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Research Paper

Economic Sentiment and Its Impact on the Global Housing Market: A Behavioral Perspective

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ABSTRACT

Purpose: This paper investigates the impact of economic sentiment, alongside key macroeconomic variables, on housing prices. It aims to illuminate the complex dynamics of the housing market, integrating the lens of Behavioral Finance to understand how sentiment influences market outcomes, providing a fresh perspective on price formation mechanisms within this sector.

Design/methodology/approach: Employing a two-stage analytical framework, the study first disentangles the Consumer Confidence Index into its fundamental (macroeconomic factors) and non-fundamental (sentiment-driven residuals) components. The second stage involves regressing the Housing Price Index against these macroeconomic variables and the distilled measure of economic sentiment. This approach builds on Lemmon & Portniaguina's (2006) methodology, enabling an examination of the interplay between economic fundamentals and sentiment in shaping housing prices. The study's international scope, encompassing a wide array of countries, allows for a robust exploration of these dynamics across diverse economic landscapes.

Findings: The analysis reveals that economic sentiment has a notable negative impact on housing prices, diverging from some strands of the literature that found positive sentiment-price correlations within specific market segments. Macroeconomic variables such as inflation and long-term interest rates exhibit a significant relationship with housing prices, while GDP shows an unexpected negative correlation. These findings underscore the complexity of the housing market's response to economic signals and sentiment, highlighting the limitations of conventional models in fully capturing these dynamics. The study also points to the potential of integrating sentiment analysis into housing market research, offering deeper insights into price formation processes.

Originality/value: The study unveils the impact of economic sentiment on housing prices, challenging prevailing assumptions and enriching our understanding of market behavior. It provides a compelling case for the inclusion of sentiment analysis in housing

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market studies, suggesting new avenues for research and offering valuable insights for policymakers, investors, and academics interested in the dynamics of housing markets.

Keywords: *Economic sentiment; housing market; behavioral finance*

1.Introduction

The housing market is foundational to the economy, serving dual roles as a consumer and investment sphere, and is a significant driver of banking finance. It is deeply intertwined with the quality of life for individuals and households, with housing purchases representing a major investment for many. The allocation of household budgets towards housing directly impacts consumption and savings, underscoring the market's broader economic significance. This market's influence extends beyond individual financial decisions, affecting both consumers and investors through its dynamics of demand, supply, and pricing. Its importance is magnified by its connections to various sectors, notably banking, and its role within both national and global economic frameworks.

The importance of this market is underscored in the context of globalization and its role in the international financial crisis that began in 2007. While there is extensive research on the influence of macroeconomic variables on property prices, the exploration of non-fundamental factors, such as economic sentiment, has been less prevalent. However, recent literature suggests that macroeconomic factors alone do not fully account for price dynamics in the housing market, highlighting the importance of psychological, emotional, and behavioral factors (Sutton, 2002; Gallin, 2006; Égert & Mihaljek, 2007; Mikhed & Zemčík, 2009; Posedel & Vizek, 2011). Behavioral finance has emerged to address these aspects, challenging traditional finance theories by incorporating insights from Psychology and Sociology. Founded on the work of Kahneman and Tversky, behavioral finance examines how heuristic rules and biases can lead to systematic errors in decision-making, influencing market dynamics. This perspective has gained attention for its potential to explain market phenomena not accounted for by traditional models (Thaler, 1985).

This paper examines the overall impact of agent sentiment on housing prices. Following Baker & Wurgler (2007) and Heinig, Nanda, & Tsolacos (2016), the sentiment variable is crucial, with literature categorizing sentiment measures into market-based (indirect) and survey/poll-based (direct) types. Our analysis spans 24 countries from 2000 to 2017, employing a two-stage methodology similar to Lemmon & Portniaguina (2006). The first stage decomposes the consumer confidence index to isolate non-fundamental sentiment, using macroeconomic variables for the fundamental component. The second stage assesses the impact of this sentiment on the Housing Price Index (HPI), alongside other macroeconomic variables. This approach, aligning with methodologies used across various financial markets, is novel in its application to the global residential housing market, offering fresh insights into the influence of sentiment on market prices.

The paper is structured into 6 sections, starting with an introduction that sets the stage for the research. In section 2, the literature review traces the evolution of behavioral finance, and its significance in understanding housing market dynamics. In sections 3 and 4 we present the methods and data used, while section 5 discusses the findings. Finally, the conclusion summarizes the study, reflecting on its implications and suggesting avenues for future research.

2.Literature review

The emergence of behavioral finance has significantly enriched financial literature by shedding light on the "irrational" behaviors of economic agents and weaving in concepts from psychology and sociology into the fabric of economic and financial theories. This advancement was partly in response to the limitations observed in traditional economic paradigms, as noted by Thaler (2005), positing that understanding certain financial phenomena necessitates models that account for less than fully rational behaviors of agents. The domain has garnered attention and sparked debates across the international scholarly community, not only due to its conceptual novelties but also because of the critical discussions it has prompted regarding the theoretical and empirical frameworks that have long underpinned finance literature.

