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Housing Market Convergence: Evidence from Germany

Abstract

This paper analyses the convergence patterns of German housing prices and rents, employing a new dataset covering the country's administrative districts. In addition to conventional tests for β-convergence and σ-convergence, we apply Phillips and Sul's (2007) approach to allow for heterogeneous transition dynamics across districts, potentially leading to different 'convergence clubs'. Our results reveal no evidence of convergence across Germany or within states; instead, we discover widespread evidence of divergence and inter-state convergence, as well as support for the existence of convergence clubs. The results of an ordered logit model suggest that differences in the variation of GDP per capita, population density, unemployment rate, and shares of immigrants and asylum seekers have played a significant role in determining club membership from 2004 to 2020.

JEL classification: R10; R30; R31
Keywords: Convergence; Germany; housing prices; district-level data; convergence clubs

Data Availability

The housing price data were purchased from a private data provider, Regional Real Estate Information System (RIWIS). We do not have permission to share these data. All other data series are available on request.

1. Introduction

The 2008/09 Global Financial Crisis, triggered by a collapse in housing prices, highlighted the role of housing markets in the economy (Canarella et al., 2012; Churchill et al., 2018). Given the risk of overinflated housing markets and disparities in housing prices across regions, the dynamic relationship or relatedness of regional housing prices warrants particularly close attention. This will assist in both preventing the creation of housing bubbles (Holmes et al., 2018) and uncovering inequalities across regional housing markets, and will provide the foundation for regionally diversified and locally adapted adjustment policies (Cai et al., 2022).

Housing prices are believed to be determined by the spatial equilibrium process, a fundamental principle in urban economics. A spatial equilibrium across cities implies that households, employers and homebuilders all meet the equilibrium conditions (Glaeser et al., 2006). For households, the location must be optimised to maximise utility, as utility is assumed to be positively correlated with amenities and wages and negatively correlated with housing costs. Employers must optimise the firms' locations and the use of production factors to achieve maximum profits (which are zero in a perfect competition world). In growing markets, the price of housing must equal the cost of producing (equivalent) new residences for homebuilders.

Because theoretically, it is utility that converges, rather than wages, housing prices, or city amenities, there is limited theoretical support for the idea that housing prices should converge (Kim and Rous, 2012; Kemeny and Storperi, 2012). In light of this, it is essential to explore empirically whether housing prices are converging at the national/state/city/region level and understand the convergence's nature and extent. Perfect convergence would imply that all prices of comparable housing in predefined regions, such as cities or districts, converge to the same price in the long run. Such an outcome would imply that aggregate regional income and the aggregate value of amenities will also converge, which we would not expect in heterogeneous or highly segmented housing markets. However, since we tend to observe income convergence over time in regions within one country (Barro and Sala-i-Martin, 1992), it would not be surprising to find a convergence of housing prices between some of these regional entities. Typically, but not necessarily, these 'convergence clubs' would be characterised by similar economic fundamentals and amenities (Kim and Rous, 2012).

The modelling of sub-national or regional house prices has received considerable attention since the early 2000s. Using a range of techniques, such as cointegration and spatial econometrics, various researchers have explored the extent to which some areas are convergence leaders and the degree to which convergence is (re)established over time (Meen, 2016). Most early research on the convergence behaviour of regional housing prices focused on the United Kingdom (UK). Cook (2003) examines the convergence of regional house prices and discovers a widespread convergence of house prices in several regions of the UK. Cook (2003 and 2005) suggests that previous studies' failure to detect convergence might originate from the inability to account for varying speeds of adjustment in regional house prices during upswings and downturns. Such a discovery has guided a subsequent analysis undertaken by Cook (2012), where the cyclical dynamics of the UK housing market, with the dynamics of regional house prices over this cycle and its constituent phases, were studied. Specifically, the varying adjustment speed of regions during different phases of the housing cycle suggests that convergence may be cycle related. Cook (2012) concludes that while significant evidence of convergence is present throughout the dataset's entire cycle, the most compelling evidence of convergence occurs during cyclical downturns. To rephrase this conclusion: long-term housing price convergence seems to be driven by recessions in the housing cycle.

Cook and Watson (2016) employ a directional forecasting technique to examine co-movement and cyclical sub-samples in the UK housing market and explore the extent to which changes in regional house prices are influenced by those in London. They show that proximity to London is positively related to the degree of co-movement between house prices in UK regions and the capital. While research into regional housing dynamics has mainly focused on the UK, where small geographic size could explain the prevalence of co-movements, an increasing body of evidence indicates that a lead city or area can also exist on an international scale. Instances of price convergence are observed, for example, in the United States of America (US) (Montanes and Olmos, 2013; Holmes et al., 2011; Barros et al., 2012), Australia (Churchill et al., 2018), China (Cai et al., 2022), Malaysia (Lean and Smyth, 2013), South Africa (Balcilar et al., 2013), and Turkey (Ganioğlu and Seven, 2021).[1]

Only a limited number of studies employ the club convergence and clustering procedure introduced by Phillips and Sul (2007, 2009) to study regional house price dynamics. For instance, Kim and Rous (2012) explore house price convergence in US states and metropolitan areas. They discover a lack of overall convergence yet identify multiple convergence clubs in the US housing market. Given the heterogeneity of the US, this finding is unsurprising. The authors also search for critical determinants of convergence club membership and identify housing supply regulation and climate as particularly important. Montagnoli and Nagayasu (2015) find that the UK housing market is complex and heterogeneous, too, and they group house prices into four regional clusters. They also document the dynamics of house price spillover effects across regions. There appear to be notable spillovers from the core regions, especially London, to the peripheral regions, but regional economic and financial developments are also important for regional house price dynamics. Apergis et al. (2015) investigate the long-run behaviour of house prices across nine provinces in South Africa and discover that they do not form a homogeneous convergence club. However, the authors lack the data to formally analyse the drivers behind convergence club formation.

