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House price dynamics in Istanbul: District-level analysis of convergence clubs, spillovers, and key drivers

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ABSTRACT

This study analyzes the dynamics of house prices across Istanbul's districts using a unique dataset of house prices and socioeconomic characteristics from 2010Q1 to 2022Q1. The log-t convergence test identifies four convergence clubs, with their formation beginning after 2015, highlighting the heterogeneity within Istanbul's housing market. The spillover index shows moderate spillovers, predominantly flowing from less affluent to more affluent districts. Additionally, LASSO regression suggests that the formation of convergence clubs in Istanbul closely reflects the city's socioeconomic conditions and levels of material prosperity. Specifically, financial wealth, middle and low-socioeconomic status households, and the presence of certain retail chains (e.g., Mado, Starbucks, and Domino's Pizza) are significant factors in the formation of these clusters. Overall, the housing divide in Istanbul appears to be largely driven by income and socioeconomic class.

1. Introduction

While there is extensive research into housing markets, the convergence of house prices in emerging market economies remains an underexplored area (Gunduz & Yilmaz, 2021; Trojanek, Gluszak, Kufel, Tanas, & Trojanek, 2023). Studies are particularly scarce at the city or intra-city level across various countries (Bashar, 2021). This paper aims to investigate house price convergence across residential districts within Istanbul. The rationale for assessing house price dynamics across Istanbul's districts is based on the perception that it is Europe's most populous city, possesses the most vibrant and largest housing market in Türkiye, and accounts for a significant portion of the country's real estate transactions. In 2019, Istanbul accounted for approximately 18% of Türkiye's total housing sales, 42% of bank loans, nearly 40% of total savings deposits, and 36% of the manufacturing industry (SEGE (Republic of Turkey Ministry of Industry and Technology), 2019). In terms of house prices, Istanbul has not only outpaced the national average and those of the two main cities (see Fig. 1) but it has also been rated among the top five European housing markets on several occasions.[1] However, given its size and complex division into numerous districts, Istanbul likely exhibits a fragmented housing market with multiple convergence clubs rather than a uniform equilibrium in house prices. Recent house price fluctuations across different districts (Gunduz et al., 2023), and variances in market behaviors within the same province or district (Vatansever et al., 2020), further support this hypothesis.

Exploring house price convergence at the inter-city or intra-city levels is particularly valuable for several reasons. Globally, local housing market shocks have been shown to impact broader real estate markets and can even affect national financial stability. House prices may react differently to supply and demand shocks depending on their synchronicity or correlations (He et al., 2018). Additionally, the varying impacts of economic policies, such as monetary policy, on real estate have sparked considerable debate. Since real estate constitutes a crucial segment of household wealth and GDP, understanding its dynamics within a city is essential for real estate investment and urban planning. Furthermore, changes in relative house prices shed light on social and economic aspects, such as residential segregation, income inequality, labor mobility, and housing affordability.

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[1] See also https://www.pwc.com/gx/en/industries/financial-services/asset-management/emerging-trends-real-estate.html and https://content.knightfrank.com/research/1026/documents/en/global-residential-cities-index-q3–2022–9617.pdf.

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A few studies have previously examined house price convergence at regional or city levels in Türkiye. Vatansever et al. (2020) identified three converging clusters among 196 districts across Türkiye's five largest provinces. Gunduz and Yilmaz (2021) found five converging clubs across 55 Turkish cities, influenced by factors such as employment rates, climate, and population density. Ganioğlu and Seven (2021) discovered seven regional clusters influenced by a number of key factors, including income, population, education, unemployment rate, location in an earthquake zone, and the presence of Syrian refugees. More recently, Balcılar et al. (2024) further highlighted the high connectedness of house prices across regions in Türkiye and the increasing role of Istanbul as a major transmitter.

This study makes three notable contributions to the existing literature. Firstly, it is the first to examine house price convergence, specifically at the district level within Istanbul, employing quarterly data from 2010Q1 to 2022Q1, sourced from the Central Bank of the Republic of Türkiye (CBRT). Unlike previous research, such as Gunduz and Yilmaz (2021) and Ganioğlu and Seven (2021), which focused on inter-city or inter-regional analyses, our work provides a granular perspective on the diverse dynamics within Istanbul's housing market. We further enrich this analysis by examining recursive convergence club dynamics to assess the impact of the COVID-19 pandemic on the evolution of house price clusters in the city. Secondly, we introduce the Diebold and Yilmaz (2009, 2012) spillover index to estimate convergence club spillovers. This approach allows us to measure the dynamic connectedness across different clubs, not only capturing spillover effects between districts but also providing a robustness check for the convergence clubs identified. By quantifying these interconnections, we gain insights into how shocks in one market can ripple through other markets within Istanbul. Additionally, low levels of spillover can serve as supplementary evidence for the existence of multiple distinct clusters with limited interconnectedness. Thirdly, we utilize a comprehensive dataset of over 110 district-level variables gathered from public and private sources. We then employ LASSO regression, a machine learning technique, to identify the key characteristics that differentiate the convergence clubs within Istanbul. This approach allows us to uncover the underlying factors driving the formation and evolution of these distinct price clusters.

The rest of the paper is structured as follows. Section 2 offers a brief review of the literature, while Section 3 explains the data and methodology. The empirical results are discussed in Section 4 and Section 5 concludes the paper with policy recommendations.

2. Literature review

House price convergence largely depends on two main theories. The first theory suggests that house prices in different regions do not move together, emphasizing the unique characteristics of local markets. Therefore, each housing market is isolated in its own terms. This perspective views each housing market as being isolated, with regional economic and demographic differences shaping price trends (Canarella et al., 2012). The second theory is the 'ripple effect' hypothesis, which posits that changes in housing prices in one region spread to others through various factors, leading to long-term price convergence (Meen, 1999). In his seminal article, Meen (1999) argued that regional house price changes could be decomposed into three distinct components: (i) movements common to all regions; (ii) variations due to economic growth disparities; and (iii) structural differences inherent to regional housing markets. He suggested that regional housing prices tend to converge due to the interdependence of regional housing markets.

Various methods have been used to study house price convergence. For instance, using the Kalman filter, Drake (1995) analyzed the convergence between regional house prices in the UK. Meanwhile, Holmes et al. (2018) used pairwise unit root tests for regional house price convergence in the US and long-term house price convergence across London, respectively. One of the latest techniques to analyze house price convergence is the log-t test developed by Phillips and Sul (2007, 2009), hereafter termed 'PS'. The log-t test detects multiple equilibria and convergence clubs and allows for finding a unique steady state for different regions instead of overall convergence (Phillips & Sul, 2007). The log-t test has become widely used in analyzing house price convergence in various advanced and emerging countries. Examples include studies on house price convergence across Australian cities (Churchill et al., 2018), inter-city convergence in England (Holmes et al., 2019), convergence in the 50 Spanish provinces (Blanco et al., 2016), US states and metropolitan cities (Kim & Rous, 2012), South African provinces (Apergis et al., 2015), and 70 major Chinese cities (Cai et al., 2022).