The foundational work of Kahneman and Tversky has been pivotal in establishing behavioral finance. They introduced the notion of heuristic rules, mental shortcuts that individuals rely on, leading to decision biases. Tversky & Kahneman (1974) identified three principal types of heuristics: availability, representativeness, and anchoring.

Availability heuristics involve evaluating the likelihood of an event based on one's recall of similar instances. Representativeness heuristics are judgments based on how well something matches our mental models. Anchoring heuristics concern the initial reference point used to make subsequent evaluations and adjustments. These heuristics often pave the way to decisions that are not optimally thought through. The behavioral deviations highlighted are attributed not to external influences or misjudgments but are deeply ingrained in the individual's character. This insight reveals that even seasoned researchers, when relying on instinct, can fall prey to these biases.

This framework introduces us to the concept of bounded rationality, where systematic errors—not random ones—permeate decision-making processes. Collectively, these biased decisions have the potential to impact the markets where these agents are active. The development of Prospect Theory (Tversky & Kahneman, 1979) offers a critique and an alternative to the Expected Utility Theory (von Neumann & Morgenstern, 1944), which is based on the premise that risks are evaluated against a specific reference point. This theory shifts the focus from utility to value, defining gains and losses relative to this point. The resulting value curve, concave for losses and convex for gains, underscores the asymmetric value investors place on losses versus gains—emphasizing the greater "pain" felt from loss compared to the "pleasure" derived from gain.

Shleifer and Summers (1990) lay the foundation of behavioral finance on two critical pillars: the limits to arbitrage and the psychological factors influencing agents. These aspects challenge the traditional view of market efficiency by highlighting how mental biases can distort decision-making in financial markets. Among the notable biases are overconfidence, conservatism, loss aversion, the disposition effect, the endowment effect, and herding behavior. Overconfidence, as detailed by Thaler (2005), describes the tendency of individuals to overestimate their predictive capabilities while underestimating risks. This bias often leads to more frequent trading and investing, with typically suboptimal outcomes (Zia & Hashmi, 2016). Gervais and Odean (2001, as cited in Jlassi, Naoui, & Mansour, 2014) argue that investors become overly confident following periods of high returns, particularly when these returns validate their private information. Shiller (2000) explains conservatism as the reluctance to adjust beliefs in the face of significant evidence or changes in the external environment. This leads to the expectation that the future will closely mirror the recent past, a belief that can delay necessary adjustments to new realities (Ritter, 2003). The disposition effect, identified by Shefrin & Statman (1985), refers to the inclination to sell winning investments prematurely while holding onto losers for too long, hoping for a turnaround. This behavior, deeply rooted in loss aversion, highlights how investors psychologically differentiate between winning and losing investments, significantly influenced by Prospect Theory's insights from Tversky & Kahneman (1979). The endowment effect, as Medeiros (2004) notes, leads investors to value assets they own more highly than those they do not, influencing their selling and purchasing decisions. This cognitive bias suggests that individuals demand a higher price to part with an asset than they would be willing to pay to acquire it. Lastly, herding behavior describes the phenomenon where investors mimic the actions of others, often driven by social pressure, the assumption of superior information in others, or a desire to align with group norms. This behavior can exacerbate market volatility and contribute to the formation of asset price bubbles.

Behavioral finance thus offers a more nuanced view of financial markets, acknowledging that investors are not always rational, and their decisions are influenced by psychological biases and social factors. This field provides valuable insights into the behavior of investors and the dynamics of financial markets, challenging traditional models that assume rational behavior and market efficiency.

2.1 Behavioral effects in the housing market

Shiller (2007) unveils the profound impact of sentiments on housing market fluctuations, illustrating how these emotional forces can override fundamental economic indicators. This insight into the psychology of buyers and sellers explains the challenges in aligning market expectations, highlighting that steadfast beliefs in price trends can significantly delay adjustments to new market realities. As supply increases in response to high prices, a lag in price correction occurs until a collective shift in expectations aligns with the increased supply, ultimately tempering market booms.

Building on this psychological perspective, Hong (2007) points out the widespread lack of financial literacy among homeowners, for whom property investment represents a major financial decision. This gap in understanding, combined with the individualized nature of property transactions, fosters inefficiencies in the housing market, a domain where amateurs often operate with limited information, as noted by Smith & Smith (2006). Further examining market behavior, Leung & Tsang (2011) and Chang et al. (2017) identify anchoring effects and loss aversion in housing markets across Hong Kong and Taiwan, respectively. These studies highlight how psychological biases correlate with transaction volumes and price dispersion, affecting both individual and institutional investors' decision-making processes.

Genesove & Mayer (2000) dive into the specifics of pricing strategies, demonstrating that loss aversion prompts sellers to set higher asking prices, a trend that Bokhari & Geltner (2011) and Li et al. (2017) confirm extends to both residential and commercial sectors. These findings reveal a general reluctance among sellers to adjust prices downward, even in the face of market realities, underscoring the pervasive influence of psychological biases in pricing decisions. Einiö et al. (2007) introduce the concept of sales at zero return, shedding light on how initial purchase prices anchor sellers' expectations, a phenomenon further explored by Paraschiv & Chenavaz (2011) and Bao & Meng (2017). Their research in different markets demonstrates how loss aversion and reference point dependence shape pricing and selling strategies, influencing market dynamics and contributing to price dispersion and transaction volumes.

