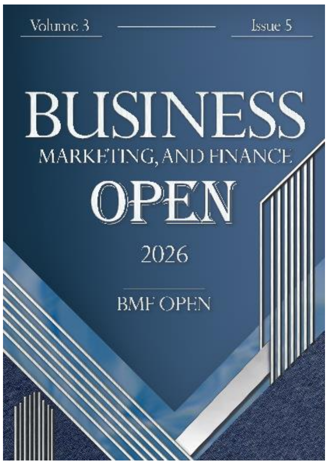
Development of a Dynamic Spatial Durbin Model with Generalized Common Effects (SDM-DPD(GCE)) to Examine the Impact of Macroeconomic Indicators on Housing Prices in Iran



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Abstract: Regional housing prices in emerging economies are simultaneously shaped by common macroeconomic shocks, geographic spillovers and local speculative behaviour. Jointly assessing their relative roles within a single framework is the aim of this paper. We study Iran's 31 provinces over 2015–2024 using a Dynamic Spatial Durbin Model with Generalised Common Effects (SDM-DPD(GCE)), estimated by Quasi-Maximum Likelihood. After removing the dominant common macro factor, a spatial ripple coefficient of 0.593 emerges, consistent with cross-border price linkages, conditional on the maintained model specification, rather than shared exposure to national shocks. A lagged provincial herding proxy (CSAD) is associated with further price divergence the following year, with a total effect of 1.721 once spatial feedback is accounted for. A structural break at 2018 marks a sharp intensification of both dynamics, coinciding with Iran's major currency shock. The paper also provides empirical evidence consistent with the view that extreme cross-sectional dependence can suppress Moran's I in raw panels, a diagnostic pitfall relevant to any high-CD empirical setting.

Keywords: Housing prices; Spatial spillovers; Herding behavior; Cross-sectional dependence; Dynamic spatial econometrics; Generalized common effects; Iran; Emerging markets.

1. Introduction

The housing market occupies a central position in modern economies because it simultaneously functions as a consumption good, an investment asset, a store of wealth, and a transmission channel for macroeconomic shocks. Fluctuations in housing prices influence household wealth, financial stability, credit expansion, investment decisions, and broader economic growth. Consequently, understanding the determinants of housing price dynamics has become one of the most important concerns in urban economics, financial economics, and regional policy analysis. Traditional theories of asset pricing argue that housing prices reflect the discounted value of future housing services and therefore respond systematically to macroeconomic fundamentals such as inflation, interest rates, credit conditions, and income growth [1, 2]. Early studies emphasized the efficiency of housing markets and the role of rational expectations in determining real estate prices, suggesting that prices should adjust in accordance with available economic information [2]. However, subsequent research increasingly demonstrated that housing markets often deviate from purely fundamental valuations and exhibit speculative dynamics, persistent regional inequalities, and spatially correlated price cycles [3, 4]. These findings challenged conventional equilibrium perspectives and encouraged the development of more sophisticated models capable of integrating macroeconomic influences, spatial spillovers, and behavioral factors within a unified framework.

Macroeconomic determinants remain one of the most extensively studied dimensions of housing price behavior. Housing markets are highly sensitive to inflationary pressures, exchange-rate fluctuations, credit availability, and monetary policy shocks because these factors directly influence purchasing power, borrowing costs, and investment incentives. Research has shown that expansionary monetary policy and rising liquidity frequently stimulate housing demand and accelerate price appreciation [5, 6]. In emerging economies, however, the transmission mechanisms are often more complex because underdeveloped mortgage systems weaken the conventional interest-rate channel and amplify the role of housing as a hedge against inflation and currency depreciation [7, 8]. Exchange-rate instability, in particular, can substantially increase speculative demand for housing as investors attempt to protect wealth from the erosion of purchasing power. Empirical studies have demonstrated that periods of macroeconomic uncertainty and policy instability tend to intensify real estate cycles and generate stronger co-movements among regional housing markets [9, 10]. Sentiment-driven reactions to uncertainty may also amplify these effects by shaping expectations regarding future inflation, investment profitability, and asset security [11]. In such settings, housing markets become increasingly vulnerable to synchronized booms and busts driven by nationwide macroeconomic shocks rather than purely local fundamentals.

At the same time, housing prices are not determined solely by macroeconomic variables. A substantial body of literature emphasizes the importance of spatial dependence and regional diffusion mechanisms in explaining housing market behavior. The spatial perspective argues that geographically proximate housing markets influence one another through migration flows, investor interactions, commuting patterns, information transmission, and substitution effects [12]. The so-called "ripple effect" suggests that price increases originating in one metropolitan center may gradually diffuse toward neighboring regions, generating spatial contagion across housing markets. Empirical evidence from the United Kingdom, the United States, and China has consistently confirmed the existence of such spatial interactions [13-15]. These findings imply that housing markets cannot be adequately analyzed as isolated regional units because local price dynamics are partially shaped by developments occurring in surrounding areas. Consequently, ignoring spatial dependence may produce biased and inconsistent estimates of the determinants of housing prices.

The emergence of spatial econometrics provided researchers with methodological tools capable of modeling these interregional interactions more accurately. Spatial autoregressive models, spatial error models, and Spatial Durbin Models were developed to capture both direct and indirect effects across geographic units [16, 17]. Among these approaches, the Spatial Durbin Model has attracted considerable attention because it allows the simultaneous estimation of endogenous spatial interaction effects and spillovers from explanatory variables. This framework recognizes that changes in macroeconomic conditions or behavioral indicators in one region may indirectly affect neighboring regions through spatial feedback mechanisms. Nevertheless, methodological debates remain regarding the identification and interpretation of spatial effects. Critics argue that estimated spatial coefficients may partly capture omitted common shocks or unobserved regional characteristics rather than genuine spillover mechanisms [18]. Therefore, separating true spatial interactions from correlated macroeconomic influences constitutes a major challenge in empirical housing research.

Another important dimension of housing price dynamics concerns behavioral and speculative factors, particularly herding behavior. Behavioral finance theories suggest that investors often imitate the actions of others rather than relying exclusively on private information and rational valuation. Informational cascades, social learning, and noise-trader behavior can therefore generate speculative bubbles and excessive volatility in asset markets [19, 20]. Housing markets are especially susceptible to these dynamics because transactions are infrequent, information is imperfect, and buyers frequently rely on observed market trends as signals of future profitability [4]. Herding behavior may intensify during periods of economic uncertainty when investors become more sensitive to the actions of other market participants. Chang et al. developed the Cross-Sectional Absolute Deviation (CSAD) framework to measure herding behavior empirically, and this methodology has subsequently been applied to a wide range of financial and real estate markets [21]. In housing markets, herding may manifest through speculative purchasing, synchronized investment behavior, and self-reinforcing price expectations that push prices away from fundamental values. Momentum trading and extrapolative expectations further contribute to these dynamics by encouraging investors to interpret past price increases as indicators of future appreciation [22].

