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Inflation or Speculative Bubbles? Observing Housing Prices in Türkiye by Using PANICCA and GSADF Methods

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Abstract. This paper delves into the fundamental reasons behind the non-stationary behavior of Housing Prices (HP) in different regions of Türkiye, which have witnessed an intensified surge fueled by recent aggressive fluctuations. The primary objective is to ascertain whether the driving force behind the escalating HP stems from a housing bubble, or if it can be predominantly attributed to the unprecedented levels of inflation that Türkiye has been experiencing in recent times. This study adopted a comprehensive approach by employing advanced panel PANICCA and GSADF cointegration test techniques to identify the presence of common factors between HPI and inflation from January 2010 to January 2023 to resolve this dilemma. The outcomes strongly suggest that the observed stationarity in HPI predominantly originates from the influence of common factors. More importantly, it has been revealed that disregard of the relevant common variables in the standard factor model may lead to misleading conclusions, such as the misidentification of housing bubbles. This underscores the significance of accurately accounting for the impact of common factors in order to avoid potential distortions in assessing market dynamics and potential risks.

Keywords: Price bubbles, house prices, inflation, panel GSADF, PANICCA.

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1. Introduction

Fluctuations in asset prices have systematically been a critical subject in economics. Researchers consider extraordinary price rises to be speculative asset bubbles, characterized by irrational optimism and market overvaluation (Hommes et al., 2008; Gürkaynak, 2008). Economists have analyzed the mechanisms underlying such bubbles, while questioning the rationality of market participants and assessing the causes and consequences of sudden price surges. Beyond speculative phenomena, modern economies are facing numerous macroeconomic challenges, with inflation is as one of the most critical aspects. Most countries have adopted stringent monetary policies to combat inflation, often involving interest rate hikes to curtail consumption and dampen demand. In contrast, Türkiye represents an exceptional case, prioritizing economic growth through low-interest policies despite enduring chronic inflationary pressures.

A higher inflation disrupts economies by eroding purchasing power and exacerbating uncertainty. Its adverse effects are particularly acute in essential sectors such as food and housing, where price bubbles and imbalances can jeopardize basic human needs. Persistent inflation challenges societal stability, as individuals struggle with diminished access to affordable housing and face significant uncertainty in the market. This issue demands urgent attention, as price imbalances in the *Housing Market* (HM) often result from structural economic problems and can become long-term constraints on welfare.

This paper aims to identify the dominant forces shaping Türkiye's HPs and to evaluate whether inflationary pressures or speculative bubbles are the primary drivers. Unlike previous studies, this research integrates the PANICCA and GSADF tests to analyze the intricate relationship between HP and inflation in Türkiye. While these techniques are widely used, their application to a market characterized by extreme volatility offers unique insights, thereby distinguishing this study from the already existing literature by testing two hypotheses: (1) Inflation predominantly drives HP increases, (2) mitigation of inflation can stabilize the HM. Türkiye provides a compelling case study due to its sustained high inflation rates, reaching 85% in 2022, which is relatively higher than that of the U.S. and Eurozone. This chronic issue necessitates an in-depth analysis of the Turkish HM in order to determine whether the observed price increases are cyclical or permanent. The findings reveal that price increases in the Turkish HM are a direct consequence of inflation rather than speculative bubbles.

This study consists of five sections. Following the introduction, the second section examines the existing literature. The third section presents the data and methodology employed, and shares the findings. Section four discusses the results of this research. Finally, the conclusion presents an evaluation of the findings and avenues for future research.

2. Literature Review

There is an extensive research on asset and HP bubbles, encompassing various markets and employing diverse methodologies (Gürkaynak, 2008; Ren et al., 2012; Dreger &

Kholodilin, 2013; Scherbina & Schlusche, 2014; Bourassa et al., 2019). These studies highlight the characteristics of bubbles. For instance, Ren et al. (2012) applied rational expectations hypothesis to the Chinese HM but found no evidence of a bubble, while Jang et al. (2018) demonstrated that speculative investments and rental price spillovers drive housing bubbles in South Korea. Vogiazas and Alexiou (2017) revealed that credit-driven economies trigger the propagation of real estate bubbles in OECD economies.

Macroeconomic variables play a critical role in shaping HP dynamics. Factors such as inflation, interest rates, credit availability, and economic growth often interact to influence prices (Case & Shiller, 2003; Tsatsaronis & Zhu, 2004). Malmendier and Wellsjo (2023) found that inflation expectations significantly drive HP, with homeowners viewing real estate as a hedge against inflation. Similarly, Balli et al. (2019) reported a positive correlation between inflation and house price increases, noting that larger regions are more sensitive to shocks.

Some researchers argue that inflation may not always lead to HP increases. Katrakilidis and Trachanas (2012) suggest that rising inflation can deter real estate investments by increasing nominal costs, while Oikarinen (2009) contends that low inflation can encourage housing demand due to money illusion and tilt effects. Cohen and Karpavičiūtė (2017) even assert that inflation is not causally linked to HPs, thus emphasizing the multifaceted nature of these relationships.