House price convergence initially emerged in studies on advanced economies, such as the UK (Drake, 1995), and later extended to emerging markets like Türkiye (Gunduz & Yilmaz, 2021). Research on emerging markets includes studies on the ripple effect in South Africa (Balcilar et al., 2013), Malaysia (Lean & Smyth, 2013), Taiwan (Lee & Chien, 2011), metropolitan cities in India (Aye et al., 2013) and in Chinese regions (Chow et al., 2016; Zhang et al., 2017). So far, few

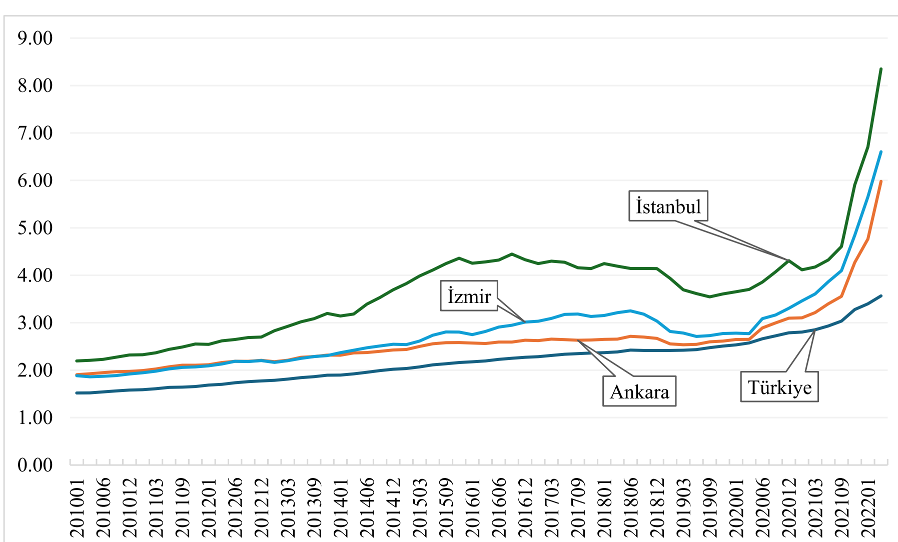

Fig. 1. House price movements in Türkiye and its main cities.
Source: Central Bank of the Republic of Türkiye, 2024.

studies have investigated house price convergence across cities/regions using the log-t test in Türkiye (Gunduz & Yilmaz, 2021; Ganioğlu & Seven, 2021). Gunduz and Yilmaz (2021) explored the convergence of house prices across 55 cities in Türkiye between 2010Q1 and 2018Q4, while Ganioğlu and Seven (2021) estimated house price convergence across 26 regions in Türkiye. Although there are few studies investigating worldwide housing price convergence at district level (see, among others, Abbott & De Vita, 2012; Kim & Rous, 2012), to date, no study has been conducted to investigate the convergence of house prices and the drivers of club formation at district-level in Türkiye. Therefore, this study is the first attempt to examine club convergence, club spillovers, and drivers of house prices in Istanbul at the district level by employing the log-t test, spillover index, and LASSO regression.

3. Methodology

This study used three main methods to analyze house prices in Istanbul at the district level. First, we applied the log-t test developed by Phillips and Sul (2007), to identify convergence clubs within Istanbul's districts. Next, the spillover method formulated by Diebold and Yilmaz (2009, 2012) was used to explore spillover effects among these convergence clubs. Finally, we utilized LASSO regression to select the key factors driving the formation of these convergence clubs.

3.1. The log-t test

We employed the log-t test to identify convergence clubs in Istanbul's house prices across 33 districts. This approach allows for temporary variations between districts over time. This method also overcomes the limitations of traditional tests that rely on small-sample properties (Phillips & Sul, 2007; 2009). We used the Phillips and Sul (2007) methodology to analyze quarterly house prices in Istanbul's districts.

$$h_{it} = \frac{X_{it}}{N^{-1}\sum_{i=1}^{N} X_{it}} = \frac{\delta_{it}}{N^{-1}\sum_{i=1}^{N} \delta_{it}} \tag{1}$$

where X_{it} represents the quarterly house prices of 33 districts of Istanbul. Cross-sectional and time-based house prices are represented by $i = 1, \ldots \ldots .N$ and $t = 1, \ldots, T$, respectively, spanning the period from 2010Q1 to 2022Q1. In $X_{it} = \delta_{it} u_t$, μ_t and δ_{it} represent time-varying common and idiosyncratic components, respectively. Phillips and Sul (2007) proposed testing the null hypothesis for convergence, which is accepted if $\alpha > 0$ and $\delta_{it} \rightarrow \delta_i$. The concept of convergence is based on utilizing a relative transition coefficient (h_{it}), which can capture both convergence and divergent behavior.

When clubs converge, the value of h_{it} approaches unity and the variance tends to zero as t approaches infinity:

$$\mathrm{H}_{\mathrm{it}} = \mathrm{N}^{-1}\sum_{i=1}^{N}(h_{it}-1)^2 \rightarrow 0 \ as \ \ t \rightarrow \infty \tag{2}$$

Subsequently, Phillips and Sul (2007) performed the following log-t test to investigate the presence of overall and club convergence.

$$log\frac{H_1}{H_t} - 2\,log[\mathrm{L}(t)] = \alpha + \beta \log(t) + u_t, with\ t = [\mathrm{r}T] + 1, \ldots, T \tag{3}$$

where the ratio of the cross-sectional variance, denoted by $H_1/\ H_t$, is employed as the dependent variable in a logarithmic regression on time, to test for overall convergence. A fraction of the total sample is used to test for convergence with a value of $r = 0.3$, estimated to be approximately one-third of the total sample.[2] A one-sided t-test was used to test the hypothesis.[3]

Phillips and Sul (2007) suggested a four-stage clustering algorithm for identifying potential converging clubs and non-conforming units. The initial phase, referred to as 'last observation ordering', involves arranging the panel (in this case, districts) based on the most recent observation. This method is considered optimal because convergence tends to be more accurately detected in recent periods.

In the second step (forming the core group), we employed the log-t test and convergence t-statistic, t_k, to calculate the subgroup size for the selected first k highest-ordered districts within a given panel. This was aimed at creating a subgroup of size $2 \leq k \leq N$. We then identified the optimal core group size, denoted as k^*, which maximizes the t-statistics, under the condition that $t_k > 1.65$. In the third step, club membership was assessed through a sieving process. This involved sequentially adding one district at a time, to the initial group. After each addition, the log-t test was conducted to check if the newly included member's t-statistic surpassed the critical value. This step ensured that the club remained in a state of convergence.

The fourth step was to form a new subgroup with the unselected districts. These districts were then tested using the log-t regression, to compare their t-statistic against the critical value. If the t-statistic exceeded this threshold, a second club was formed. If not, the first three steps were repeated to identify smaller subgroups of converging clusters. Any remaining districts were classified as diverging if no core group formed in the second step.

The house price series was analyzed using the Hodrick–Prescott (HP) filter, to extract its cyclical and trend components (Hodrick & Prescott, 1997). In the case of divergent units, a modified version of Von Lyncker and Thoennessen's (2017) club merging algorithm was used. The logarithmic districts' house price data was used to detect convergence clubs. Logarithmic values of the district house price data were used to identify convergence clubs.