Recent studies increasingly emphasize the interaction between macroeconomic instability, spatial spillovers, and behavioral speculation in shaping housing market fluctuations. Spatial contagion can amplify speculative behavior by transmitting optimistic expectations across regions, while macroeconomic uncertainty may intensify both herding and spatial diffusion simultaneously [14, 15]. This multidimensional interaction is particularly relevant in emerging economies characterized by inflation volatility, exchange-rate instability, and centralized policy structures. In such economies, nationwide shocks often affect all regions simultaneously, creating strong cross-sectional dependence among regional housing markets. Conventional panel-data models generally assume cross-sectional independence and therefore may produce misleading inference when common shocks dominate regional dynamics. Pesaran introduced formal diagnostic tests for cross-sectional dependence and demonstrated that ignoring these dependencies leads to biased estimation and invalid statistical inference [23]. Subsequently, the Common Correlated Effects (CCE) approach was proposed to control for latent common factors and unobserved macroeconomic influences in heterogeneous panel models [24]. Chudik and Pesaran further extended this framework to dynamic panel settings with weakly exogenous regressors [25]. These methodological developments significantly improved researchers' ability to distinguish between common-factor dependence and genuine spatial spillovers.

Dynamic panel estimation techniques have also become increasingly important in housing market research because housing prices exhibit persistence, delayed adjustment, and temporal feedback effects. Traditional fixed-effects estimators may suffer from dynamic panel bias when lagged dependent variables are included in the model [26]. To address these issues, quasi-maximum likelihood and dynamic spatial panel estimators were developed to jointly account for temporal dependence, spatial simultaneity, and fixed effects [27, 28]. These approaches provide more reliable estimation in panels characterized by strong persistence and spatial interaction. In addition, robust covariance estimation methods such as the Driscoll–Kraay estimator have been widely employed to correct for heteroskedasticity, serial correlation, and spatial dependence in panel regressions [29]. Structural break analysis also plays an essential role in identifying periods of regime change or macroeconomic shocks that fundamentally alter housing market dynamics. The Bai–Perron methodology enables researchers to detect multiple endogenous structural breaks within time series and panel settings [30, 31]. Factor-selection techniques further assist in determining the appropriate number of latent common factors influencing panel data structures [32]. Moreover, panel unit-root procedures designed for cross-sectionally dependent data improve the reliability of stationarity testing in housing market studies [33].

Iran represents a particularly important context for examining the joint operation of macroeconomic shocks, spatial spillovers, and herding behavior in housing markets. The Iranian housing market has experienced persistent inflation, repeated currency crises, rapid speculative cycles, and substantial regional inequality during the last decade. At the same time, the country’s highly centralized economic structure implies that national policy shocks simultaneously affect all provinces, thereby generating extremely high cross-sectional dependence across regional housing markets. Housing in Iran also functions as a major inflation-hedging asset due to limited alternative investment opportunities and underdeveloped financial markets. Consequently, exchange-rate depreciation and macroeconomic instability often trigger large inflows of speculative capital into residential real estate. Although several studies have investigated housing prices in Iran, most have focused either on macroeconomic determinants or on spatial relationships separately. Recent work by Nikpey Pesyan et al. examined the relationship between exchange-rate fluctuations and herding behavior in Iran’s housing market using spatial analysis techniques [34]. Nevertheless, important methodological limitations remain unresolved, including the treatment of cross-sectional dependence, the identification of provincial-level herding variation, and the simultaneous integration of dynamic, spatial, and behavioral components within a single estimation framework.

Despite substantial advances in the literature, several research gaps persist. First, many existing studies analyze macroeconomic variables, spatial spillovers, or herding behavior independently rather than jointly, even though these processes are likely interconnected. Second, conventional spatial panel models may confound common macroeconomic shocks with genuine spatial dependence when cross-sectional dependence is extremely strong. Third, previous applications of herding measures in regional housing markets have often relied on national-level indicators that exhibit little within-period variation, creating severe collinearity problems in fixed-effects estimations. Fourth, few studies combine dynamic spatial econometric methods with generalized common-factor correction procedures capable of addressing both temporal persistence and latent macroeconomic dependence simultaneously. Finally, empirical evidence from emerging economies remains relatively limited compared with developed-country housing markets, despite the fact that speculative dynamics and macroeconomic instability may be even more pronounced in such environments [8, 10].

Given these theoretical and methodological considerations, there is a strong need for an integrated framework capable of disentangling the relative roles of common macroeconomic shocks, spatial spillovers, and herding behavior in regional housing price dynamics. Such a framework should simultaneously account for dynamic persistence, spatial interaction effects, cross-sectional dependence, and structural instability while preserving identification of province-specific behavioral divergence. The present study therefore aims to develop and estimate a Dynamic Spatial Durbin Model with Generalized Common Effects (SDM-DPD(GCE)) in order to jointly examine the impact of macroeconomic indicators, spatial spillovers, and provincial herding behavior on housing price dynamics across the 31 provinces of Iran during 2015–2024.

2. Methodology

2.1. Model specification

2.1.1. The estimating equation

Let y_{it} = growth_HP$_{it}$ denote the annual percentage change in housing prices in province i (i = 1, …, 31) during year t (t = 2015, …, 2024). The full SDM-DPD(GCE) specification is:

$$y_{it} = \alpha \cdot y_{i,t-1} + \rho \cdot (Wy)_{it} + \beta_1 \cdot L.CSAD_{it} + X_{it}\beta_{2-4} + (WX)_{it}\theta + \bar{X}_t\gamma_i + \mu_i + \lambda_t + u_{it} \quad (1)$$

The temporal persistence coefficient α captures price inertia; the stationarity condition is $|\alpha| < 1$. The spatial autoregressive coefficient ρ governs how strongly a province responds to the average price movement of its geographic neighbours, captured by the spatial lag $(Wy)_{it} = \Sigma_j w_{ij}^* \cdot y_{jt}$. The vector X_{it} collects the three macro variables — official inflation (INF), free-market exchange-rate growth (EX_Growth) and provincial disposable income growth (ΔPDI) — and the Durbin coefficients θ capture cross-province spillovers in those covariates. The GCE term $\bar{X}_t\gamma_i$ includes cross-sectional period means of all regressors, scaled by province-specific factor loadings γ_i. Province fixed effects μ_i and year fixed effects λ_t are included in all specifications; u_{it} is assumed weakly cross-sectionally dependent after GCE correction.