In the Turkish context, Coskun and Jadevicius (2017) and Coskun et al. (2020) found no evidence of bubbles in Türkiye's HM, by attributing price increases to lax credit regulations and macroeconomic conditions. Kırca and Canbay (2022) and Akça (2023) identified inflation, exchange rates, and housing loans as key drivers of HP, while Korkmaz (2020) highlighted bidirectional causality between HP and inflation; likewise, Muddasir and Dondaş (2023) revealed significant correlations between HP and factors such as the GDP growth, interest rates, and inflation, providing insights into the economic determinants of HM dynamics in Türkiye. Yıldırım and Ivrendi (2021) demonstrated that monetary policy and housing demand shocks significantly influence prices. Similarly, Akpolat (2024) revealed that real effective exchange rates symmetrically affect housing prices.

Beyond Türkiye, researchers have explored the role of speculative bubbles and credit expansion in driving price increases. Jordà et al. (2020) emphasized how loose lending standards and credit availability encourage speculative behavior, leading to unsustainable HP growth. Hoffman and Schnabl (2011) linked credit expansion to price bubbles, while Glaeser and Nathanson (2017) demonstrated a strong correlation between credit easing and HP appreciation in the U.S.

There is a growing body of research in recent years on HPs for emerging markets. For instance, Chenguang (2025) investigates the presence of housing bubbles across six cities in China. The study concludes that price bubbles are observed only in the smaller cities, based on a classification of the cities according to their level of economic development. In addition to inflation, factors such as the housing demand, economic growth outlook, exchange rate volatility, stock market fluctuations, credit expansion, and depreciation

of local currencies have also been identified as key triggers of HP bubbles in emerging markets (Mahmoudinia et al., 2022; Chee Yin et al., 2024; Doruk, 2024).

Collectively, these studies underscore the complex and multifaceted nature of HP dynamics, shaped by macroeconomic factors, speculative behavior, and policy interventions. This study contributes to the literature by focusing on the interplay between inflation and HPs in Türkiye, offering insights into how inflationary pressures shape market dynamics and drive price imbalances.

3. Methodology and Data

3.1. Panel unit root tests and panel right-tailed test

3.1.1. The PANICCA test process

The *Data Generation Process* (DGP) for the interest variable $y_{i,t}$ is supposed to follow a *Common Factor* (CF hereafter) model shown as (Reese and Westerlund, 2016):

$$y_{i,t} = a_i' D_{t,p} + \lambda_i' F_t + e_{i,t}$$
(3.1)

where $D_{t,p}$ is a polynomial trend structure; λ_i is the corresponding vector of factors; F_i is an rxI dimensional vector of CFs, and $e_{i,t}$ is an $idiosyncratic\ Error$ (IE hereafter). The $D_{t,p}$ element involves that constant where p=0, whereas the other element is a constant and trend where p=1. With the rising findings of co-movements among HPI and major macroeconomic variables such as the inflation rate, exchange rate (e.g., Katrakilidis and Trachanas, 2012; Christou et al., 2019; Xu and Zhang, 2023), this approach seems emphatically acceptable then to allow for additional variables (in other words, covariate), as proposed by Reese and Westerlund (2016). Hence, a vector of covariates demonstrated as $x_{i,t}$ is described with the following DGP:

$$x_{i,t} = \beta_i' D_{t,p} + \delta_i' F_t + u_{i,t} \tag{3.2}$$

where $x_{i,t}$ is an $m \times l$ dimensional vector of covariates; $u_{i,t}$ is an $m \times l$ dimensional vector of IE. Eventually, $x_{i,t}$ is supposed to share the CFs of $y_{i,t}$, and then the DGP for the mixed variables demonstrates:

$$z_{i,t} = B'_i D_{t,p} + \varphi'_i F_t + \nu_{i,t}$$
(3.3)

Here, $\mathrm{B}i=(a_i\beta_i); \varphi_{t,p}=(\lambda_i\delta_i)$ following the rx(m+1) matrix dimension and, $v_{i,t}=(e_{i,t};u_{i,t})'$. Reese and Westerlund (2016) suggest that, since the first differenced interest variable, which removes any uncertainty concerning its order of integration, is employed in the estimation procedure, then, any proposed method for CF models can be applied to estimate Eq. (3.3). Reese and Westerlund (2016) also estimated $\hat{e}_{i,t}=\rho\hat{e}_{i,t}+\varepsilon_{i,t}$ and $\hat{F}_t=\rho\hat{F}_t+\varepsilon_t$ with the null hypothesis of $\rho_1=\rho_2=...=\rho_k=1$. Three test statistics are suggested by the unit root test of $\hat{e}_{i,t}$ each for p=0, and p=1 are demonstrated as $P_{a,p}, P_{b,p}$, and $PMSB_p$ (Panel Modified Sargan–Bhargava) tests. When p=0 (in Equations 3.4 and 3.5):