3.2. Spillover method

This study used the Diebold and Yilmaz (2009, 2012) spillover method to analyze the spreading effect of house price changes from one club to another. This econometric technique uses the idea of the generalized vector autoregressive (VAR) model, which is often used to compute the forecast error variance decomposition (FEVD), to develop the spillover effect in the time domain. One of the key attractions of this model is its dynamic composition, which allows flexibility to account for time variation in its spillover results. Diebold and Yilmaz (2009, 2012) suggested several ways to measure the magnitude and direction of spillovers, namely: the total spillover index, the net spillover index, the net pairwise spillover index, and the dynamic spillover index. This paper used a VAR(p) model to measure connectedness across convergence clubs following the Diebold and Yilmaz (2009, 2012) methodology:

$$y_t = \sum_{i=1}^{p} \varnothing_i y_{t-1} + \varepsilon_i \tag{4}$$

where y_t is an endogenous variable with a n-dimensional vector, and $\varepsilon \sim (0, \Sigma)$ is a vector of iid errors. The moving average (MA) representation of Equation (4) can be represented as:

$$y_t = \sum_{i=1}^{\infty} A_i \varepsilon_i \tag{5}$$

where A_i is a nxn matrix of coefficients. $A_i = \varnothing_i A_{i-1} + \ldots + \varnothing_p A_{i-p}$, A_0 is a nxn identity matrix and $A_i = 0$ for $i < 0$.

[2] To test the robustness of our empirical application, we also used r values of 0.15, 0.20 and 0.25. However, the results remained unchanged.

[3] A t-statistic of less than −1.65 at the 5% significance level indicates rejection of the null hypothesis. Since our sample size is less than 60, we took the t-statistic to be −1.70.

In order to avoid the results being affected by the order of the variables, we used the generalized VAR framework, which provides a variance decomposition that is irrelevant to the order of the variables. Thus, the h-step-ahead FEVD was computed at horizon $h = H$ in the generalized VAR approach.

$$d_{kj}^{H} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_k' \theta_h \Sigma_u e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_k' \theta_h \Sigma_u e_j\right)} \tag{6}$$

where e_k represents the column kth of the I_K matrix. The share of shock j in the variance of the forecast errors of variable k is given by $FEVD^k(h) = \sum_{j=1}^{K} FEVD_j^k(h)$. However, it should be noted that the generalized FEVD does not ensure that the sum of the rows or the sum of the columns is equal to one. Therefore, Diebold and Yilmaz (2012) suggested the following normalization.

$$\widetilde{d_{kj}^{H}} = \frac{d_{kj}^{H}}{\sum_{j=1}^{K} d_{kj}^{H}} \tag{7}$$

such that $\sum_{j=1}^{N} \widetilde{d_{kj}^{H}} = 1$ and $\sum_{k,j=1}^{K} \widetilde{d_{kj}^{H}} = K$.

The spillover index, which measures spillover among clubs, was given by normalizing the row sum of the variance decomposition:

$$Spillover\ Index = \frac{\sum_{k,j \in \{i..K\}, k \neq j} FEVD_j^k(h)}{\sum_{k,j \in \{1..K\}} FEVD_j^k(h)} \tag{8}$$

According to Diebold and Yılmaz (2014), total spillover *from others* to club ith and *to others* from club jth is defined as $C_{i \leftarrow *} = \sum_{j=1, j \neq i}^{N} d_{ij}^{H}$ and $C_{* \leftarrow j} = \sum_{i=1, i \neq j}^{N} d_{ij}^{H}$, respectively. Therefore, net total directional spillovers are measured as $C_i^H = C_{* \leftarrow i} - C_{i \leftarrow *}$, and pairwise directional connectedness between club ith and club jth is simply $C_{ij}^H = C_{j \leftarrow i}^H - C_{i \leftarrow j}^H$. For example, the pairwise directional connectedness between Club 1 and Club 2 is represented as $C_{12}^H = d_{21}^H - d_{12}^H$ in our case. The model presented in this analysis was based on the VAR (1) method, determined by the SIC.[4] Additionally, we implemented a generalized impulse response function to obtain robust results, as suggested by Koop et al. (1996) for the multivariate nonlinear model.

4. Empirical analysis

In this section, we present the empirical findings for convergence clubs across Istanbul's districts, utilizing the log-t test. We examined the spillover connectedness between these clubs using the Diebold and Yilmaz (2012) spillover index and identified the drivers of these convergence clubs by employing the LASSO technique.

4.1. Data

We obtained quarterly median house prices (Turkish Lira per square meter) from the CBRT.[5] Istanbul has 39 districts but our available data set covered 33 districts over the period 2010Q1-2022Q1. In the main convergence analysis, we used price data up to the end of 2019, to avoid the extraordinary effects of the COVID-19 pandemic. However, we investigated the role of the pandemic period in a further recursive convergence analysis. Our second data set encompassed the socioeconomic attributes specific to the districts at 2019, which was employed in the analysis of the drivers of the convergence clubs. The latter set of variables was collected from various public and private sources, and is presented in Appendix A.[6] Using district-level data is important because it allowed us to pinpoint price convergence across heterogeneous districts of Istanbul.

Table 1
Classification of convergence club across 33 districts of Istanbul.

Clubs	Districts	Beta coefficient	t-value
Panel A: Club convergence tests		−0.6032	−33.760
Club 1	Beşiktaş, Bakırköy, Sarıyer, Kadıköy	0.442	9.898
Club 2	Şişli, Üsküdar, Ataşehir	0.004	0.280
Club 3	Maltepe, Beyoglu, Zeytinburnu, Ümraniye, Fatih	0.972	13.852
Club 4	Kağıthane, Kartal, Eyüp, Bağcılar, Küçükçekmece, Pendik	0.292	5.081
Club 5	Bayrampaşa, Bahçelievler, Esenler, Başakşehir, Güngören, Avcılar, Tuzla, Gaziosmanpaşa, Çekmeköy, Beylikdüzü, Büyükçekmece, Sultangazi, Sancaktepe, Silivri, esenyurt	−0.042	−0.501
Number of divergent units	–		
Panel B: Club merging analysis			
Club 1	Beşiktaş, Bakırköy, Sarıyer, Kadıköy	0.442	9.898
Club 2	Şişli, Üsküdar, Ataşehir	0.004	0.280
Club 3 (merging Club 3 and Club 4 above)	Maltepe, Beyoglu, Zeytinburnu, Ümraniye, Fatih, Kağıthane, Kartal, Eyüp, Bağcılar, Küçükçekmece, Pendik	0.195	3.970
Club 4	Bayrampaşa, Bahçelievler, Esenler, Başakşehir, Güngören, Avcılar, Tuzla, Gaziosmanpaşa, Çekmeköy, Beylikdüzü, Büyükçekmece, Sultangazi, Sancaktepe, Silivri, esenyurt	−0.042	−0.501
Number of divergent units			

Notes: This table gives the results of the log-t test. It shows that, after merging analysis, there are four converging clubs across Istanbul's districts. For testing the one-sided null hypothesis, $b \geq 0$ against $b < 0$, we used the critical value $t0.05 = -1.65$ in all cases.

4.2. Convergence clubs of housing prices

Table 1 presents five convergence clubs of Istanbul's house prices. The results of the log-t test, where the slope coefficient is equal to −0.60 and the t-statistic is equal to −33.76, indicate that price convergence is rejected at the 1% significance level in 33 districts of Istanbul between 2010 and 2019. Club 1 includes the districts of Beşiktaş, Bakırköy, Sarıyer, and Kadıköy. These districts share several characteristics. First, they rank highly on the socioeconomic development index. Second, they are among the most populous districts. Additionally, all are situated along the shores of the Bosphorus.

Furthermore, these districts are essential hubs, in terms of transportation options, trade, and a suitable environment for business. The housing market has a specific stability in these districts, where construction activities are predominantly based on renovating old buildings. The average population growth rate of Kadıköy and Beşiktaş, one of the oldest districts of Istanbul, in this period, was −1.05 and −0.10, respectively. Club 2 includes Şişli, Üsküdar and Ataşehir. Üsküdar and

[4] When we used the median of the clubs to measure connectedness across clubs, the results did not change.