Blanco et al. (2016) study regional housing prices in Spain. They report that the Spanish housing market is segmented, and regional house prices do not converge to a common trend. Instead, similar to the results in the UK, the housing market is grouped into four separate convergence clubs. The study finds that differences in population growth, rental market size, initial house supply, and geographical situation play significant roles in determining club membership. Holmes et al. (2019) examine the extent of convergence club formation in England and Wales. Their analysis is based on a disaggregated panel dataset comprising multiple housing types across the local authorities. They conclude that prices for flats are more likely to converge, whereas prices for terraced housing are less likely to converge. In the case of terraced housing, relative price divergences could worsen the affordability of housing in certain areas. Regarding the formation of convergence clubs, crime rate and congestion issues are significant factors in bringing about these clusters.

As seen in the literature, most of the existing studies have analysed the convergence of sales prices in the residential market; existing research on the identification of rental housing convergence clubs are very limited. Only lately has Tomal (2022) studied the overall and cluster convergence of housing rents across Polish provincial capitals and identified drivers of convergence club formation. The results of the study indicated that although rental prices across cities do not share a common path in the long run, rents are moving towards a club-specific steady state. Furthermore, the likelihood of any two cities belonging to the same

[1]Meen (2016) provides an extensive review of literature on spatial housing economics.

convergence club depends mainly on similar levels in terms of the unemployment rate, housing stock, city area, and the number of students in the city.

In light of this literature, gaining further insights into how relative regional or even local house prices change over time is of great importance. These factors can affect the economic activity of a region, as well as the affordability of housing, relocation costs, and labour mobility between areas. Although a considerable body of literature explores state- or city-level house price convergence using aggregated region time-series data, little is known about the evolution of intra-regional housing prices, especially rental prices, and the increased disparities within regions.

Against this background, the aim of this paper two fold. First, to the best of our knowledge, no previous study has investigated Germany's long-term housing price dynamics, including sales prices and rental prices. The present study examines district-level housing price convergence across 401 administrative districts in Germany from 2004 to 2020. It employs conventional methods to analyse convergence and Phillips and Sul's (2007, 2009) club convergence and clustering procedures. Second, the potential formation of clubs implies the existence of common factors within district clusters that may lead them to converge towards comparable price levels. Thus, in addition to examining whether certain German districts share common patterns of housing market convergence, this research seeks to shed light on the underlying factors driving the formation of district clusters in Germany. To improve our understanding of why housing prices escalate faster in certain districts than in others, we employ ordered logit models to analyse which factors influence the likelihood of club membership.

To summarise our main findings, our utilisation of conventional convergence methods, the log t convergence test, and Phillips and Sul's clustering algorithm (2007), reveals that the German housing market does not exhibit overall convergence towards a single trend across the country. This lack of overarching convergence prompted an investigation into the possible existence of convergence clubs. The application of the clustering procedure to housing price panels indicates that individual housing prices can be classified into several sub-groups, the so-called 'convergence clubs', in which there are distinct commonalities in housing prices. This classification leads to a significant reduction in the dispersion of cross-sectional variances within each convergence club. Note that the members of these clubs do not necessarily share geographic proximity, suggesting that traditional definitions of economic districts may not be optimal for studying regional disparities in housing prices.

In essence, our findings suggest the existence of a highly segmented housing market in Germany. In a further step, we examine the common characteristics of sub-groups and explore potential factors influencing the formation of convergence clubs. Our results from an ordered logit model indicate that variations in GDP per capita, population density, unemployment rate, and the share of immigrants and asylum seekers have a significant impact on housing price and rent club membership at the district level from 2004 to 2020.

Beyond any academic interest, given that housing affordability is a major concern in many countries, including Germany, house price convergence/divergence across different housing tenures (owner-occupied and rental) and dwelling types (existing and new flats, houses) is of potential interest to policymakers. Moreover, gaining an understanding of the dynamics of regional house prices is crucial for obtaining a comprehensive understanding of the housing market in Germany. Therefore, it is valuable to provide empirical evidence of convergence/divergence and its presence across different dwellings types and tenures.

The remainder of the paper is structured as follows: Section II discusses the data and methodology employed in the study, Section III presents a discussion of the results, and Section IV concludes the paper.

2. Methodology and Data

2.1 Review of Convergence

Examining regional inequality and its evolution over time is a prominent area of investigation in the economics literature. Various methodologies were developed to study how and to what extent regional entities converge. The two most widely-used methods for studying convergence are β-convergence and σ-convergence. In our context, β-convergence indicates that regions with lower housing prices at the beginning of the observation window experienced faster growth in housing prices compared to regions that initially had higher housing prices.

To determine whether there is absolute convergence over the sample period, an absolute (unconditional) β-convergence model is estimated with the following equation:

$$\ln\left(\frac{y_{i,2020}}{y_{i,2004}}\right) = \alpha + \beta_0 \ln\left(y_{i,2004}\right) + \varepsilon_{i,t} \qquad Eq(1)$$

where α is a constant, β_0 is a coefficient vector, $y_{i,t}$ denotes the median house price/flat price/rental price of district i in year t, ln is the natural logarithm, 2004 is the initial year and $\varepsilon_{i,t}$ is the error term.

When heterogeneity between districts is allowed, or, in other words, when districts exhibit variations in various aspects that are subsequently accounted for, the notion of convergence becomes applicable in a conditional context. This phenomenon is called conditional convergence, which refers to convergence that occurs after accounting for the differences in the steady states across districts. The central concept here revolves around the idea that housing prices experience accelerated growth the further they deviate from their respective steady-state values. Therefore, when examining convergence within a cross-sectional framework, it is imperative to take into account the differences in steady-state conditions across districts.

