Family house prices in the US: Convergence clubs by county (1975-2022)

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Convergence clubs by county (1975-2022)

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Abstract

This paper studies convergence in family house prices across 364 counties in the US from 1975 to 2022. We use the club convergence test to contrast the null hypothesis of full convergence, and if it is rejected, to identify endogenously convergence clubs that follow the same convergence pattern. We reject the hypothesis of absolute convergence and identify six different convergence clubs. We also explore some determinants that could explain the formation of clubs, and find that certain weather conditions, income level and education variables are correlated with the final subgroups identified by the club convergence test. Specifically, clubs with low family house price indexes are characterized by a lower income levels, a higher percentage of the population with college degrees, and a greater frequency of extreme weather conditions over the last two decades, such as extreme hot and cold days. In the current emergency context where these extreme weather conditions are becoming more frequent, and climate models continue to predict that their importance will continue increasing, these results are important to understand the impacts of climate change on family housing markets and adopt suitable mitigation policies.

Keywords: Family house prices, convergence clubs, US counties, income, education, weather.

JEL Codes: E31, R31

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1. Introduction

Housing is an important asset, accounting for the largest share of household wealth for most families. However, it is a highly volatile and cyclical component, generally rising during economic expansions and falling during economic downturns. All these fluctuations over economic cycles have important consequences for the economy, with the prominent example being the Global Financial Crisis (GFC) of 2008. This economic downturn led to a growing interest among economists in understanding the role of housing markets in economic activity in general and the dynamics of house prices through time (see Duca et al., 2021 for a review). Given the significant share of housing in family wealth, analyzing whether housing price disparities have narrowed contains significant information for policymakers about how the distribution of wealth is changing over time and the feasibility of certain monetary policies (Füss & Zietz, 2016). At this point, if housing price disparities have decreased over time, this supports the hypothesis that wealth is becoming more equal, labor mobility is easier and monetary policies have common effects across regions. This is the hypothesis on which this paper focuses.

One of the most pressing challenges of the current century is climate change, which has important implications across the population worldwide from different perspectives. Current greenhouse gas emissions from economic activities are causing an increase in extreme weather events. As climate change progresses, extreme temperatures and the frequency, intensity and impact of natural disasters continue to increase (Stott, 2016). Over the past decades, heat and cold waves, droughts, earthquakes, and wildfires have occurred more frequently and intensively, significantly impacting livelihoods and daily lives through a multitude of dimensions, such as water scarcity or biodiversity losses. World temperatures have reached unprecedented levels, posing severe threats to human health (Hua et al., 2023; Liao et al., 2023; Mullins & White, 2020) and economic development (Kiley, 2024; Liu & Yin, 2023; Newell et al., 2021), aggravating existing economic disparities (Paglialunga et al., 2022; Pleninger, 2022) and boosting regional migration to urban areas (Cattaneo & Peri, 2016; Helbling & Meierrieks, 2023).

The current change in the distribution of temperatures toward their tails will not only increase the likelihood of experiencing extreme weather conditions and natural disasters but may also take a toll on housing markets, impacting their structure, demand and supply, ultimately affecting housing prices. With the growing evidence that all these extreme weather conditions are likely to get more intense, frequent, and long-lasting in the future, it becomes mandatory to develop appropriate adaptation policies. Hence, it is central to analyze the distributional—regional—effects of global warming on housing markets, and whether it has heterogeneous impacts on housing markets across regions.

Within this framework, this paper addresses the question of whether global warming relates to housing markets. To do so, we first use a well-known framework to analyze whether disparities in housing prices across counties have reduced during the last five decades. That is, we study convergence in housing markets using the club convergence test (Phillips & Sul, 2007, 2009). The results from this methodology provide an ordinal ranking of counties according to their long-run steady state levels in housing prices, and we then examine whether global warming plays a role in the club convergence results as an environmental amenity. To do so, we analyze the relationship between extremely hot and cold temperatures on club membership, using ordinal models, together with other economic, demographic, and environmental variables. Our results suggest that extreme hot and cold temperature days are a significant determinant of club membership, and that those counties which are characterized by lower house price indexes, have experienced a greater frequency of extreme hot and cold temperature days over the last two decades, while the opposite is observed for counties with higher house price indexes. All this points to the distributional impacts of climate change and suggests that counties with lower family house prices are most affected by extreme temperatures. This latter result can be used by policymakers to adopt climate change mitigation policies.

The contributions of this paper to the literature are then twofold. First, this paper is the first to study long-run club convergence in housing markets at the county level in the US. So far, the literature on US housing markets has examined convergence either at the Metropolitan Statistical Area (MSA) or state level (Barros et al., 2012; Holmes et al., 2011; Kim & Rous, 2012; Montañés & Olmos, 2013). However, the insights from these more aggregated analyses could omit significant differences and have limited meaning within those geographical units across the US, as it is well-known that enormous housing price differentials may arise even within a state (Holmes et al., 2011, 2019). That is precisely what we find in our data based on a sample of 364 counties in the US from 1975 to 2022, as we report a larger number of clubs than those previously documented. We attribute these differences to two distinct features of our data: its more granular geographical information, on the one hand, and its larger timespan which accounts for different stages of the business cycle on a historical basis, on the other hand. Second, we examine the determinants of club membership, using ordinal models. Prior research mainly focuses on convergence analyses, and omits an analysis of the drivers of convergence, which can produce important insights for housing—regional—planners. Specifically, our results suggest that extreme weather conditions, economic development, and education level are important drivers behind the club convergence results. Those results allow us to identify the different features of each convergence club, and point to the importance of the frequency of extreme weather conditions during the last two decades as a determinant of convergence clubs in housing prices across the US, which is a novel outcome and contributes to our understanding of housing market responses to climate change.

The rest of the paper is organized as follows. Section 2 sets the background of the article and provides a review of the related literature. Section 3 describes the variables and their main sources, together with a preliminary convergence check. Section 4 presents the econometric strategy, while Section 5 discusses the main results. Finally, Section 6 concludes the paper.

2. Background and review of literature

This paper studies convergence on family house prices in the US at the county level. Hence, it is related to a large strand of the literature that examines the convergence behavior of housing-related variables, such as house sales prices, the predominant focus in all these convergence analyses, or residential rents. The economic intuition behind house price convergence refers to the ripple effect, according to which changes in the housing market are transmitted from the core region to the adjacent regions due to migration, spatial arbitrage profits and equity transfer (Meen, 1996, 1999), to take advantage of housing price differentials. This causes the original shocks in one region to ripple out to other ones and generates a trend for house prices to equalize in the long run.

This literature uses a variety of econometric approaches to test for convergence, such as cross-sectional (i.e., beta- and sigma-convergence analysis), time series (i.e., stochastic convergence), or conditional/relative convergence (i.e., club convergence) methods. Theoretically, beta-convergence assumes that when regions with initially lower house price levels grow faster than regions with initially higher house price levels, then the gap between them is reduced and they experience a beta-convergence process with the leaders (Sala-i-Martin, 1996). On the other, sigma-convergence concerns a reduction in the differential between low- and high-priced regions (Barro & Sala-i-Martin, 1992). For stochastic convergence to exist, a pair of house price series should cointegrate, so the differential between them should follow a stationarity process, and shocks to house price should have temporary effects that dissipate over time. Finally, the club convergence notion admits the particularities of each region, so that some may converge to each other through specific groupings according to their long-run steady state, leading to different subgroups that represent distinct steady state levels and have similar characteristics (Durlauf & Johnson, 1995).

The literature on stochastic convergence dates to the works of Carlino and Mills (1993, 1996) and Bernard and Durlauf (1995, 1996). In the context of house price convergence, Holmes et al (2011) investigate long-run convergence between US house prices at both state and MSA levels, finding that about a quarter of the sample converges, while Barros et al. (2012) find evidence of unit roots in eight states using fractional cointegration techniques. Consequently, they reject stochastic convergence in US housing prices at different geographical levels. In the UK, Abbott and De Vita (2013) find no evidence of long run convergence either. Similarly, Zhang and Morley (2014) use data from 35 Chinese cities (i.e., 30 Chinese capitals and 5 municipalities) from 1998Q1 to 2010Q4 and show little evidence of stochastic convergence, as later reported by Gong et al. (2016) in 10 Chinese cities from June 2005 to May 2015, while Apergis and Payne (2019) obtain no evidence for stochastic convergence across 21 metropolitan areas within the state of Florida, the third most populous state in the US.