In the Singapore condominium market, Hong, Loh, & Warachka (2014) find that loss aversion influences not only pricing but also the likelihood of a sale, with potential gains prompting more aggressive selling strategies. This behavior mirrors findings in the stock market by Barberis & Xiong (2008), underscoring the universal impact of psychological factors on financial decisions. Lastly, Seiler & Lane (2012) and Clapp & Lu-Andrews (2016) delve into the nuances of mental accounting and the importance of local fundamental factors in setting asking prices. These studies collectively highlight the multifaceted influence of psychological biases, market dynamics, and economic fundamentals in shaping the housing market, offering a comprehensive view of the factors driving pricing and investment behaviors.

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2.2 The Sentiment effect in the housing market

The integration of psychological and behavioral variables alongside macro and microeconomic factors has been shown to enhance the performance of market pricing models, thereby increasing their explanatory power. This assertion, supported by various studies (Shleifer & Summers, 1990; Ho & Hung, 2008; Jin et al., 2014; Ling et al., 2015; Heinig et al., 2016), highlights how these variables add valuable information to markets, addressing existing gaps and omissions often pointed out in research. This discussion does not aim to analyze any specific behavior or sentiment, but rather to explore the impact of the overall sentiment level of market participants on the price levels of the analyzed market, particularly within the housing sector.

Identifying the most suitable and comprehensive sentiment measure that can be transformed into a variable is crucial, regardless of the market in focus. According to Heinig et al. (2016), existing literature on sentiment can be categorized into two groups: market-based sentiment, considered an indirect measure, and survey/poll-based sentiment, often referred to as direct measures. A review of literature on the impact of sentiment on prices (among other factors) in both capital markets and the housing market will be provided, showcasing different types of measures and offering a comparative analysis between them.

Consumer Confidence Index (CCI) and consumer/investor sentiment indices are among the most commonly used measures in the literature, with some studies breaking down these indices into fundamental and sentimental components. The CCI is employed by Qiu & Welch (2004), Lemmon & Portniaguina (2006), Rouwendal & Longhi (2007), Hsu, Lin, & Wu (2011), and Lacerda (2013), with the first three and the last focusing on capital markets, and the second last on the housing market. The consumer sentiment index is utilized by Jin et al. (2014) for the housing market. Other researchers, such as Baker & Wurgler (2006), Lacerda (2013), and Fernandes (2015) for capital markets, and Ling, Naranjo, & Scheick (2010) for the housing market, use composite indices of economic sentiment formed from various survey-based proxies.

Other measures have also been referenced in research, albeit less frequently. For instance, in the context of capital markets, Brown & Cliff (2005) and Han (2008) use direct sentiment measures derived from the research and analysis of newsletters. In the housing market, Ling et al. (2015) employ a similar survey-based method. Zheng, Sun, & Kahn (2014) develop a confidence index specifically targeted at the housing market. Subscription rates of closed-end funds and housing investment funds are considered in some studies focused on capital markets (Qiu & Welch, 2004; Lacerda, 2013), but these typically serve as comparative bases to the aforementioned indices rather than as primary measures of agent sentiment.

Exploring the role of sentiment in the housing market, Ling et al. (2015) uncover how sentiment, gauged through surveys among key market players—buyers, builders, and financiers—serves as a significant predictor of housing price movements. Their innovative approach, using regression residuals to capture sentiment, demonstrates that heightened sentiment levels can forecast strong price appreciation, outstripping the predictive power of fundamental variables and market liquidity. This revelation underscores the critical influence of psychological factors on the U.S. housing market dynamics, where models enriched with sentiment indicators outperform traditional benchmark models in predicting price trends and volatility across economic cycles.

In a similar vein, Marcato & Nanda (2016) assess the efficacy of sentiment indices in capturing the pulse of the housing market. Their comparison against economic indicators reveals that sentiment not only provides key insights into future market returns but also that housing prices are sensitive to shifts in sentiment, albeit predominantly within the residential sector. This finding highlights the added value of market-specific sentiment indices over generic business indicators in decoding housing market trends.

Zheng et al. (2014) delve into the Chinese market, crafting a confidence index that reflects city-specific market outlooks based on online survey data. This localized sentiment gauge, influenced by perceptions of housing policies, offers predictive insights into price growth and market activity, with its impact modulated by regional supply-demand dynamics. This approach illustrates the complex interplay between public sentiment, policy perceptions, and market outcomes, varying significantly across cities.

Turning to the non-residential sector, Heinig et al. (2016) explore sentiment through both direct and proxy measures, finding evidence of sentiment-driven price and return deviations from fundamental valuations. Their analysis suggests a degree of "irrationality" among market participants, with models incorporating unconventional data sources like Google Trends showing superior performance.