The conditional housing price convergence model is estimated as follows:

$$\ln\left(\frac{y_{i,2020}}{y_{i,2004}}\right) = \alpha + \beta_0 \ln(y_{i,2004}) + \mu_i\left(X_{i,\overline{2004-2020t}}\right) + \varepsilon_{i,t} \qquad Eq(2)$$

α is a constant, β_0 is a coefficient vector, $y_{i,t}$ denotes the median house price/flat price/rental price of district i in year t, ln is the natural logarithm, $t-1$ is the initial year, $X_{i,t}$, indicates the averages of the explanatory variables during the period under consideration, and $\varepsilon_{i,t}$ is the error term.

However, β-convergence test can be misleading, particularly when poorer regions experience significantly higher growth rates than their wealthier counterparts, leading to a situation where an even wider income gap exists at the end of the examination period compared to the beginning (Lichtenberg, 1994). Another disadvantage of the β-convergence concept is that it focuses on the overall distribution and not on the dynamics of individual units in a panel. Since it is based on cross-section regression, β-convergence is potentially subject to Galton's fallacy (Quah, 1993).

The other conventional method for examining convergence, σ-convergence, measures the decline in regional dispersion by comparing the standard deviation at the beginning of the sample period with the value at the end (Lau, 2010). However, time-series data are often characterised by increasing variance over time, which renders the application of the σ-convergence concept problematic (Phillips and Sul, 2007). A simple approach to addressing this issue is dividing the standard deviation by the mean of the series, i.e. employing the coefficient of variation for the σ-convergence test. Still, at best, this is only a partial solution to these problems, and at worst, it is entirely ineffective.

Reflecting on these methods, Phillips and Sul (2007) introduce a novel approach to analysing economic transition behaviour that considers different time paths and individual heterogeneity. This methodology is particularly effective in measuring progress towards a long-term growth path or a common steady state. The authors emphasise that failure to detect convergence in a panel does not necessarily imply a lack of convergence in its sub-groups. A situation where different groups converge to distinct steady-state levels is called 'club convergence'. Moreover, this data-driven statistical approach to identifying convergence clubs is more accurate than regional convergence research that relies on defining clubs solely based on geographic location (Tian et al. 2016).

2.2 Log t *test*

To analyse the transitional behaviour of housing prices across German districts between 2004–2020, we apply the log *t* test developed by Phillips and Sul (2007):

$$log y_{it} = (\varphi_{it} + \frac{\varepsilon_{it}}{\mu_t})\mu_t = \delta_{it}\mu_t, \qquad Eq(3)$$

where φ_{it} is the district *(i)* characteristic component, δ_{it} the time-varying idiosyncratic element that captures the deviation of district *i* from the common growth path μ_t, and ε_{it} the error term, which is weakly dependent over *t*, but *iid*(0,1) across *i*. The test focuses on the evolution of individual transition paths compared to the common growth component. Removing the common growth path in the form of the cross-sectional average from the original variable yields h_{it}, the relative transition coefficient:

$$h_{it} = \frac{\log y_{it}}{(1/N)\sum_{i=1}^{N} log y_{it}} = \frac{\delta_{it}}{(1/N)\sum_{i=1}^{N}\delta_{it}} \qquad Eq(4)$$

Equation (4) identifies the relative deviation of district *i* from the common growth path μ_t and measures individual behaviour concerning other districts. The log *t* test is based on time series regressions, where the transformation of the cross-section variance of $h_{it}(\sigma_{it}^2)$ is regressed on log(*t*). Coefficient *b* is then employed to test for convergence:

$$\text{Log}\left(\frac{\sigma_{h1}^2}{\sigma_{ht}^2}\right) - 2\log[L(t)] = c + b\ log(t) + u_t \qquad Eq(5)$$

$$\text{for } t = [rT], [rT] + 1, \dots, T$$

where $r \in (0,1)$ and $L(t)$ are slowly varying functions. For $T \leq 50$, Phillips and Sul (2007) suggest using $L(t)$ = log(t) and r = 0.3. In the case of convergence, $h_{it} \rightarrow 1$ for all i as $t \rightarrow \infty$. Applying a one-sided test, the null hypothesis of convergence ($b \geq 0$) is tested against the alternative $b < 0$. The null hypothesis of convergence is rejected at the 5% significance level if $t_{\hat{b}} <$ -1.65.

Phillips and Sul (2007) developed a four-step clustering algorithm for identifying so-called 'convergence clubs' in the relevant panel of cross-sectional units. In the first step, the units are sorted in descending order based on the last period in the time series dimension of the panel. Second, convergence clubs are identified using the log t test. This is done by adding regions one by one to a group consisting of the two highest housing price regions at the beginning and running the log t test until the convergence test statistic for this group is greater than |-1.65| (adopting a 5% significance level). The next step is to repeat the log t test for this group and all the units remaining in the sample, one by one, to check whether they converge. If they do not converge, the first three steps are applied to the remaining units. If no clubs are found, it can be concluded that the geographical units diverge over time.

Since this algorithm tends to overestimate the number of convergence clubs, Phillips and Sul (2009) propose merging the groups formed according to the clusters using the same test at a later stage. In this context, the algorithm commences by taking the first and second groups and running the log t test. We do not reject the null hypothesis as long as the t-statistic is smaller than |-1.65|, concluding that both groups form a club. We repeat the test after adding the next group and continue until the log t test indicates a rejection of the convergence hypothesis. From this, it can be concluded that all groups except the last one converge. Finally, we repeat the test with the group for which the convergence hypothesis was rejected.