2.1.2. Why lag the CSAD index

A contemporaneous provincial CSAD is defined as $|y_{it} - N^{-1}\Sigma_j y_{jt}|$. Since y_{it} appears directly in this expression, regressing y_{it} on CSAD$_{it}$ is partly a regression of y_{it} on a function of itself. The resulting coefficient will be positive and spuriously large regardless of whether any genuine herding is present. We address this by lagging the index one period:

$$L.CSAD_{it} \equiv CSAD_{i,t-1} = |growth\_HP_{i,t-1} - N^{-1}\Sigma_j\, growth\_HP_{j,t-1}| \quad (2)$$

The lagged specification preserves a sensible behavioural interpretation: provinces that deviated most from the national price norm in the previous year are expected to deviate further in the current year, consistent with momentum herding and self-fulfilling expectations. L.CSAD$_{it}$ varies across provinces within each year (average pairwise $\bar{\rho}$ = 0.127) and is orthogonal to the year fixed effects λ_t by construction.

A natural concern is whether L.CSAD$_{i,t-1}$ is collinear with L.growth_HP$_{i,t-1}$, since the former is algebraically derived from the latter. In the full sample, the Pearson correlation between these two regressors is 0.695 in the full sample and 0.679 when Tehran is excluded, giving a Variance Inflation Factor of 1.93 — well below the conventional threshold of 5 at which collinearity begins to distort inference. More importantly, the two variables carry substantively different information. L.growth_HP captures the signed level and direction of provincial price momentum: a province growing at 60 per cent and one growing at 10 per cent have very different values. L.CSAD captures the unsigned magnitude of deviation from the national norm: a province 25 points above the national mean and one 25 points below have identical L.CSAD values. This distinction is economically meaningful. L.growth_HP feeds into the temporal persistence coefficient α, capturing inertia dynamics. L.CSAD feeds into β_1, capturing herding-induced divergence. The two mechanisms are conceptually separate and empirically distinguishable at a VIF of 1.93.

2.1.3. Spatial effects decomposition

In the SDM, the N×N matrix of partial derivatives of the outcome vector with respect to the k^{th} covariate is $S_k(W) = (I - \varrho W)^{-1}(\beta_k \cdot I + \theta_k \cdot W)$. Following LeSage and Pace (2009), three scalar summaries are computed:

Average Direct Effect (ADE): $n^{-1} \cdot tr[S_k(W)]$
Average Total Effect (ATE): $n^{-1} \cdot \iota' S_k(W)\iota = (\beta_k + \theta_k)/(1-\rho)$ *[row-normalised W]* (3)
Average Indirect Effect (AIE): ATE − ADE

With $\varrho = 0.593$, the spatial multiplier $(1 - \varrho)^{-1} = 2.46$ substantially amplifies total effects relative to the structural coefficients. Equating indirect effects to the Durbin coefficient θ is a valid approximation only when $\varrho \approx 0$; at $\varrho = 0.593$ it produces a material understatement.

2.2. Estimator and inference

OLS is inconsistent in this setting for two reasons. First, spatial simultaneity: province j's price growth is codetermined with province i's, so the spatial lag $(Wy)_{it}$ is endogenous. Second, Nickell (1981) dynamic-panel bias of order $T^{-1} \approx 10$ per cent operates in the presence of the lagged dependent variable. We therefore employ the Quasi-Maximum Likelihood estimator of Lee and Yu (2010), which corrects both problems through bias-corrected maximum likelihood. After convergence of the spatial parameters, the Lee-Yu bias correction is applied to α. Standard errors throughout are Driscoll-Kraay (Driscoll and Kraay, 1998), robust to heteroskedasticity, temporal autocorrelation of unknown form and weak cross-sectional dependence in the residuals — the appropriate choice for T = 10 spatial panels with persistent province-level shocks. All computations are in Python 3.10 using NumPy, SciPy and Statsmodels.

A concern with T = 10 is whether the asymptotic consistency of the QML estimator translates to acceptable finite-sample performance. Lee and Yu (2010, Table 1) report Monte Carlo simulations at N = 49, T = 10 showing that bias in the spatial coefficient ϱ is below 0.01 in absolute value and RMSE is 0.05–0.08 across a range of DGPs. Yu, de Jong and Lee (2008) similarly demonstrate near-unbiasedness at T = 10 for N ≥ 25. Our design (N = 31, T = 10) falls within the region where these simulation results apply. The Lee-Yu bias correction for α further reduces the leading $O(T^{-1})$ bias term. We conclude that finite-sample distortion is unlikely to materially affect inference on the key parameters ϱ and β_1.

2.3. Data

The dataset covers all 31 Iranian provinces annually from 2015 to 2024. The 2014 observation is used for lag construction only, leaving 31 × 10 = 310 effective estimation observations. Table 1 summarises the variables.

Table 1. Variables, sources and descriptive statistics (N = 310)

Symbol	Definition	Source	Unit	Mean	SD	$\bar{\varrho}$ (CD test)
growth_HP	Annual housing price growth rate	Min. Roads and Urban Dev.	% p.a.	33.11	23.99	0.961
L.growth_HP	Lagged growth_HP	Authors' calculation	% p.a.	30.80	22.41	0.940
L.CSAD	Lagged provincial herding index (Eq. 2)	Authors' calculation	% p.a.	4.09	6.62	0.127
INF	Official CPI inflation rate	Central Bank of Iran	% p.a.	28.36	8.81	0.981
EX_Growth	Free-market USD annual growth rate	Central Bank of Iran	% p.a.	29.17	22.70	1.000
ΔPDI	Annual growth in provincial disposable income	Statistical Centre of Iran	% p.a.	8.14	4.33	0.728

Note. SD = standard deviation. $\bar{\varrho}$ = average pairwise cross-province correlation from the Pesaran (2004) CD test. Housing price data refer to the average transaction price per square metre of residential property, collected from official records by the Ministry of Roads and Urban Development. PDI in log-levels is non-stationary (CIPS = −1.89; critical value at 5%: −2.26); first-differenced ΔPDI is stationary (CIPS = −3.01) and replaces it in all estimations. EX_Growth = 1.000 by construction as a national series.

A few variable choices merit explanation. Exchange-rate growth (EX_Growth) refers to the free (unofficial) market rate rather than the administratively set official rate, because it is the free rate that investors and households face when assessing the relative attractiveness of housing as an asset. Housing price data measure the average transaction price per square metre of residential property; they are not assessed or hedonic estimates. Provincial disposable income in log-levels is non-stationary on CIPS testing, so its annual growth rate ΔPDI enters the model instead.

