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Co-moving systems with explosive regressors and time-varying volatility: Evidence from the Spanish housing market

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Abstract

This study investigates the co-explosivity between Spain's nominal house price index and the housing credit-to-GDP ratio over the period 1971–2024, with particular emphasis on the housing bubble years from 1998 to 2008. Applying the framework proposed by Chen et al. (2017), the analysis reveals an asymmetric relationship: house prices exhibit a stronger sensitivity to credit expansion than credit does to price increases, underscoring the disproportionate influence of credit on housing market dynamics. During the 1998–2008 bubble phase, the relationship becomes more symmetric, suggesting a feedback loop in which relaxed lending standards fueled housing demand, while rising prices reinforced further credit growth. This period is characterized by tighter coupling between the two variables, stronger co-movement, and faster correction dynamics—indicative of speculative lending behavior. The findings highlight the importance of monitoring credit conditions to better understand and manage housing market volatility.

Keywords: Housing market; house prices; Housing credit; Explosive behavior; Co-explosivity; Co-moving systems

JEL classification: C22; E31; E44; E51; E51; G21; R31

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1 Introduction

The 2008–2009 financial crisis exposed the close link between housing prices and household debt, following a mortgage-driven boom across the U.S. and several European countries—including Spain. These surges, peaking in 2007, had broad economic spillovers, making their transmission channels central to policy analysis[1]. Evidence shows that debt-fueled booms heighten crisis risk and long-term output losses[2]. Spain's housing boom (1995–2007) offers a key case for studying credit-growth dynamics[3]. Recent research highlights how rising house prices expanded bank credit via securitization, initially crowding out non-housing lending before boosting credit economy-wide[4].

Several compelling reasons justify the focus on the Spanish housing market as an economically significant case study. First, Spain experienced one of the most substantial housing bubbles in the early 2000s, culminating in the severe economic recession and banking crisis of 2008. Second, Spain's unique context, characterized by a history of robust regulatory frameworks and notable political interventions in the housing sector, makes it particularly interesting. Third, the deep interlinkage between the Spanish housing market and its banking sector is a critical factor. Therefore, investigating the dynamics of housing bubbles in Spain offers vital insights into the intricate interaction between financial markets and housing, information invaluable for both policymakers and financial analysts.

In recent years, Spain's housing bubble problem has re-emerged, characterized by a significant rebound in housing prices. This recovery has been propelled by two main forces: a reduction in mortgage interest rates, and robust housing demand stemming from substantial migration inflows, a strong labor market, and vibrant foreign investment. Compounding this, new housing supply, while gradually expanding, has proven inadequate to absorb the high demand. This persistent disparity between strong demand and constrained supply has been a key factor driving house price appreciation since 2015.

An issue that has been extensively dealt in the literature concerns the long run relationship between housing prices and housing credit in several countries. The empirical literature on housing markets—particularly on the fundamental determinants of house prices, including mortgage credit—is extensive; see Duca et al. (2021) for a recent and comprehensive survey.

In a recent paper, Blanco-Arroyo et al. (2025) analyze the interaction between housing prices and housing credit in Spain during the period from 1971 to 2024. First, they employ recursive unit root tests for explosiveness, proposed by Phillips, Wu, and Yu (2011) and Phillips, Shi and Yu (2015a, 2015b), to investigate whether nominal house prices and housing credit exhibit bubble-like

[1] Jordà et al. (2015).

[2] See: Cerra and Saxena (2008) and Baron et al. (2021).

[3] On the origins of Spanish housing boom, see Jimeno and Santos (2014) and Santos (2017).

[4] See, among others: Estrada et al. (2009); Gimeno and Martinez-Carrascal (2010); Rodriguez and Bustillo (2010); Gonzalez and Ortega (2013); Neal and García-Iglesias (2013); Arrazola et al. (2015); Alves and Urtasun (2019); Bank of Spain (2024); López-Rodríguez and de los Llanos Matea (2019); Jiménez et al. (2020); Martín et al. (2021).

behavior at any point in the time series. Blanco-Arroyo et al. (2025) identify exuberance periods for nominal house from 1988 to 1991 (coinciding with economic expansion before the 1992 Barcelona Olympics and Seville Universal Exposition) and from 2001 to 2007 (preceding the subprime mortgage crisis and coinciding with the "Spanish housing boom"). For housing credit, they detect two exuberance episodes from 1992 to 1993 (following the 1992 Barcelona Olympics and Seville Universal Exposition) and from 1999 to 2008 (preceding the sub-prime mortgage crisis and coinciding with the "Spanish housing boom"). These findings reinforce the interconnected dynamics of housing prices and housing credit.

In this article, we extend the previous analysis by Blanco-Arroyo et al. (2025) in two ways. First, the tests for recurrent explosive bubbles (Phillips, Wu and Yu (2011); Phillips, Shi and Yu (2015a, 2015b)) assume constant unconditional volatility in the underlying error process. However, Harvey, Leybourne, Sollis, and Taylor (2016) and Harvey, Leybourne and Zu (2019) recently demonstrated that the asymptotic null distribution of these tests depend on the nature of the volatility through the variance profile under heteroskedasticity, leading to uncontrolled test size under time-varying volatility. This lack of size control typically results in serious over-sizing and, consequently, frequent spurious identification of a bubble. To overcome the problem identified in Harvey, Leybourne, Sollis, and Taylor (2016) and Harvey, Leybourne and Zu (2019), in this article we extend previous analysis of Blanco-Arroyo et al. (2025) using recent procedures to test for explosive bubbles under time-varying volatility (Harvey, Leybourne, Sollis, and Taylor (2016); Harvey, Leybourne and Zu (2019, 2020); Kurozumi, Skorobotov and Tsarev (2023)) in order to identify the explosive behavior of housing prices and housing credit. Second, we augment the analysis of co-explosiveness between housing credit and house prices using the methodology of Evripidou et al. (2022) with the recent approach developed by Chen et al. (2017), who introduced a framework for analyzing co-moving systems with explosive processes to evaluate co-explosiveness in a bivariate setting.