[5] This dataset is not publicly available and is classified as confidential.

[6] Almost all the data is sourced from Maptriks (https://maptriks.com/), which is Türkiye's first location analytics company, with fifteen years of experience. Only building permit statistics and the share of Syrians in each district are obtained from the Turkish Statistical Institute (https://biruni.tuik.gov.tr/medas/?kn=135&locale=en) and Gunduz et al. (2022), respectively, as they are found to be locally significant variables in the previous studies.

Ataşehir are central locations on the Anatolian side of the country. Ataşehir experienced growth in the housing sector, especially after the 2000s, when construction and new housing stock increased rapidly. The Istanbul Financial Center Project also increased the value of Ataşehir. On the other hand, Şişli is located at the intersection of key districts on the European side.

Club 3 is formed of Maltepe, Beyoglu, Zeytinburnu, Ümraniye, and Fatih. Club 4 contains Kağıthane, Kartal, Eyüp, Bağcılar, Küçükçekmece and Pendik. Generally, these districts located in Clubs 3 and 4 are adjacent to the members of Clubs 1 and 2. Club 5 consists of Bayrampaşa, Bahçelievler, Esenler, Başakşehir, Güngören, Avcılar, Tuzla, Gaziosmanpaşa, Çekmeköy, Beylikdüzü, Büyükçekmece, Sultangazi, Sancaktepe, Silivri and Esenyurt. Districts such as Başakşehir, Beylikdüzü, Çekmeköy, Esenyurt, Sancaktepe, and Sultangazi have experienced massive growth in the housing sector, especially after the 2000s, when the construction and stocks of new houses began increasing more rapidly. These districts are further away from the Bosphorus, one of Istanbul's primary focal points.

To go one step further, smaller convergence clubs can be identified using the Phillips and Sul (2007) clustering algorithm, by assessing the possibility of merging two consecutive clubs into a single group. As depicted in Panel B of Table 1, Clubs 3 and 4 are combined. Fig. 2 presents the final classification of convergence clubs in Istanbul. Fig. 3 demonstrates that the trend lines across the convergence clubs show minimal convergence. For example, Club 1, which includes Beşiktaş, Bakırköy, Sarıyer, and Kadıköy, exhibits a slight downward trend, whereas Club 4 displays an upward trend, particularly post-2017, suggesting convergence among these clubs.

Fig. 4 illustrates that districts within each convergence club gradually move towards the mean, particularly after 2014, and are likely influenced by changing economic conditions (Cecen & Atas, 2017). Such conditions encompass liquidity and labor market dynamics. A general pattern in house prices shows that they tend to rise and diverge during economic expansion but start to fall and converge during downturns. For instance, significant volatility was triggered in the Turkish financial markets by the Federal Reserve's tapering announcement in 2013. This was compounded by domestic political challenges, including the unsuccessful coup attempt in 2016 and shifts in global risk appetite, all of which dampened sentiment in the housing market. Meanwhile, certain districts displayed unique trends. For example, Kadıköy, in Club 1, exhibited distinct behavior compared to the others. Başakşehir and Silivri, in Club 4, diverged from their counterparts post-2014 but converged more swiftly towards the averages, driven by a heightened demand from foreign buyers, which sharply increased property prices in these areas. Pendik, in Club 3, followed a similar path.

The recursive analysis detailed in Table 2 reveals that the number of convergence clubs initially decreased from six to five and then settled at four by the end of 2018Q4. This reduction over different periods underscores the diverse nature of Istanbul's housing market. Moreover, it is clear that the districts which have diverged have not been part of any convergence club. For example, districts like Şişli, Üsküdar, Ataşehir, Esenyurt, and Silivri consistently diverged from early 2015 to mid-2016, with the exception of the second quarter of 2016. Beşiktaş and Ataşehir appeared as divergent only once in early 2015. There were no divergent districts in late 2016 and late 2019. Esenyurt was the only divergent district in late 2018. The number of convergence clubs fluctuated between early 2015 and late 2019, initially showing a decline, then a slight increase, and ultimately decreasing again. This variability highlights the heterogeneity within the Istanbul housing market, reflected through the presence of multiple convergence clubs.

Considering the impact of the COVID-19 pandemic and funding costs on house prices (Kartal et al., 2021), we further examined the pandemic's effects on house prices in Istanbul's districts. The data in Table 3 show a reduction in the number of convergence clubs from four to three, with no further changes until the end of the period, when the data cut-off was updated. Members of Club 1 (Bakırköy, Beşiktaş, Kadıköy, Sarıyer) remained unchanged during the pandemic but there were significant shifts in the composition of Club 2 and Club 3. Club 2 expanded from 3 to 25 districts, while Club 3 shrank from 5 to 3 districts (Sancaktepe, Sultangazi, Çekmeköy). Esenyurt continued to show diversity, probably due to its substantial foreign population.[7] This district has also been a popular choice for foreigners buying properties to obtain a Turkish passport since 2018 (Gunduz et al., 2022). The overall results suggest that more districts tend to cluster together in the same club, in response to a common negative shock, such as the pandemic. Specifically, while the top-tier housing market districts in Club 1 seem to maintain their status, most other districts are merging into a single cluster.

4.3. Convergence club spillovers

Table 4 presents the convergence club spillovers of house prices across 33 districts of Istanbul. The *kj* cell is the estimate of the contribution of club *k*'s innovation to the club *j*'s forecast error variance. Therefore, by adding the off-diagonal elements in each row of the matrix, one can obtain a representation of *Contributions from Others* and, by summing the terms in the columns, *Contributions to Others* are obtained. Each cell represents the error variance of one club to another when summing them up. For instance, innovation in Club 1 (Beşiktaş, Bakırköy, Sarıyer, and Kadıköy) is responsible for 10.6% of the error variance in forecasting Club 2 but only 5.3% of the error variance in forecasting Club 4 (Şişli, Üsküdar, and Ataşehir). According to the results, as expected, there are spillover effects across adjacent districts (clubs), with relatively higher reciprocal spillovers between Club 3 and Club 4.

From Table 4, the Total Spillover Index is obtained by dividing the sum of spillovers defined as *From Others* by the *Contributions to Others*, including its contributions. This index indicates that spillovers explain 53.9% of the variance in forecast errors for the clubs. The average percentage of forecast error variances occurring across clubs can be attributed to shocks in another club, which can be defined as moderate spreading effects and is 53.9%. The diagonal elements represent the individual contributions of each club; whereas, the off-diagonal elements indicate the collective contributions of cross-clubs. For instance, the first column illustrates the contributions of Club 1 to other clubs, including itself. The amounts contributed by Club 1 to other clubs are provided in the row labeled *to others*. It is noteworthy that spillovers from Club 1, and partly from Club 2, to the rest of the clubs are relatively low. On the other hand, Club 3 districts, including Maltepe, Beyoğlu, Zeytinburnu, Ümraniye, Fatih Kağıthane, Kartal, Eyüp, Bağcılar, Küçükçekmece, and Pendik, have the highest spillover effects to other districts as they are adjacent to all other districts, followed by Club 4 districts. The spillover effects are transmitted from the Club 3 and 4 districts to Club 1 and 2.