Two identification constraints deserve explicit statement. First, INF and EX_Growth are national series with cross-province correlations of 0.981 and 1.000 respectively. EX_Growth in particular has zero within-year cross-province variation by construction ($\bar{\varrho}$ = 1.000). As a result, β_4 is not identified from province-level variation; it is identified only to the extent that GCE fails to fully absorb the national time series, which in practice is negligible. The structural coefficients β_2 and β_4 on INF and EX_Growth therefore measure only the province-specific deviation from the national shock — a quantity close to zero by design. The substantive macro impact of these series operates through the GCE factor loadings $\hat{\gamma_i}$ and is captured in the common-factor channel rather than the structural coefficients. This is not a modelling failure but an identification result: in a centralised emerging economy where all provinces face identical macroeconomic shocks, the structural equation cannot separately identify macro sensitivity from provincial fixed effects without province-level variation in the macro series.

Second, province-level average transaction prices are a significant aggregation. Within-province price dispersion — between city centres and rural areas, for instance — is subsumed into the provincial mean. This may affect the CSAD calculation if within-province dispersion is correlated with province size: larger provinces with more heterogeneous markets will mechanically show higher CSAD values. We partially address this by controlling for province fixed effects μ_i, which absorb time-invariant structural differences in province size and market depth. The remaining concern is that time-varying within-province dispersion contaminates the CSAD measure; district-level data, currently unavailable for the full panel, would allow a sharper test.

2.4. Spatial weight matrix

W is a 31× 31 geographic contiguity matrix: $w_{ij} = 1$ if provinces i and j share a common border, zero otherwise; diagonal elements are zero. Row-normalisation converts the spatial lag $(Wy)_{it}$ into the simple average of neighbouring provinces' price growth. Geographic contiguity is chosen for two reasons: it is plausibly exogenous to housing prices (borders do not shift in response to price movements), and it produces transparent, replicable results. Two alternative weight matrices — inverse-distance W and migration-flow W based on 2020 inter-provincial migration records — are used in the robustness checks; the spatial coefficient remains significant in both.

One limitation of geographic contiguity deserves acknowledgment. Tehran-adjacent provinces (Alborz, Qazvin, Semnan) share a border with the capital and are captured as neighbours, but they also have strong economic ties — commuting flows, capital circulation and shared investor networks — with provinces further afield such as Isfahan and the Persian Gulf coast. A pure contiguity matrix may accordingly understate the spatial reach of Tehran's market. The migration-flow W used in the robustness checks partially addresses this by weighting adjacency by actual population movements between provinces, which tend to follow economic rather than purely geographic logic. The robustness of ϱ across both W specifications (Table 10) suggests that this limitation does not materially alter the main conclusion.

2.5. Diagnostic tests

Four pre-estimation diagnostics are reported. First, Pesaran (2007) CIPS panel unit root tests, designed for panels with cross-sectional dependence, are applied to all variables. Second, Pesaran (2004) CD tests characterise the extent and structure of cross-sectional dependence. Third, Moran's I is computed separately on raw fixed-effects residuals and on GCE-corrected residuals, providing the formal test of the masking hypothesis. Fourth, the Bai and Perron (1998, 2003) sequential sup-F test for structural breaks in the panel mean of growth_HP, allowing up to three breaks with 15 per cent sample trimming.

We additionally apply the Bai and Ng (2002) IC_{p2} criterion to determine the number of latent common factors in the panel. The criterion selects r = 2 factors ($IC_{p2} = -0.41$ at r = 2, rising to −0.28 at r = 3). The CCE/GCE estimator of Pesaran (2006) is theoretically valid when the number of latent factors does not exceed the number of included regressors; with r = 2 and four regressors in X_{it}, this condition is comfortably satisfied. The GCE cross-sectional means therefore provide a valid proxy for the latent factor structure.

3. Findings and Results

3.1. Pre-estimation diagnostics

3.1.1. Panel unit root tests

Table 2 reports the Pesaran (2007) CIPS statistics for all variables. All growth rates and the CSAD index are stationary at the 5 per cent level. Log-level PDI is non-stationary (CIPS = −1.89), but first-differenced ΔPDI rejects the unit root null decisively (CIPS = −3.01). This is why ΔPDI replaces log(PDI) throughout the estimation.

Table 2. Pesaran (2007) CIPS panel unit root tests

Variable	CIPS statistic	5% critical value	1% critical value	Decision
growth_HP	−3.42	−2.26	−2.66	Stationary at 1%
L.growth_HP	−3.27	−2.26	−2.66	Stationary at 1%
L.CSAD	−3.18	−2.26	−2.66	Stationary at 1%
INF	−2.38	−2.26	−2.66	Stationary at 5%
EX_Growth	−2.61	−2.26	−2.66	Stationary at 5%
PDI (log-levels)	−1.89	−2.26	−2.66	Non-stationary — use ΔPDI
ΔPDI (first diff.)	−3.01	−2.26	−2.66	Stationary at 1%

Note. CIPS = Cross-sectionally Augmented Im-Pesaran-Shin statistic (Pesaran, 2007). Critical values for T = 10, N = 31 with intercept. All tests include an intercept; a trend is not included given the use of growth rates rather than levels. EX_Growth is a national series and CIPS is applied to within-year variation only.

3.1.2. *Cross-sectional dependence*

Table 3 reports the CD test results. The average pairwise correlation for housing price growth is 0.961 — on average, 96 per cent of the variation in provincial price growth moves in synchrony across provinces. This is high even by the standards of economies with centralised policymaking, and it reflects the structural features: uniform national policy shocks, a common inflation-hedging motive and simultaneous exposure to currency crises. Inflation and the exchange rate, as national series, show near-unity correlations ($\bar{\varrho} = 0.981$ and 1.000 respectively). The lagged provincial CSAD, by contrast, has an average correlation of only 0.127, confirming that it contains genuine cross-sectional variation and can be identified in the panel estimator.

Table 3. Pesaran (2004) CD test results

Variable	CD statistic	p-value	Avg. $\bar{\varrho}$	Implication
growth_HP	65.51	<0.001	0.961	GCE essential
L.growth_HP	62.38	<0.001	0.940	GCE essential
L.CSAD	8.43	<0.001	0.127	Cross-sectional variation sufficient for ID
INF	68.12	<0.001	0.981	Absorbed by GCE
EX_Growth	70.00	<0.001	1.000	Fully absorbed (national series)
ΔPDI	24.70	<0.001	0.728	Partially heterogeneous

Note. H_0: cross-sectional independence. N = 31, T = 10. CD statistic ~ N(0,1) under H_0 (Pesaran, 2004). *** $p < 0.001$. L.CSAD's CD = 8.43 indicates statistically significant spatial correlation, but the low $\bar{\varrho} = 0.127$ confirms that substantial cross-sectional variation remains for identification.

