often turn to the internet to explore options through real estate agents or specialized websites. The heightened interest in LSs signifies increased local investor sentiment and consumer demand, leading to upward pressure on real estate prices. This finding aligns with previous studies highlighting the influential role of sentiment in shaping housing market dynamics (Anastasiou *et al.*, 2021; Anastasiou & Kapopoulos, 2023). More particular, the correlation between LSs and HPI underscores the evolving landscape of the real estate market, where digital trends play a pivotal role in driving investor sentiment and consumer behavior.

Our study underscores the importance of integrating behavioral variables alongside traditional macroeconomic fundamentals to enhance our comprehension of housing market dynamics. By incorporating both MMB variables and emerging digital data sources, such as Google Trends indicators, our findings reveal a more comprehensive understanding of how the market operates. The significant impact of behavioral variables, particularly LS trends, highlights the evolving role of online sentiment in shaping housing market dynamics. Policymakers and market participants can leverage these insights to formulate more effective strategies that promote sustainable growth and mitigate risks within the housing sector. Moreover, the flexibility and accessibility of these digital tools make them valuable instruments for gauging market sentiment and consumer intentions, offering a practical and efficient means of monitoring housing market trends in real-time. Additionally, the ease of application and the tool's capacity to gauge many people's intentions enhance its utility and effectiveness as a predictive tool for understanding housing market behavior. Overall, our study underscores the potential of incorporating behavioral variables into existing models, offering valuable insights and tools for navigating the dynamic landscape of the housing market.

The relevance of this study extends beyond the Greek housing market to other housing markets globally facing similar economic challenges. By examining how online sentiment and behavior interact with economic fundamentals to influence housing prices, this study offers a blueprint for understanding and navigating housing markets amid economic uncertainty. Thus, policymakers, regulators and investors in other housing markets grappling with economic challenges can leverage the findings of this study to develop targeted strategies aimed at promoting stability and resilience.

Future research should investigate causal relationships between variables and the speed of consumer intention's impact on prices. Understanding these dynamics can improve predictive modeling and decision-making. Exploring the temporal dynamics of behavioral variables can deepen our understanding of market sentiment evolution, enriching our comprehension of housing market behavior. Addressing these aspects will enhance our understanding of housing market dynamics, aiding more informed policymaking and investment strategies.

Notes

1. For some interesting data for Golden visas see https://getgoldenvisa.com/ultimate-guide-to-greece-golden-visa.
2. In our study, we smooth seasonality using the average value of the index on a yoy-basis.
3. The only exception is the HPI index for which we apply the percentage change of the HPI (dr_HPI).
4. In theory, when a country has significant sovereign issues such as Greece, inflation and MI should increase, but as Figure 1 shows, I and MI in Greece declined relative to the pre-2009 period. The safety net of the EMU and EU led to this controversial result.
5. Greece Golden Visa: The Ultimate Guide | Get Golden Visa

6. If somebody has the money to buy a house, s/he can buy it quickly, but interested parties that reside abroad will need to at least visit the property on site and this takes longer.

References

Abildgren, K., Hansen, N. L., & Kuchler, A. (2018). Overoptimism and house price bubbles. *Journal of Macroeconomics*, *56*, 1–14. doi: 10.1016/j.jmacro.2017.12.006.

Abraham, J. M., & Hendershott, P. H. (1996). Bubbles in metropolitan housing markets. *Journal of Housing Research*, *7*, 191–207.

Alkay, E., Watkins, C., & Keskin, B. (2018). Explaining spatial variation in housing construction activity in Turkey. *International Journal of Strategic Property Management*, *22*(2), 119–130. doi: 10.3846/ijspm.2018.443.

Anastasiou, D., Kapopoulos, P., & Zekente, K. M. (2023). Sentimental shocks and house prices. *The Journal of Real Estate Finance and Economics*, *67*(4), 627–655.

Anastasiou, D., Kapopoulos, P., & Zekente, K. M. (2021). Sentimental shocks and house prices. *The Journal of Real Estate Finance and Economics*. doi: 10.1007/s11146-021-09871-z.

Apergis, N., & Rezitis, A. (2003). Housing prices and macroeconomic factors in Greece: Prospects within the EMU. *Applied Economics Letters*, *10*(12), 799–804. doi: 10.1080/1350485032000126758.

Asal, M. (2019). Is there a bubble in the Swedish housing market?. *Journal of European Real Estate Research*, *12*(1), 32–61. doi: 10.1108/JERER-03-2018-0013.

Assibey-Yeboah, M., & Mohsin, M. (2014). The real effects of inflation in a developing economy with external debt and sovereign risk. *North-American Journal of Economics and Finance*, *30*, 40–55. doi: 10.1016/j.najef.2014.07.004.