To the best of our knowledge, the first studies to use the club convergence test in housing analysis correspond to Apergis and Payne (2012) and Kim and Rous (2012). They examine club convergence of US house prices by state and metropolitan area, and obtain evidence for different convergence clubs. Since then, many published works have implemented that econometric framework. For example, Montañés and Olmos (2013) study convergence in US housing prices in 19 MSAs from 1991Q1 to 2013Q3, and find evidence for three convergence clubs. On the other hand, Churchill et al. (2018) find two convergence clubs using quarterly data during 2003-2017 in eight capital cities of Australian states and report heterogeneity within the period, as the null hypothesis of full panel convergence cannot be rejected before 2009.

This result has also been obtained in other recent studies focusing on alternative geographical regions, such as the UK. Specifically, Lin and Robberts (2024) obtain full convergence in regional house prices in the UK from 1992 to the GFC, so all areas in the UK converge into one club during that time span. That result has significant policy implications, as it indicates the efficiency of the inflation-targeting monetary policy implemented in the country since 1992 to achieve price stability. In contrast, in the non-inflation-targeting scenario (i.e., before the implementation of the inflation target in 1992), three convergence clubs emerge, which combine some spatial features. Furthermore, from 2008Q3 onwards, the post-crisis classification reveals three convergence clubs and one diverging club. Prior studies in England using this econometric framework at different regional levels include Montagnoli and Nagayasu (2015) and Holmes et al. (2019).

Studies in other regional contexts include Blanco et al. (2016) in Spain, Ganioğlu and Seven (2021) and Gunduz and Yilmaz (2021) in Turkey, Cai et al. (2022) in China, Tomal (2022) and Trojanek et al. (2023) in Poland, Akram and Mukherjee (2024) and Rajesh and Rath (2023) in India, and Unal et al. (2024) in Germany. Blanco et al. (2016) test house price convergence in 50 Spanish provinces from 1995 to 2007, and show four subgroups that converge to different steady states regarding house price levels. On the other hand, Cai et al. (2022) test for club convergence across 70 Chinese regions from 2006 to 2017 and show four convergence clubs, while Tomal (2022) finds evidence of club convergence in housing rents. Consequently, most works have focused on convergence at the regional level, and there exists a limited number of works on convergence in housing prices at the country level. In this context, Maynou et al. (2021) examine club convergence in twelve European countries from 2004Q2 to 2016Q3 and identify five housing market clubs.

3. Econometric methodology

We use the econometric methodology developed by Phillips and Sul (2007, 2009) to test for convergence in our house price series. This methodology has several advantages over other econometric approaches proposed based on either cross-sectional or time series properties. Specifically, it explicitly tests the null hypothesis of convergence for a pool of data, and if it is rejected, a clustering algorithm developed by the authors permits to identify, endogenously, convergence clubs (i.e., groups of cross-section units within the heterogeneous panel that follow the same long-run equilibrium). Consequently, it does not require the selection of a cross-section unit of reference, an arbitrary condition that is likely to condition the results in time series convergence tests based on stationary properties, and can distinguish among subgroups of convergence and identify explicitly what regional units converge to each other, against standard cross-sectional approaches.[1]

Given all these superior properties of this test, it has generated a new boost in economic studies regarding certain convergence behaviors. Specifically, this framework has been used by an extensive body of literature to examine convergence in variables such as GDP (Apergis et al., 2010; Herrerias & Ordoñez, 2012; Ursavaş & Mendez, 2023), income (Bartkowska & Riedl, 2012; Cutrini & Mendez, 2023; von Lyncker & Thoennessen, 2017), inequality (Arčabić et al., 2021; Ogundari, 2023), economic freedom (Payne et al., 2023), greenhouse gas emissions (Apergis & Payne, 2017; Belloc & Molina, 2023; Ivanovski & Churchill, 2020), happiness (Apergis & Georgellis, 2015), healthcare expenditure (Ivanovski & Churchill, 2021; Panopoulou & Pantelidis, 2013), and COVID-19 infection rates (Churchill et al., 2023), among others.

This methodology is based on a non-linear time-varying common factor model of the variable under analysis, X_{it}. The model begins with the decomposition of X_{it} into two components:

$$X_{it} = g_{it} + a_{it}, \tag{1}$$

Where subscripts i and t denotes the cross-section units ($i = 1, \dots, N$) and the periods ($t = 1, \dots, T$), respectively. g_{it} is a systematic component and a_{it} is a transitory component. Both components may consist of common and idiosyncratic elements. To isolate idiosyncratic from common elements, Eq. (1) is rewritten as[2]:

$$X_{it} = \left(\frac{g_{it}+a_{it}}{\mu_t}\right)\mu_t = \delta_{it}\mu_t, \tag{2}$$

X_{it} now consists of two components: a common component across cross-section units, indicated by μ_t, and an idiosyncratic component, indicated by δ_{it}, both of which are time varying. However, δ_{it} cannot be estimated due to over-parametrization (i.e., the number

[1] We refer to Tomal (2023) for a recent review of the econometric methodology developed by these authors.

[2] As the club convergence test is interested in the long-run behavior, prior to the implementation of the club convergence test, the trend component from X_{it} is extracted, while the cyclical components are removed, using the Hodrick and Prescott (1997) filter. We use a smoothing parameter of 400 to annual data.

of parameters is greater than the number of observations) without imposing a specific structure, and the following semi-parametric form for δ_{it} is assumed:

$$\delta_{it} = \delta_i + \frac{\sigma_i \xi_{it}}{L(t) t^{\alpha}}, \tag{3}$$

Where δ_i is constant, $\xi_{it} \sim iid(0,1) \forall i$ depends on t, σ_i is the scale parameter, $L(t)$ is a slowly varying penalty function over time (i.e., $L(t) \to \infty$ as $t \to \infty$), and α represents the speed of convergence.

The authors based their convergence test on the behavior of δ_{it}, by analyzing whether it converges toward a common element in all cross-section units, δ. To do so, they define the relative transition parameter, h_{it}, as follows:

$$h_{it} = \frac{X_{it}}{N^{-1} \sum_{i=1}^{N} X_{it}} = \frac{\delta_{it}}{N^{-1} \sum_{i=1}^{N} \delta_{it}}, \tag{4}$$

Where the h_{it} measures the possible divergence from the common growth path, μ_t, and the transition path with respect to the panel average. By definition, the cross-sectional mean of h_{it} is equal to 1. The cross-sectional variation of h_{it} is defined as follows:

$$H_t = \frac{1}{N} \sum_{i=1}^{N} (h_{it} - 1)^2, \tag{5}$$

If the convergence hypothesis holds, then δ_{it} converges towards a constant δ, and the relative transition parameter h_{it} converges to 1, so the cross-sectional variation H_t converges to zero. Therefore, the null hypothesis of convergence is $H_0 \colon \delta_{it} = \delta$ and $\alpha \geq 0$ against the alternative hypothesis of $H_1 \colon \delta_{it} \neq \delta$ for all i or $\alpha < 0$.

Formally, Phillips and Sul (2007) propose testing for the null hypothesis of full convergence by estimating the following equation, the commonly known log-t equation, and testing whether $\beta \geq 0$:

$$\log\left(\frac{H_1}{H_t}\right) - 2\log[\log(t)] = \alpha + \beta \log(t) + \varepsilon_t, \;\; t = [rT] + 1, \dots, T, \tag{6}$$

Where r is positive (i.e., a first fraction of the data discarded) and usually set to 0.3 for small samples ($T \leq 50$). Hence, the null hypothesis of convergence for all i can be tested using the estimated coefficient β by a one-sided t-test of $\beta \geq 0$, against $\beta < 0$. Based on heteroskedasticity and autocorrelation-consistent standard errors (HAC methods), the null hypothesis of convergence is rejected if the computed one-sided t-statistic for the β coefficient takes a value lower than -1.65 at the 5% significance level, as this t-statistic follows the standard normal distribution N (0,1).