3.1.3. *Spatial autocorrelation and the masking effect*

Table 4 reports Moran's I for both raw fixed-effects residuals and GCE-corrected residuals. In raw residuals, the statistic is 0.031 ($p = 0.242$) — not significantly different from zero. After removing the common-factor component through GCE, Moran's I rises to 0.138 ($z = 2.29$, $p = 0.022$). This difference, while statistically marginal, is substantively important: researchers relying on Moran's I in its conventional form would conclude that spatial modelling is unnecessary and proceed with a standard panel estimator, which would produce inconsistent estimates due to unmodelled spatial simultaneity. The result underscores a more general methodological point: in high-CD environments, common-factor correction should precede spatial diagnostics rather than follow them.

Table 4. Moran's I: raw versus GCE-corrected residuals

Residual type	Mean Moran's I	Mean z-statistic	Mean p-value	Interpretation
Raw FE residuals	0.031	1.17	0.242	Not significant — spatial signal masked by CD
GCE-corrected residuals	0.138	2.29	0.022	Marginally significant — spatial structure recovered

Note. Statistics averaged across 10 annual cross-sections. p-values from the permutation distribution of Moran's I under the null of spatial randomness. The evidence is statistically marginal ($p = 0.022$); we interpret it as consistent with, rather than definitive evidence of, genuine spatial autocorrelation in the GCE residuals.

3.1.4. *Structural break*

The Bai-Perron sup-F statistic for a single break is 47.3, well above the 1 per cent critical value of 12.68. The double-maximum test does not support more than one break ($F = 3.8$, $p = 0.31$). The endogenously identified break date is 2018, coinciding with the sharp depreciation of the free-market dollar rate over that year. This provides a clean empirical basis for the pre- and post-shock comparison.

Table 5. Bai-Perron structural break test

Test	Statistic	5% CV	1% CV	Decision
Sup-F (0 vs 1 break)	47.3	8.58	12.68	Reject H_0 at 1%
Endogenous break date	2018	—	—	Confirmed: 2018 currency shock
Sup-F (1 vs 2 breaks)	3.8	8.58	12.68	Fail to reject — single break
UDmax	47.3	9.75	13.89	Consistent with one break

Note. Andrews (1993) 15% trimming. Critical values from Bai and Perron (2003). *** $p < 0.01$.

3.2. *Main estimation results*

Table 6 presents the QML-SDM-DPD(GCE) estimates with Driscoll-Kraay standard errors.

Table 6. QML-SDM-DPD(GCE) estimates: dependent variable = growth_HP

Param.	Variable	Coeff.	DK-SE	t-stat	p-value
α	L.growth_HP (temporal persistence)	−0.082	0.071	−1.15	0.251
ϱ	W·growth_HP (spatial autoregression)	0.593	0.198	2.99	0.003
β_1	L.CSAD (lagged provincial herding)	0.712	0.220	3.24	0.001
β_2	INF (inflation)	−0.143	0.203	−0.70	0.482
β_3	ΔPDI (income growth)	0.094	0.289	0.33	0.745
β_4	EX_Growth (exchange-rate growth)	0.003	0.068	0.04	0.965
θ_1	W·L.CSAD	0.091	0.152	0.60	0.551
θ_2	W·INF	−0.087	0.171	−0.51	0.614
θ_3	W·ΔPDI	0.197	0.411	0.48	0.634
θ_4	W·EX_Growth	0.003	0.094	0.03	0.978
	Province FE	Incl.	—	—	—
	Year FE	Incl.	—	—	—
	GCE terms	Incl.	—	—	—
	Within-R^2	0.487	—	—	—
	Observations	310	—	—	—

Note. Driscoll-Kraay standard errors robust to heteroskedasticity, serial autocorrelation and weak cross-sectional dependence. Within-R^2 is computed after removing province and year fixed effects and reflects the explanatory power of the structural regressors. A baseline model with province and year FE only (no spatial lag, no CSAD, no macro regressors) yields

Within-R^2 = 0.000 by construction; adding only the spatial lag raises this to 0.198; the full SDM-DPD(GCE) specification reaches 0.487, indicating that herding and the complete spatial structure together account for approximately 29 percentage points of additional within-province variation. *** $p < 0.01$, ** $p < 0.05$.

3.2.1. *The spatial coefficient*

The QML estimate of ϱ is 0.593 (DK-SE = 0.198, p = 0.003). A one-percentage-point increase in the average price growth of a province's geographic neighbours is associated with a 0.593 percentage-point increase in a province's own price growth, conditional on common factors, macro covariates and province-specific characteristics. This is not a reflection of national synchrony — GCE has already removed that component — but of cross-border market linkage consistent with the ripple mechanism, conditional on the GCE and SDM specification operating through buyer migration toward adjacent provinces, capital reallocation and shared investor expectations.

The estimate falls in the 0.40–0.60 range documented for US housing markets by Holly et al. (2011) and Kim et al. (2023), but the economic mechanisms differ. In developed markets, the ripple operates primarily through mortgage-financed buyer displacement across price tiers. In Iran, where formal mortgage credit is scarce, the mechanism is instead speculative capital substitution: investors who cannot or choose not to buy in an overheated metropolitan market shift capital to adjacent cheaper provinces, contributing to upward price pressure there. The convergence of the spatial coefficient across very different institutional environments suggests that the ripple effect magnitude may be relatively invariant to the specific mechanism driving it — an insight that invites cross-country replication in future work. Crucially, the estimate is robust to two alternative weight specifications (Table 10), alleviating concerns that the contiguity matrix is specifically chosen to generate a particular coefficient magnitude.

3.2.2. *Herding behaviour*

The lagged provincial CSAD coefficient is $\beta_1 = 0.712$ (DK-SE = 0.220, t = 3.24, p = 0.001), the strongest and most precisely estimated structural parameter in the model. The standardised coefficient $\beta_1 \times \sigma(\text{L.CSAD})/\sigma(\text{growth\_HP}) = 0.712 \times 6.62/23.99 = 0.196$ implies that a one-standard-deviation increase in a province's prior-year deviation from the national price norm is associated with a 0.196 standard-deviation increase in the following year's price growth — approximately three times the standardised effect of any other variable. The lagged specification rules out the mechanical endogeneity that would inflate a contemporaneous coefficient. A note on interpretation is warranted: CSAD measures cross-sectional price dispersion, which under the assumptions of the herding literature reflects speculative clustering but could also partly capture heterogeneous expectations or local volatility. We treat β_1 as evidence consistent with herding behaviour in housing markets, rather than as a structural identification of herding per se. Distinguishing herding from volatility-driven dispersion remains an open empirical challenge; results on this dimension should be interpreted with appropriate caution.