The rest of the paper is organized as follows. Section 2 discusses the nexus between housing prices and housing credit. Section 3 presents the methodology. Section 4 reports the empirical results. Section 5 concludes.

2 Theoretical Framework

Economic theory identifies a bidirectional relationship between housing prices and credit availability. On one side, easier access to bank credit—driven by low interest rates, optimistic expectations, and relaxed liquidity constraints—stimulates housing demand and raises prices (Oikarinen, 2009). Lending conditions depend on borrower creditworthiness and property collateral, while limited supply further amplifies price growth (Arestis and Gonzalez, 2012). Conversely, rising housing prices can increase credit supply and demand (Goodhart and Hofmann, 2008), though central banks regulate debt standards to prevent over-leveraging. Since housing loans form a large share of bank portfolios, higher property values improve balance sheets and encourage lending, while price declines raise default risks and restrict credit.

The "financial accelerator mechanism" also explains the feedback loop between housing market volatility and financial stability (Bernanke and Gertler, 1995; Bernanke et al., 1999). Rising prices increase collateral values and household borrowing capacity, while reducing asset risk and incentivizing banks to expand credit—amplifying price appreciation (Herring and Wachter, 2003; Pavlov and Wachter, 2006).

Additionally, housing prices affect borrowing through wealth effects. Credit and housing cycles have moved in tandem across countries (IMF, 2000; BIS, 2001; Goodhart and Hofmann, 2007; Alburquerque et al., 2025; Hoynck et al., 2025), though empirical evidence on causality remains mixed (Anundsen and Jansen, 2013; Hoffmann, 2004).

3 Econometric methodology

3.1 Tests of stationary volatility

To address the issue of time-varying volatility, Cavaliere and Taylor (2008) proposed four tests of the null hypothesis of stationary volatility: H_{KS} (Kolmogorov-Smirnov test), H_R (Range test), H_{CvM} (Cramer-von Mises test) and H_{AD} (Anderson-Darling test). By stationary volatility, it means that asymptotically the variance profile of the stochastic process driving volatility is given by $\eta(s) = s$.

The Cavaliere and Taylor tests assess variance stability using the cumulative variance profile of squared residuals, normalized by the long-run variance. These four volatility tests detect unconditional structural changes in time series volatility,

- $H_{KS} : \sup_{s\in[0,1]} |W_T(s)|$
- $H_R : \max_{s\in[0,1]} W_T(s) - \min_{s\in[0,1]} W_T(s)$
- $H_{CvM} : \int_0^1 W_T(s)^2\, ds \approx \frac{1}{M}\sum_{i=1}^{M} W_T(s_i)^2$
- $H_{AD} : \int_0^1 \frac{W_T(s)^2}{s(1-s)}\, ds \approx \frac{1}{M}\sum_{i=1}^{M} \frac{W_T(s_i)^2}{s_i(1-s_i)}$

The tests are based on the normalized process,

$$W_T(s) = \sqrt{T}\frac{\eta(s) - s}{\lambda_v}. \tag{1}$$

where an AR(1), $y_t = \phi y_{t-1} + \varepsilon_t$, is fitted. Here $\eta(s)$ is the estimated variance profile, λ_v is the standard deviation of the squared residuals, and $s \in [0, 1]$ is the normalized time.

For all statistics the null hypothesis (H_0) is that the variance is constant (stationary volatility) for all $t = 1, \ldots, T$ and the alternative hypothesis (H_1) is that the variance exhibits at least one structural break (non-stationary volatility).

3.2 Test for explosive bubbles under stationarity volatility

Phillips, Wu and Yu (2011) and Phillips, Shi and Yu (2015a, 2015b) proposed test for explosive bubbles based on recursive right-tailed Dickey-Fuller-type unit root tests which can detect evidence of the explosive behavior of a time series $\{y_t\}$.

Phillips, Wu and Yu (2011) proposed the maximum of the ADF test statistics constructed using subsamples. The testing procedure developed from a regression model of the form,

$$\Delta y_t = \mu + \delta y_{t-1} + \varepsilon_t. \tag{2}$$

for $t = \lfloor \tau_1 T \rfloor + 1$ to $\lfloor \tau_2 T \rfloor$.

The key parameter of interest is δ. We want to test the null hypothesis of a unit root, $H_0 : \delta = 1$, against the right-tailed alternative, $H_1 : \delta > 1$, al least in some subsample. The model is estimated by Ordinary Least Squares (OLS) and the t-statistics associated with the estimated δ is referred to as ADF statistic.

The $SADF$ test is then a supremun statistic based on the forward recursive regression and is simply defined as,

$$SADF(r_0) = \sup_{r_2 \in [r_0, 1]} ADF_0^{r_2}. \tag{3}$$

where the right-tail is the rejection region. This test can be used for testing for a unit root against explosive behavior in some subsample.

Second, Phillips, Shi and Yu (2015a, 2015b) proposed a generalized version of the sup ADF ($SADF$) test of Phillips, Wu and Yu (2011). Their Generalized Supremum ADF ($GSADF$) test is,

$$GSADF(r_0) = \sup_{r_2 \in [r_0,1], r_1 \in [0, r_2 - r_0]} ADF_0^{r_2}. \tag{4}$$

The statistic (4) is used to test the null of a unit root against the alternative of recurrent explosive behavior, as the statistic (3).