$$P_{a,p=0} = \frac{\sqrt{NT}(\hat{\rho}_0^{+}-1)}{\sqrt{\frac{2\hat{\varphi}_{\epsilon}^{2}}{\hat{\omega}_{\epsilon}^{2}}}}; P_{b,p=0} = \frac{\sqrt{NT}(\hat{\rho}_0^{+}-1)}{\sqrt{\frac{\hat{\varphi}_{\epsilon}^{4}}{[\hat{\omega}_{\epsilon}N^{-1}T^{-2}\sum_{l=1}^{N}(\hat{e}_{l,-1}^{0})'\hat{e}_{l,-1}^{0}]}};$$
(3.4)

$$PMSB_{p=0} = \frac{\sqrt{N} \left(N^{-1} T^{-2} \sum_{i=1}^{N} (\hat{e}_{i,-1}^{0})' \hat{e}_{i,-1}^{0} - \frac{\widehat{\omega}_{\varepsilon}^{2}}{2} \right)}{\sqrt{\frac{\widehat{\varphi}_{\varepsilon}^{4}}{3}}}$$
(3.5)

and, when p = 1 (in Equations 3.6 and 3.7):

$$P_{a,p=1} = \frac{\sqrt{NT}(\hat{\rho}_{1}^{+} - 1)}{\frac{\sqrt{36\hat{\sigma}_{\varepsilon}^{4}\hat{\varphi}_{\varepsilon}^{4}}}{5\hat{\omega}_{\varepsilon}^{8}}}; P_{b,p=1} = \frac{\sqrt{NT}(\hat{\rho}_{1}^{+} - 1)}{\sqrt{\frac{6\hat{\sigma}_{\varepsilon}^{4}\hat{\varphi}_{\varepsilon}^{4}}{\left[5\hat{\omega}_{\varepsilon}^{6}N^{-1}T^{-2}\sum_{i=1}^{N}(\hat{e}_{i,-1}^{0})'\hat{e}_{i,-1}^{0}\right]}};$$
(3.6)

$$PMSB_{p=1} = \frac{\sqrt{N} \left(N^{-1} T^{-2} \sum_{i=1}^{N} (\hat{e}_{i,-1}^{0})' \hat{e}_{i,-1}^{0} - \frac{\widehat{\omega}_{\varepsilon}^{2}}{6} \right)}{\sqrt{\frac{\widehat{\varphi}_{\varepsilon}^{4}}{45}}}$$
(3.7)

where, $\hat{\rho}_0^+$ and $\hat{\rho}_1^+$ are AR(1) coefficients, respectively, computed as $\hat{\rho}_0^+ = \hat{\rho}_0 + \frac{\hat{\tau}_{\mathcal{E}}}{NT^{-1}\sum_{l=1}^N(\hat{e}_{l,-1}^0)'\hat{e}_{l,-1}^0}$ and $\hat{\rho}_1^+ = \hat{\rho}_1 + \frac{3\hat{\sigma}_{\mathcal{E}}^2}{T\hat{\omega}_{\mathcal{E}}^2}$. The null hypothesis, which posits the presence of a unit root in the idiosyncratic components across all panels, is tested by using the $P_{a,p}$, $P_{b,p}$, and PMSB_p test statistics.

3.1.2.CIPS panel unit root test process

Pesaran (2007) developed a new approach to cope with the issue of cross-section dependence (CSD) and considered a one-factor structure with heterogeneous loading factors for residual series. On the other hand, the test extends the classic *Augmented Dickey-Fuller* (ADF) regression with the CSD mean of lagged levels, and first-differences of the series (Dickey & Fuller, 1979). If residual series are not serially correlated, the model used for the *i.th* cross-section is described as follows:

$$\Delta y_{it} = a_i + \rho_i y_{i,t-1} + c_i \bar{y}_{t-1} + d_i \Delta \bar{y}_t + u_{it}$$
(3.8)

where $\bar{y}_{t-1} = \left(\frac{1}{N}\right) \sum_{i=1}^{N} y_{i,t-1}$, and $\Delta \bar{y}_t = \left(\frac{1}{N}\right) \sum_{i=1}^{N} y_{it}$. $t_i(N,T)$ statistics are calculated through ρ_i in Equation (3.8). Pesaran (2007) unit root test is based on the individual cross-sectionally ADF statistics (CADF). CADF statistic (let us remark that there is also truncated version of this statistic, denoted by CADF*) works as follows:

$$CIPS = \frac{1}{N} \sum_{i=1}^{N} t_i(N, T)$$
 (3.9)

Pesaran (2007) proposed simulated critical values of CIPS for various sample sizes.