Ling et al. (2010) investigate the interplay between investor sentiment and market returns, identifying a short-term positive correlation, particularly pronounced in the public sector due to its higher transparency and investor sophistication. However, their long-term analysis reveals an inevitable correction towards fundamental valuations, highlighting the ephemeral nature of sentiment-driven price gains.

Jin et al. (2014) employ a deviation correction model to dissect the impact of consumer sentiment on price normalization, utilizing the Consumer Confidence Index as a proxy. Their findings point to a significant long-term influence of irrational sentiment on price adjustments in the residential market, with sentiment variables enhancing the predictive accuracy of their models.

Lastly, Rouwendal & Longhi (2007) focus on a period marked by sharp price increases, attributing a significant part of the housing market dynamics to consumer confidence as captured by the Consumer Confidence Index. Their analysis suggests that while consumer confidence can drive short-term price fluctuations, the market tends to realign with fundamental values over the long term, albeit with variations influenced by supply and interest rate conditions.

3.Methodology

Following Lemmon & Portniaguina (2006), our econometric framework comprises two multiple linear regressions for panel data. The initial phase decomposes the Consumer Confidence Index into fundamental and non-fundamental components to capture "irrational" or excessive sentiment (optimism and pessimism), referred to as economic sentiment in this study. Control variables for the fundamental component include unemployment rate, stock indices, inflation, real GDP growth rate, short-term and long-term interest rates. This empirical approach, decomposing the index into fundamental factors, has been adopted in various markets by researchers like Qiu & Welch (2004) and

Baker & Wurgler (2006) for the stock market, Ling et al. (2015) for the housing market, and Fernandes (2015) for both stock and bond markets.

The residuals from this regression are used as a measure of economic sentiment in the second regression, which analyzes the relationship between the Housing Price Index and independent variables such as real GDP growth, inflation, short-term and long-term interest rates, and the economic sentiment derived from the first regression's residuals. This method has been applied in different contexts by Han (2008) for the options market, Lacerda (2013) for the stock market, Jin et al. (2014) for the North American residential market, and Zheng et al. (2014) for the Chinese housing market, although Lacerda (2013)'s study diverges in terms of the financial market, explanatory variables, and sample period analyzed.

As noted, the first equation to estimate decomposes the Consumer Confidence Index into macroeconomic (fundamental) and non-fundamental components, aiming to capture the residuals as economic sentiment for the second stage of the empirical study. This also helps understand the dynamics between the variables under analysis. The equation is as follows:

$$CCI\,t = \alpha + \beta 1\; Unemp\,t + \beta 2\; Index\,t + \beta 3\; Inf\;t + \beta 4\;\mathrm{GDP}\;t + \beta 5\;\mathrm{STi}\;t + \beta 6\;\mathrm{LTi}\;t + \epsilon\;t \qquad (1)$$

In this equation, $CCI\,t$ is the dependent variable representing the Consumer Confidence Index at time t, with α as the model intercept, and the independent variables include unemployment rate ($Unemp\;t$), stock market index ($Index\;t$), inflation ($Inf\;t$), real GDP growth rate ($\mathrm{GDP}\;t$), short-term interest rate ($\mathrm{STi}\;t$), and long-term interest rate ($\mathrm{LTi}\;t$), with $\epsilon\;t$ being the residual.

We aim to isolate "irrational" sentiment, or economic sentiment, from the impact of macroeconomic variables, using the residuals obtained from the first regression as an explanatory variable in the second stage of the empirical study. This approach provides insights into the influence of economic sentiment on the housing market, differentiating between rational (based on economic fundamentals) and irrational (excessive sentiment) influences on market dynamics.

$$HPI\,t = \alpha + + \beta 1\; Inf\;t + \beta 2\;\mathrm{GDP}\;t + \beta 3\;\mathrm{STi}\;t + \beta 4\;\mathrm{LTi}\;t + \beta 5\; Sent\;t + \gamma\;t \qquad (2)$$

In equation (2), HPI_t represents the real housing market price index in quarter t, while $Sent_t$, whose coefficient is of particular interest in this analysis, refers to the economic sentiment variable derived from the residuals of regression (1) – ϵ_t – and γ_t represents the regression's residual value.

Before conducting the regression analyses, all variables were standardized to ensure stationarity. Standardization involves subtracting the mean from each observation and dividing by the standard deviation, resulting in a series with a mean of zero and a standard deviation of one. This transformation helps to stabilize the mean and variance of the time series, reducing the impact of trends and seasonality on the regression results. By standardizing the variables, we can mitigate the risk of spurious regression results that may arise from non-stationary data. Also, he study employs pooled least squares (PLS) to estimate the regression models, a decision based on the results of Chow and Lagrange Multiplier (LM) tests. The Chow test is used to determine whether the coefficients in a regression model are equal across different subgroups or time periods, while the LM test assesses the presence of individual-specific effects in panel data models. The results from both tests suggest the presence of a common effect running through the model, with heterogeneity diminishing across the series, partially due to the standardization procedure. This allowed for a more parsimonious and efficient estimation of the model parameters compared to random or fixed effects methods.