Note that the $SADF$ test previously proposed by Phillips, Wu and Yu (2011) is a special case of $GSADF$ test, obtained by setting $r_1 = 0$ and $r_2 = r_\omega \in [r_0, 1]$.[5]

The $SADF$ and $GSADF$ assume constant unconditional volatility in the underlying error process, and recently Harvey, Leybourne, Sollis, and Taylor (2016) and Harvey, Leybourne and Zu (2019) demonstrated that the asymptotic null distribution of the Phillips, Wu and Yu (2011), Phillips, Shi and Yu (2015a, 2015b) test depends on the nature of the volatility through the variance profile

[5] Phillips and Shi (2018) showed that although $GSADF$ procedure is designed to detect the bubble behaviour, it can also detect crisis periods (see also Phillips and Shi (2019), Phillips and Shi (2020)) which are often observed in empirical applications.

$\eta(s)$ under the existence of heteroskedasticity, so if the test is compared to critical values derived under a homoskedastic error assumption, its size is not controlled under time-varying volatility. This lack of size control typically leads to serious over-sizing, and consequently frequent spurious identification of a bubble.[6]

3.3 Test for explosive bubbles under time-varying volatility

Several recent tests for explosive bubbles have been proposed under the assumption of time-varying volatility:

- Harvey, Leybourne, Sollis, and Taylor (2016), Harvey, Leybourne and Zu (2019) and Kurozumi, Skorobotov and Tsarev (2023) developed a wild bootstrap algorithm for $SADF$ test and $GSADF$ test. They propose using this bootstrap scheme, applied to the first differences of the data, in order to replicate in the bootstrap data the pattern of non-stationarity volatility present in the original innovations. We refer to these test as $SADF_b$ and $GSADF_b$.
- Harvey, Leybourne and Zu (2019) proposed several tests:
  - A weighted least squares (WLS) modification of Phillips, Wu and Yu (2011) test. Their supremum based test is,

$$SBZ(r_0) = \sup_{r \in [r_0, 1]} BZ. \tag{5}$$

and $GSBZ$ for $GSADF$ test.

-
  - A union U test of rejections testing strategy because none of the tests, SBZ and $SADF$ dominate each other across all volatility specifications. We refer to these tests as SBZ_u and $GSBZ_u$ in the context of the $GSADF$ test.
- Harvey, Leybourne and Zu (2020) proposed another method which controls size under time-varying volatility. They proposed several tests:
  - A sign-based variant of the Phillips, Shi and Yu (2015a, 2015b) test for explosive behavior, the supremum sign-based test is,

$$sGSADF(r_0) = \sup_{r_2 \in [r_0,1], r_1 \in [0, r_2 - r_0]} sADF_{r_1}^{r_2}. \tag{6}$$

[6]Some classical unit root tests are severely oversized because their limiting distributions depend on a particular function, the so-called variance profile, of the underlying volatility process (see Cavaliere (2004), Cavaliere and Taylor (2007a, 2007b, 2008, 2009) and references therein).

The special case of $sGSADF$ test is the $sSADF$ with the restriction $r_1 = 0$.

- – A union U test of rejections-based testing strategy is implemented using wild bootstrao with $GSADF$ and $sGSADF$ tests, following the same approach by Harvey, Leybourne and Zu (2019). We refer to these tests as $sGSADF_u$ test and $sSADF_u$, for the union test with $SADF$ and $sSADF$ tests.

- Kurozumi, Skorobotov and Tsarev (2023) proposed a test based on the sup-type t-statistics expanded under the null hypothesis, using the time transformed data based on the variance profile, $\eta(s)$. They consider the $SADF$ and $GSADF$ test statistics with a version of the GLS-type demeaning. Their test statistics based on the time-transformed ADF test statistics is,
$$STADF = \sup_{r_2 \in [r_0, 1]} TADF_{r_0}^{r_2}. \tag{7}$$
and
$$GSTADF(r_0) = \sup_{r_2 \in [r_0, 1], r_1 \in [0, r_2 - r_0]} TADF_{r_1}^{r_2}. \tag{8}$$

3.4 The co-moving systems with explosive processes

We employ the recent approach by Chen et al. (2017), who developed a framework for analyzing co-moving systems with explosive processes to evaluate co-explosiveness in a bivariate setting. They propose the following continuous time system in two variates $y(t)$ and $x(t)$ that co-moves as,

$$y(t) = \beta x(t) + u_0(t). \tag{9}$$

$$dx(t) = \kappa(\mu - x(t))\,dt + dB_x(t), \quad x(0) = x_0 = O_p(1), \quad \kappa < 0. \tag{10}$$

The parameter of central interest for inference is the coefficient β, which captures the co-movement between $y(t)$ and $x(t)$. The driver process $x(t)$ follows an Ornstein–Uhlenbeck process (the OU process). The co-movement is captured by the residuals of the linear relationship $u_0(t) = y(t) - \beta x(t)$, which are assumed to follow an OU process to reflect the stationary or less explosive nature of the co-moving system. The κ for co-movement is estimated from the residuals of the β-adjusted relationship, reflecting the speed at which deviations from the co-moving equilibrium revert to their mean, μ. The parameter κ reflects the strength of the co-explosive or cointegrating relationship. A higher κ indicates that deviations from the equilibrium are corrected faster, stabilizing the system.