3.1.3. Panel generalized supremum ADF (GSADF) right tailed test

To catch price bubbles, we employ the GSADF procedure proposed by Phillips et al. (2015) since GSADF was a more effective process in an attempt to identify multiple bubbles (Li et al., 2020; Su et al., 2020). The Supremum ADF (SADF) and standard ADF unit root test contributed to the development of GSADF. As emphasized by Khan et al. (2021); El Montasser et al. (2018); Bettendorf & Chen (2013), the GSADF test does not lose power when the time series analyzed is long, even in the case of multiple bubble scenarios. This is critical in the long period adopted in this study. The GSADF test (time series format) procedure is defined as follows (Phillips et al., 2015; Caspi, 2017; Hu & Oxley, 2018):

$$GSADF(r_0) = \sup_{r_2 \in [r_0, 1], r_1 \in [0, r_2 - r_0]} ADF_{r_1}^{r_2}$$
(3.10)

In Eq. (3.10), r_0 is the min. length of the *Test Window* (TW); r_1 is the start point of TW; r_2 is the end point of TW, and ADF is the standard ADF test statistic value. The test statistic's value takes into account not only the change at the test's endpoint but also various starting points for TW (Su et al., 2020; Potrykus, 2023). Price bubbles arise in cases when the GSADF statistic crosses the critical values obtained by Bootstrap methods or MC simulations. If the GSADF test statistic falls below the obtained critical value, there is no significant evidence for rejecting the null hypothesis of the absence of bubbles. In case bubbles are detected within the analyzed feature, the next step involves utilizing the backward SADF (BSADF) test to pinpoint the date when these bubbles emerged. This process is also explained in (Phillips et al., 2015), and the calculation way for the presently mentioned test is as outlined in Eq. 3.11 (Caspi, 2017; Hu and Oxley, 2018):

$$BSADF_{r_2}(r_0) = \sup_{r_1 \in [0, r_2 - r_0]} ADF_{r_1}^{r_2}$$
(3.11)

What regards the part of this research which is related to prices bubbles, the investigation of the individual 26 HPI series for the analyzed aspects, the bubble analysis was also conducted for the panel data format, and the technique for detecting and date-stamping bubbles was employed. The value of the panel BSADF (abbreviated as PBSADF hereafter) test statistic and the value of the panel GSADF test (PGSADF hereafter) statistic, employed to identify the temporal occurrence of price bubbles, for N individual series were defined as follows, respectively (Vasilopoulos et al., 2020):

$$PBSADF_{r_2}(r_0) = \frac{1}{N} \sum_{i=1}^{N} BSADF_{i,r_2}(r_0)$$
(3.12)

$$PGSADF(r_0) = \sup_{r_2 \in [r_0, 1]} PBSADF_{r_2}(r_0)$$
(3.13)

The following method is suggested to calculate the r_0 value in (3.10), (3.11), (3.12), and (3.13) (Phillips et al., 2015; Caspi, 2017; Vasilopoulos et al., 2022):

$$r_0 = \left(0.01 + \frac{1.8}{\sqrt{T}}\right) * T \tag{3.14}$$

where T is the time dimensional (number of observations).

3.2. Panel cointegration analysis

Pedroni (1999, 2004) developed a residual-based cointegration test for the null hypothesis of cointegration relationship for dynamic panels with multiple features in which the long-run coefficients and the short-run dynamics are permitted to be non-homogenous across groups (individuals). This cointegration test allows for individual heterogeneous *Fixed Effects* (FEs) and trend (deterministic), while no exogeneity restrictions are imposed on the features of the cointegrating equations. This test requires residual estimation from the cointegrating long-run relation for y_{ij} (Pedroni, 1999, 2004; Barbieri, 2009):

$$y_{it} = a_i + \delta_i t + \beta_{1i} x_{1it} + \beta_{2i} x_{2it} + \dots + \beta_{Ki} x_{Kit} + e_{it};$$

$$i = 1, \dots, N; \ t = 1, \dots, T \text{ and } k = 1, \dots, K$$
(3.15)

where T is the time dimensional, N is the number of individuals, and K is the number of independent variables y_{it} , whereas x_{kit} is assumed to be first-degree integrated for each individual of the panel, and under the null hypothesis of no cointegration. Also, in the equation, a_i and δ_i are FEs and individuals-based linear deterministic trend, respectively, and β_{ki} parameters are the slopes. In this test, Pedroni (1999, 2004) employs seven statistics. Four of these are based on within-dimension (panel) statistics: the panel t-statistic (nonparametric), the panel t-statistic (parametric), the panel t-statistic. The remaining three statistics are based on between-dimension (group) statistics: the group t-statistic (nonparametric), the group t-statistic (parametric), and the group t-statistic.

3.3. Data description

This study evaluates the behavior of HPIs in Türkiye with the monthly data from January 2010 to January 2023. The HPIs data were collected from the Turkish Central Bank (CBRT) Electronic Data Delivery System (EVDS) (Table 1).

The HPI value (2010=100), as provided by EVDS, is divided into hedonic and non-hedonic HPI. The non-hedonic HPI is available for all 26 regions in Türkiye (please see the metadata).

The hedonic HPI is divided into two subcategories: new dwellings and existing dwellings. It is available only for the three larger cities in Türkiye, namely Istanbul, Ankara, and Izmir. The general HPI covering 26 regions and the hedonic new HPI covering three provinces and the hedonic non-new HPI were adjusted for inflation. In this process, adjustment techniques similar to those employed in Glaeser and Nathanson (2017)'s study¹ were used.