Overall, the results from Table 4 demonstrate that house price spillovers between districts are not limited within the same convergence club but also occur between neighboring districts belonging to different clubs. Club 1 and Club 2, composed primarily of districts along the Bosphorus strait, are particularly exposed to external price spillovers from other districts. According to the *From Others* spillover values, 48.3% of Club 1's and 58.3% of Club 2's forecast error variance is explained by price shocks originating in other clubs. This indicates that housing prices in these areas are significantly influenced by developments in neighboring districts, underscoring the strong interconnectedness of the housing market in Istanbul and the heightened sensitivity of Bosphorus districts to external price dynamics. Interestingly, spillovers from Club 1 and Club 2 to the rest of the clubs are relatively low. These clubs' members have some standard features and are the most populous districts, compared with the others, in terms of

[7] https://www.hurriyetdailynews.com/istanbuls-esenyurt-under-spotlight-amid-restrictions-on-foreign-residence-permits-161996.

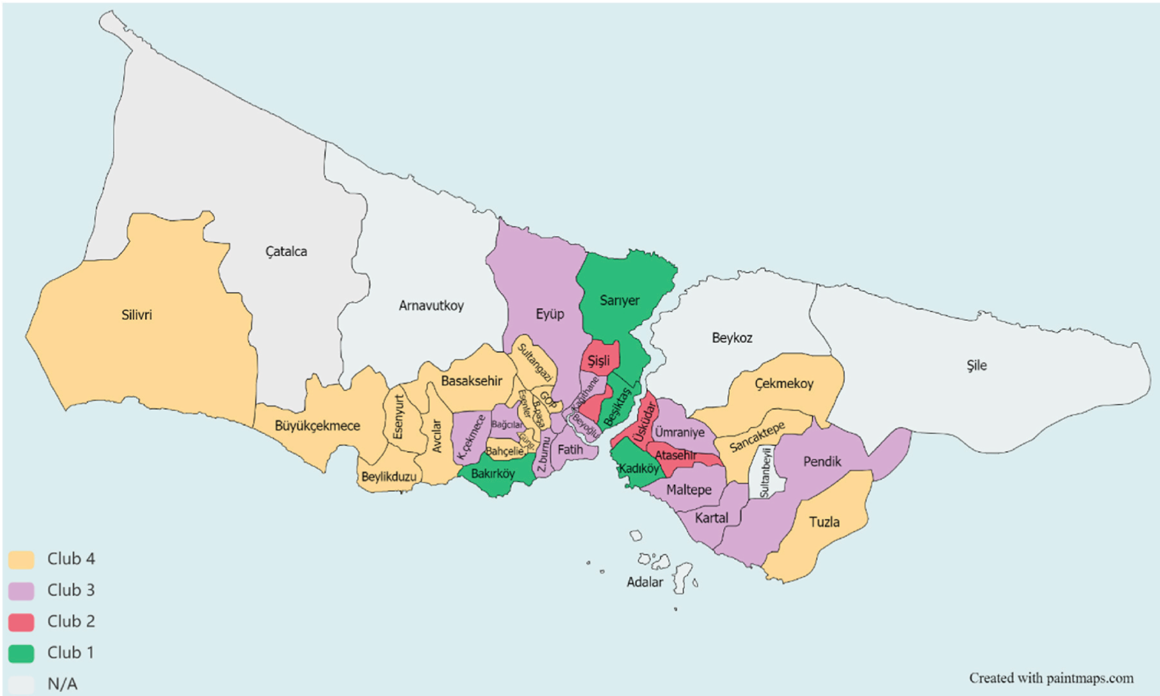

Fig. 2. Map of Istanbul: Convergence clubs.
Notes: The map illustrates the convergence clubs of Istanbul's districts, as determined by the results of the log-t test. Districts not included in the analysis are marked with "N/A".

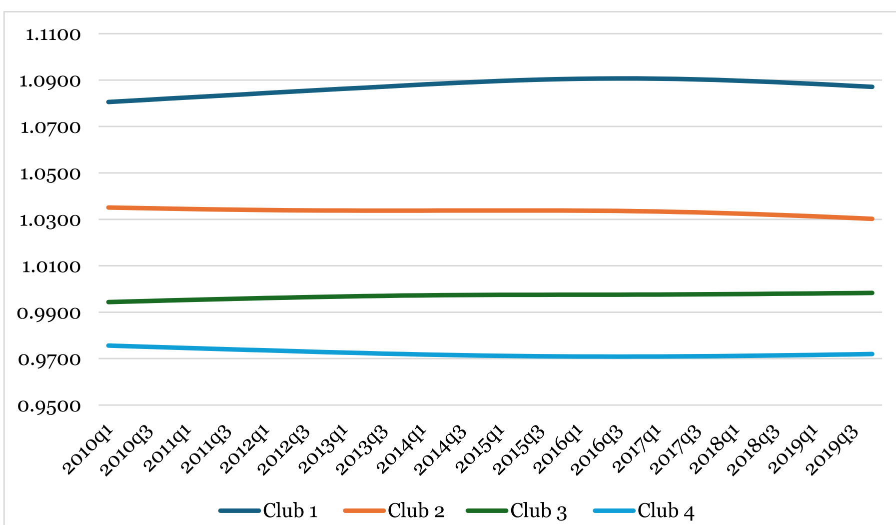

Fig. 3. Relative transition paths across converging clubs.
Notes: This figure gives the relative transition paths between convergence clubs, which depicts a distinct trajectory for each club to the overall mean. The relative transition parameters converge when house prices in different clubs converge to unity. In general, the relative transition curves indicate no convergence between clubs.

their locations. These districts are important hubs with respect to transportation opportunities, trade, and suitable business environments. The housing market has specific stability in these districts, where construction activities are predominantly based on renovating old buildings. Our findings suggest that spillovers are mainly transmitted from relatively less affluent districts to more affluent districts, which makes sense, given that huge economic and real estate developments are taking place outside of the Bosphorus straits.

4.4. *Drivers of convergence clubs*

A considerable body of empirical literature exists on the determinants of house prices worldwide. Among others, Holly and Jones (1997) found that real income is the most significant factor influencing real house prices. Furthermore, they suggested that real house prices have largely increased in parallel with income over the last 60 years. Jacobsen and Naug (2005) also highlighted the role of construction costs and the prices of new dwellings in determining house prices. Several other factors also influence house prices, including demographic factors