For testing $H_0 : \beta = \beta^0$, Chen et al. (2017) use the t-statistics,

$$t_\beta = \frac{\hat{\beta} - \beta^0}{s_\beta} = \frac{(\hat{\beta} - \beta^0)\, a_h^N / \sqrt{h}}{\left\{ s_0^2 \left(a_h^{-2N} h \sum_{t=1}^N \tilde{x}_{th}^2 \sigma_{xx}^2 h \right)^{-1} \right\}^{1/2}} \Rightarrow U_0 \overset{d}{=} N(0, 1). \tag{11}$$

and the least square estimator $\hat{\beta}$ of the slope coefficient in (9) is,

$$\hat{\beta}-\beta=\left(\sum_{t=1}^{N}x_{th}^{2}\right)^{-1}\left(\sum_{t=1}^{N}x_{th}u_{0,th}\right)=\frac{1}{\lambda_h}\left(\sum_{t=1}^{N}\tilde{x}_{th}^{2}\right)^{-1}\left(\sum_{t=1}^{N}\tilde{x}_{th}u_{0,th}\right). \quad (12)$$

For testing $H_0:\kappa=\kappa^0$, Chen et al. (2017) use the t-statistics,

$$t_\kappa=\frac{\hat{\kappa}-\kappa_0}{s_\kappa}=\frac{a_h^N\left(\hat{\kappa}-\kappa_0\right)}{\left\{s_x^2\left(\frac{1}{a_h^{2N}/h^2}\sum_{t=1}^{N}x_{(t-1)h}^2-\frac{1}{N}\left(\frac{1}{a_h^N/h}\sum_{t=1}^{N}x_{(t-1)h}\right)^2\right)^{-1}\right\}^{1/2}}\Rightarrow U_x\overset{d}{=}N(0,1). \quad (13)$$

Chen et al (2017) proposed including the C-test as a complement to the t-test for analysing time series with potential explosive behavior. This approach is highly effective. While the t-test provides a standard parameter estimation under stationarity assumptions, the C-test adjusts statistical inferences by accounting for the presence of explosivity, enabling the derivation of more robust and accurate confidence intervals, especially during periods where the series exhibits nonlinear dynamics or economic bubbles. This combination enriches the analysis by mitigating biases that might arise from relying solely on the t-test in contexts of instability, offering a more comprehensive tool for detecting and characterizing co-explosivity in the data. C-test adjusts the standard errors of κ and β by accounting for co-explosiveness in the data, utilizing a correction based on the sample size (N^α) and the residual variance. The double asymptotic theory proposed by Wang and Yu (2016) allows for the construction of 95% confidence intervals for κ and β using the C-test.

4 Empirical application

4.1 Data

Drawing on time-series data for Spain from 1971 to 2024, we analyze a 54-year sample that aligns well with the econometric framework adopted.[7] The dataset comprises credit to housing (CTH_t), nominal GDP (Y_t), credit housing to GDP ratio ($cth_t=CTH_t/Y_t$), nominal house price (nhp_t), and real house price index (rhp_t). Credit to housing is sourced from Jordà et al. (2017) for 1971-1991, based on mortgage loans to the non-financial private sector, and from the Bank of Spain (2025a, Table 4.12, column 15) for 1992-2024, reflecting credit to construction and housing. Nominal GDP is obtained from Prados de la Escosura (2017, Table 1) and Bank of Spain (2025a, Table 11.1, colum 12), while nominal and real house price indices are sourced from OECD (2025). Figure 1 illustrates the evolution of the nominal house price index (nhp_t) and the credit housing to GDP ratio (cth_t).

[7] Data are available upon request from the authors.

Between 1995 and 2023, Spain experienced three successive housing price cycles. First, from 1995 to 2007, a major housing boom: nominal and real house prices rose by 235.1% and 133.8%, while the housing credit-to-GDP ratio surged by 310.4% (Figure 2).[8] This coincided with strong economic growth (average real GDP growth of 3.7% from 1994 to 2007) and a housing-driven credit boom, including loans to construction, real estate, and mortgages. Domestic savings fell short, prompting banks to access international debt markets. Total housing credit grew nearly a thousandfold, increasing its share of total credit from 39.1% to 62.4%.[9] The buildup of non-performing loans led to a severe banking crisis (Baudino et al., 2023; Bank of Spain, 2017, 2019).

From 2007 to 2013, both housing and economic booms collapsed: nominal and real house prices fell by 35.1% and 41.3%, and the credit ratio dropped by 18.2%.

Finally, between 2013 and 2023, prices rebounded—nominal by 66.6% and real by 33.6%—with nominal prices returning to 2007 levels, possibly indicating a new bubble. Demand, fueled by low interest rates, job growth, and foreign investment, has outpaced housing supply, which remains insufficient despite expansion. This imbalance continues to drive price increases (Bank of Spain, 2024). Finally, from 2009 to 2024, the housing credit-to-GDP ratio fell by 64.1%.

4.2 The stationary volatility tests

As a first step we apply the four tests for stationary volatility proposed by Cavaliere and Taylor (2008). The critical values are simulated for T=53 with 10,000 Monte Carlo repetitions under H_0 (constant variance). The test statistics are denoted by H_{KS}, H_R, H_{CvM} and H_{AD} in Table 1. The results show that for nhp_t all statistics exceed critical value at all significant levels, rejecting H_0 and confirming structural changes in variance. In contrast, for cth_t only the test H_R exceeds the 10% critical values, but not 5% or 1% significant levels. Other statistics are below critical values, failing to reject H_0 suggesting constant variance. The Cavaliere and Taylor tests confirm structural change in the variance of the nhp_t series, but not in cth_t series, where only weak evidence is detected at 10% with the H_R test.

4.3 Test for explosive bubbles under non-stationary volatility

Since co-explosiveness requires explosive autoregressive regimes in the individual series in this section, we test for such behavior in the nominal house price index (nhp_t) and the credit housing to GDP ratio (cth_t). We employ several recent tests for explosive bubbles proposed under assumption of time-varying volatility by Kurozumi, Skorobotov and Tsarev (2023). The findings from the tests for

[8] Data from BIS (2025).

[9] Non-housing credit was influenced by factors such as declining interest rates following the euro's introduction and population growth.

stationary volatility support the use of tests for explosive bubbles under non-stationary volatility.