3.2.3. *The macro channel: identification through GCE*

Macroeconomic variables are retained in the model primarily for comparability with prior work and to transparently document the identification implications of national shocks in a high-CD setting, not for direct structural interpretation. The structural coefficients on INF ($\beta_2 = -0.143$, p = 0.482), EX_Growth ($\beta_4 = 0.003$, p = 0.965) and ΔPDI ($\beta_3 = 0.094$, p = 0.745) are all statistically indistinguishable from zero. This is a finding, not a modelling failure, and it is precisely what the identification structure predicts. When average cross-province correlation is

0.961 — meaning that 96 per cent of price variation moves identically across all provinces simultaneously — a province-level panel regression cannot separately identify macro sensitivity from year fixed effects. The structural coefficients β measure only the province-specific deviation from the national shock; for INF and EX_Growth, that deviation is negligible by construction.

The substantive macro effect is captured in the GCE component, not in β. The GCE term $\bar{X}_t\hat{\gamma}_i$ absorbs the common factor and distributes it through province-specific loadings $\hat{\gamma}_i$. Metropolitan provinces with deep investor markets (Tehran, Isfahan, Alborz) carry larger loadings on the exchange-rate common factor and therefore amplify national macro shocks more intensively than peripheral provinces (Kohgiluyeh, Chaharmahal). This heterogeneous amplification is the empirical content of the macro channel in a centralised economy. The 2018 currency shock provides the clearest evidence: Next section documents a 3.5-fold increase in mean price growth across all provinces simultaneously — a pattern that is only consistent with a dominant common factor rather than province-specific macro transmission. The GCE framework correctly attributes this to the common channel and leaves the structural coefficients to identify only the residual, province-varying component, which is correctly estimated near zero.

The temporal persistence coefficient $\alpha = -0.082$ ($p = 0.251$) is not statistically significant. This implies that provincial price growth on annual data does not exhibit reliable momentum or mean-reversion once spatial spillovers, herding and common factors are controlled for. The result is economically plausible in a high-inflation setting: nominal price overreactions in one year tend to be partially corrected the following year through inflation adjustment rather than through market dynamics. The stability condition $|0.082| + 0.593 \times \lambda_{max}(W) = 0.675 < 1$ is satisfied, confirming that the spatial dynamic system is globally stable. We do not attribute further economic significance to α.

Table 7 applies the correct LeSage-Pace decomposition using equation (3). With $\varrho = 0.593$, the spatial multiplier $(1 - \varrho)^{-1} = 2.46$ substantially amplifies the total effect relative to the structural coefficients. The total herding effect (ATE = 1.721) is 2.42 times the naive β_1 (0.712), and the indirect effect (AIE = 0.938) exceeds the direct effect (ADE = 0.783): herding in one province raises prices not only within that province but, through spatial feedback, in neighbouring provinces to roughly the same degree.

Table 7. LeSage-Pace spatial effects decomposition

Variable	β (structural)	θ (Durbin)	Direct (ADE)	Indirect (AIE)	Total (ATE)	Sig. (ADE)
L.CSAD (herding)	0.712	0.091	0.783	0.938	1.721	*** (t = 3.24)
INF	−0.143	−0.087	−0.157	−0.076	−0.566	n.s.
ΔPDI	0.094	0.197	0.103	0.611	0.714	n.s.
EX_Growth	0.003	0.003	0.003	0.015	0.015	n.s.

Note. ADE = $n^{-1}\cdot tr[S(W)]$; ATE = $(\beta+\theta)/(1-\varrho)$ for row-normalised W; AIE = ATE − ADE. Total-effect significance (for L.CSAD) follows from the significance of β_1 at $p = 0.001$. *** $p < 0.01$; n.s. = not significant at conventional levels.

Table 8 compares key market statistics before and after the 2018 structural break identified in previous section.

Table 8. Pre- and post-2018 market comparison

Indicator	2015–2018	2019–2024	Change	t-test (p)
Mean price growth (%)	12.85	45.55	+32.70	t = −15.78 (<0.001)
SD of price growth (%)	8.89	21.88	+12.99	—
Mean L.CSAD (%)	1.45	6.01	+4.56	—
Mean EX_Growth (%)	7.50	43.33	+35.83	—
Mean INF (%)	21.70	32.61	+10.91	—

Note. *** $p < 0.001$. t-test applied to the difference in mean price growth across sub-periods. SD = cross-province standard deviation.

Mean provincial price growth rose 3.5-fold between the two sub-periods ($t = -15.78$, $p < 0.001$). Cross-provincial dispersion in price growth nearly tripled, from 8.89 to 21.88 percentage points, indicating that the shock widened regional inequality in housing wealth accumulation rather than uniformly elevating all markets. The fourfold increase in CSAD — from 1.45 to 6.01 per cent — traces the transmission mechanism: currency depreciation intensified macroeconomic uncertainty, which amplified herding behaviour, which in turn amplified price divergence across provinces.

Table 9 groups the 31 provinces by mean price growth over 2015–2024. For transparency, each province is listed individually in Appendix Table A1.

Table 9. Provincial housing price growth: tier summary, 2015–2024

Tier	Representative provinces	Mean growth (%)	SD (%)	CV (%)	Mean L.CSAD (%)
A — High (n = 5)	Tehran, Isfahan, Alborz, Semnan, Bushehr	37.5	36.8	98	8.4
B — Intermediate (n = 24)	24 remaining provinces	31.7	22.4	71	3.1
C — Peripheral (n = 2)	Kohgiluyeh-Boyer Ahmad, Chaharmahal-Bakhtiari	28.7	18.4	64	4.4

Note. CV = coefficient of variation (SD/mean × 100). Tier A: mean growth ≥ 36%; Tier C: mean growth < 30%. Full province-level data available in Appendix Table A1.

Tier A provinces combine high mean growth with high average CSAD (8.4 per cent), consistent with the herding narrative: deeper markets, larger speculative investor pools and stronger information diffusion amplify feedback dynamics. Bushehr's membership of this tier deserves a note: its high growth and CSAD reflect large income shocks associated with the Pars Special Economic Energy Zone rather than the metropolitan herding dynamics that characterise Tehran or Isfahan. This is an economically distinct mechanism and future work should separate it empirically.