Some drawbacks of the log t test include the loss of observations due to the computation of the long-term component using the Hodrick-Prescott filter and the specification of the null hypothesis as 'convergence', which implies that the inferential support for convergence, as well as convergence clubs, is, at best, weak (the non-rejection of H_0).

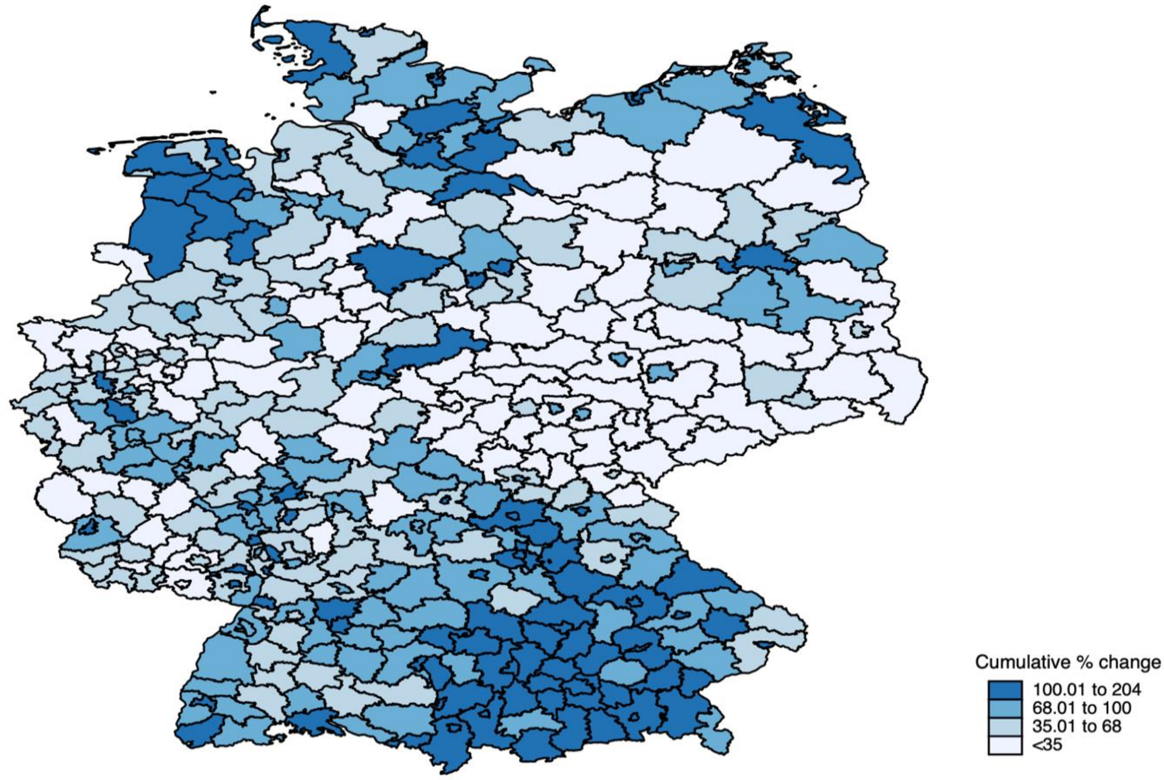
2.3 Data

We use data from two main sources: the Regional Real Estate Information System (RIWIS)[2] and the Federal Statistical Office of Germany (Destatis). The transaction price of a given house is measured as an absolute value in euros; flat prices and rents are all measured as the average price (in euros) per square metre (sqm) and are obtained from RIWIS; unemployment rate, population density, GDP per capita, share of immigrants, and the share of asylum seekers at the district level are obtained from Destatis. House/flat prices and rents are constructed using both unit-specific valuations and transaction data from building societies, loan associations, research institutes, estate agents' associations, and chambers of industry and commerce (see Boddin et al., 2023). By combining these two sources, the dataset employed for the regression analysis covers the period from 2004 to 2020 and includes 401 German administrative districts.

[2] RIWIS is a commercial property price analyst, collecting and analysing data on regional property markets for over 30 years to create indices for various residential and commercial market sectors throughout Germany. The data provided by RIWIS are a widely accepted source of information and are used by a number of reputable institutions, including the Bundesbank (Kholodilin et al., 2018).

To achieve a broad overview of the degree of convergence in the markets for different types of dwellings in Germany, we employ various housing prices and rents in our study. Such an approach can facilitate the identification of housing markets for which prices exhibit diverging trends, which may signify potential imbalances. For instance, when house prices increase considerably faster than rents, this may imply an overheated market and foreshadow an impending correction. Conversely, when rents rise swiftly while house prices remain relatively stable, this may denote a shortage of rental properties relative to demand, thereby offering an opportunity for real estate investors. In sum, incorporating various types of measures in a convergence study can furnish a more comprehensive outlook of the overall housing market, which, in turn, may equip policymakers, investors, and analysts with greater insight to make informed decisions.