Tables 2 and 3 present the results of tests for explosive bubbles under stationary volatility and the tests for explosive bubbles under time-varying volatility for nhp_t and cth_t, respectively.[10]

First, the analysis reveals a complex bubble dynamic in the nhp_t series. Several $SADF$ tests provide strong and consistent evidence of a bubble. Specifically, the $_sSADF$, $sSADF_u$ and $STADF$ tests offer very strong evidence of explosive behavior, indicating robust detection. Furthermore, the $GSADF$ analysis reveals strong evidence of multiple explosive episodes, with a consistent p-value in $GSADF$, $_sGSADF$, $_sGSADF_u$ and $GSTADF$ tests reinforce very strong evidence. These results suggest a pervasive bubble potentially linked to speculative demand and housing market overvaluation.

Second, for the cth_t series, the analysis also indicates complex bubble dynamics. Several $SADF$ tests provide strong and consistent evidence of a bubble. Specifically, the $_sSADF$, $SADF$ and $_sSADF_u$ tests offer the strongest evidence, consistently rejecting the null hypothesis of no bubble. Furthermore, the $GSADF$ analysis yields strong evidence of multiple explosive episodes. The consistent p-value observed in the $GSBZ$, $_sGSADF$, and $_sGSADF_u$ tests further corroborate this strong evidence, indicating a pervasive bubble potentially linked to speculative lending or credit expansion.

Therefore, under the assumption of time-varying volatility of time series, we find evidence of explosive behavior in both series, consistent with Blanco-Arroyo et al. (2025). Our empirical application demonstrates the importance of accounting for non-stationary volatility when testing for bubbles in a time series with unstable volatility. The methods employed in our work are significantly more robust, as they accommodate episodes of explosivity and heteroskedasticity, thereby enhancing the reliability of bubble detection.

4.4 Evidence of co-explosiveness

In this section, we present a co-explosivity analysis between the logarithms of housing prices and housing credit in Spain for the period 1971-2024. Following the methodology of Chen et al. (2017), our focus is on the co-explosive period from 1998 to 2008. The choice of this sample period is guided by recent work by Blanco-Arroyo et al. (2025), which documents the presence of explosive behavior in the Spanish housing market during this time. We focus on the parameters β (long-run relationship), κ (mean-reversion speed) and ρ (correlation). Based on the evidence found in the tests for stationary volatility, the data are logarithmically transformed to stabilize the variance.

[10] Following Kurozumi, Skorobotov and Tsarev (2023) for the wild bootstrap p-values, B = 999 bootstrap replications were used. For the standard $SADF$ and $GSADF$ tests and the time-transformed tests $STADF$ and $GSTADF$, the p-values are obtained by simulations of the asymptotic distributions of the test statistics under homoskedasticity. We use $r_0 = \lfloor 0.01{+}1.8/\sqrt{T} \rfloor$ for calculations of the p-values.

First, we assess whether housing prices and housing credit exhibit co-movement by estimating the coefficient β using least squares in a linear regression, as defined by equations (9) and (10). The parameter β, defining the long-run relationship (the bidirectional co-movement) between the nhp_t and cth_t series, is estimated via Ordinary Least Squares (OLS) regression within the discretized version of the continuous-time model, as proposed by Chen et al. (2017). Second, we estimate the persistence parameter κ as defined by equations (9) and (10). The OU process estimates the mean reversion speed κ, measuring how quickly the series return to their long-term level after a shock. Estimation of the κ parameter is performed using the residuals derived from the β-fitted relationship. More precisely, Chen et al. (2017) utilize Quasi-Maximum Likelihood Estimation (QMLE) to estimate κ within the discretized OU model. Tables 4 and 5 present the statistical results for 1971-2024 and 2001-2007, respectively, focusing on key parameters for both directions of analysis. We report the LS estimate of β coefficients along with their t-statistics, and confidence intervals based on the C-test and t-test.

1971-2024 period For the regression of housing prices on housing credit ($nhp_t \sim cth_t$), the β parameter is estimated at 1.3565 (t-statistic = 16.0404), indicating high elasticity. This reflects a significant positive relationship, with $\beta > 1$, where a 1% increase in cth_t is associated with a 1.3565% increase in nhp_t. This result suggests that house prices are highly sensitive to housing credit expansions, amplifying housing market responses over the long term. Evidently, the 95% confidence intervals are quite tight and reject the null hypothesis $\beta = 0$, reinforcing the robustness of the estimated relationship.[11]

Conversely, for the regression of housing credit on housing prices ($cth_t \sim nhp_t$), the β parameter is estimated at 0.6178 (t-statistic = 16.0404). This value, with $\beta < 1$, suggests that nhp_thas a more moderate effect on cth_t, indicating lower elasticity. Specifically, a 1% increase in housing prices leads to a 0.6178% increase in credit, highlighting constraints on credit expansions driven by house price growth. Similar to the previous case, the C-test provides tighter intervals, confirming the significance of β under explosive conditions. The asymmetry in β values (1.3565 vs. 0.6178) indicates a non-symmetric directional relationship, where cth_t has an amplified impact on nhp_t, while the reverse effect is weaker. This is consistent with economic theories highlighting credit's role in driving housing bubbles (Kiyotaki and Moore, 1997). In both cases, the low estimated values of the mean reversion parameter κ (0.0495, 0.0317), along with the strong correlation ($\rho = 0.9154$) suggest mean reversion and robust long-term co-movement.

1998-2008 period In contrast, the 1998-2008 subperiod, -identified as co-explosive in Blanco-Arroyo et al. (2025)- exhibits β estimates of 0.9546

[11] The C test adjust the standard error using the estimated explosive root $\hat{c}_x = (\hat{\rho}_x - 1)N^{0.5}$, yielding narrower intervals that the t-test, reflecting greater precision when accounting for explosivity. For more details, see Chen et al. (2017).