¹ The real price index is calculated by using the inflation-adjusted nominal price index.

Table 1. Information about data

Variables	Number of	Abbreviation	Transformation	Data Sources
	Regions			
Housing Prices Index	26	HPI	Raw (Non-inflation adjustment)	EVDS
Real Housing Prices Index	26	RHPI	Inflation Adjustment	EVDS
Real Hedonic New Housing Prices Index	3	RHNHPI	Inflation Adjustment	By authors
Real Hedonic Non-new Housing Prices Index	3	RHNNHPI	Inflation Adjustment	By authors
Hedonic New Housing Prices Index	3	HNHPI	Raw (Non-inflation adjustment)	EVDS
Hedonic Non-New Housing Prices Index	3	HNNHPI	Raw (Non-inflation adjustment)	EVDS
Consumer Prices Index	Non- regional	СРІ	Raw	EVDS

4. Results

Table 2 illustrates a summary of the variables. The peaks of HPIs and inflation coincide with the latter stages of the current period without exception. Furthermore, the HPIs and the max. and min. points of inflation in Türkiye changed significantly.

Table 2. Descriptive statistics

Variables	Observation (NxT)	Mean	Median	St. Deviation	Maximum	Minimum
HPI	4.082 (26x157)	127.6137	92.4000	120.7135	1072	36
RHPI	4.082 (26x157)	61.8202	52.9161	64.4403	756.2908	-271.562
CPI	157 (1x157)	364.8669	261.76	220.8546	1203.48	174.07
RHNNHPI	471 <i>(3x157)</i>	57.9476	50.3116	59.5608	603.2897	-258.964
RHNHPI	471 <i>(3x157)</i>	60.2455	51.2691	62.0965	573.5661	-253.511
HNHPI	471 <i>(3x157)</i>	129.4932	90.30	140.4061	854.10	35.9
HNNHPI	471 <i>(3x157)</i>	121.1724	90.50	119.4296	717.60	35.9

Before proceeding with the panel right tailed test (panel GSADF test for explosive behaviors), we investigate the stationarity of variables, and the CIPS and PANICCA for exploring unit roots are utilized. The core superiority of the second generation tests is that they are able to allow for CSD. CSD between series can lead these tests to overreject the null hypothesis of a unit root (O'Connell, 1998), and we examine the significance of CSD by utilizing the Breusch and Pagan (1980)'s LM test before employing panel unit root tests.

Variables	LM Test Statistics	p-value
HPI	50728.76***	0.0000
RHPI	49226.52***	0.0000
RHNNHPI	457.6091***	0.0000
RHNHPI	465.6886***	0.0000
HNHPI	468.5942***	0.0000
HNNHDI	468 8020***	0.0000

Table 3. Cross-section dependence (CSD) test results

Note. *** indicates significance level for 0.01.

LM test results provide compelling evidence of a significant CSD in HPI across regions in Türkiye in Table 3. The results imply that HPs across all 26 regions are interconnected, thus suggesting that price fluctuations in one region influence those in others. CSD demonstrates the absence of independence between regions and highlights the potential for price movements to propagate across the HM. CSD emerges as a result of shared economic factors, regional linkages, or the transmission of macroeconomic shocks nationwide. The LM test result demonstrates a strong interdependence among the HPI of the regions, reflecting the interconnected nature of the HM. Therefore, second generation panel unit root tests should be employed in the rest of the analysis in order to avoid the tendency to overreject the unit root hypotheses.

4.1. Stationary analysis and bubble detection

We first apply a conventional second generation panel unit root test (i.e., CIPS) for the HPIs, as presented in Table 4. The CIPS test is employed to evaluate the stationarity process of both inflation-adjusted and non-inflation-adjusted HP indices, aiming to identify their mean reverting behaviors or deviations from the mean over time. Such behaviors are critical, as non-mean reverting movements may correspond to the unit root process, but they can also imply an explosive root behavior associated with speculative price bubbles. Rejection of the null hypothesis indicates a stationary process, where bubble dynamics are not significant. However, failure to reject the null hypothesis suggests that the process may either exhibit unit root characteristics, or potentially include explosive root behaviors.

Table 4.	Panel	unit root	test	reculte
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Variables	CIPS Sta	tistics (Level)	CIPS Statist	ics (I. Difference)
	Intercept	Intercept & Trend	Intercept	Intercept & Trend
HPI	-1.216	-1.386	-5.714***	-5.893***
RHPI	-5.342***	-5.940***	-	-
RHNNHPI	-5.967***	-6.420***	-	-
RHNHPI	-5.443***	-5.699***	-	-
HNHPI	-1.050	-0.253	-6.190***	-6.420***
HNNHPI	-0.918	-1.865	-6.189***	-6.355***

Note. i. *** indicates a significance level for 0.01.

ii. '-' indicates variables for which the difference operation is not applied (i.e., it is not required).