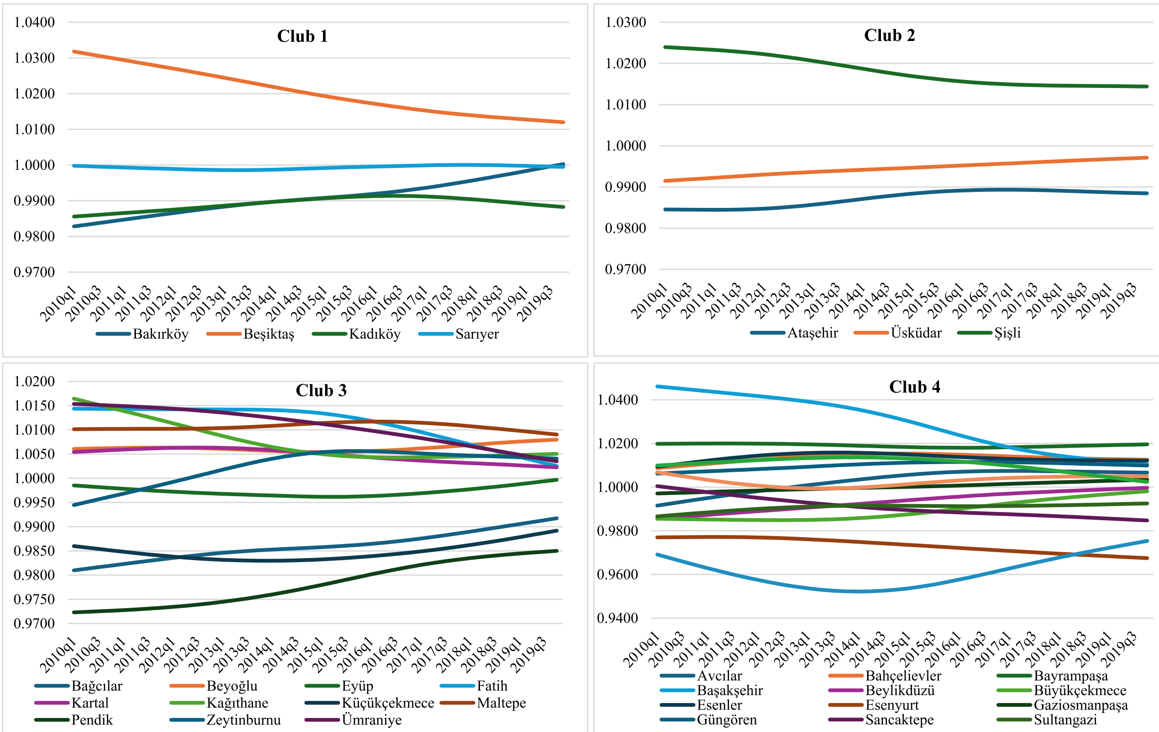

Fig. 4. Relative transition paths within each converging club.
Note: These figures give the relative transition paths within convergence clubs to show whether district house prices in each club converge to unity.

Table 2
Recursive convergence club analysis.

Period	Number of convergence clubs	Divergent districts
2015Q1	6	Beşiktaş, Şişli, Üsküdar, Ataşehir, esenyurt, Silivri
2015Q2	5	Şişli, Üsküdar, Ataşehir, esenyurt, Silivri
2015Q3	5	–
2015Q4	5	–
2016Q1	5	–
2016Q2	5	–
2016Q3	7	Şişli, Üsküdar, Ataşehir, esenyurt, Silivri
2016Q4	6	–
2017Q1	6	–
2017Q2	5	–
2017Q3	5	–
2017Q4	5	–
2018Q1	5	–
2018Q2	5	–
2018Q3	5	–
2018Q4	4	Esenyurt
2019Q1	4	–
2019Q2	4	–
2019Q3	4	–
2019Q4	4	–

Note: This table reflects the cluster analysis results by changing the sample's end.

(Holly & Jones, 1997), housing bubbles, housing finance, and housing quality (Ooi et al., 2014; Égert & Mihaljek, 2007), as well as migration, investment expectations, unemployment, and mortgage rates (Janet Ge, 2009).

However, there is limited empirical literature on the determinants of house prices in Türkiye and Istanbul. Among these, Selim (2009) found that house type and size, location characteristics, and building type are the most critical factors affecting house prices in Türkiye. According to Tunc (2020), an exogenous expansion in housing and consumer loans had a large and significant impact on house prices in Türkiye. Duran and

Table 3
Recursive convergence club analysis after the COVID-19 pandemic.

Period	Number of convergence clubs and club members	Divergent districts
2020Q4	**Club1:** Bakırköy, Beşiktaş, Kadıköy, Sarıyer **Club2:** Ataşehir, Avcılar, Bahçelievler, Bayrampaşa, Bağcılar, Başakşehir, Beylikdüzü, Beyoğlu, Büyükçekmece, Esenler, Eyüp, Fatih, Gaziosmanpaşa, Güngören, Kartal, Kağıthane, Küçükçekmece, Maltepe, Pendik, Silivri, Tuzla, Zeytinburnu, Ümraniye, Üsküdar, Şişli **Club3:** Sancaktepe, Sultangazi, Çekmeköy	Esenyurt
2021Q4	Same as above	Esenyurt
2022Q1	Same as above	Esenyurt

Note: This table gives the post-COVID-19 cluster analysis to show the effects of the COVID-19 pandemic on house prices in Istanbul's districts.

Table 4
Spillover effects across convergence clubs.

To (k)↓ *From* (j)→	Club 1	Club 2	Club 3	Club 4	From Others
Club 1	51.7	12.4	20.6	15.2	48.3
Club 2	10.6	41.7	28.2	19.5	58.3
Club 3	6.2	12	47.8	34	52.2
Club 4	5.3	9.6	41.9	43.2	56.8
Contribution to others	22.1	34.1	90.7	68.7	215.5
Contribution including own	73.8	75.7	138.5	111.9	Spillover index 53.9%

Notes: This table presents the convergence club spillovers of house prices across 33 districts of Istanbul. The kj cell is the estimate of the contribution of club k's innovation to the club j's forecast error variance. One can obtain Contributions from Others by adding the off-diagonal elements in each row of the matrix and Contributions to Others by summing the terms in the columns. Each cell represents the error variance of one club to others when summing them. The variance decomposition (Diebold & Yilmaz, 2009, 2012) is based on a VAR of 1 using Koop et al. (1996) and Pesaran and Shin's (1998) generalized VAR model.

Özdoğan (2020) found that speculative behavior, high urbanization rates, crime rate, trade openness, and cultural density are among the significant factors affecting house price increases in 26 regions in Türkiye. Özmen et al. (2019) investigated the relationship between income distribution and housing prices. The study found that the share of the lowest income brackets was positively related to changes in housing prices, while the share of the top income brackets was negatively related to changes in house prices. Moreover, Gunduz and Yilmaz (2021) identified a number of significant factors, such as employment rate, climate, population density, and the presence of a metropolitan municipality, affecting house price variations in 55 major Turkish cities. Among others, average household income, neighbor satisfaction, and the earthquake risk of the region (Keskin, 2008), decentralization, accessibility, distance to the coast (Koramaz & Dokmeci, 2012), and size, elevator, security, central heating unit and view (Özsoy & Şahin, 2009), as well as the Turkish citizenship by investment program (Gunduz et al., 2022) are significant determinants of house prices in Istanbul. It is noteworthy that most of the previous studies mentioned employed aggregate house prices and suffered from a lack of data at the district level, including socioeconomic and consumption-based behavioral indicators (Vatansever et al., 2020).

In this section, we employed a multinomial logistic regression model with LASSO regularization, to investigate the determinants that influence the formation of convergence clubs among the house prices in Istanbul's districts, using 104 district-based variables (see Appendix A).[8] The LASSO method is particularly useful in this context, as it selects the most significant variables, while reducing the impact of multicollinearity and irrelevant predictors. By focusing on the key drivers of club formation, our approach effectively identifies the socioeconomic factors that differentiate the convergence clubs, providing valuable insights into the underlying structure of Istanbul's housing market.