($nhp_t \sim cth_t$) and 1.0308 ($cth_t \sim nhp_t$), indicating near-unit elasticity and a more symmetric relationship. Higher κ values (0.403, 0.4085) and a near-perfect correlation ($\rho = 0.9920$) reflect faster correction of deviations and tight coupling during the housing-credit bubble, driven by speculative lending and demand. The nearly-unit elasticity highlights the bubble feedback loop, where relaxed lending fueled housing demand, and rising house prices justified further credit growth.

These dynamics underscore the self-reinforcing nature of credit-fueled housing booms, where financial and real estate variables become tightly interlinked, amplifying systemic risk.

5 Conclusions

The relationship between asset prices and credit dynamics has long been a cornerstone of macroeconomic research, particularly in the context of financial crises and economic bubbles. In this paper, we conduct the first investigation into explosive behavior in the Spanish housing market by employing the continuous-time framework of Chen et al. (2017), which is based on a novel limit theory for co-moving systems with explosive regressors. We apply this methodology to study co-explosiveness between the nominal house price index and the housing credit-to-GDP ratio over 1971-2024, with a particular focus on the co-explosive phase from 1998 to 2008, corresponding to a pronounced housing boom.

For 1971-2024 period, in the regression of housing prices on housing credit, the regression coefficient is estimated at 1.3565, indicating high elasticity. This suggests that housing prices are highly sensitive to housing credit expansions, amplifying market responses over the long term.

Conversely, for the regression of housing credit on housing prices, the estimated parameter is 0.6178. This value, less than one, suggests that housing prices have a more moderate effect on housing credit, indicating lower elasticity. The asymmetry in the regression coefficient values indicates a non-symmetric directional relationship, in which housing credit has an amplified impact on housing prices, whereas the reverse effect is weaker. This is consistent with economic theories highlighting credit's role in driving housing bubbles (Kiyotaki and Moore, 1997). In both cases, the low values estimate for the mean reversion parameter and strong correlation suggest mean-reverting behavior and robust long-term co-movement between the two series.

In contrast, the 1998-2008 subperiod exhibits estimated regression coefficients of 0.9546 (the regression of housing prices on housing credit) and 1.0308 (the regression of housing credit on housing prices), indicating near-unit elasticity and a more symmetric relationship compared to the full 1971-2024 period. This nearly-unit elasticity highlights the bubble feedback loop, where relaxed lending fueled housing demand, and rising house prices justified further credit growth. The higher estimated values of the mean reversion parameter and the near-perfect correlation reflect faster correction of deviations and tight coupling during the housing credit bubble, driven by speculative lending and demand.

Given that our econometric analysis identifies credit dynamics as a key driver of housing bubbles, policy interventions should encompass macroprudential and microprudential measures, alongside fiscal and structural policies. Regarding macroprudential policies, Royal Decree-Law 22/2018 and Royal Decree-Law 102/2019 empower for the Bank of Spain to impose limits on the standards applied by banks in new lending to households. For instance, in the cases of mortgages, the Banco de España could set limits on loan-to-price (LTP), loan-to-income (LTI) and loan-service-to-income (LSTI) ratios, and establish the maximum terms for new mortgages, among other measures (Bank of Spain, 2025b).

These results have significant implications for economic policy and research. The super-elastic response of house prices to credit over the full period underscores the need for macroprudential policies to mitigate credit-driven housing booms, while the sub-elastic credit response suggests that lending standards may limit the feedback from house prices to credit markets. The symmetric, near-unit elastic co-movement in 1998-2008 period highlights the risks associated with bidirectional feedback loops in bubble environments, offering valuable insights into the design of early warning systems aimed at preserving financial stability. Meanwhile, the long-term asymmetric co-movement points to the influence of structural factors -such as credit regulations- in shaping market dynamics, warranting further investigation into the underlying drivers of this asymmetry.

There remains scope for further research. First, the annual data employed in this study could be integrated with alternative and complementary co-explosivity methodologies, such as the common bubble factor framework proposed by Chen, Phillips, and Shi (2023). In addition, a promising extension of the analysis would involve the use of higher-frequency data, such as monthly or quarterly observations, even at the cost of a shorter sample period.

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Table 1
Tests for stationary volatility from Cavaliere and Taylor (2008):
nominal house price index, nhp_t and credit housing to GDP ratio, cth_t

	H_{KS}				H_R			
Variables	Value	1%	5%	10%	Value	1%	5%	10%
nhp_t	3.007*	1.870	1.486	1.296	3.120*	2.289	1.884	1.678
cth_t	1.088	1.870	1.486	1.296	1.790***	2.289	1.884	1.678

	H_{CvM}				H_{AD}			
Variables	Value	1%	5%	10%	Value	1%	5%	10%
nhp_t	2.925*	1.026	0.609	0.440	15.452*	7.333	4.421	3.248
cth_t	0.283	1.026	0.609	0.440	1.738	7.333	4.421	3.348

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

Table 2
Test for explosive bubbles under non-stationary volatility from Kurozumi et. al. (2023): nominal house price index, nhp_t

Panel (a) $SADF$ tests

Test	p-values	Evidence of bubble
$SADF$	0.7127	None
$SADF_b$	0.4867	None
SBZ	0.0768^{***}	Weak
SBZ_u	0.0983^{***}	Weak
$sSADF$	0.0001^{*}	Very Strong
$sSADF_u$	0.0018^{*}	Strong
$STADF$	0.0001^{*}	Very Strong

Panel (b) $GSADF$ tests

Test	p-values	Evidence of bubble
$GSADF$	0.001^{*}	Strong
$GSADF_b$	0.0249^{**}	Moderate
$GSBZ$	0.0770^{*}	Weak
$GSBZ_u$	0.0697^{**}	Weak
$sGSADF$	0.0074^{*}	Very Strong
$sGSADF_u$	0.0001^{*}	Very Strong
$GSTADF$	0.0001^{*}	Very Strong