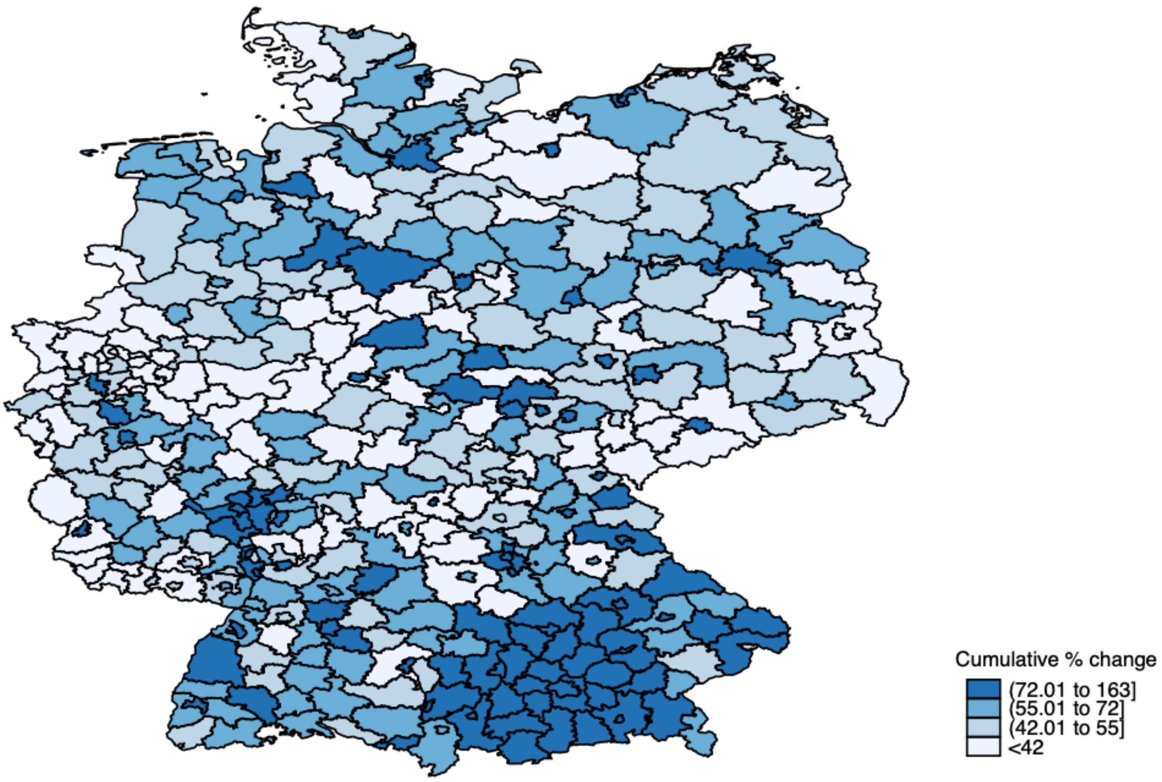
Figure 1: Cumulative Changes in Flat Prices/sqm by Administrative Districts in Germany (2004−2020)



From 2004 to 2020, housing prices and rents across Germany exhibited heterogeneous dynamics. Specifically, the median price of a single-family house increased by 54%, the rate of increase per sqm for flats was 69%, and the median rent per sqm increased by 46%. These aggregate developments in housing prices were accompanied by substantial variations across the country's districts. For example, Figure 1 shows notable increases in the price of flats in Bavaria and parts of Lower Saxony and Mecklenburg. The highest increases in the prices of flats occurred in Munich, Rostock and Ingolstadt.[3] Similarly, the largest price hikes for single-family houses were recorded in Jena, Furstenbeldbruck, and Munich, as shown in Figure 2.

[3] Rental prices follow a similar pattern (Unal et. al., 2020).

Figure 2: Cumulative Changes in House Prices by Administrative Districts in Germany (2004-2020)



3. Empirical Results

Applying a 5%-significance level, our results reveal no evidence of unconditional β-convergence employing district-level data for housing prices and rents across Germany or within states (Table A1). Regarding standard deviations, our statistical tests for σ-convergence suggest significant divergence across almost all regions (Table A2). Using coefficients of variation instead of standard deviations reveals significant evidence of σ-divergence at the federal level for all housing prices (Table A3). At the state level, the occurrence of significant σ-divergence varies depending on the type of housing price. For instance, concerning new flat prices (new flat rents), 11 (4) out of 13 states evince significant σ-divergence. We observe significant evidence of σ-convergence in only one case, new flat prices in Saarland.

In the light of these considerations, we try to identify the factors that facilitate or limit the convergence processes of housing prices and rents that are found when employing the concept of conditional β-convergence. Research has shown that regional economic performance is a key determinant of house price movements; regions with strong economic growth and employment opportunities tend to have higher house prices than regions with weaker economic performance. This is because housing demand is driven by income and population growth (Mallick and Mahalik, 2015). In Germany, there are notable regional disparities in economic performance, with some regions experiencing strong growth and others facing economic challenges (OECD, 2018). Similarly, differences in housing demand are another reason for house price dispersion. Housing markets are inherently local, with differences in demand between regions and districts (Cheshire et al., 2015). In Germany, there are notable regional differences in population growth and migration patterns, which can affect housing demand and lead to housing market dispersion (Unal et al., 2022). Given the limited availability of data at the district level in Germany, we consider several key variables that capture district heterogeneity, namely the unemployment rate, the natural logarithm of GDP per capita, population density, and the shares of immigrants and asylum seekers.[4] The results are presented in Table A4.

For the sake of brevity, we limit our interpretation of the results to Germany as a whole, which can be found in the first column of these tables. Regarding the explanatory variables, our findings show that income, population density and the unemployment rate are the most robust determinants, as they are statistically significant in all model specifications. In terms of immigration variables, our analysis reveals that migration only significantly has a positive impact on the convergence patterns of existing rents, whereas the number of asylum seekers exerts a significantly positive influence on the convergence patterns of existing flat prices and new flat rents.

In a broader context, our analysis reveals a conditional convergence phenomenon occurring within the German rental market highlighted by significantly negative beta coefficients in Table A4. Conversely, the sales market does not exhibit a converging pattern.[5] Although there is substantial evidence of convergence in rental prices across all districts in Germany, the state-level analysis (columns 2 to 13) indicates that this trend occurs in only 8 out of 13 German states. These results point to a fragmented rental market. Given these findings, we have decided to include rental prices in our club analysis, in addition to the sales market, which will allow us to fully identify the factors contributing to the fragmented state of rental markets at a later stage.