The findings based on the CIPS test demonstrate that the RHPI, RHNNHPI, and RHNHPI, which represent the HPI adjusted for inflation, are stationary, while the variables HPI, HNHPI, and HNNHPI, which are not adjusted for inflation, are non-stationary (I(I)). This finding is extremely critical because all inflation-adjusted HPIs move under a stationary process, and it clearly reveals that inflation significantly directs the uncertainty level of HPIs.

Table 5. Panel GSADF test results

Variables	t Statistics	Sieve Bootstrap CV 90	Sieve Bootstrap CV 95	Sieve Bootstrap CV 99	Ongoing
HPI	24.9810***	0.4828	0.5354	0.6330	Yes
RHPI	-0.1500	0.0476	0.0573	0.0936	-
RHNNHPI	0.1588	0.3438	0.4589	0.7574	-
RHNHPI	0.5216	0.5522	0.6951	0.9617	-
HNHPI	6.2284**	5.0735	5.9653	9.6983	Yes
HNNHPI	5.1207**	3.8683	4.4891	6.3443	Yes

Note. ** and *** indicate significance levels 0.05 and 0.01, respectively.

The panel GSADF test is a recently developed method to identify explosive behaviors and price bubbles in the panel data operating under the null hypothesis of no speculative bubbles. A main advantage of the panel GSADF test is its ability to detect multiple bubbles over time while accounting for dependency between regions, which makes it particularly appropriate for interconnected markets, such as Türkiye's 26 regions where interdependence has been detected. Moreover, the test effectively captures both the emergence and persistence of speculative price behaviors, providing findings into Türkiye's HM.

The results of the panel GSADF test for HPIs provide strong evidence that there is no presence of any rational price bubble in inflation-adjusted HPIs, while, in non-inflation-adjusted indices, they indicate the existence of an ongoing price bubble. The findings are parallel to expectations since the ongoing inflation problem in Türkiye is also reflected in the HPIs through the market.

Table 6 demonstrates the findings of the Pedroni² panel cointegration analysis. It is clearly observed from both the panel and the group statistics that there is cointegration between non-inflation-adjusted indices and inflation. Therefore, HPIs and inflation possess common factors. To robustly check out the findings and make the analysis as detailed as possible, we employ tests based on common factors and idiosyncratics.

Once we have established that inflation and HPIs share common factors (see Table 6), we proceed to apply the PANICCA test by Reese and Westerlund (2016). This test allows us to conduct separate stationary analyses of the CFs and ICs.

² Reese and Westerlund (2016) recommend that the variable to be assigned as a covariate in the PANICCA test should be determined by the Pedroni panel cointegration test.

Table 6. Panel cointegration test results

	Statistics	3.829***	8.816***	6.335***	
PI-CPI	Group Statistics	ρ (rho)	t	ADF	
HNNHPI-CPI	Statistics	-1.128	2.729**	6.071***	4.010***
	Panel Statistics	Λ	ρ (rho)	t	ADF
	Statistics	3.096***	6.122***	5.842***	
HNHPI-CPI	Group Statistics	ρ (rho)	t	ADF	
HNHE	Statistics	1.856	2.766**	4.501***	4.441***
	Panel Statistics	Λ	ρ (rho)	t	ADF
	Statistics	5.780***	8.393***	6.553***	
CPI	Group Statistics	ρ (rho)	t	ADF	
HPI-CPI	Statistics	-3.054***	4.623***	6.610***	5.049***
	Panel Statistics	ν	ρ (rho)	t	ADF

Note. i.** and *** indicate significance levels 0.05 and 0.01, respectively.

ii. Critical values at the 0.05 and 0.01 significance levels are 1.960 and 2.576, respectively.

Table 7. PANICCA panel unit root tests results

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		Statistics		0.343	0.556	2.316
	INHPI	Idiosyncratic	Components	P_a	P_b	PMSB
	H	Statistics		10.9003		
		Common	Factors	ADF		
		Statistics		-1.933**	-1.427	-0.592
	HPI	Idiosyncratic	Components	P_a	P_b	PMSB
		Statistics		11.4378		
		Common	Factors	ADF		
		Statistics		628'0-	-0.943	0.224
ariate	NHPI	Idiosyncratic	Components	P_a	P_b	PMSB
Vithout Cov	H	Statistics		12.2752		
Panel A. V		Common	Factors	ADF		
	Panel A. Without Covariate		HPI Hranic Statistics Common Statistics Idiosyncratic Statistics Common Statistics	ncratic Statistics	vneratic Statistics Sonents -a -0.879	onents Statistics -a -0.879

Note. ** indicates significance levels 0.05.

Panel B. I	Panel B. Inflation as Covariate	ovariate									
	H	HNHPI				HPI			HINN	HNNHPI	
Common	Common Statistics Idiosyn	Idiosyncratic	icratic Statistics	Common	Statistics	Common Statistics Idiosyncratic Statistics Common Statistics	Statistics	Common	Statistics	Idiosyncratic Statistics	Statistics
Factors		Components		Factors		Components		Factors		Components	
MQ_c	MQ_c -18.713***	P_a	-1.836**	MQ_c	MQ_c 8.722***	P_a	-8.023**		MQ_c -19.594***	P_a	-1.484*
MO_f	MQ_f -4.887*** P_b		-1.665**	MQ_f	MQ_f 4.661*** P_b	P_b	-2.718** MQ_f		-8.408***	P_b	-1.141
		PMSB	-0.614			PMSB	-1.051			PMSB	-0.502

Note. ** and *** indicate significance levels 0.05 and 0.01, respectively.