Nevertheless, if the null hypothesis of convergence for the whole panel is rejected, they propose a clustering algorithm to identify the existence, if any, of convergence clubs throughout the panel. The algorithm specifically involves five steps, which can be sketched as follows:

1. *Cross-sectional ordering*. Order the N regions in the panel in descending order, according to the last period house price observations.
2. *Core club formation*. Form all possible core clubs C_k, starting with the k highest regions in the panel for some $2 \leq k \leq N$ and run the log *t* test sequentially. Define the core club C^* of size k^* by maximizing the value of the log *t*-statistic, subject to the restriction that it is greater than -1.65.
3. *Club membership*. From the remaining $N - k^*$ regions outside the core club, run the log *t* test adding regions one by one to the core club C^* and run the log *t* test. If the test satisfies the sign criterion (the log *t*-statistic is greater than a chosen critical value c^*, which is usually set to 0 for small samples), include the region in the core club C^*. This is accomplished by adding all units that strongly support the convergence hypothesis, and converge to the same equilibrium with C^*. These added units and the core club form the first convergence club if the log *t*-statistic is greater than -1.65. Otherwise, repeat step 3 but firstly raise the critical value c^*.
4. *Recursion and stopping*. For the remaining regions in the sample, run the log *t* test to see if they are converging (the log *t*-statistic is above -1.65) and form a second convergence club. If not, repeat steps 1-3 iteratively until clubs can no longer be formed. If the last group does not have a convergence pattern, conclude that its members have a divergent behavior.
5. *Club merging*. Employing a sign criterion in step 3 and increasing successively the critical value c^* may lead to creating more clubs than actually exist. In order to avoid this over-estimation, Phillips and Sul (2009) propose to conduct club convergence tests for all pairs of the initial convergence clubs. If the null hypothesis is not rejected, the corresponding clubs are merged.

Based on the results of the club convergence approach, we next examine the underlying drivers of the club formation in our empirical strategy. Given that the club convergence test provides an ordinal ranking of the convergence clubs, sorted from the highest (1) to the lowest (K, with K denoting the number of clubs) house prices indexes in our empirical application, we use ordinal models to test whether specific characteristics, economic, demographic and environmental, could predict the formation of clubs (Bartkowska & Riedl, 2012; Unal et al., 2024). Specifically, we estimate the following equation using the Ordered Logit Model (OLM):

$$Y_i^* = X_i'\beta + \varepsilon_i, \tag{7}$$

Where the dependent variable Y_i^* refers to a continuous latent variable that indicates membership to a certain club and the individual steady-state house price level from 1 to K, X_i represents a vector which includes explanatory variables that are correlated with the convergence clubs, β corresponds to the regression coefficients, and ε_i is the regression error term.

4. Data and variables

Our primary source of data is the Federal Housing Finance Agency (FHFA), which publishes an accurate indicator of single-family house price trends at a variety of geographic aggregation levels (i.e., national, census division, state, metro area, county, ZIP code, and census tract levels) and time frequency details (i.e., annual, quarterly, monthly) during a long-horizon timespan called the House Price Index (henceforth, HPI). The FHFA HPI is a broad measure of the movement of single-family house prices in the United States and is a weighted, repeat-sales, index. This means that it measures average price changes in repeat sales or refinancings on the same properties.[3]

In this paper we use data from the annual HPI at the county level from 1975 to 2022 with a based period 1975 = 100, the widest timespan available, from a total of 364 counties.[4] These counties are located in densely populated areas and contain approximately one-third (30.3 percent) of the total US 2022 population, according to the U.S. Bureau of Economic Analysis (BEA).

Figure 1 shows a preliminary analysis of the convergence behavior of the house price data, based on the sigma-convergence notion, and displays the coefficient of variation

[3] For more information on this index, we refer to https://www.fhfa.gov/DataTools (accessed in December 2023).

[4] The largest timespan available at the time of writing this article ranges from 1975 to 2022. This information is initially available for 417 counties, but we end with a sample of 364 counties due to data limitations and missing values on certain economic, demographic and environmental variables for some counties.

(CV) for our sample of 364 counties. Specifically, Figure 1 presents the cross-sectional coefficient of variation for our HPI during 1975-2022 and shows a clear increasing trend. According to sigma-convergence, a group of regions converges if the cross-sectional variance of the variable under analysis declines across time, as discussed in Section 2. However, we obtain a clear opposite pattern, which indicates that differences in house prices across counties have increased during the whole period under study. Consequently, Fig. 1 shows a steady rise in the dispersion in house prices across counties, and suggests absence of sigma-convergence.

In addition to the HPIs, we also consider a set of explanatory variables that are assumed to predict convergence club formation, as detailed in Eq. (7). They refer to economic, demographic and environmental variables. First, we include the 2022 GDP in real terms and the population, both of them sourced from the BEA at the county level. From the number of persons in each county, we compute the population growth rate from 1975 to 2022. Besides that, we include the percentage of population in urban areas from the 2023 rural-urban continuum from the Economic Research Service of the U.S. Department of Agriculture at the county level, which ranges from one (most urban) to nine (most rural). This dataset provides information regarding metropolitan (counties in metro areas of +1 million population, of 250,000 to 1 million population, or in metro areas of fewer than 250,000 population) and nonmetropolitan counties (urban population of 20,000 or more, of 5,000 to 20,000, and of fewer than 5,000, either adjacent or not adjacent to a metro area), based on the Office of Management and Budget (OMB) delineation as of July 2023. For demographic variables, we consider the percentage of population with a college degree, and use data from the 2017-2021 Economic Research Service of the U.S. Department of Agriculture at the county level.

Finally, we include a vector of weather conditions gathered from the National Climatic Data Center (NCDC) of the National Atmospheric Administration (NOAA), a US government agency. This dataset provides daily summaries at the county level for specific weather conditions on a historical basis. Specifically, we consider daily summaries for maximum temperature (degrees Fahrenheit, ºF) and precipitation (inches) from the period from 2003 to 2022 for a total of 23,044 meteorological stations throughout the US at the county level. For these daily summaries, we first calculate daily weather variables for each county on each day from 2003 to 2022 and collapse the data from the station-date level to the county-date level using no weights. Later, we compute the total rainy days during each year, defined as days with at least 0.1 inches of precipitation (Belloc et al., 2022; Connolly, 2008), and the days with extreme hot and cold temperatures, defined as the number of days where temperatures were (strictly) greater than the 90th and (strictly) lower than the 10th percentile of the historical temperature distribution for the whole county sample throughout the US (approximately 89.8 ºF and 38.67 ºF), from 2003 to 2022. Hence, we use the historical (2003-2022) daily temperature distribution of the whole sample to define percentile-based thresholds for extremely hot and low temperatures, which is essential for accurately assessing extremes. From these yearly observations, we collapse the data for the whole-time horizon to have information about the average number of rainy days and extreme hot and cold days during the last two decades for each county, respectively.

All these determinants are included by considering prior research that studies drivers of house prices. For instance, we include the GDP per-capita as a proxy for income, which is assumed to have a positive relationship with housing demand and house prices (Oikarinen et al., 2023). In line with prior research, the growth rate of total population is included to measure changes in demand across counties (Blanco et al., 2016; Cai et al., 2022; Churchill et al., 2018). On the other hand, education level and urbanization rate have been considered as determinants of house prices by many works (Gunduz & Yilmaz, 2021; Holmes et al., 2019; Kim & Rous, 2012). For climate conditions, most of the literature has included controls for the percent of daylight hours that are sunny as a measure of nice weather (Kim & Rous, 2012) or annual average temperature (Gunduz & Yilmaz, 2021). Against these works, we focus on exposure to extreme temperatures on a long-term basis at the county level.