The log *t* test results for districts at the country and within-state levels are presented in Table A5. The results indicate the rejection of the null hypothesis of full panel convergence at the 5% level of significance, with the exception of new flat prices in Saarland. Given the rejection of convergence, we consider it interesting to study the potential existence of multiple housing price steady states in the form of convergence clubs between states and districts at the state level. The club clustering algorithm identifies 13 clubs across Germany regarding housing prices (house prices, existing flat prices, and new flat prices) and 14 and 7 clubs for existing and new flat rents, respectively (Table 1, Panel A and Table A6).

While it was possible to merge small clubs into larger clubs in the club-merging analysis, the results shown in Table 1 (Panel B) and Table A7 indicate that the merging of clubs is only supported in a small number of cases. The club merging algorithm reduces the number of identified clubs to 11 for existing flat prices, 8 for house prices, 7 for existing flat rents and new flat prices, and 5 for new flat rents.[6] These numbers are higher than those reported for other European countries, such as the UK (Montagnoli and Nagayasu, 2015) and Spain (Blanco et al., 2016). Regarding the case of the UK, it seems likely that we do not observe such a large number of clubs because of the City of London, which dominates the country. To a lesser extent, this is also the case in Spain, where about 15% of the Spanish population lives in the

[4] Erol and Unal (2022) offer comprehensive insights into the period of migration policy liberalization in Germany spanning from 2005 to 2018, providing in-depth information and analysis.

[5] At the state level, the only exceptions to this convergence trend are observed in Hesse, North Rhine-Westphalia, Rhineland-Palatinate and Saarland for flat prices and in Brandenburg, Baden-Wurttemberg, and Saxony-Anhalt for house prices.

[6] The log *t* test results for the convergence clubs within each state are provided in Table A5. Maps showing within-state convergence are presented in Figures A1-A13.

metropolitan region of Madrid. We have no such dominant market in Germany (its largest city Berlin hosts about 5% of the German population), which is much more decentralised than the UK and Spain. Another possible explanation is based on the fact that house ownership is more widespread in the UK and Spain. This could help create a broader base for price competition and less market fragmentation.

More generally, Germany, a federal country without a clear centre, has a highly diverse and decentralised economy, with significant variations between districts in terms of industrial structure, economic performance, and development. Some districts serve as economic powerhouses, while others rely on tourism and agriculture. This diversity could facilitate the formation of distinct clubs, where districts with similar economic profiles converge among themselves but not with others. This, in turn, can result in different growth paths and consequently, higher numbers of convergence clubs. Historical factors can also play an important role in explaining the relevant differences between Germany, Spain and the UK. This is especially true when considering Germany's historical division and reunification, which has had a long-standing impact on its regional economies.

Finally, differences in local housing policies and regulations may cause divergence among districts. Regulations, such as rent controls and restrictions on new construction, can affect the supply and demand for housing, which in turn can impact house prices (Cheshire et al., 2015). In Germany, there are significant regional differences in housing market regulations, with some states imposing stricter regulations than others (Dathe et al., 2021). Each German state has its own building laws, with further variations at the district level. There are numerous differences between German states regarding the sale of public plots for building houses. For instance, in North Rhine-Westphalia, public land can be sold without a proper tendering procedure (Article 15(3) HHG, Budget Law). Additionally, real estate taxes can vary considerably across states and districts. There are also ‘rent breaks’ operating in various regions based on Article 556d(1) of Germany’s civil law (Bürgerliches Gesetzbuch, BGB). According to Article 556d(2) BGB, most German states, except Saxony, Saxony-Anhalt, and Saarland, regulate rents based on average rents or housing experts and review these rules every five years (Wissenschaftliche Dienste des Deutschen Bundestages 2021). These regulatory differences are likely to cause divergence house prices across regions and cities.

The estimated geographical segmentation of the housing markets is illustrated graphically in Figures 3 to 7. The convergence club members do not necessarily neighbour each other geographically, suggesting that conventional definitions of regions, such as administrative districts, may not be the best choice for studying regional housing market dynamics.

Table 1 shows that although some states (e.g. Bavaria, Baden-Wurttemberg, Lower Saxony and Hesse) feature at least 6 convergence clubs for housing prices, most of the states have a lower number of convergence clubs (e.g. Brandenburg and Mecklenburg-Vorpommern), or even evince convergence across all districts (Saarland). Hence, the heterogeneity of district-level housing markets within German states is smaller than that across Germany. This suggests that state-level differences in economic development or housing laws matter for housing dynamics.

Given the variation in regulation across states, some results are puzzling. One would generally expect districts in more regulated states, such as Brandenburg and Mecklenburg-Vorpommern, to show a higher degree of homogeneity and a greater tendency to converge than in other states. Although our analysis cannot directly address this issue, the evidence we find suggests that state-level rent regulation does not exert a particularly strong influence in Germany. Our conjecture is that the number of convergence clubs is primarily determined by the size of the state and the homogeneity of its economic dynamics, rather than state government regulation (see also the club analysis below). For instance, Saarland, a small state without notable economic powerhouses, has only one convergence club. It is important to note, however, that there is no counterfactual scenario that describes how the number of clubs would appear in the absence of regulation.