The selection of explanatory variables in regression (1) – *Consumer Confidence: Classic Determinants and Economic Sentiment* – is naturally tied to their potential relationship with the Consumer Confidence Index, as they relate to variables that can impact income, tax burden, career prospects, quality of life, and the confidence levels of economic agents, factors that are related (potentially and predictably) to consumer confidence levels. GDP, a global indicator representing the country's productive capacity and income generation, is usually considered by consumers when evaluating their country's economic situation. This variable was included in Lemmon & Portniaguina (2006) and Ling et al. (2015). This variable is expressed in real terms to avoid collinearity with inflation. Including the inflation variable is crucial (Lemmon & Portniaguina, 2006) since we are measuring consumer confidence, and this variable represents the general price level in the country (including all goods and services), thus impacting their net income and influencing their current and future consumption capacity and purchasing power. The unemployment rate

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reflects the current and future employment prospects of the country, which can affect both the incomes (potential or actual) and the quality of life and satisfaction levels of its residents. Lemmon & Portniaguina (2006), Jin et al. (2014), Fernandes (2015), and Ling et al. (2015) included this variable in their analyses. Interest rates, addressed in Lacerda (2013), Jin et al. (2014), Zheng et al. (2014), and Fernandes (2015), can be seen from both the investor and borrower perspectives; for investors, interest rates represent a source of income (primary or secondary), while for borrowers, they represent a financial burden. Stock indices complement the already mentioned interest rates, not only from an income perspective but also from an expectation perspective, for consumers who hold such investments (investors) and those who follow financial market developments and incorporate this information into their expectations. The rationale for including this variable is present in several studies, although they do not always directly use stock indices but rather portfolio returns, securities returns, or treasury bill returns (Qiu & Welch, 2004; Lemmon & Portniaguina, 2006; Lacerda, 2013; Jin et al., 2014).

Regarding equation (2) – *The Impact of Economic Sentiment on the Housing Market* – variables were selected that potentially and expectedly relate to the dependent variable and have impacts on it. GDP, prominently featured in the literature on this topic (Einiö et al., 2007; Goodhart & Hofmann, 2008; Mikhed & Zemčík, 2009; Posedel & Vizek, 2011; Figueiredo, 2012), is introduced as a representative indicator of the state and development of national economies, which have an intrinsic and bilateral relationship with the housing market and its price evolution. The inflation variable, also considered by Iacoviello (2000) and Zhu & Tsatsaronis (2004), assumes the same definition presented in the previous regression and is included here because it is a general price index (encompassing all categories of goods and services defined in the OECD CPI), which directly or indirectly affects the dependent variable, also defined in real terms to avoid collinearity with inflation. Interest rates are introduced in the equation by the majority of analyzed studies (Iacoviello, 2000; Capozza et al., 2002; Sutton, 2002; Zhu & Tsatsaronis, 2004; Himmelberg et al., 2005; Égert & Mihaljek, 2007; Posedel & Vizek, 2011; Figueiredo, 2012; Hirata et al., 2012) and can be addressed from both the investor and borrower sides, as mentioned earlier. Their inclusion in this second regression is justified by the potential influence of these variables on the housing market demand, with changes in demand levels (as with supply side changes) impacting property prices. The sentiment variable, extracted from the first estimation, is the focus of this analysis and has been used, under various

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perspectives, as an explanatory variable for price fluctuations in the housing market (Jin et al., 2014; Ling et al., 2015; Heinig et al., 2016; Marcato & Nanda, 2016) and the stock market (Baker & Wurgler, 2006; Lacerda, 2013), among others. According to the earlier discussion, fundamental and macroeconomic factors seem insufficient to explain price fluctuations in the housing market, with sentiment of the agents involved playing an increasingly relevant role in the price formation of financial markets, including the housing market. In this paper we aim to determine the magnitude and significance of this potential relationship.

4.Data

Our study encompasses 24 countries (Australia, Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, Korea, Mexico, Netherlands, New Zealand, Poland, Portugal, Spain, Sweden, Switzerland, United Kingdom, and the United States of America). We use data on a quarterly frequency for the period from 2000 to 2017, in order to examine regular fluctuations during pre-Covid period. Other countries had to be excluded from the analysis due to the lack or discontinuity of data for a significant portion of the variables. Poland and Mexico had the most significant number of missing observations, with the Housing Price Index (HPI) showing the most substantial omissions (the series only starts in 2005 for Mexico, in 2007 for Hungary, in 2008 for the Czech Republic, and in 2010 for Poland). The Consumer Confidence Index and interest rates (short and long term) also had some missing data, but these were not significant (about 30 observations missing across the three variables for the entire sample). The rest of the variables included in the study are complete for all countries for the selected sample period.

The data, except for most stock indices, were collected from the OECD statistical portal at https://stats.oecd.org/. Attempts to obtain the missing data for this variable for the four countries with incomplete series (Hungary, Mexico, Poland, and the Czech Republic, as indicated in table 1.7 of Annex I) from the Bank for International Settlements (BIS) database were unsuccessful due to the same gaps in this second database.