5. Results

5.1. Club convergence results

Table 1 shows the results of the club convergence test for convergence among all sample counties. Panel A of Table 1 shows the results for the null hypothesis of full convergence (i.e., convergence among all counties) while Panel B displays the results for the club clustering procedure.[5] According to Panel A, the null hypothesis of overall convergence

[5] The HPI is log-transformed for the econometric analysis.

is clearly rejected at the 5% significance level. Specifically, the coefficient estimated for $\hat{\beta}$ is -1.4193 and the associated t-statistic equals to -320.1925, which is lower than -1.65, indicating that family house prices do not converge to the same steady state. Consequently, having rejected the null hypothesis of full convergence among the panel of 364 counties, conditional convergence should be investigated within convergence clubs. Panel B displays the results of the club clustering algorithm, and suggests the presence of eight distinct convergence clubs for family house prices over the period 1975-2022. The number of counties included in each estimated subgroup of convergence significantly varies within convergence clubs, from a minimum of 4 for Club 1 to a maximum of 125 for Club 4.

However, a well-known issue of the club clustering algorithm is that it tends to overestimate the current number of clubs (Phillips and Sul, 2009). Hence, club merging tests should be conducted among adjacent clubs, to test whether the final number of clubs is reduced by merging smaller clubs (i.e., clubs with a lower number of counties) into larger clubs (i.e., clubs with a higher number of counties). In this context, we apply the Phillips and Sul (2009) test for club merging in Table 2. Results confirm that the null hypothesis of club merging between Club 1 and Club 2, Club 2 and Club 3, Club 5 and Club 6, and Club 6 and Club 7 cannot be rejected at the 5% significance level (log t-statistic greater than -1.65). Consequently, the number of final clubs is strictly lower than that initially detected by the clustering algorithm and Clubs 1, 2 and 3 can be merged, on the one hand, and Clubs 5, 6 and 7 can be merged, on the other.

Table 3 displays the final composition of the estimated clubs over the period 1975-2022, which consists of six clubs. Club 1 consists of 17 counties, and given that the algorithm sorts the counties from the highest to the lowest HPI, it corresponds to counties with the largest increase in house prices. Club 2 consists of 17 counties too, while Club 3 and 4 are the largest and include 125 and 154 counties, respectively. Club 5 is formed by 37 counties. Finally, Club 6 consists of 14 counties and mainly refers to counties which are characterized by the lowest HPIs in our sample. In addition, the speed of convergence within these different clubs (the $\hat{\beta}$-coefficient provides a scaled measure of the speed of convergence parameter $\hat{\alpha} = \frac{\hat{\beta}}{2}$) ranges from -7.52 percent for Club 3—a negative but not statistically significant coefficient which suggests that Club 3 is the weakest convergence club— to 26.18 percent for Club 5.

Following Phillips and Sul (2007), we alternatively estimate the relative transition paths in Figure 2, h_{it}, defined in Eq. (4) for the estimated final clubs. They capture the transition paths with respect to the panel average and, under the assumption of convergence, the relative transition paths should converge to unity. However, under the assumption of club convergence, the relative transition paths tend to distinct constants. That is what we find in our data, as Clubs 1, 2 and 3 are above the panel average (by definition, the cross-sectional mean of h_{it} is one), while Clubs 4, 5 and 6 are below unity.[6]

5.2. **Forces driving club formation**

The Phillips and Sul (2007, 2009) club convergence test allows the endogenous formation of convergence clubs. However, this procedure does not allow us to study factors that might lead to the club convergence and house price dynamics. Consequently, we combine the club convergence results with an analysis of the underlying channels driven the club convergence formation, using ordinal models as detailed in Eq. (7). In this way, we can examine the relationship between the convergence clubs and certain economic, demographic and environmental characteristics.

Table 4 reports the estimated coefficients of the ordered logit model for the convergence clubs identified for HPI across counties in the US.[7] Estimates suggest that the underlying channels driving the convergence clubs for HPI across counties are the number of days of extreme hot and cold temperatures, the GDP per-capita, and the percentage of population with some college. Specifically, we report positive statistically significant coefficients at the 5% level for the number of days with extreme temperatures and the proportion of the population with college, while the coefficient for the GDP per-capita is negative and statistically significant at the 5% level. This indicates that extreme temperature days and the percentage of population with college are positively related to the probability of becoming a member of clubs with lower HPIs, and those counties with higher GDP per-capita have a greater HPIs.

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[6] In Appendix Figure A1 we present the evolution of average HPIs corresponding to the estimated final convergence clubs. The cumulative annual average growth rate ranges from 6.288 in Club 1 to 2.933 in Club 6.

[7] See Appendix Table A1 for the summary statistics.

In Table 4 we also display the marginal effects of the associated variables to the probability of belonging to each club, evaluated at sample means. In terms of the size of our coefficients, an additional day with an extreme hot day over the period 2003-2022 is associated to an increase of 0.13 percent in the probability of joining Club 4 and Club 5, while it is related with an increase of 0.1 percent in the probability of joining Club 6, the club formed by the counties with the cheapest house prices. By contrast, it is related to a decrease in the probability of joining Club 1, 2 and 3 by 0.08, 0.06 and 0.22 percent, respectively. For an additional number of extreme cold day over 2003-2022, we find that it is correlated with an increase of 0.11 and 0.12 percent in the probability of belonging to Club 4 and Club 5, while it is associated with an increase of 0.09 percent in the probability of joining Club 6. On the other hand, it is associated with a decrease of 0.07, 0.06 and 0.2 percent in the probability of joining Clubs 1, 2 and 3, respectively. Consequently, we find that counties with lower HPI are characterized by a higher frequency of extreme temperature days, at both tails of the distribution (i.e., extreme cold and hot temperature days).

For the GDP per-capita, we find that an increase of 1 percent in the GDP per-capita is negatively correlated with the probability of joining Clubs 4, 5 and 6. Numerically, it is associated with a decrease of 4.94, 5.27 and 3.90 percent in the probability of joining those clubs, respectively. However, an increase of one percent in the GDP per-capita is associated with an increase of 3, 2.39 and 8.72 percent in the probability of joining Clubs 1, 2 and 3, respectively, Hence, counties with higher increases in house prices (i.e., counties which are part of Clubs 1, 2 and 3) are characterized by greater economic levels, which is something intuitive. Finally, we find that the percentage of population with college degrees is negatively associated with the probability of belonging to Clubs 1, 2 and 3, while it is positively related to the probability of belonging to Clubs 4, 5 and 6. Quantitatively, the coefficients indicate that is associated with an increase of 0.78, 0.83 and 0.62 percent in the probability of joining Clubs 4, 5 and 6, while it is related to a decrease of 0.47, 0.38 and 1.38 percent in the probability of belonging to Club 1, 2 and 3, respectively.

For other determinants considered, the coefficients of the average number of rainy days during 2003-2022, the proportion of metropolitan areas and the population growth rate are not statistically significant at standard levels. All this suggests that these factors do not play a significant role in the convergence process of house prices between US counties.

5.3. Comparison with prior research

Our results support the hypothesis that aggregating housing prices at the state level may serve to smooth fluctuations across locations (Holmes et al., 2011, 2019). This may lead to finding a smaller number of clubs, thus masking significant heterogeneity in housing prices within states. Although state-level data provides an adequate overview of the state, it is unable to capture county-level idiosyncrasies of each county within that economy.

The results from the forces driving the club convergence results suggest that climate is an important amenity, which fits prior research in the US (Kim & Rous, 2012) or India (Gunduz & Yilmaz, 2021). However, it suggests that extreme weather events are incorporated in housing prices, and those counties with higher increases in house prices are less likely to experience such extreme weather conditions. Consequently, house prices incorporate environmental factors, and cheaper houses are more likely to experience extreme temperatures, all else equal. All this points to the potential climate change effects on population location and housing markets, which have been documented using specific disasters such as earthquakes (Cheung et al., 2018; Singh, 2019).