Table 1. Number of Clubs Based on the Initial Convergence and Testing for Club Merging

	A: Initial Convergence Club Specification					B: After Club Merging				
	House Price	Existing Flat Price	New Flat Price	Existing Flat Rent	New Flat Rent	House Price	Existing Flat Price	New Flat Price	Existing Flat Rent	New Flat Rent
Federal level										
Germany	13	13	13	14	7	8	11	7	7	5
States (Lander) level										
Baden-Wurttemberg	7	7	5	5	3	5	5	5*	4	3*
Bavaria	12	9	9	6	7	9	8	6	5	5
Brandenburg	4	4	2	4	2	4*	4*	2*	4*	2*
Hesse	6	7	5	4	3	5	5	3	3	3*
Lower Saxony	6	8	3	7	5	5	7	3*	4	4
Mecklenburg-Vorpommern	2	2	3	2	2	2*	2*	3*	2*	1
North Rhine-Westphalia	5	6	8	9	5	5*	5	5	6	2
Rhineland-Palatinate	6	6	3	8	7	6*	6*	3*	7	4
Saarland	2	1	1	1	1	2*	1*	1*	1*	1*
Saxony	4	4	4	5	3	4*	4*	4*	5*	3*
Saxony-Anhalt	5	3	4	2	5	4	3*	4*	1	5*
Schleswig-Holstein	3	2	3	4	4	2	2*	3*	3	2
Thuringia	3	6	4	5	3	3*	6*	4*	5*	3*

Notes: *indicates that no clubs can be merged. 'City states' (Hamburg, Bremen, and Berlin) are excluded from the within-state analysis.

Another interesting observation emerging from Table 1 is that existing flat prices are characterised by a higher number of clubs compared to new flats. Again, we cannot directly learn about the reason from our empirical analysis. However, this observation may be due to the fact that housing markets in Germany are fragmented. In some districts, there is a severe shortage of flats, while others have an oversupply. In other words, the majority of existing flats can be found in both expanding and declining districts. However, construction activity leading to an increase in new flats is predominantly concentrated in expanding districts, which reduces the number of distinctive clubs. On the other hand, new developments or projects tend to be more homogeneous and share similar characteristics, such as analogous construction technology and costs, comparable profit margins, identical age of the stock, similar building heights, and so forth. However, when considering the existing stock of flats or houses, we may find renewals, improvements, better locations (while in new development areas location does not differ significantly), diverse qualities and ages of buildings, etc. These factors are generally less uniform than the ones in newly constructed buildings, which potentially result in a lower number of distinctive clubs.

Overall, the results of our club convergence analysis indicate that prices in Germany's various housing markets are not converging towards a single uniform price. Instead, we find evidence of sub-groups of districts at the national and state level where housing prices tend to converge. In this context, a higher number of clusters could indicate a higher degree of fragmentation within the respective sub-market, with different regions experiencing different economic conditions and housing market dynamics. Correspondingly, fewer clusters may indicate a lower degree of housing market heterogeneity within the respective sub-market. In contrast to Holmes et al. (2019), who report that flat prices are more likely to converge than terraced house prices in England and Wales, we find the opposite in Germany. House prices are more likely to converge than flat prices, either across all districts or within convergence clubs.

In the next step, we investigate the potential drivers of convergence club formation. To analyse the interaction between our control variables and house price club membership, we employ an ordered logit model (Blanco et al., 2016). This model aims to predict how local characteristics affect the probability of a district being classified as a member of a particular convergence club. In our model, the dependent variable represents the club to which a district belongs, and is considered as an ordinal variable, as the observed clubs can be ranked according to the convergence level of district housing prices in the respective club. For the sake of brevity, we conduct this analysis only for Germany as a whole.

To facilitate the interpretation of the impact of explanatory variables on the probability of belonging to a particular club, we report the resulting marginal effects from the estimated ordered logit model in Table A8. The marginal effects are computed at the mean of all explanatory variables and quantify the change in the probability of belonging to a specific club given a small change in the explanatory variables. For flat prices and rents, increases in GDP per capita, population density and the share of immigrants generally raise the likelihood of membership in a club characterised by a higher housing price steady-state value. Greater economic prosperity, as measured by an increase in GDP per capita, is associated with districts belonging to more expensive flat clubs. This suggests a correlation between more affluent areas and higher flat prices and rents, presumably due to increased demand. Similarly, areas with greater population density are more likely to be in clubs with higher steady-state prices, suggesting that urban areas are characterised by higher housing demand, which pushes up flat prices and flat rents. Furthermore, a large immigrant population in certain regions increases the likelihood of these districts being classified in clubs with higher housing prices. This is consistent with the findings of Unal et al. (2022), who show that immigration has a positive effect on housing prices, especially at the lower end of the respective markets

Conversely, a fall in the unemployment rate and the share of asylum seekers is associated with an increased likelihood of belonging to a higher steady-state value club for flat prices and rents. Lower unemployment rates are associated with districts in pricier clubs, suggesting that economic stability has a positive impact on flat prices and rents. Districts with a lower share of asylum seekers also tend to be in the more expensive clubs. In some cases, social tensions, cultural differences, or perceptions about the integration of asylum seekers may influence housing choices. This could result in some local residents preferring to live in areas with fewer asylum seekers, which is likely to reduce demand in these areas.