Table 7 Panel A presents the findings of the PANICCA test for non-inflation-adjusted HPI. Notably, the test procedure refrains from including a common factor. The findings robustly indicate that the null hypothesis, which posits the presence of a unit root, remains unassailable for both hedonic HPI and the HPI.

Table 7 Panel B demonstrates the findings of the PANICCA test for non-inflation-adjusted HPI. However, a notable distinction is made this time by incorporating inflation, which has been proofed as a common factor through the *Pedroni Panel Cointegration Test* (PPCT) into the test procedure. The findings unequivocally reject the null hypothesis, positing the presence of the unit root for both hedonic HPI and the HPI (both for common factors and idiosyncratic components). These results foreground the stationarity of HPIs. Hence, the significant finding of stationarity resulting from the inclusion of inflation as a common factor demonstrates that the predictability of HPI can be possible by taking inflation into account. This underscores the importance of considering inflationary factors when analyzing and forecasting HM dynamics.

5. Discussion

The findings of the LM cross-section dependence test, the CIPS panel unit root test, the panel GSADF explosive behavior test, PPCT, and the PANICCA unit root test provide six critical insights, as follows.

Firstly, the LM statistics present strong evidence, indicating the presence of CSD in HPIs, irrespective of whether they are adjusted for inflation or not. Therefore, it is imperative to acknowledge and into take account this identified dependence among Türkiye's regions when conducting tests for stationarity and investigating price bubbles. Such considerations can only be effectively addressed through the application of advanced panel data analysis techniques. This research distinguishes itself by employing the panel GSADF test, which does not ignore this CSD issue, particularly in its exploration of the presence of price bubbles.

Secondly, in the examination of HPIs behavior, the study initially employed the CIPS panel unit root test, revealing strong evidence that inflation-adjusted HPIs are stationary, while non-adjusted indexes are non-stationary. This observation highlights the influence of inflation on occurring uncertainty into HPIs. Regarding the important question of whether housing bubbles do actually exist, the study turned to the panel GSADF test, which, under the assumption of CSD (with the sieve bootstrap), can detect multiple bubble formations. The panel GSADF statistics demonstrate the persistent presence of multiple bubble formations in non-adjusted HPI. However, when the inflation effect is removed from the HPI, the GSADF statistics fail to provide any substantiation of bubble formation throughout the examined period. This finding stands as a significant contribution of this study, as it highlights that inflation not only adds uncertainty but also creates the illusion of an explosive behavior with its pronounced and aggressive surges.

Thirdly, the findings obtained thus far have demonstrated the need to scrutinize inflation. Thus, in the subsequent phase, we investigated the presence of a common component

between inflation and HPI (non-adjusted indexes) through the employment of the PPCT (it was used to determine the variable to be assigned as a covariate in the PANICCA test). Both the group and panel statistics of the test yielded mutually reinforcing outcomes, indicating the existence of shared factors between inflation and all non-adjusted HPI.

Fourthly, where there are not any covariates, the findings demonstrate that nonstationarity behavior in non-inflation adjustment HPIs of Türkiye's regions is due to both the common factors (ADF and its probability) and idiosyncratic components as all the statistics (P a, P b, and PMSB) are not statistically significant.

Fifthly, the addition of common factors alters the findings of the test for all data samples (according to regions). This result is a robustness check against alternative possibilities when evaluating the PANICCA test. These new pieces of evidence provided from the inclusion of common factors demonstrate that the nonstationarity behavior of HPI is linked to common factors. Furthermore, these findings demonstrate a remarkable alignment with the results acquired from the comparatively less complex CIPS test (see Table 4, where adjusted HPI series were stationary).

While inflation is widely recognized as the primary driver of HP fluctuations, other macroeconomic factors, such as interest rates (Kuttner & Shim, 2016), credit availability (Favara & Imbs, 2015), and demographic shifts (Zavisca & Gerber, 2016), also exert significant influence. For example, access to affordable credit can stimulate the housing demand, whereas demographic changes might reshape the long-term patterns of HPs. Although these factors are beyond the immediate focus of this study, their potential interactions with inflationary dynamics highlight valuable avenues for exploration in future research.

As a conclusion based on these new pieces of evidence, an attempt at ignoring the covariate(s) (as a macroeconomic indicator of inflation) in the panel unit root examining processes of regional HPIs may lead to misleading inferences.