Prior research has shown that climate acts as an environmental amenity in housing price convergence in different contexts, such as across states within the US (Kim & Rous, 2012) and cities within Turkey (Gunduz & Yilmaz, 2021), as population growth appears to be correlated with certain weather conditions (Rappaport, 2007). However, all these works focus on either the percent of daily sunlight (Kim & Rous, 2012) or the annual average temperature (Gunduz & Yilmaz, 2021), while we are focusing on a different component of climate, that of extreme temperature days. In this context, our findings suggest that the demand for better climate and the willingness to pay for comfortable (temperate) weather conditions are reflected in a positive correlation with house price trends, a finding which is similar to some recent research on air quality or sunlight, and house prices (Choi et al., 2023; Fleming et al., 2018). All in all, climate plays the role of an amenity that positively influences household utility and increases housing demand and prices.

6. Conclusions and policy implications

This paper studies the convergence is US housing prices. We differ from prior research by taking a more detailed geographical level and testing for long-run convergence. To do so, we study US family house prices convergence at the county level using data spanning from 1975 to 2022. Later, we examine whether certain economic, demographic and environmental characteristics are determinants of the club convergence results. Our results suggest evidence for six convergence clubs and that economic development, level of education, and extreme weather conditions are important determinants of club formation. Specifically, we report that those counties frequently experiencing extreme hot and cold days over the last two decades tend to have lower increases in house prices, highlighting the distributional effects of climate change on housing markets.

Our club convergence results suggest important insights for current monetary policies of the Federal Reserve. Specifically, they support the notion of implementing distinct monetary policies to result in similar outcomes across counties, and achieve overall convergence in the long run. Otherwise, monetary policies, which affect asset returns and cost of financing a home, would have asymmetric effects on the family house prices across counties, and differentials in family house prices will increase rather than decrease across regions. Besides, policymakers could implement specific targeted measures to reach overall convergence, which would ease labor mobility across regions and reduce wealth disparities. These policies include reducing income disparities, the primary driver of club convergence, to reach a single convergence process in the US family housing market, as well as implementing other targeted policies that include improving access to housing in high-priced counties. For instance, housing planners may consider increasing public housing stock to reduce regional disparities and promote convergence. This would require specific land-use planning measures. Otherwise, some recent research in the UK points to the role of inflation-targeting policy to achieve house price convergence (see Lin & Robberts, 2024).

From the forces driving the club convergence results, we find that climate change has a role in the club convergence results. Specifically, those counties who have experienced more extreme temperature days during the last two decades, either at the top or bottom of the distribution, are characterized by lower increases in house price. This points to the willingness to pay for specific environmental conditions. Specifically, comfortable temperatures are valued by consumers and house prices incorporate that information. With climate change, extreme weather conditions are predicted to become more frequent, and all this suggests that global warming may act as an obstacle to achieving overall convergence in housing prices. Hence, this result underscores the importance of developing a comprehensive adaptation policy to address such distributional effects of climate change on housing markets.

Future research should analyze data from different settings to gain a full understanding of the impact of extreme temperatures on family housing markets. We strongly recommend testing all these hypotheses by incorporating rural areas, which are largely overlooked in this study. In addition, we suggest conducting further research to test for the role of housing regulation. Unfortunately, we are unable to capture such information because there is no index for legislation regarding housing at the county level.

References

Abbott, A., & De Vita, G. (2013). Testing for long-run convergence across regional house prices in the UK: a pairwise approach. *Applied Economics*, 45(10), 1227-1238. https://doi.org/10.1080/00036846.2011.613800

Akram, V., & Mukherjee, R. (2024). Housing price convergence: new evidence from Indian cities. *Journal of Economic Studies*, 51(2), 424-436. https://doi.org/10.1108/JES-02-2023-0100

Apergis, N., & Georgellis, Y. (2015). Does happiness converge? *Journal of Happiness Studies*, 16, 67-76. https://doi.org/10.1007/s10902-013-9495-y

Apergis, N., & Payne, J. E. (2012). Convergence in US house prices by state: evidence from the club convergence and clustering procedure. *Letters in Spatial and Resource Sciences*, 5, 103-111. https://doi.org/10.1007/s12076-011-0075-7

Apergis, N., & Payne, J. E. (2017). Per capita carbon dioxide emissions across US states by sector and fossil fuel source: evidence from club convergence tests. *Energy Economics*, 63, 365-372. https://doi.org/10.1016/j.eneco.2016.11.027

Apergis, N., & Payne, J. E. (2019). Florida metropolitan housing markets: examining club convergence and geographical market segmentation. *Journal of Housing Research*, 28(2), 145-163. https://doi.org/10.1080/10527001.2019.1769966

Apergis, N., Panopoulou, E., & Tsoumas, C. (2010). Old wine in a new bottle: Growth convergence dynamics in the EU. *Atlantic Economic Journal*, 38, 169-181. https://doi.org/10.1007/s11293-010-9219-1

Arčabić, V., Kim, K. T., You, Y., & Lee, J. (2021). Century-long dynamics and convergence of income inequality among the US states. *Economic Modelling*, 101, 105526. https://doi.org/10.1016/j.econmod.2021.105526

Barro, R. J., & Sala-i-Martin, X. (1992). Convergence. Journal of Political Economy, 100(2), 223-251. https://doi.org/10.1086/261816

Barros, C. P., Gil-Alana, L. A., & Payne, J. E. (2012). Comovements among US state housing prices: Evidence from fractional cointegration. *Economic Modelling*, 29(3), 936-942. https://doi.org/10.1016/j.econmod.2012.02.006

Bartkowska, M., & Riedl, A. (2012). Regional convergence clubs in Europe: Identification and conditioning factors. *Economic Modelling*, 29(1), 22-31. https://doi.org/10.1016/j.econmod.2011.01.013

Belloc, I., & Molina, J. A. (2023). Are greenhouse gas emissions converging in Latin America? Implications for environmental policies. *Economic Analysis and Policy*, 77, 337-356. https://doi.org/10.1016/j.eap.2022.11.022

Belloc, I., Gimenez-Nadal, J. I., & Molina, J. A. (2022). Weather conditions and daily commuting. IZA Discussion Papers, No. 15661.

Bernard, A. B., & Durlauf, S. N. (1995). Convergence in international output. *Journal of Applied Econometrics*, 10(2), 97-108. https://doi.org/10.1002/jae.3950100202

Bernard, A. B., & Durlauf, S. N. (1996). Interpreting tests of the convergence hypothesis. *Journal of Econometrics*, 71(1-2), 161-173. https://doi.org/10.1016/0304-4076(94)01699-2

Blanco, F., Martín, V., & Vazquez, G. (2016). Regional house price convergence in Spain during the housing boom. *Urban Studies*, 53(4), 775-798. https://doi.org/10.1177/0042098014565328

Cai, Y., Zhu, Y., & Helbich, M. (2022). Club convergence of regional housing prices in China: evidence from 70 major Cities. *The Annals of Regional Science*, 69(1), 33-55. https://doi.org/10.1007/s00168-021-01107-5

Carlino, G. A., & Mills, L. O. (1993). Are US regional incomes converging?: A time series analysis. *Journal of Monetary Economics*, 32(2), 335-346. https://doi.org/10.1016/0304-3932(93)90009-5

Carlino, G., & Mills, L. (1996). Convergence and the US states: a time-series analysis. Journal of Regional Science, 36(4), 597-616. https://doi.org/10.1111/j.1467-9787.1996.tb01120.x

Cattaneo, C., & Peri, G. (2016). The migration response to increasing temperatures. *Journal of Development Economics*, 122, 127-146. https://doi.org/10.1016/j.jdeveco.2016.05.004

Cheung, R., Wetherell, D., & Whitaker, S. (2018). Induced earthquakes and housing markets: Evidence from Oklahoma. *Regional Science and Urban Economics*, 69, 153-166. https://doi.org/10.1016/j.regsciurbeco.2018.01.004

Choi, A., Kim, P., & Park, A. (2023). The effects of air quality on housing prices: Evidence from the Aliso Canyon gas leak. *Journal of Housing Economics*, 62, 101966. https://doi.org/10.1016/j.jhe.2023.101966