All Confidence Index and stock indices are available on a monthly frequency, while the short-term interest rate and real GDP growth rate are only available quarterly. Inflation is

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disaggregated annually, quarterly, and monthly. Unemployment rates are accessible monthly and quarterly, and the long-term interest rate is available annually and quarterly. Finally, the HPI data are available on an annual, semi-annual, and quarterly basis. Therefore, the quarterly frequency is the most harmonized disaggregation possible, and this will be the data frequency used in the following estimations, with simple arithmetic averages calculated for variables where only monthly data were available (Consumer Confidence Index and stock indices) to achieve the desired quarterly frequency. The economic sentiment variable, naturally, is of a quarterly nature, since it was extracted from a regression with quarterly frequency variables.

The sample consists of 8 variables (excluding sentiment) from 24 countries over 18 years, making it a sample of vast scope, international character, and heterogeneous nature. Among similar studies on the dynamics of prices in the housing market, only a few are comparable in sample size: Zhu & Tsatsaronis (2004), covering 17 industrialized countries over 33 years; Égert & Mihaljek (2007), encompassing 27 countries (8 transition economies and 19 developed economies) over 30 years; Goodhart & Hofmann (2008) over 36 years and 17 industrialized countries; and Hirata et al. (2012) analyzing 18 OECD countries over 40 years. However, our sample is the second more heterogeneous (surpassed only by Égert & Mihaljek, 2007), as it includes the largest number of countries at different stages of economic and financial development. Except for Égert & Mihaljek (2007), other studies only include developed or industrialized countries in their segment. Also, studies with a longer sample period than the present analysis (between 20 to 30 years) have a narrower scope, focusing on just one country or a small set of countries – 3 to 6 (Iacoviello, 2000; Himmelberg et al., 2005; Posedel & Vizek, 2011; Figueiredo, 2012; Jin et al., 2014; Ling et al., 2015; Marcato & Nanda, 2016).

Table 1 summarizes the main descriptive statistics for each analyzed variable with an equal number of observations for all variables, it's noted that the Consumer Confidence Index (CCI) and economic sentiment are the variables showing the highest concentration around their means, which are 100.05 and 0.01, respectively. During the analyzed period, the maximum value observed for the CCI was 104.53, and the minimum was 93.97, with this variable having a standard deviation of 1.4. Both the minimum and maximum values for this variable relate to Ireland. The minimum value of the CCI was recorded at the beginning of 2019 (a time when the CCI values reached their lows in several countries

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included in the analysis, having started to decrease in 2017), while the maximum took place at the beginning of 2000. On the other hand, stock indices constitute the variable with the most dispersion from the mean (standard deviation of 8652.6), with a significant disparity between its maximum value, recorded in Mexico, and minimum, recorded in Denmark. For this variable, it becomes difficult to establish comparisons, given that national stock indices vary greatly in their composition, in terms of the number, type, and size of companies included.

Table 1: Descriptive statistics

	CCI	*Unemp*	*Index*	*Inf*	*GDP*	*STi*	*LTi*	*HPI*	*Sent*
Mean	100.05	7.45	6672.22	90.99	1.87	2.38	3.88	99.32	0.01
Median	100.14	6.43	3691.81	92.86	2.10	2.12	4.00	98.79	0.046
Max	104.53	27.73	50856.14	111.30	29.07	10.49	25.40	176.38	3.51
Min	93.97	2.43	183.83	64.73	(10.28)	(0.84)	(0.51)	42.18	(3.42)
Std dev.	1.40	4.08	8652.58	9.36	2.87	2.19	2.32	21.15	1.04
Assim.	(0.39)	2.38	2.56	(0.55)	0.54	0.74	2.05	0.49	(0.14)
Kurtosis	3.55	10.22	10.05	2.16	16.10	3.04	17.27	4.53	3.19
Obs.	1561	1561	1561	1561	1561	1561	1561	1561	1561

Source: Authors' calculations based on data collected from OECD statistics.

5.Results

Table 2 showcases the estimation results for equation (1), considering the Consumer Confidence Index (*CCI*) as the dependent variable. With this regression, we intend not only to explore the relationships between the variables in question but also to extract the residual vector from the estimation and examine its significance in the pricing dynamics of the housing market, as further analyzed in the subsequent model. The overall significance of the model is tested through an F-test, which assesses the model's explanatory power by comparing it to a baseline model without any explanatory variables. The null hypothesis posits that the model with explanatory variables does not significantly differ from a model with only an intercept. This hypothesis is rejected at a significance level of 1% (or even 0.1%), suggesting that the model's explanatory variables significantly contribute to explaining the variation in the *CCI*. The results highlight that all explanatory variables are statistically significant at a 1% significance level, except for stock indices, which achieve significance at a 3% level. The marginal impact of stock indices on the *CCI* suggests that, within the sample, these indices do not play a crucial role in consumer

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confidence variations. This could be attributed to the sample population not holding such investments or not closely following financial markets.