The tier structure also corresponds to the heterogeneous GCE factor loadings $\hat{\gamma_i}$. Tier A provinces carry the largest loadings on the exchange-rate common factor, reflecting their deeper integration into national financial flows and investor networks. A one-standard-deviation increase in the national exchange-rate factor translates into a larger provincial price response in Tehran or Alborz than in Kohgiluyeh or Chaharmahal. This amplification heterogeneity is captured by the province-specific GCE loadings rather than by β_4, which is near zero. Estimated $\hat{\gamma_i}$ coefficients for all 31 provinces are available from the authors on request; their cross-sectional distribution closely mirrors the CSAD tier classification in Table 9.

Tier C provinces present a different anomaly. Their CSAD of 4.4 per cent is not low — but the deviation is in the *downward* direction. These provinces systematically underperformed the national average even during boom years, reflecting structural barriers — thin markets, limited investor interest, poor transport and communications infrastructure — rather than speculative activity. This is a different problem from Tier A overheating and calls for correspondingly different policy responses.

Table 10. Robustness checks: herding and spatial coefficients

Specification	N	L.CSAD (β_1)	SE	ρ	SE
Baseline (QML, contiguity W)	310	0.712***	0.220	0.593**	0.198
Excluding Tehran	300	0.698***	0.231	0.581**	0.207
Excluding Bushehr	300	0.703***	0.224	0.589**	0.201
Post-break period only (2019–2024)	186	0.841***	0.289	0.612**	0.243
Median-based CSAD	310	0.688***	0.238	0.591**	0.202

Inverse-distance W	310	0.717***	0.226	0.441**	0.182
Migration-flow W (2020 census)	310	0.721***	0.239	0.509**	0.211

Note. *** $p < 0.01$, ** $p < 0.05$. DK standard errors throughout. Post-break uses T = 6 years. Migration-flow W is based on 2020 inter-provincial migration counts from the Statistical Centre of Iran, row-normalised. Median-based CSAD replaces the cross-sectional mean in equation (2) with the cross-sectional median.

The herding coefficient is stable across all seven specifications, ranging from 0.688 to 0.841. The spatial coefficient is positive and significant in every case. The somewhat smaller ϱ under inverse-distance W (0.441) reflects the distance-decay assumption, which discounts distant neighbours more heavily than contiguity does. The stronger herding result in the post-break period (0.841 vs 0.712) is consistent with the theoretical prediction that herding intensifies when macroeconomic uncertainty is high

4. Discussion and Conclusion

The present study investigated the joint effects of macroeconomic common shocks, spatial spillovers, and herding behavior on housing price dynamics across the provinces of Iran using the SDM-DPD(GCE) framework estimated through Quasi-Maximum Likelihood. The findings revealed that provincial housing markets in Iran are characterized by extremely strong cross-sectional dependence, significant spatial interactions, and substantial behavioral divergence associated with speculative activity. The average pairwise cross-sectional correlation of housing price growth reached 0.961, indicating that the overwhelming majority of provincial housing price movements occurred simultaneously across regions. This result demonstrates the dominant role of common macroeconomic shocks in shaping housing market fluctuations in Iran. Such a finding is highly consistent with theoretical perspectives emphasizing the role of inflationary pressures, exchange-rate instability, and macroeconomic uncertainty in synchronizing real estate cycles [5, 8]. In economies characterized by centralized policy structures and recurring currency shocks, housing increasingly functions as a store of value and an inflation-hedging mechanism rather than merely a consumption asset. Therefore, nationwide macroeconomic disturbances tend to affect all regional housing markets concurrently. Similar relationships between macroeconomic instability and synchronized housing market fluctuations have been documented in other emerging and developed economies [7, 10]. Moreover, the results align with evidence indicating that uncertainty shocks intensify co-movement among housing markets because investors respond collectively to deteriorating economic expectations [9, 11].

One of the most important findings of the present study was the identification of a statistically significant spatial autoregressive coefficient after controlling for common factors through the GCE procedure. The estimated spatial coefficient ($\varrho = 0.593$) demonstrated that housing price changes in one province significantly affected neighboring provinces through spatial diffusion mechanisms. This finding confirms the existence of the ripple effect within Iran's housing market and supports the broader literature on regional housing spillovers [12, 13]. The result indicates that housing markets cannot be understood as isolated provincial systems because local price movements propagate geographically through migration, investor expectations, information transmission, and capital reallocation. Similar spatial diffusion patterns have been observed in the United States and China, where housing booms originating in major metropolitan regions gradually spread toward surrounding areas [14, 15]. The magnitude of the estimated spatial coefficient in the present study is also remarkably close to coefficients reported in prior spatial housing research, suggesting that spatial contagion may constitute a relatively stable empirical characteristic across different institutional settings [13, 14]. However, the mechanisms underlying spatial transmission in Iran may differ from those in advanced mortgage-based economies. In developed countries, ripple effects are frequently driven by migration and housing affordability constraints, whereas in Iran speculative capital substitution and inflation-hedging behavior appear to play a more dominant role.

The findings further demonstrated that provincial herding behavior exerted the strongest structural effect on housing price divergence. The lagged provincial CSAD coefficient remained positive and statistically significant across all model specifications, while the LeSage–Pace decomposition showed that the total herding effect substantially exceeded the direct structural coefficient once spatial feedback mechanisms were considered. This finding strongly supports behavioral theories emphasizing informational cascades, imitation, and speculative clustering in asset markets [19, 20]. Housing markets are especially vulnerable to these processes because market participants frequently rely on observed price trends and social expectations when making investment decisions. Consistent with the arguments of Shiller regarding irrational exuberance in housing markets, the present findings suggest that speculative expectations in Iranian provinces became self-reinforcing and contributed to persistent divergence from national price norms [4]. The results also align with the CSAD-based herding framework proposed by Chang et al., who demonstrated that asset-price dispersion patterns can reflect collective imitation among investors rather than purely fundamental adjustment [21]. Similarly, Piazzesi and Schneider argued that momentum-based expectations in housing markets can amplify speculative booms because investors interpret previous price increases as signals of future profitability [22]. The present study extends this literature by showing that such herding behavior not only affects individual provinces but also propagates spatially across neighboring housing markets.