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

Table 3
Test for explosive bubbles under non-stationary volatility from Kurozumi et. al. (2023): credit housing to GDP ratio, cth_t

Panel (a) $SADF$ tests

Test	p-values	Evidence of bubble
$SADF$	0.003*	Strong
$SADF_b$	0.030**	Moderate to strong
SBZ	0.056***	Weak
SBZ_u	0.0388**	Moderate
$sSADF$	0.0005*	Very Strong
$sSADF_u$	0.0093*	Strong
$STADF$	0.042**	Moderate

Panel (b) $GSADF$ tests

Test	p-values	Evidence of bubble
$GSADF$	0.1011	None
$GSADF_b$	0.0602***	Weak
$GSBZ$	0.0256*	Strong
$GSBZ_u$	0.0507**	Moderate
$sGSADF$	0.0074*	Very Strong
$sGSADF_u$	0.0225**	Strong
$GSTADF$	0.1451	None

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

Table 4
Co-explosivity results, 1971-2024

Parameter	$nhp_t \sim cth_t$	$cth_t \sim nhp_t$
β	1.3565	0.6178
$t(\beta)$	16.4004	16.4004
t-test 95% (β) $[CI_L, CI_U]$	[1.1943, 1.5186]	[0.5440, 0.6916]
C-test 95% (β) $[CI_L, CI_U]$	[1.3296, 1.3833]	[0.6055, 0.6301]
κ	0.0495	0.0317
$t(\kappa)$	1.3558	0.8646
t-test 95% (κ) $[CI_L, CI_U]$	[-0.0221, 0.1212]	[-0.0402, 0.1036]
C-test 95% (κ) $[CI_L, CI_U]$	[-0.4375, 1.1655]	[-0.4792, 0.9452]
ρ	0.9154	

Notes: β is the co-movement parameter.
κ is the persistence parameter mean reversion).
ρ is the Pearson correlation.
CI_L and CI_U stand for lower and upper limits of the confidence intervals, respectively.
$nhp_t \sim cth_t$ is the regression of housing prices on housing credit and
$cth_t \sim nhp_t$ is the regression of housing credit on housing prices.

Table 5
Co-explosivity results, 1998-2008

Parameter	$nhp_t \sim cth_t$	$cth_t \sim nhp_t$
β	0.9546	1.0308
$t(\beta)$	23.6196	23.6196
t-test 95% (β) $[CI_L, CI_U]$	[0.8754, 1.0339]	[0.9452, 1.1163]
C-test 95% (β) $[CI_L, CI_U]$	[0.9437, 0.9656]	[1.0230, 1.0386]
κ	0.4034	0.4085
$t(\kappa)$	1.3676	1.3566
t-test 95% (κ) $[CI_L, CI_U]$	[-0.1747, 0.9816]	[-0.1817, 0.9989]
C-test 95% (κ) $[CI_L, CI_U]$	[1.2398, 1.4363]	[1.2535, 1.4566]
ρ	0.9920	

Notes: β is the co-movement parameter.

κ is the persistence parameter mean reversion).

ρ is the Pearson correlation.

CI_L and CI_U stand for lower and upper limits of the confidence intervals, respectively.

$nhp_t \sim cth_t$ is the regression of housing prices on housing credit and

$cth_t \sim nhp_t$ is the regression of housing credit on housing prices.

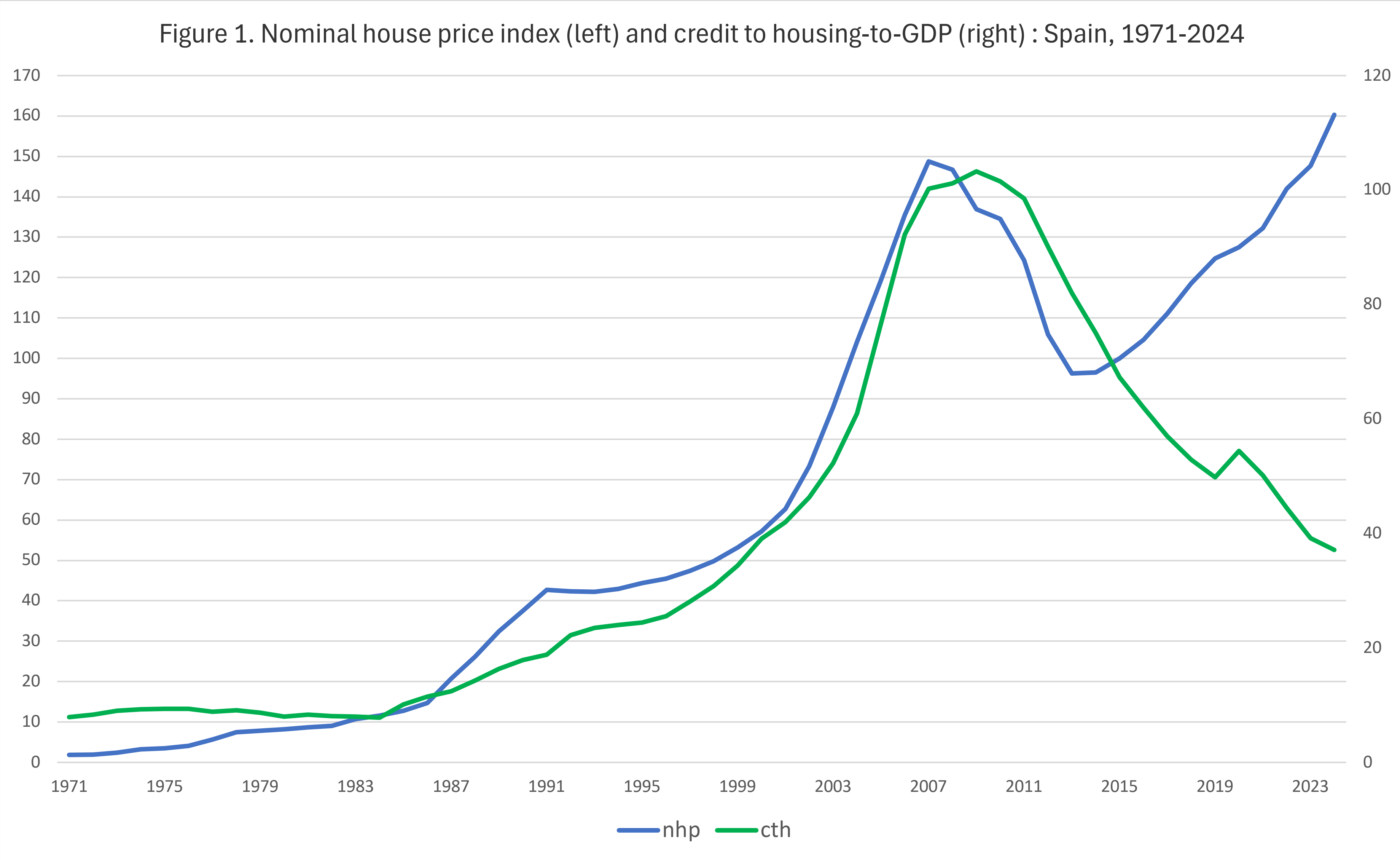
Figure 1. Nominal house price index (left) and credit to housing-to-GDP (right) : Spain, 1971-2024
170
160
150
140
130
120
110
100
90
80
70
60
50
40
30
20
10
0
120
100
80
60
40
20
0
1971
1975
1979
1983
1987
1991
1995
1999
2003
2007
2011
2015
2019
2023
nhp
cth