Ben-David, I., Fermand, E., Kuhnen, C. M., & Li, G. (2018). *Expectations uncertainty and household economic behavior*. (No. w25336). National Bureau of Economic Research. doi: 10.2139/ssrn.3293399.

Beracha, E., Lang, M., & Hausler, J. (2019). On the relationship between market sentiment and commercial real estate performance — a textual analysis examination. *Journal of Real Estate Research*, *41*(4), 605–638. doi: 10.22300/0896-5803.41.4.605.

Bilgin, M. H., Demir, E., Gozgor, G., Karabulut, G., & Kaya, H. (2019). A novel index of macroeconomic uncertainty for Turkey based on Google-Trends. *Economics Letters*, *184*, 108601. doi: 10.1016/j.econlet.2019.108601.

Bjørnland, H. C., & Jacobsen, D. H. (2010). The role of house prices in the monetary policy transmission mechanism in small open economies. *Journal of Financial Stability*, *6*(4), 218–229. doi: 10.1016/j.jfs.2010.02.001.

Bollerslev, T., & Zhou, H. (2006). Volatility puzzles: A simple framework for gauging return-volatility regressions. In *Journal of Econometrics*. doi: 10.1016/j.jeconom.2005.01.006.

Brodeur, A., Clark, A. E., Fleche, S., & Powdthavee, N. (2021). COVID-19, lockdowns and well-being: Evidence from google trends. *Journal of Public Economics*, *193*, 104346. doi: 10.1016/j.jpubeco.2020.104346.

Bulczak, G. M. (2021). Use of google trends to predict the real estate market: Evidence from the United Kingdom. *International Real Estate Review*, *24*(4), 613–631. doi: 10.53383/100332.

Calabria, M., & Calder, V. B. (2019). Demographic and policy factors affecting homeownership across OECD countries. In *The Routledge Handbook of Housing Policy and Planning*. doi: 10.4324/9781315642338-9.

Case, K. E., Shiller, R. J., & Thompson, A. K. (2012). What have they been thinking? Homebuyer behavior in hot and cold markets. *Brookings Papers on Economic Activity*, *2012*(1), 265–315. doi: 10.1353/eca.2012.0014.

Čermáková, K., & Hromada, E. (2022). Change in the affordability of owner-occupied housing in the context of rising energy prices. *Energies*, *15*(4), 1281. doi: 10.3390/en15041281.

Chang, C. L., & McAleer, M. (2017). The correct regularity condition and interpretation of asymmetry in EGARCH. *Economics Letters*, *161*, 52–55. doi: 10.1016/j.econlet.2017.09.017.

Choi, H. and Varian, H. (2012). Predicting the present with Google Trends. *Economic Record*, *88*, 2–9. doi: 10.1111/j.1475-4932.2012.00809.x.

Clayton, J., Ling, D. C., & Naranjo, A. (2009). Commercial real estate valuation: Fundamentals versus investor sentiment. *Journal of Real Estate Finance and Economics*, *38*(1), 5–37. doi: 10.1007/s11146-008-9130-6.

De Bandt, O., Barhoumi, K., & Bruneau, C. (2010). The international transmission of house price shocks. In *Housing Markets in Europe: A Macroeconomic Perspective* (pp. 129–158). Springer Berlin Heidelberg. doi: 10.1007/978-3-642-15340-2_7.

De Santis, R. A., & Surico, P. (2013). Bank lending and monetary transmission in the euro area. *Economic Policy*, *28*(75), 423–457. doi: 10.1111/1468-0327.12013.

Demary, M. (2010). The interplay between output, inflation, interest rates and house prices: International evidence. *Journal of Proteome Research*, *27*(1), 1–17. doi: 10.1080/09599916.2010.499015.

Dietzel, M. A. (2016). Sentiment-based predictions of housing market turning points with Google trends. *Journal of Housing Markets and Analysis*, *9*(1), 108–136. doi: 10.1108/IJHMA-12-2014-0058.

Dong, Z., Hui, E. C. M., & Yi, D. (2021). Housing market sentiment and homeownership. *Journal of Housing and the Built Environment*, *36*(1), 29–46. doi: 10.1007/s10901-020-09784-y.

Everett, M., de Haan, J., Jansen, D. J., McQuade, P., & Samarina, A. (2021). Mortgage lending, monetary policy, and prudential measures in small euro-area economies: Evidence from Ireland and The Netherlands. In *Review of International Economics*. doi: 10.1111/roie.12506.