The LASSO aspect of the model introduces a regularization term $\left(\lambda\sum_{f-1}^{k}\left|\beta_j\right|\right.$ into the objective function, effectively penalizing the absolute size of the regression coefficients and thereby encouraging sparsity. The model's general equation is as follows:

$$\min_{\beta}\left\{-\frac{1}{N}\sum_{i-1}^{N}\left[y_1(\beta_0+\beta_1x_{i1}+\ldots+\beta_kx_{ik})-\ln\left(1+e^{(\beta_0+\beta_1x_n+\ldots+\beta_kx_k)}\right)\right]+\lambda\sum_{j=1}^{k}\left|\beta_j\right|\right\}$$

where $P(Y=j)$ represents the probability of a district belonging to convergence club j (for $j=;1,2,\ldots,J$ classes). $X_1,X_2,\ldots,X_k$ are the explanatory variables derived from the dataset, including socioeconomic indicators, demographic metrics, or other district-specific features that may influence house price dynamics. $\beta_{j0},\beta_{j1},\ldots,\beta_{jk}$ are the coefficients corresponding to each explanatory variable for each club j, which quantify the impact of each variable on the likelihood of belonging to a particular convergence club. In this context, λ is the regularization parameter that controls the degree of shrinkage applied to the coefficients. Selecting an optimal value for λ allows the model to balance between fit and complexity, removing less significant variables by shrinking their coefficients to zero. N is the total number of districts in the study, y_1 represents the actual club membership for district i, and $x_{i1},\ldots,x_{ik}$ represent the values of the explanatory variables for district i.

By applying this model to our dataset, we aimed to identify the most significant factors differentiating different house price convergence clubs in Istanbul's districts. Variables whose coefficients were reduced to zero by the LASSO penalty were deemed less significant and excluded from the final model, simplifying interpretation and focusing on the most impactful factors. This methodology allowed us to ascertain the key drivers behind the formation of house price convergence clubs, while accounting for overfitting and multicollinearity among explanatory variables. In our multinomial logistic regression model, we used the SAGA solver to optimize the cost function, where the SAGA solver stands for "SAGA: A Fast-Incremental Gradient Method with Support for Non-Strongly Convex Composite Objectives." It is an iterative algorithm for optimizing the likelihood function of logistic regression and is especially efficient for large datasets. The SAGA solver is particularly suitable for models with LASSO regularization because it supports the L1 penalty, which induces sparsity in the coefficients, leading to simpler, more interpretable models. This solver is a variation of the Stochastic Average Gradient (SAG) methods, designed to converge faster by incorporating a component that helps reduce variance in the gradient updates.

Additionally, we implemented 10-fold cross-validation to ensure our model's robustness and selected an appropriate regularization strength (λ). The dataset was randomly divided into ten subsets of equal size in 10-fold cross-validation. One of the ten subgroups was selected to serve as a validation dataset, with the remaining nine subgroups being used for training. This process was repeated ten times (the folds), with each of the ten validation sets being used exactly once. The results from each fold were then averaged, or otherwise combined, to provide a single estimate. In contrast to repeated subsampling, the advantage of this method is that all observations are used in both the training and validation processes, and they are utilized exclusively on a single occasion. This approach helps tune the model to find the best regularization parameters and estimate the model's predictive performance on an independent dataset, thereby mitigating the risk of overfitting. In the context of our study, the SAGA solver aids in efficiently handling logistic regression computation with LASSO. Meanwhile, the 10-fold cross-validation ensures that our model's performance is evaluated accurately, leading to the reliable identification of key factors influencing the convergence clubs of house prices in Istanbul districts. This methodological approach underpins the robustness and credibility of our findings.

Table 5 displays the parameter estimates from our analysis and identifies the predictors associated with each convergence club membership. Out of a pool of 112 potential variables, factors like minimum household income, socioeconomic status, total savings, and total deposits prove to be the most significant. There are notable differences between Club 1 and Club 4 predictors, especially regarding socioeconomic status and material wealth. For instance, increases in income level, total deposits, or car ownership reduce the likelihood of joining

[8] Our analysis employed socioeconomic data from 2019 to examine the factors driving convergence club formation across Istanbul's districts. We acknowledge that our dataset for socioeconomic factors is limited to the year 2019. However, while this constraint may limit our ability to observe the evolution of these variables over time, we believe that the use of cross-sectional data still provides valuable insights into the structural drivers of convergence club formation. Socioeconomic attributes, such as income, retail presence, and population characteristics, tend to change gradually over time and their relative stability allows us to capture their role in explaining differences across districts in the formation of convergence clubs. Future research could benefit from accessing time-varying socioeconomic data, if available. This would allow for a more nuanced understanding of how changes in district-level attributes, such as income growth or migration patterns, impact convergence club dynamics over time.

Table 5
Parameter estimates for the predictors of the convergence clubs with Lasso.

Predictors	Club 1	Club 2	Club 3	Club 4
Mado	0.0051			
Starbucks	0.5067			
Socioeconomic status C	−0.3805		0.8657	
Total savings	0.1253			
Adidas store		1.0066		
Universities		0.0698		
BİM store			0.1872	
Conservative urban population (ages 15–64)			0.8795	
Socioeconomic status C2			0.2433	
Year average temperature			0.3203	
Domino's Pizza				−0.2766
Minimum household income				−0.5263
Number of cars				−0.2668
Socioeconomic status C1				−0.5301
Socioeconomic status DE				0.7909
Total deposits				−0.2380

Note: Positive coefficients suggest the factors that may lead to a higher likelihood of being in the corresponding convergence club; whereas, negative coefficients suggest the factors that may decrease this likelihood.

Club 4, suggesting that its membership mainly consists of lower-middle-income households. Additionally, it is important to note that districts in Club 4 are typically located further from the city center and the Bosphorus Strait.

It is well recognized that Club 1, encompassing districts such as Besiktas, Bakirkoy, Sariyer, and Kadikoy, benefits from its scenic location along the Bosphorus and higher housing prices and is home to wealthier residents. Furthermore, the presence of a greater number of Starbucks and Mado stores correlates with a higher likelihood of a district being part of Club 1, supporting the notion of the 'Starbucks effect', as described by Donner and Loh (2019). This suggests that areas with more Starbucks locations might see quicker increases in property values. Alternatively, it could indicate that Starbucks and Mado tend to establish outlets in areas with higher incomes or property values as a strategic business decision. Mado is particularly noted for its traditional Turkish ice cream and a variety of desserts, including baklava and Turkish delight, served in a warm and inviting setting.

On a different note, Club 2 membership is associated with a higher number of Adidas stores and universities, while Club 3 membership correlates with more BİM stores. BİM, inspired by ALDI—a globally recognized discount supermarket chain—pioneered the hard discount model in Türkiye. These stores are often located in urban areas with high population densities and cater to price-sensitive consumers, mainly from the middle to lower income brackets. Consequently, it is not surprising that a larger presence of BİM stores, alongside individuals with a socioeconomic status of C2, increases the likelihood of belonging to Club 3. This club generally comprises districts with lower-middle-income households and a relatively conservative urban demographic. Overall, it can be argued that Istanbul's housing heterogeneity or convergence club formation largely reflects its residents' socioeconomic status and material well-being.[9] These findings are also consistent with previous studies, pointing out that residential segregation in Turkish cities reflects distinct characteristics where the highest and the lowest status groups never share a common border in urban areas (Atac, 2017). Moreover, as suggested by Kim & Rous, 2012, convergence clubs are often characterized by similar economic fundamentals.

[9] This observation also seems to be in parallel with the recent findings in related literature. For instance, Howard and Liebersohn (2023) argued that regional divergence in income and house prices are not only correlated but, more importantly, regional divergence explains most of the movements in US house prices since 1939.