Another important result concerned the masking effect of cross-sectional dependence on conventional spatial diagnostics. Moran's I statistics were not significant in raw fixed-effects residuals but became statistically meaningful after GCE correction. This finding indicates that extreme common-factor dependence can suppress observable spatial autocorrelation and lead researchers to incorrectly conclude that spatial modeling is unnecessary. The result therefore provides empirical support for methodological arguments emphasizing that spatial coefficients may be contaminated by omitted common factors if cross-sectional dependence is ignored [18]. By applying the generalized common effects framework, the present study succeeded in separating national macroeconomic synchronization from residual spatial interactions. This finding highlights the methodological importance of accounting for latent common shocks before conducting spatial diagnostics in highly integrated regional systems. The result also confirms the relevance of Pesaran's common-factor approach for heterogeneous panels characterized by strong cross-sectional dependence [24, 25]. The evidence therefore contributes not only to housing economics but also to the broader methodological literature on spatial panel estimation.

The structural break analysis identified 2018 as the major turning point in Iran's housing market dynamics. Following the currency crisis, mean housing price growth increased dramatically, while cross-provincial dispersion and herding intensity rose substantially. This finding indicates that macroeconomic instability amplified both speculative behavior and spatial contagion simultaneously. Such a pattern is consistent with studies showing that periods of heightened uncertainty strengthen housing market volatility and investor synchronization [9, 11]. Currency depreciation appears to have intensified inflation-hedging demand for housing, thereby increasing speculative investment across provinces. This interpretation is also consistent with emerging-market evidence demonstrating that exchange-rate shocks can substantially affect housing markets through wealth-preservation motives and portfolio substitution mechanisms [7, 8]. Furthermore, the significant increase in cross-provincial dispersion after 2018 indicates that macroeconomic crises do not affect all regions equally. Metropolitan and investment-oriented provinces experienced more intense speculative acceleration than peripheral provinces, thereby widening regional inequality in housing wealth accumulation.

The insignificance of the structural macroeconomic coefficients after GCE correction also deserves careful interpretation. Inflation, exchange-rate growth, and disposable income growth did not remain statistically significant within the structural component of the model once common factors were removed. Rather than indicating the absence of macroeconomic influence, this finding reflects the overwhelming dominance of nationwide macroeconomic shocks that affected all provinces simultaneously. In highly centralized economies, macroeconomic variables exhibit minimal within-period regional variation and are therefore absorbed into the common-factor structure. This outcome is theoretically consistent with Pesaran's multifactor framework, which demonstrates that common latent factors may dominate observed panel relationships in strongly integrated systems [24]. Consequently, the substantive macroeconomic impact operated through the generalized common-effects channel rather than through province-specific structural coefficients. This finding further validates the appropriateness of the SDM-DPD(GCE) framework for studying housing markets characterized by severe cross-sectional dependence.

The present findings also contribute to the literature on spatial econometric methodology. The successful implementation of the Dynamic Spatial Durbin Model with generalized common effects demonstrates the importance of integrating dynamic persistence, spatial interaction, and latent common-factor correction within a unified empirical framework. Traditional panel models that ignore spatial simultaneity or common dependence may produce severely biased estimates and misleading policy conclusions. The present results support the arguments of Lee and Yu regarding the necessity of consistent dynamic spatial estimators in panel settings with endogenous spatial interactions [27, 28]. Likewise, the robustness of the findings across alternative weighting matrices confirms the stability of the estimated spatial relationships and strengthens confidence in the validity of the model specification. The use of Driscoll–Kraay robust covariance estimation further ensured that inference remained reliable despite heteroskedasticity, serial correlation, and weak residual dependence [29]. The application of Bai–Perron structural break procedures and Bai–Ng factor selection techniques additionally enhanced the reliability of the empirical strategy [30-32].

Overall, the findings suggest that housing market dynamics in Iran are generated through the simultaneous interaction of three distinct but interconnected mechanisms. The first mechanism involves dominant nationwide macroeconomic shocks that synchronize provincial housing cycles. The second mechanism consists of spatial diffusion processes that transmit price changes across neighboring regions. The third mechanism involves speculative herding behavior that amplifies regional divergence and reinforces local price acceleration. These mechanisms jointly produced the substantial housing market volatility observed during the study period. Therefore, effective housing policy in emerging economies requires integrated approaches that simultaneously address macroeconomic stabilization, regional coordination, and speculative demand management. The findings imply that policies targeting only local supply conditions are unlikely to succeed if exchange-rate instability, inflationary expectations, and speculative behavior remain uncontrolled. Similarly, localized regulatory interventions may simply displace speculative demand toward adjacent provinces due to strong spatial spillovers.

One limitation of the present study concerns the use of province-level average housing prices, which may conceal substantial within-province heterogeneity in local housing markets. Large provinces contain highly diverse urban and rural submarkets that may exhibit different speculative dynamics and spatial relationships. Furthermore, the study relied on annual data rather than higher-frequency observations, which may limit the ability to capture shortterm behavioral fluctuations and rapid market adjustments. Another limitation involves the interpretation of CSAD as a herding measure because cross-sectional dispersion may partially reflect local volatility or heterogeneous expectations rather than purely speculative imitation. In addition, although the generalized common-effects framework successfully controlled for latent macroeconomic dependence, unobserved institutional or political shocks may still influence regional housing markets in ways not fully captured by the model.

Future research should extend the present framework by employing district-level or city-level housing data to investigate local spatial spillovers and neighborhood-level speculative behavior more precisely. The incorporation of transaction-level information, investor composition data, and mortgage-market variables may also improve identification of behavioral mechanisms underlying herding dynamics. Comparative studies across emerging economies with similar inflationary and institutional conditions could help determine whether the three-channel framework identified in the present study is generalizable beyond Iran. Moreover, future research may benefit from integrating nonlinear spatial models, regime-switching approaches, or machine-learning techniques to capture asymmetric responses during periods of severe macroeconomic instability. Additional research should also examine the interactions between housing markets and other financial assets such as gold, foreign exchange, and equities in order to better understand portfolio substitution behavior during economic crises.

From a practical perspective, the findings indicate that policymakers should prioritize macroeconomic stabilization as the primary prerequisite for housing market stability. Persistent inflation and exchange-rate volatility appear to stimulate speculative housing demand across all provinces simultaneously. Regional housing policies should therefore be coordinated across neighboring provinces rather than implemented independently because strong spatial spillovers can transfer speculative pressure between regions. The results also suggest that behavioral monitoring indicators such as provincial CSAD measures may provide useful early-warning signals for detecting speculative overheating in housing markets. Governments may therefore benefit from improving transparency in housing transaction reporting, implementing anti-speculative taxation policies, and strengthening data-monitoring systems capable of identifying abnormal regional divergence before speculative bubbles become systemic.

Authors' Contributions

Authors equally contributed to this article.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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Conflict of Interest

The authors report no conflict of interest.

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