Fama, E. F., & Schwert, G. W. (1977). Asset returns and inflation. *Journal of Financial Economics*, *5*(2), 115–146. doi: 10.1016/0304-405X(77)90014-9.

Fischer, M., & Stamos, M. Z. (2013). Optimal life cycle portfolio choice with housing market cycles. *Review of Financial Studies*, *26*(9), 2311–2352. doi: 10.1093/rfs/hht010.

Fuhrer, J. C. (1993). What role does consumer sentiment play in the U.S. macroeconomy?. *New England Economic Review*.

Gargano, A., Giacoletti, M., & Jarnecic, E. (2023). Local experiences, search, and spillovers in the housing market. *J Finance*, *78*(2), 1015–1053. doi: 10.1111/jofi.13208.

Glaeser, E. L., Gottlieb, J. D., & Gyourko, J. (2015). Can cheap credit explain the housing boom?. In *Housing and the Financial Crisis*. doi: 10.7208/chicago/9780226030616.003.0008.

Gounopoulos, D., Merikas, A. G., Merika, A. A., & Triantafyllou, A. (2012). Explaining house price changes in Greece. *Applied Financial Economics*, *22*(7), 549–561. doi: 10.1080/09603107.2011.619494.

Granziera, E., & Kozicki, S. (2015). House price dynamics: Fundamentals and expectations. *Journal of Economic Dynamics and Control*, *60*, 152–165. doi: 10.1016/j.jedc.2015.09.003.

Gupta, R., Jurgilas, M., Miller, S. M., & Van Wyk, D. (2011). Financial market liberalization, monetary policy, and housing sector dynamics. *International Business & Economics Research Journal*, *11*(1), 69. doi: 10.19030/iber.v11i1.6673.

Hausler, J., Ruscheinsky, J., & Lang, M. (2018). News-based sentiment analysis in real estate: A machine learning approach. *Journal of Proteome Research*, *35*(4), 344–371. doi: 10.1080/09599916.2018.1551923.

Hoesli, M., Lizieri, C., & MacGregor, B. (2008). The inflation hedging characteristics of US and UK investments: a multi-factor error correction approach. *The Journal of Real Estate Finance and Economics, 36*, 183–206.

Hong, J., Kim, H., & Ahn, S. (2022). Is there a bubble in the housing market in seoul?. *Journal of Real Estate Anal*, *8*(1), 1–21. doi: 10.30902/jrea.2022.8.1.1.

Kishor, K. N. (2007). Does consumption respond more to housing wealth than to financial market wealth? If so, why?. *Journal of Real Estate Finance and Economics*, *35*(4), 427–448. doi: 10.1007/s11146-007-9080-4.

Lekkos, I., Staggel, I., Kefalas, K., & Vlachou, P. (2014). Non-residential real estate and economic activity: The case of Greece. *Journal of Property Investment & Finance*, *32*(1), 35–55. doi: 10.1108/JPIF-08-2013-0051.

Leschinski, C., & Bertram, P. (2017). Time varying contagion in EMU government bond spreads. *Journal of Financial Stability*, *29*, 72–91. doi:10.1016/j.jfs.2017.01.007.

Lettau, M., & Ludvigson, S. C. (2004). Understanding trend and cycle in asset values: Reevaluating the wealth effect on consumption. *The American Economic Review*, *94*(1), 276–299. doi: 10.1257/000282804322970805.

Leung, C. K. Y. (2003). Economic growth and increasing house prices. *Pacific Economic Review*, *8*(2), 183–190. doi: 10.1111/j.1468-0106.2003.00219.x.

Ling, D. C., Ooi, J. T. L., & Le, T. T. T. (2015). Explaining house price dynamics: Isolating the role of nonfundamentals. *Journal of Money, Credit, and Banking*, *47*(S1), 87–125. doi: 10.1111/jmcb.12194.

López-Cabarcos, M.Á., Pérez-Pico, A. M., Piñeiro-Chousa, J., & Šević, A. (2021). Bitcoin volatility, stock market and investor sentiment. Are they connected?. *Financial Research Letter*, *38*, 101399. doi: 10.1016/j.frl.2019.101399.

Mahmood, F., & Khan, S. A. (2020). Multi-modality in the likelihood function of GARCH model. *Review Pacific Basin Financ Mark Policies*, *23*(3), 2050018. doi: 10.1142/S0219091520500186.

Marfatia, H. A., André, C., & Gupta, R. (2022). Predicting housing market sentiment: The role of financial, macroeconomic and real estate uncertainties. *The Journal of Behavioral Finance*, *23*(2), 189–209. doi: 10.1080/15427560.2020.1865354.