Churchill, S. A., Inekwe, J., & Ivanovski, K. (2018). House price convergence: Evidence from Australian cities. *Economics Letters*, 170, 88-90. https://doi.org/10.1016/j.econlet.2018.06.004

Churchill, S. A., Inekwe, J., & Ivanovski, K. (2023). Has the COVID-19 pandemic converged across countries? *Empirical Economics*, 64(5), 2027-2052. https://doi.org/10.1007/s00181-022-02319-0

Connolly, M. (2008). Here comes the rain again: Weather and the intertemporal substitution of leisure. *Journal of Labor Economics*, 26(1), 73-100. https://doi.org/10.1086/522067

Cutrini, E., & Mendez, C. (2023). Convergence clubs and spatial structural change in the European Union. *Structural Change and Economic Dynamics*, 67, 167-181. https://doi.org/10.1016/j.strueco.2023.07.009

Duca, J. V., Muellbauer, J., & Murphy, A. (2021). What drives house price cycles? International experience and policy issues. *Journal of Economic Literature*, 59(3), 773-864. https://doi.org/10.1257/jel.20201325

Durlauf, S. N., & Johnson, P. A. (1995). Multiple regimes and cross-country growth behaviour. *Journal of Applied Econometrics*, 10(4), 365-384. https://doi.org/10.1002/jae.3950100404

Fleming, D., Grimes, A., Lebreton, L., Maré, D., & Nunns, P. (2018). Valuing sunshine. *Regional Science and Urban Economics*, 68, 268-276. https://doi.org/10.1016/j.regsciurbeco.2017.11.008

Füss, R., & Zietz, J. (2016). The economic drivers of differences in house price inflation rates across MSAs. *Journal of Housing Economics*, 31, 35-53. https://doi.org/10.1016/j.jhe.2015.12.002

Ganioğlu, A., & Seven, Ü. (2021). Do regional house prices converge? Evidence from a major developing economy. *Central Bank Review*, 21(1), 17-24. https://doi.org/10.1016/j.cbrev.2021.03.001

Gong, Y., Hu, J., & Boelhouwer, P. J. (2016). Spatial interrelations of Chinese housing markets: Spatial causality, convergence and diffusion. *Regional Science and Urban Economics*, 59, 103-117. https://doi.org/10.1016/j.regsciurbeco.2016.06.003

Gunduz, L., & Yilmaz, M. K. (2021). Club convergence and drivers of house prices across Turkish cities. *International Journal of Emerging Markets*. https://doi.org/10.1108/IJOEM-10-2020-1157

Helbling, M., & Meierrieks, D. (2023). Global warming and urbanization. *Journal of Population Economics*, 36(3), 1187-1223. https://doi.org/10.1007/s00148-022-00924-y

Herrerias, M. J., & Ordoñez, J. (2012). New evidence on the role of regional clusters and convergence in China (1952–2008). *China Economic Review*, 23(4), 1120-1133. https://doi.org/10.1016/j.chieco.2012.08.001

Hodrick, R. J., & Prescott, E. C. (1997). Postwar US business cycles: an empirical investigation. *Journal of Money, Credit, and Banking*, 29(1), 1-16. https://doi.org/10.2307/2953682

Holmes, M. J., Otero, J., & Panagiotidis, T. (2011). Investigating regional house price convergence in the United States: Evidence from a pair-wise approach. *Economic Modelling*, 28(6), 2369-2376. https://doi.org/10.1016/j.econmod.2011.06.015

Holmes, M. J., Otero, J., & Panagiotidis, T. (2019). Property heterogeneity and convergence club formation among local house prices. *Journal of Housing Economics*, 43, 1-13. https://doi.org/10.1016/j.jhe.2018.09.002

Hua, Y., Qiu, Y., & Tan, X. (2023). The effects of temperature on mental health: evidence from China. *Journal of Population Economics*, 36(3), 1293-1332. https://doi.org/10.1007/s00148-022-00932-y

Ivanovski, K., & Churchill, S. A. (2020). Convergence and determinants of greenhouse gas emissions in Australia: A regional analysis. *Energy Economics*, 92, 104971. https://doi.org/10.1016/j.eneco.2020.104971

Ivanovski, K., & Churchill, S. A. (2021). Has healthcare expenditure converged across Australian states and territories?. *Empirical Economics*, 61(6), 3401-3417. https://doi.org/10.1007/s00181-021-02016-4

Kiley, M. T. (2024). Growth at risk from climate change. *Economic Inquiry*, forthcoming, 1-18. https://doi.org/10.1111/ecin.13206

Kim, Y. S., & Rous, J. J. (2012). House price convergence: Evidence from US state and metropolitan area panels. *Journal of Housing Economics*, 21(2), 169-186. https://doi.org/10.1016/j.jhe.2012.01.002

Liao, H., Zhang, C., Burke, P. J., Li, R., & Wei, Y. M. (2023). Extreme temperatures, mortality, and adaptation: Evidence from the county level in China. *Health Economics*, 32(4), 953-969. https://doi.org/10.1002/hec.4649

Lin, P. T., & Robberts, A. (2023). Regional house price convergence: implications of monetary policy. *Regional Studies*, 58(5), 968-980. https://doi.org/10.1080/00343404.2023.2233559

Liu, T. Y., & Lin, Y. (2023). Does global warming affect unemployment? International evidence. *Economic Analysis and Policy*, 80, 991-1005. https://doi.org/10.1016/j.eap.2023.09.028

Maynou, L., Monfort, M., Morley, B., & Ordonez, J. (2021). Club convergence in European housing prices: The role of macroeconomic and housing market fundamentals. *Economic Modelling*, 103, 105595. https://doi.org/10.1016/j.econmod.2021.105595

Meen, G. (1996). Spatial aggregation, spatial dependence and predictability in the UK housing market. *Housing Studies*, 11(3), 345-372. https://doi.org/10.1080/02673039608720862

Meen, G. (1999). Regional house prices and the ripple effect: a new interpretation. *Housing Studies*, 14(6), 733-753. https://doi.org/10.1080/02673039982524

Montagnoli, A., & Nagayasu, J. (2015). UK house price convergence clubs and spillovers. *Journal of Housing Economics*, 30, 50-58. https://doi.org/10.1016/j.jhe.2015.10.003

Montañés, A., & Olmos, L. (2013). Convergence in US house prices. *Economics Letters*, 121(2), 152-155. https://doi.org/10.1016/j.econlet.2013.07.021

Mullins, J. T., & White, C. (2020). Can access to health care mitigate the effects of temperature on mortality?. *Journal of Public Economics*, 191, 104259. https://doi.org/10.1016/j.jpubeco.2020.104259

Newell, R. G., Prest, B. C., & Sexton, S. E. (2021). The GDP-temperature relationship: implications for climate change damages. *Journal of Environmental Economics and Management*, 108, 102445. https://doi.org/10.1016/j.jeem.2021.102445

Ogundari, K. (2023). Club Convergence in Income Inequality in Africa. *Social Indicators Research*, Forthcoming. https://doi.org/10.1007/s11205-023-03108-7

Oikarinen, E., Bourassa, S. C., Hoesli, M., & Engblom, J. (2023). Revisiting metropolitan house price-income relationships. *Journal of Housing Economics*, 61, 101946. https://doi.org/10.1016/j.jhe.2023.101946

Paglialunga, E., Coveri, A., & Zanfei, A. (2022). Climate change and within-country inequality: New evidence from a global perspective. *World Development*, 159, 106030. https://doi.org/10.1016/j.worlddev.2022.106030

Panopoulou, E., & Pantelidis, T. (2013). Cross-state disparities in us health care expenditures. *Health Economics*, 22(4), 451-465. https://doi.org/10.1002/hec.2816

Payne, J. E., Saunoris, J. W., Nazlioglu, S., & Karul, C. (2023). The convergence dynamics of economic freedom across US states. *Southern Economic Journal*, 89(4), 1216-1241. https://doi.org/10.1002/soej.12629