Table 2: Consumer Confidence – Classical Determinants and Economic Sentiment

Dependent variable	CCI
Unemp	(0.039340) ***
	(0.0000)
	(5.279664)
Ind	6.74E-06 **
	(0.0300)
	2.172410
Inf	(0.028724) ***
	(0.0000)
	(7.469802)
GDP	0.254805 ***
	(0.0000)
	26.27844
STi	(0.058389) ***
	(0.0027)
	-3.007198
LTi	(0.111573) ***
	(0.0000)
	-6.472657
R2	0.435597
Obs.	1661

Notes: PLS regression results for eq. (1) - coefficients, t-tests, and probabilities - whose dependent variable is the Consumer Confidence Index (*CCI*) and the explanatory variables are Unemployment (*Unemp*), stock indices (*Index*), inflation (*Inf*), gross domestic product (*GDP*), short-term interest rate (*STi*) and long-term interest rate (*LTi*), respectively. All original variables are in levels, except for GDP, which is in year-over-year growth rate, and have been standardized to ensure stationarity. The model includes 1661 observations, and asterisks indicate the statistical significance of the variables: *** α=1%; ** α=5%; * α=10%. Source: Authors' calculations based on data collected from OECD statistics.

Inflation and unemployment negatively correlate with the CCI, as expected, with unemployment's effect slightly more pronounced. A 1 percentage point increase in unemployment leads to an approximate 0.4 basis point decrease in the CCI, while inflation causes a 0.28 basis point reduction. Conversely, GDP movements align positively with the CCI, indicating a direct relationship between these variables. These findings are consistent with previous studies by Lemmon & Portniaguina (2006) and Fernandes (2015), though Fernandes did not specify the variables individually.

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Short and long-term interest rates negatively impact the CCI, implying that higher interest rates dampen consumer confidence. This reflects the perspective of consumers/borrowers, for whom interest rates represent a financial burden, rather than investors who might see them as a source of income. The long-term interest rate has roughly double the impact compared to the short-term rate, with coefficients of -0.11 and -0.058, respectively. This negative relationship between interest rates and the CCI echoes findings by Lacerda (2013), Jin et al. (2014), and Zheng et al. (2014), though Lacerda used a risk-free interest rate, not included in this analysis. The low standard errors associated with the coefficients underline the estimation's precision.

The model boasts an adjusted R^2 of 43.4%, indicating that 43.4% of the variation in the dependent variable, Consumer Confidence Index (CCI), is accounted for by the variations in the model's explanatory variables. While this represents a significantly positive fit, it leaves 56.6% of the CCI's fluctuation unexplained. In comparison, similar models in the study by Lemmon & Portniaguina (2006) reported R^2 values ranging between 50% and 70%. Lacerda (2013), focusing on the Portuguese stock market, found R^2 values between 57% and 63%, and Fernandes (2015), analyzing Greece, Portugal, and Ireland, identified R^2 values as high as 80%. However, these studies differ in scope and sample size; Lemmon & Portniaguina's research was confined to the American stock market, Lacerda's to the Portuguese market, and Fernandes' to three European countries. The current analysis, encompassing 24 diverse countries, naturally results in a more moderate R^2. Given the heterogeneity and the broader geographical span, additional explanatory factors likely influence consumer confidence fluctuations in each country, which are not accounted for in this model. It's important to note that while the first study used the CCI, the second utilized the Economic Sentiment Indicator. Both studies included varied additional variables such as consumption, imports, exports, risk-free interest rates, and industrial production growth rates, among others.

The residuals from the first regression are stored as economic sentiment (sentiment not based on fundamental factors), representing the portion of the dependent variable's variation unexplained by the model's R^2. These residuals will serve as the sentiment variable in the second stage of the analysis, aiming to explore the relationship between housing market prices and this sentiment variable.

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The model represented by equation (2) aims to explore the relationships between the Housing Price Index (*HPI*) and "economic" sentiment, as well as between HPI and various selected macroeconomic variables at this stage of the analysis. The "economic" sentiment refers to the residual vector extracted from regression (1) - ϵt, that is, the sentiment after the fundamental factors associated with it have been extracted, marking the first step of the analysis. The second step seeks to understand which variables influence the variations in housing prices (based on a wide range of existing literature) and the importance and effect of sentiment on this variable, a phenomenon still relatively unexplored in the housing market. All explanatory variables in this model are statistically significant (at the 5% or 10% significance level), except for the short-term interest rate, which shows a negative coefficient but is not statistically significant at any level of significance. Economic sentiment shows a negative and statistically significant relationship (at a 5% significance level) with HPI, aligning with previous studies (Rouwendal & Longhi, 2007; Ling et al., 2010; Zheng et al., 2014; Heinig et al., 2016). It's noteworthy that studies defining or constructing a specific sentiment index for the housing market (Ling et al., 2015; Marcato & Nanda, 2016) posit a positive relationship between this variable and the HPI. The impact magnitude of the sentiment variable, possessing the highest magnitude coefficient among all variables in the model (coefficient of 1.1), suggests that a decrease of 1 point in economic sentiment leads to a 1.1 basis point decrease in the HPI. This underscores the significance of economic or "irrational" sentiment in housing market analysis.