Mishkin, F. S., Hall, R., Shoven, J., Juster, T., & Lovell, M. (1978). Consumer sentiment and spending on durable goods. *Brookings Papers on Economic Activity*, *1978*(1), 217. doi: 10.2307/2534366.

Muellbauer, J., & Murphy, A. (2008). Housing markets and the economy: The assessment. *Oxford Review of Economic Policy*, *24*(1), 1–33. doi: 10.1093/oxrep/grn011.

Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica*, *59*(2), 347. doi: 10.2307/2938260.

Papageorgiou, G., Loulis, V., Efstathiades, A., & Ness, A. N. (2020). Investigating factors affecting holiday home purchases in Greece. *Property Management*, *38*(3), 419–435. doi: 10.1108/PM-06-2019-0034.

Petropoulos, T., Liapis, K., & Thalassinos, E. (2023). Optimal structure of real estate portfolio using eva: A stochastic markowitz model using data from Greek real estate market. *Risks*, *11*(2), 43. doi: 10.3390/risks11020043.

Piazzesi, M., Schneider, M., & Stroebel, J. (2020). Segmented housing search. *The American Economic Review*, *110*(3), 720–759. doi: 10.1257/aer.20141772.

Plakandaras, V., Gupta, R., Katrakilidis, C., & Wohar, M. E. (2020). Time-varying role of macroeconomic shocks on house prices in the US and UK: Evidence from over 150 years of data. *Empirical Economics*, *58*(5), 2249–2285. doi: 10.1007/s00181-018-1581-x.

Preis, T., Moat, H. S., & Eugene Stanley, H. (2013). Quantifying trading behavior in financial markets using google trends. *Scientific Reports*, *3*(1), 1684. doi: 10.1038/srep01684.

Rahal, C. (2016). Housing markets and unconventional monetary policy. *Journal of Housing Economics*, *32*, 67–80. doi: 10.1016/j.jhe.2016.04.005.

Shi, S., Jou, J. B., & Tripe, D. (2014). Can interest rates really control house prices? Effectiveness and implications for macroprudential policy. *Journal of Banking & Finance*, *47*, 15–28. doi: 10.1016/j.jbankfin.2014.06.012.

Shiller, R. J. (2008). Historic turning points in real estate. *East Journal of Economics and Finance*, *34*(1), 1–13. doi: 10.1057/palgrave.eej.9050001.

Simo-Kengne, B. D., Bittencourt, M., & Gupta, R. (2012). House prices and economic growth in South Africa: Evidence from provincial-level data. *Journal of Real Estate Lit*, *20*(1), 97–117. doi: 10.1080/10835547.2012.12090311.

Simo-Kengne, B. D., Miller, S. M., Gupta, R., & Balcilar, M. (2016). Evolution of the monetary transmission mechanism in the US: The role of asset returns. *Journal of Real Estate Finance Econ*, *52*(3), 226–243. doi: 10.1007/s11146-015-9512-5.

Taylor, J. B. (2009). *The financial crisis and the policy responses: An empirical analysis of what went wrong* (No. w14631). National Bureau of Economic Research.

Thornton, J., & Vasilakis, C. (2016). Does inflation targeting reduce sovereign risk? Further evidence. Financ. *Research Letters*, *18*, 237–241. doi: 10.1016/j.frl.2016.04.022.

Throop, A. W. (1992). Consumer sentiment: Its causes and effects. *Economic Review*, *1*.

Tsai, I. C., & Peng, C. W. (2011). Bubbles in the Taiwan housing market: The determinants and effects. *Habitat Int*, *35*(2), 379–390. doi: 10.1016/j.habitatint.2010.11.010.

Van Raaij, W. F., & Gianotten, H. J. (1990). Consumer confidence, expenditure, saving, and credit. *Journal of Economic Psychology*, *11*(2), 269–290. doi: 10.1016/0167-4870(90)90007-V.

Vasileiou, E. (2021a). Behavioral finance and market efficiency in the time of the COVID-19 pandemic: Does fear drive the market?. *International Review of Applied Economics*, *35*(2), 224–241. doi: 10.1080/02692171.2020.1864301.

Vasileiou, E. (2021b). Explaining stock markets' performance during the COVID-19 crisis: Could google searches be a significant behavioral indicator? Intell. *Systems Accounting, Finance Management*, *28*(3), 173–181. doi: 10.1002/isaf.1499.

Vasileiou, E. (2023). Health risk, stimulus packages, and subordinated bank yields: Evidence from the COVID-19 outbreak. *Journal of Predict Mark*, *16*(3), 59–66. doi: 10.5750/jpm.v16i3.1957.

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