Phillips, P. C., & Sul, D. (2007). Transition modeling and econometric convergence tests. *Econometrica*, 75(6), 1771-1855. https://doi.org/10.1111/j.1468-0262.2007.00811.x

Phillips, P. C., & Sul, D. (2009). Economic transition and growth. *Journal of Applied Econometrics*, 24(7), 1153-1185. https://doi.org/10.1002/jae.1080

Pleninger, R. (2022). Impact of natural disasters on the income distribution. *World Development*, 157, 105936. https://doi.org/10.1016/j.worlddev.2022.105936

Rajesh, R., & Rath, D. P. (2023). House price convergence: evidence from India. *Asia-Pacific Journal of Regional Science*, 1-27. https://doi.org/10.1007/s41685-023-00285-8

Rappaport, J. (2007). Moving to nice weather. *Regional Science and Urban Economics*, 37, 375-395. https://doi.org/10.1016/j.regsciurbeco.2006.11.004

Sala-i-Martin, X. X. (1996). The classical approach to convergence analysis. *The Economic Journal*, 106(437), 1019-1036. https://doi.org/10.2307/2235375

Singh, R. (2019). Seismic risk and house prices: Evidence from earthquake fault zoning. *Regional Science and Urban Economics*, 75, 187-209. https://doi.org/10.1016/j.regsciurbeco.2019.02.001

Stott, P. (2016). How climate change affects extreme weather events. *Science*, 352(6293), 1517-1518. https://doi.org/10.1126/science.aaf7271

Tomal, M. (2022). Testing for overall and cluster convergence of housing rents using robust methodology: evidence from Polish provincial capitals. *Empirical Economics*, 62(4), 2023-2055. https://doi.org/10.1007/s00181-021-02080-w

Tomal, M. (2023). A review of Phillips-Sul approach-based club convergence tests. *Journal of Economic Surveys*, forthcoming. https://doi.org/10.1111/joes.12563

Trojanek, R., Gluszak, M., Kufel, P., Tanas, J., & Trojanek, M. (2023). Pre and post-financial crisis convergence of metropolitan housing markets in Poland. *Journal of Housing and the Built Environment*, 38(1), 515-540. https://doi.org/10.1007/s10901-022-09953-1

Unal, U., Hayo, B., & Erol, I. (2024). Housing market convergence: Evidence from Germany. *Applied Economics*, forthcoming, 1-16. https://doi.org/10.1080/00036846.2024.2315094

Ursavaş, U., & Mendez, C. (2023). Regional income convergence and conditioning factors in Turkey: revisiting the role of spatial dependence and neighbor effects. *The Annals of Regional Science*, 71(2), 363-389. https://doi.org/10.1007/s00168-022-01168-0

Von Lyncker, K., & Thoennessen, R. (2017). Regional club convergence in the EU: evidence from a panel data analysis. *Empirical Economics*, 52, 525-553. https://doi.org/10.1007/s00181-016-1096-2

Zhang, F., & Morley, B. (2014). The convergence of regional house prices in China. *Applied Economics Letters*, 21(3), 205-208. https://doi.org/10.1080/13504851.2013.848021

Figure 1. Sigma-convergence analysis, county HPI

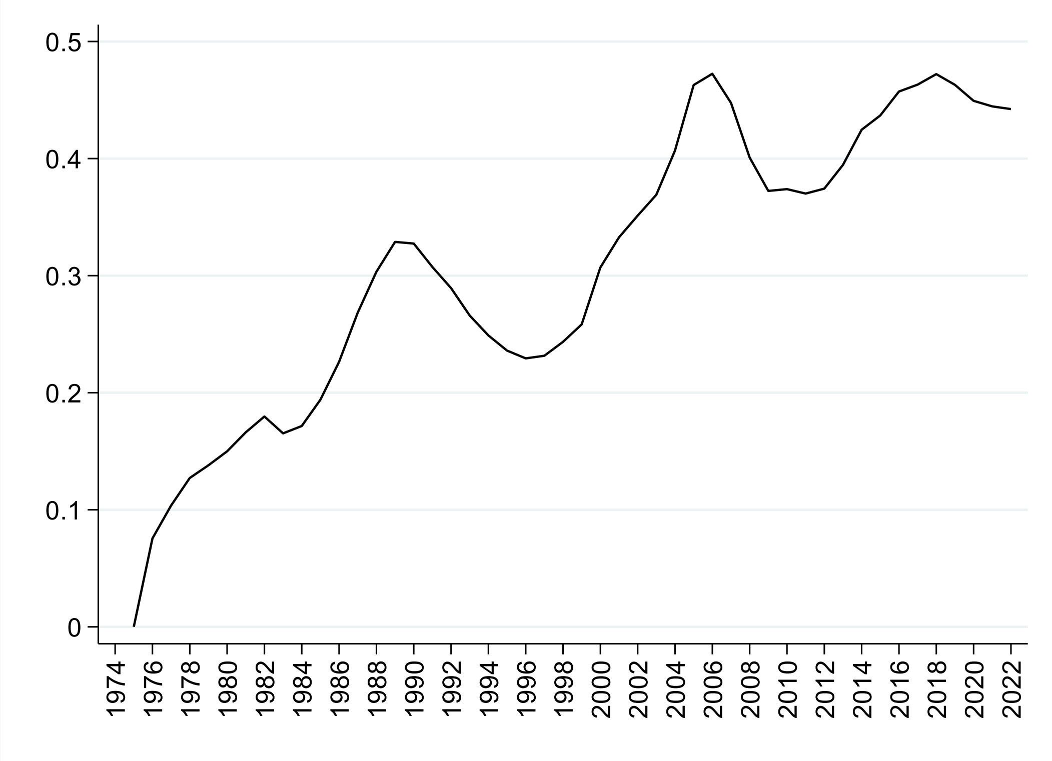

Table 1. Club convergence results

	$\hat{\beta}$-coefficient	log t-statistic	$\hat{\alpha}$-coefficient
Panel A. Full convergence			
	-1.4193**	-320.1925	-0.7097
Panel B. Convergence clubs			
Club 1 [4]	0.8394	4.0675	0.4197
Club 2 [13]	0.5332	12.5509	0.2666
Club 3 [17]	0.3229	5.4835	0.1615
Club 4 [125]	-0.1504	-1.5278	-0.0752
Club 5 [87]	0.4711	3.2260	0.2356
Club 6 [67]	0.7220	4.3987	0.3610
Club 7 [37]	0.5235	3.7254	0.2618
Club 8 [14]	0.0337	0.9284	0.0169

Notes: ** indicates rejection of the null hypothesis of absolute convergence at the 5% significance level (the critical value is -1.65). Numbers in brackets in Panel B stand for the number of counties within a given club.

Table 2. Club merging tests

	$\hat{\beta}$-coefficient	log t-statistic
Merging Clubs 1+2	0.1549	4.7005
Merging Clubs 2+3	0.1823	5.0853
Merging Clubs 3+4	-0.4648**	-6.7017
Merging Clubs 4+5	-0.7190**	-15.2043
Merging Clubs 5+6	-0.0243	-0.1972
Merging Clubs 6+7	0.1883	1.3773
Merging Clubs 7+8	-0.4509**	-26.7467

Notes: ** indicates rejection of the null hypothesis of club merging at the 5% significance level (the critical value is -1.65).

Table 3. Final club classification

	$\hat{\beta}$-coefficient	log t-statistic	$\hat{\alpha}$-coefficient
Club 1 [17]	0.1549	4.7005	0.0775
Club 2 [17]	0.3229	5.4835	0.1615
Club 3 [125]	-0.1504	-1.5278	-0.0752
Club 4 [154]	-0.0243	-0.1972	0.0122
Club 5 [37]	0.5235	3.7254	0.2618
Club 6 [14]	0.0337	0.9284	0.0169

Notes: ** indicates rejection of the null hypothesis of absolute convergence at the 5% significance level (the critical value is -1.65). Numbers in brackets stand for the number of counties within a given club.