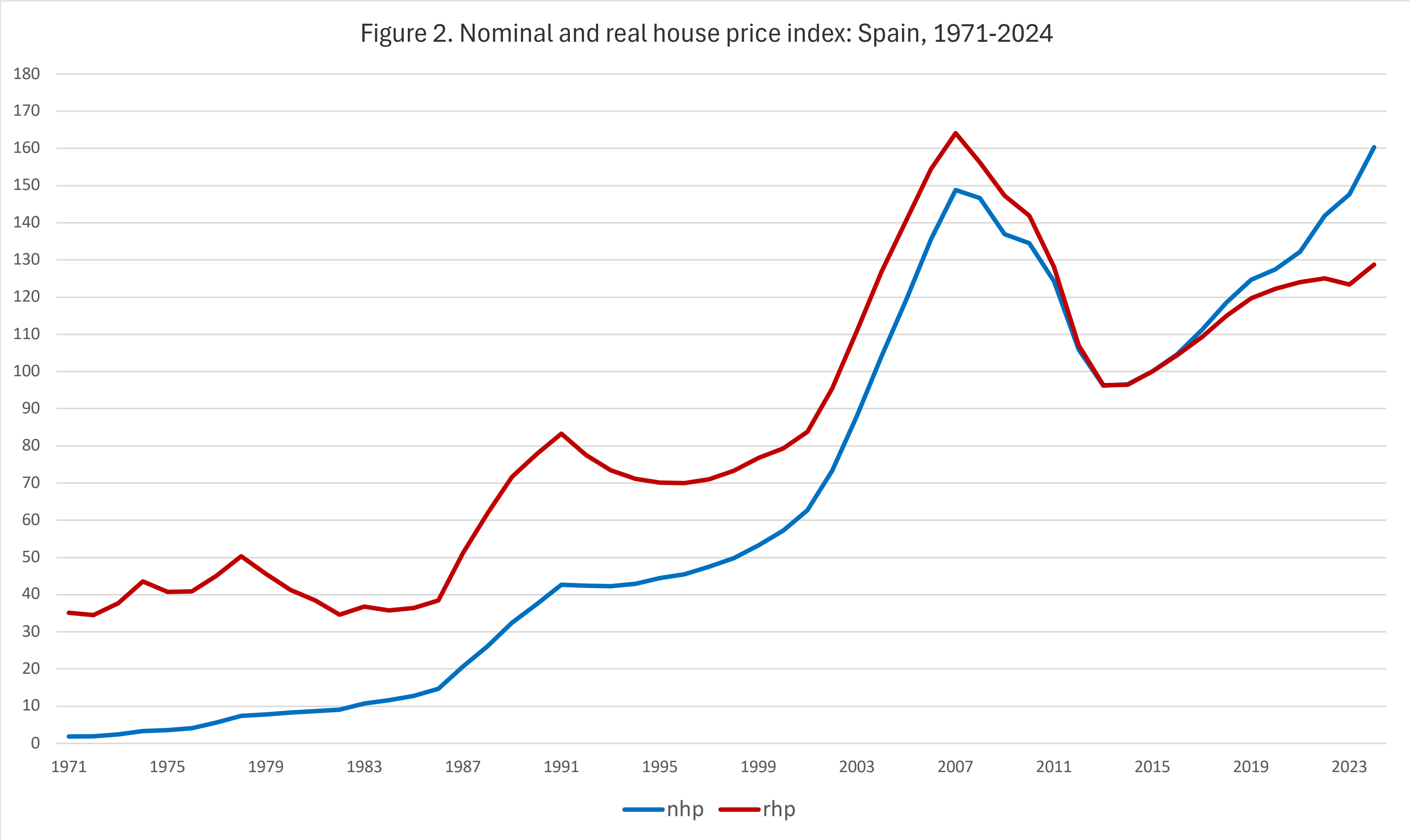
Figure 2. Nominal and real house price index: Spain, 1971-2024
180
170
160
150
140
130
120
110
100
90
80
70
60
50
40
30
20
10
0
1971
1975
1979
1983
1987
1991
1995
1999
2003
2007
2011
2015
2019
2023
nhp
rhp