5. Conclusion

House prices in Istanbul have notably risen over the last decade, with variations across districts reflecting the city's diverse economic landscape. This variability, heightened after the global financial crisis, has underscored the importance of monitoring house price dynamics for policymakers, investors, and residents. This study provides a comprehensive analysis of the club convergence of house prices in Istanbul's districts by using a unique dataset from 2010Q1 to 2022Q1. We used three tests to analyze the convergence clubs. Firstly, the log-t convergence test was used to classify the convergence clubs. Secondly, the spillover index was applied to find the connectedness across the clubs and, finally, the least absolute shrinkage and selection operator (LASSO) regression was applied to determine the key drivers of convergence club formation. Our analysis identified four main convergence clubs with distinct characteristics and geographical placements, reflecting the heterogeneity of Istanbul's housing market. For example, Club 1 comprises high-value districts along the Bosphorus, such as Beşiktaş and Kadıköy, which are central to business and lifestyle activities. On the other hand, more peripheral districts like Başakşehir and Esenyurt form Club 4, illustrating the broader spread of Istanbul's urban and economic development.

The study also observed dynamic changes in the composition of these clubs, particularly post-2016, with some districts showing divergent price trends during economic upturns, indicating possible overvaluations or 'bubbles'. This trend stabilized somewhat after the COVID-19 pandemic, reducing the number of convergence clubs and further highlighting the city's market heterogeneity. The spillover analysis shows moderate connectivity between these clubs, suggesting that, while local conditions predominantly drive house price movements, external factors also play a significant role. Districts in Club 3 and Club 4, for instance, are central in transmitting price changes, influencing and being influenced by economic conditions across the city. Furthermore, our LASSO regression results align district convergence with socioeconomic indicators, suggesting that economic disparities are a significant driver of house price segregation. This split, especially pronounced between affluent Bosphorus districts and peripheral areas, highlights the stark contrasts in living conditions and economic opportunities.

Our findings carry significant implications for urban policy development. Firstly, it appears unlikely that Istanbul will achieve balanced and equitable house price growth across its districts without addressing the socioeconomic disparities that underpin the formation of convergence clubs. Reducing income and socioeconomic disparities could decrease price disparities at the district level and encourage greater price convergence. Without such measures, the ongoing segmentation of the housing markets and the uneven distribution of wealth are likely to persist. Secondly, the moderate connectivity of the housing market suggests that, while local factors predominantly drive market dynamics, shocks in one district can impact others. This interconnectedness should be factored into risk assessments and strategic planning to account for market interdependencies. Consequently, housing policies should be customized to reflect the specific yet connected nature of district markets, bridging the gap between localized independence and broader market dependencies.

While this study focuses specifically on the dynamics of house prices within Istanbul's districts, the implications of our findings extend to broader discussions of housing affordability and urban development across Türkiye. The pronounced socioeconomic disparities driving house price segregation in Istanbul likely mirror trends in other major Turkish cities, highlighting a nationwide challenge in achieving balanced and equitable housing markets. Furthermore, the moderate connectivity observed in Istanbul's housing market suggests that similar interdependencies may exist across different regions or cities. Future research could expand upon our findings by examining house price convergence and its socioeconomic drivers across multiple Turkish cities, contributing to a more comprehensive understanding of the nation's housing landscape.

CRediT authorship contribution statement

Lokman Gunduz: Conceived and designed the analysis, Collected the data, Contributed data or analysis tools, Performed the analysis, Wrote the paper,. **Mustafa Çakır:** Conceived and designed the analysis, Contributed data or analysis tools, Performed the analysis, Wrote the paper. **Oğuzhan Cepni:** Conceived and designed the analysis, Contributed data or analysis tools, Performed the analysis, Wrote the paper.

Appendix A. The socioeconomic features of the districts used in the LASSO regression

No	Variable	No	Variable
1	A101 (discount store #)	53	AB + C1 population
2	AB + C1 population (percent)	54	Adidas stores (#)
3	Adult population (ages 35–44 - share)	55	Conservative urban population between 15 and 64 (ordinal level)
4	Ages 15–64 C+ urban population (ordinal level)	56	Apartments (#)
5	Average household income	57	Average household size
6	Average age	58	Average years of schooling
7	BİM (discount store #)	59	Burger King (#)
8	Business centers (#)	60	Cars for handicapped (#)
9	Child population (ages 0–14 -share)	61	Commercialization rate
10	Conservative population (ordinal level)	62	Consumer loans used (in TL)
11	Corporate loans used (in TL)	63	Defacto stores (clothing brand #)
12	District area (square kilometers)	64	District population
13	Domino's Pizza (#)	65	Elderly population (65+ share)
14	Female population	66	Foot traffic index (1–100 points)
15	Foreign resident ratio	67	High school and above graduates (in proportion)
16	Hospitals (#)	68	Hotels (#)
17	Housing density (per square km)	69	Industrial companies (#)
18	LCW stores (popular clothing company #)	70	Lighting electricity consumption (MWh) (ordinal level)
19	MADO (chain of cream and pastry brands #)	71	Male population
20	Maximum household income (level)	72	McDonald's (#)
21	Middle-age population (ages 45–54 - share)	73	Minimum household income (ordinal level)
22	Mosque (#)	74	Number of cars owned (#)
23	Number of fixed-internet subscribers	75	Number of foreign residents
24	Number of households (#)	76	Number of households (ordinal level)
25	Number of local tourists (in ordinal scale)	77	Number of mobile internet subscribers
26	Number of mobile subscribers	78	Number of office workplaces (#)
27	Number of visiting relatives (#)	79	Number of workplaces (#)
28	Occupancy permits for dwelling units in 2019	80	Occupancy permits for residential buildings in 2019
29	Parks and gardens (#)	81	Pharmacy (#)
30	Population density	82	Population outside the labour force
31	Post office (#)	83	Primary school graduates (in proportion)
32	Private schools (#)	84	Public schools (#)
33	Residential dwellings (#)	85	Residential electricity consumption (MWh) (ordinal level)
34	Retired population	86	Secondary and high school graduates (in proportion)
35	Shopping malls (#)	87	Simit Sarayı (chain of fast-food franchise bakeries #)
36	Socioeconomic status A (people)	88	Socioeconomic status AB (in per cent)
37	Socioeconomic status B (people)	89	Socioeconomic status C (in per cent)
38	Socioeconomic status C1 (people)	90	Socioeconomic status C2 (people)
39	Socioeconomic status D (people)	91	Socioeconomic status DE (people)
40	ŞOK (discount store #)	92	Socioeconomic status E (people)
41	Student population	93	Starbucks (#)
42	Syrians (share in total)	94	The number of dwelling units given in occupancy permits
43	The total common area given in occupancy permits (m2)	95	Total credits (in TL)
44	Total deposits (in TL)	96	Total deposits (TL/month)
45	Total immigrant population	97	Total married persons
46	Total other areas given in occupancy permits (m2)	98	The floor area of residential buildings given in occupancy permits (m2)
47	Total savings (TL/month)	99	Total single persons
48	Unemployed population	100	Universities (#)
49	University graduates (in proportion)	101	Upper-middle population (ages 55–64 - share)
50	Urbanization rate	102	Value of buildings given occupancy permits in 2019 (in TL)
51	Workplace density (per square km)	103	Year average temperature (degrees)
52	Young adolescent population (ages 15–24 - share)	104	Young adult population (25–34 – share)

Notes: Almost all the data is sourced from Maptriks, Türkiye's first location analytics company (https://maptriks.com/en/). Only building permit statistics and the share of Syrians in each district are obtained from the Turkish Statistical Institute and Gunduz et al. (2022), respectively, as these were identified as locally significant variables in previous studies.

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