Figure 2. Transition paths, county HPI

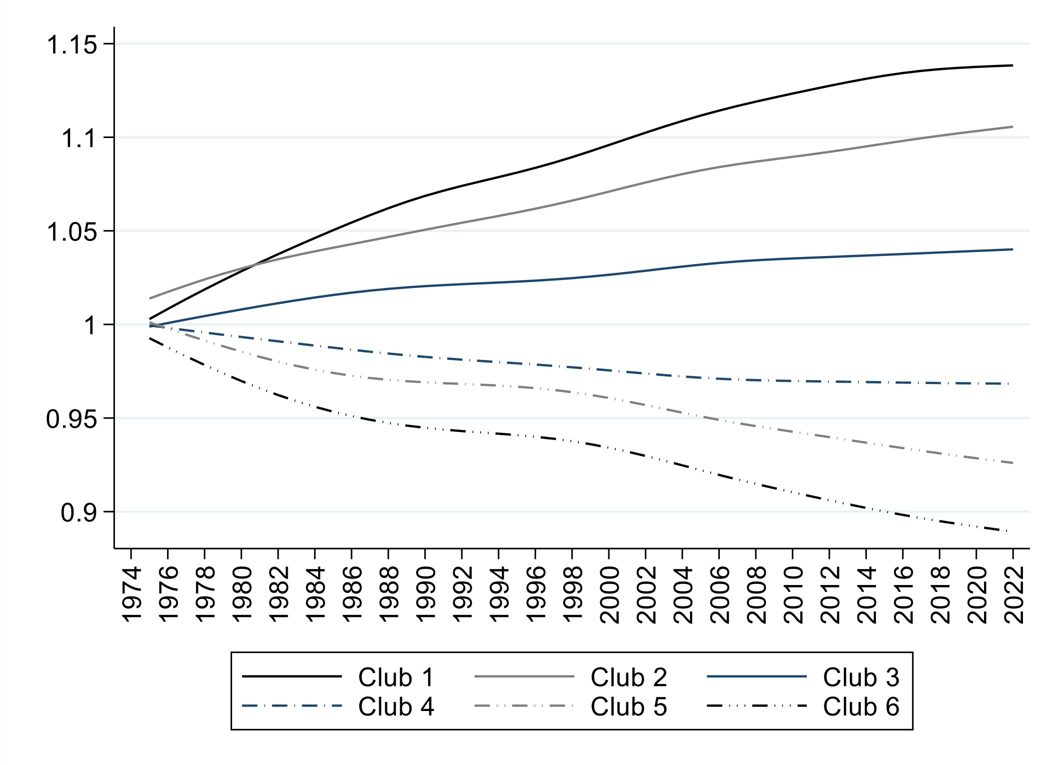

Table 4. Ordered Logit Model estimates

	Final club	Average marginal effects Club 1	Club 2	Club 3	Club 4	Club 5	Club 6
Number of extreme hot days	0.0404***	-0.0008***	-0.0006***	-0.0022***	0.0013***	0.0013***	0.0010***
	(0.0088)	(0.0002)	(0.0002)	(0.0005)	(0.0004)	(0.0004)	(0.0002)
Number of extreme cold days	0.0369***	-0.0007**	-0.0006**	-0.0020***	0.0011**	0.0012**	0.0009**
	(0.0134)	(0.0003)	(0.0002)	(0.0007)	(0.0005)	(0.0005)	(0.0004)
Number of rainy days	0.0002	0.0000	0.0000	-0.0000	0.0000	0.0000	0.0000
	(0.0054)	(0.0001)	(0.0001)	(0.0003)	(0.0002)	(0.0002)	(0.0001)
Log of GDP per-capita	-1.5951**	0.0300**	0.0239**	0.0872**	-0.0494*	-0.0527**	-0.0390**
	(0.6400)	(0.0122)	(0.0107)	(0.0378)	(0.0255)	(0.0227)	(0.0161)
Population growth rate	-0.2532	0.0048	0.0038	0.0138	-0.0078	-0.0084	-0.0062
	(0.4068)	(0.0078)	(0.0060)	(0.0222)	(0.0129)	(0.0134)	(0.0099)
% of metropolitan areas	0.1609	-0.0030	-0.0024	-0.0088	0.0050	0.0053	0.0039
	(0.6872)	(0.0129)	(0.0103)	(0.0376)	(0.0212)	(0.0228)	(0.0168)
% of population with some college	0.2519***	-0.0047***	-0.0038***	-0.0138***	0.0078***	0.0083***	0.0062***
	(0.0499)	(0.0011)	(0.0011)	(0.0029)	(0.0026)	(0.0020)	(0.0015)
State F.E.	Yes						
Pseudo-R^2	0.4908						
Observations	364						

Notes: Ordered Logit Model estimates. Robust standard errors in parentheses. Estimates also include state fixed effects, but not shown for brevity. Columns (2-7) report marginal effects calculated at the means. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

APPENDIX

Figure A1. Mean values by final clubs, county HPI

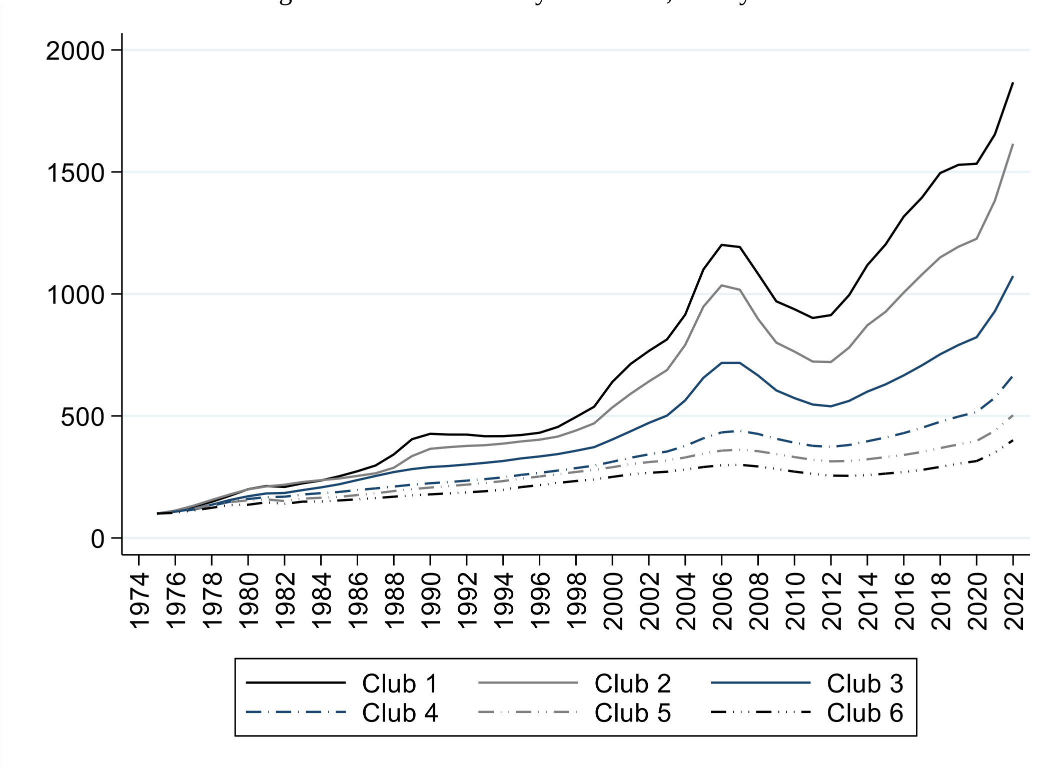

Table A1. Summary statistics

	Mean	Std. Dev.
Final convergence club	3.602	1.025
Historical number of extreme hot days	36.275	35.551
Historical number of extreme cold days	36.027	32.782
Historical number of rainy days	186.954	45.083
GDP per-capita	63,922.870	29,774.790
Population growth rate	0.547	0.490
% of metropolitan areas	95.330	21.129
% of population with some college	29.706	4.885