Conclusion

Economic and social transformations have led to diversification of the factors influencing HPs. However, particularly in the context of emerging economies, it remains a subject of debate whether the current trends in HPs reflect the formation of a speculative bubble or a consequence of the broader global inflationary environment. The reason behind the rationale of the argument that direct inflation is the primary driver of HPs in this research is that Türkiye has been facing chronic inflation since its establishment. Thus, demand in the Turkish HM is linked directly to inflation and is utilized as a hedging tool by people. Demand shifts caused by inflation trigger price anomalies in the market, leading to volatility. Our findings suggest the presence of ongoing price bubbles; however, these were largely attributed to the inflation effect. After purging the HP indices of inflation, no evidence of bubbles was found, either regionally or nationally. It shows that the observed price increases are driven by inflation rather than speculative behavior.

The findings align with studies such as Coskun et al. (2020) and Coskun and Jadevicius (2017), which also found no evidence of bubbles in Türkiye's HM, instead attributing

price increases to fundamental economic factors like credit regulations, demand, and construction costs. Similarly, Akça (2023) emphasizes inflation, exchange rates, and housing loans as key drivers of housing inflation in Türkiye. The study also corroborates results obtained in Yıldırım and Ivrendi (2021) and Akpolat (2024), which explore the role of monetary policy and macroeconomic asymmetries in shaping HPs. The assumption that inflation expectations directly determine or influence HPs is consistent with the findings of Malmendier and Wellsjo (2023). Similarly, recent research by Kırca and Canbay (2022) focusing on the Turkish context reached comparable conclusions. In this regard, the existing literature supports our argument that inflation stands out as a major determinant of HPs, particularly in developing countries, such as Türkiye. These comparisons strengthen the argument that Türkiye's HM is influenced more by structural economic factors than by speculative bubbles. In contrast to the findings of Cohen and Karpavičiūtė (2017), differences might be explained by the level of socio-economic development between countries. Moreover, the paradigm shift like political and financial crises, uncertainties, population growth, changes in consumer behaviors, as discussed in Katrakilidis and Trachanas (2012) and Oikarinen (2009), provide a rationale for these observed differences. Distinctively, this research underscores the amplifying role of speculative behavior in inflation-driven price surges, resonating with findings from Abildgren et al. (2018) and Case and Shiller (2003). However, unlike studies that focus on broader macroeconomic factors or sector-specific impacts (e.g., tourism in Balli et al., 2019), this study prioritizes inflation as the central explanatory variable.

While our findings indicate the absence of speculative bubbles at the aggregate level, it is essential to acknowledge that this may lead to the possibility of micro-level speculative activities or short-term price fluctuations. Investigating these dynamics would necessitate access to high-frequency or transaction-level data, which were not available for this study. Future research could delve into these micro-level phenomena in order to offer a more detailed understanding of speculative behaviors in HMs.

The data for the study from the EVDS provides reliable and consistent macroeconomic indicators. Nevertheless, the dataset does not capture informal housing transactions or region-specific disparities, thereby potentially limiting the comprehensiveness of the findings. Future research could overcome these limitations by incorporating data from alternative and/or supplementary sources.

The analysis is restricted to Türkiye and the January 2010 to January 2023 period, thus limiting the generalizability of findings to other contexts or longer-term trends. Comparative cross-country analyses could yield valuable insights into whether these findings reflect universal trends or are specific to particular economic contexts.

The findings underscore the need for targeted inflation control strategies to stabilize the HM. Policymakers should focus on inflation mitigation by implementing monetary policies aimed at reducing inflation so that to address HM imbalances and price volatility. With this perspective, it is essential that CBRT should manage the money supply and credit volume through commercial banks, acting within the framework of their independence and their role as lenders of last resort. Implementation of higher interest rates on housing

loans can suppress demand in the HM, thereby contributing to a decline in prices. However, it is equally vital for policymakers to consider broader macroeconomic balances and support the housing supply through complementary fiscal measures. In this context, the coordinated use of both monetary and fiscal policy instruments is crucial to ensure effective and sustainable market outcomes. Additionally, development of forecasting models by incorporating inflationary trends into predictive models contributes to improving HM forecasts and policy planning. Housing affordability can be achieved by introducing subsidies, tax incentives, and affordable housing programs to mitigate the adverse effects of inflation on low- and middle-income households. Zoning reforms, by enhancing the housing supply elasticity through streamlined zoning regulations and public-private partnerships with the objective to increase housing availability, may be of use.

This study opens the way for further research on HP dynamics. The relationship between house prices and inflation is most likely bidirectional. While this study is interested in the impact of inflation on house prices, it must be noted that rising house prices can also cause inflation through their impact on household wealth and consumption. Future research could use structural modelling to explore these dynamics further. Additionally, future studies could investigate the role of migration patterns, rental price increases, and the total factor productivity in HMs. They may apply the methodology used in this study to other countries or regions with varying macroeconomic and HM conditions. These future studies may also explore the long-term impacts of inflationary pressures on housing affordability and ownership trends in emerging and developed economies.

Author contributions

Mustafa KEVSER: conceptualization, investigation, writing – original draft, writing – review and editing.

Merve ALTAYLAR: methodology, formal analysis, writing – original draft, visualization. Ufuk BİNGÖL: conceptualization, writing – original draft, writing – review and editing. Zaim Reha YAŞAR: conceptualization, writing – original draft.

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