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Table 1 – Impact of Economic Sentiment on the Housing Market

Dependent variable	HPI
Inf	0.489964 ***
	(0.0000)
	6.267198
GDP	(0.451152) **
	(0.0217)
	(2.297853)
STi	(0.171665)
	(0.6456)
	(0.459944)
LTi	0.585944 **
	(0.0465)
	1.992033
Sent	(1.107255) **
	(0.0265)
	(2.220436)
R2	0.057239
Obs.	1561

Notes: PLS regression results for eq. (2) - coefficients, t-tests, and probabilities - whose dependent variable is the Housing Price Index (*HPI*) and the explanatory variables are inflation (*Inf*), gross domestic product (*GDP*), short-term interest rate (*STi*) and long-term interest rate (*LTi*), respectively, and sentiment (*Sent*), which corresponds to the vector of residuals extracted from regression (1) - ϵt, and represents the "irrational" sentiment of agents. All original variables are in levels, except for GDP, which is in year-over-year growth rate, and have been standardized to ensure stationarity. The model includes 1561 observations and asterisks indicate the statistical significance of the variables: *** α=1%, ** α=5%, and * α=10%. Source: Authors' calculations based on data collected from OECD statistics.

The relationship between GDP and the HPI is also negative (coefficient of -0.45), indicating that a one percentage point increase in real GDP growth rate results in a 0.45 basis point decrease in the Housing Price Index. This finding diverges from most reviewed studies, in which this relationship is positive and statistically significant. Differences in the sample period might account for some of these discrepancies. Although many cited studies are also multicountry in scope, none include data from the second decade of the millennium, except for Figueiredo (2012). Only a few studies, such as Jin et al. (2014) in the USA and Zheng et al. (2014) in China, found a negative relationship between GDP and the HPI, although only in some specifications of their models. Methodologically, there are differences among the studies: while some use OLS models, others employ vector autoregressive models of different specifications. The choice of methodology may impact results, as the studies finding a negative relationship between GDP and HPI use OLS models.

Inflation shows a positive and significant relationship with the HPI, with a coefficient of 0.49. A positive relationship is understandable, as many price indices already include housing components. There's also a significant positive relationship between the long-term interest rate and HPI (coefficient of 0.59), contrary to expectations based on empirical evidence suggesting that higher long-term interest rates should decrease housing demand. This discrepancy may be explained by fundamental or sentimental factors on the supply side, as property ownership is not considered in this analysis. As discussed, diverse behavioral biases affecting purchase and sale decisions could globally influence HPI. The model's adjusted R^2 is considerably lower than previous models and similar studies with the HPI as the dependent variable, indicating a need for further exploration into the factors influencing housing prices, including variables such as credit volume, population, construction costs, and others not incorporated into this study.

6.Conclusion

In the realm of behavioral finance, our research delves into its application within the housing sector, a market of paramount importance for both economic and financial stability. This paper aims to dissect the influence of economic sentiment and macroeconomic variables on housing prices, offering a nuanced understanding of market dynamics. Our methodology unfolded in two phases: initially, we dissected the Consumer Confidence Index to isolate macroeconomic influences and sentiment-driven residuals. Subsequently, we explored the impact of these factors on the Housing Price Index, employing a technique inspired by Lemmon & Portniaguina (2006) to discern the effects of what we term "economic sentiment."

The results consolidate the view that macroeconomic variables like inflation and unemployment adversely affect consumer confidence, consistent with prior studies (Fernandes, 2015; Lemmon & Portniaguina, 2006). Interest rates, particularly long-term ones, also dampen the CCI, reflecting the borrowers' viewpoint. In contrast, GDP and

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stock market performance positively correlate with consumer confidence, though the impact of stocks is minimal.

This paper also revealed economic sentiment's negative correlation with housing prices, diverging from findings by Ling et al. (2015) and Marcato & Nanda (2016), who noted a positive sentiment-price relationship with market-specific sentiment indicators. Inflation showed a positive connection with housing prices, while short-term interest rates bore no statistical significance. Notably, we observed a rare negative GDP-HPI relationship and a positive link between long-term rates and housing prices, deviations potentially explained by methodological and sample variations.

Our findings suggest that standard determinants fall short in fully explaining housing price variations in a broad, international context, advocating for a more nuanced approach that includes additional economic variables. This study enriches the discourse on sentiment's role in housing price formation from an international perspective, bridging a gap in literature predominantly focused on capital markets within narrow geographic confines. It underscores the necessity for further research tailored to the housing market's unique dynamics, advocating for a more homogeneous sample and the inclusion of variables that capture the sentiments and behavioral biases of key market players.

Future investigations could enhance understanding by focusing on more consistent country clusters, integrating sentiment and behavioral biases of sellers, and refining property classification. Exploring alternative sentiment indicators could also shed new light on their applicability and effectiveness in housing market analyses, paving the way for a deeper comprehension of market mechanisms and the intricate interplay of economic sentiment and housing prices.

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