Figure 3: Convergence of House Prices across German Districts

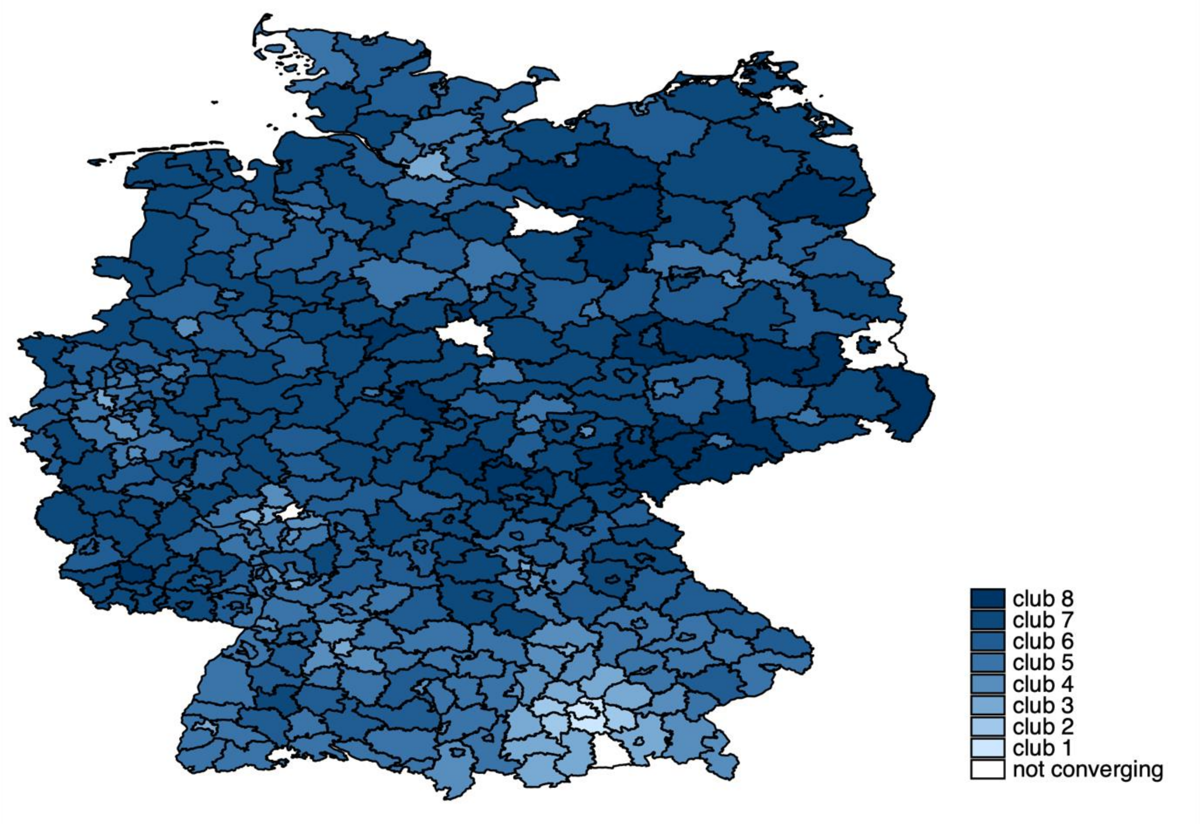


Figure 4: Convergence of Existing Flat Prices across German Districts

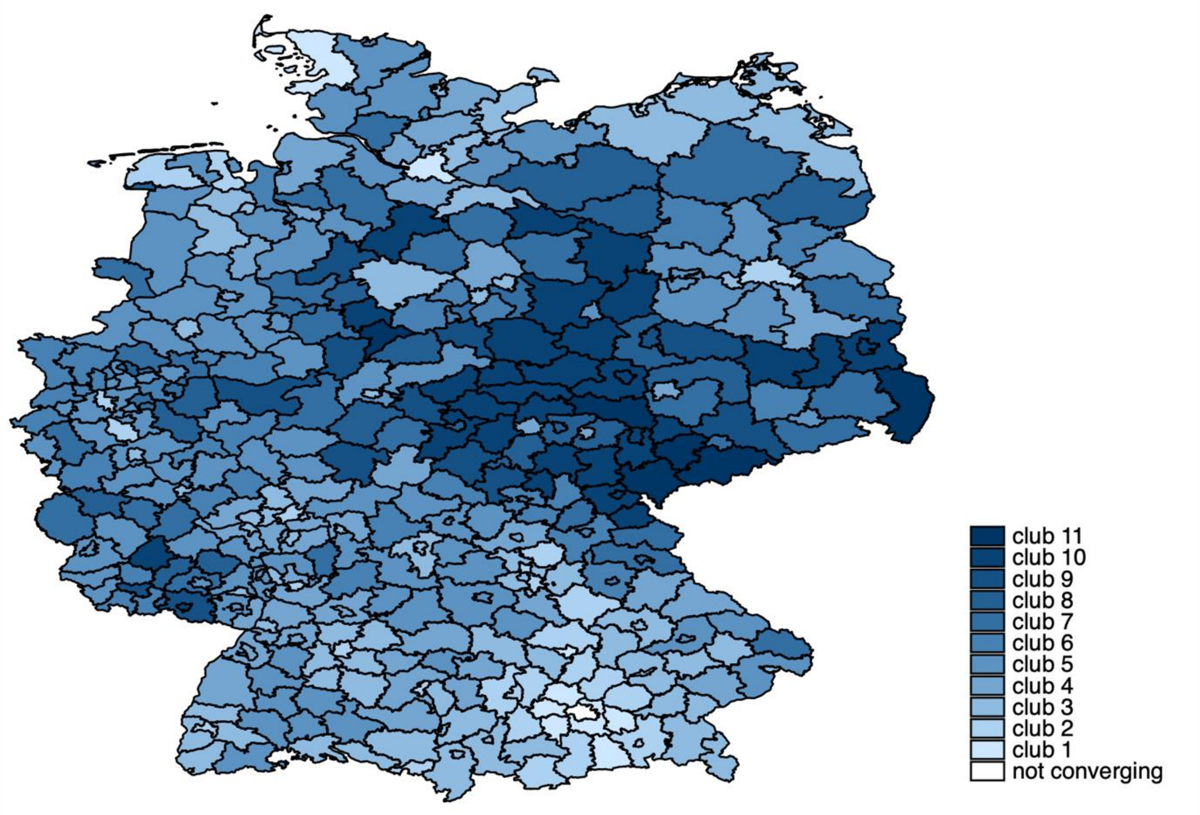


Figure 5: Convergence of New Flat Prices across German Districts

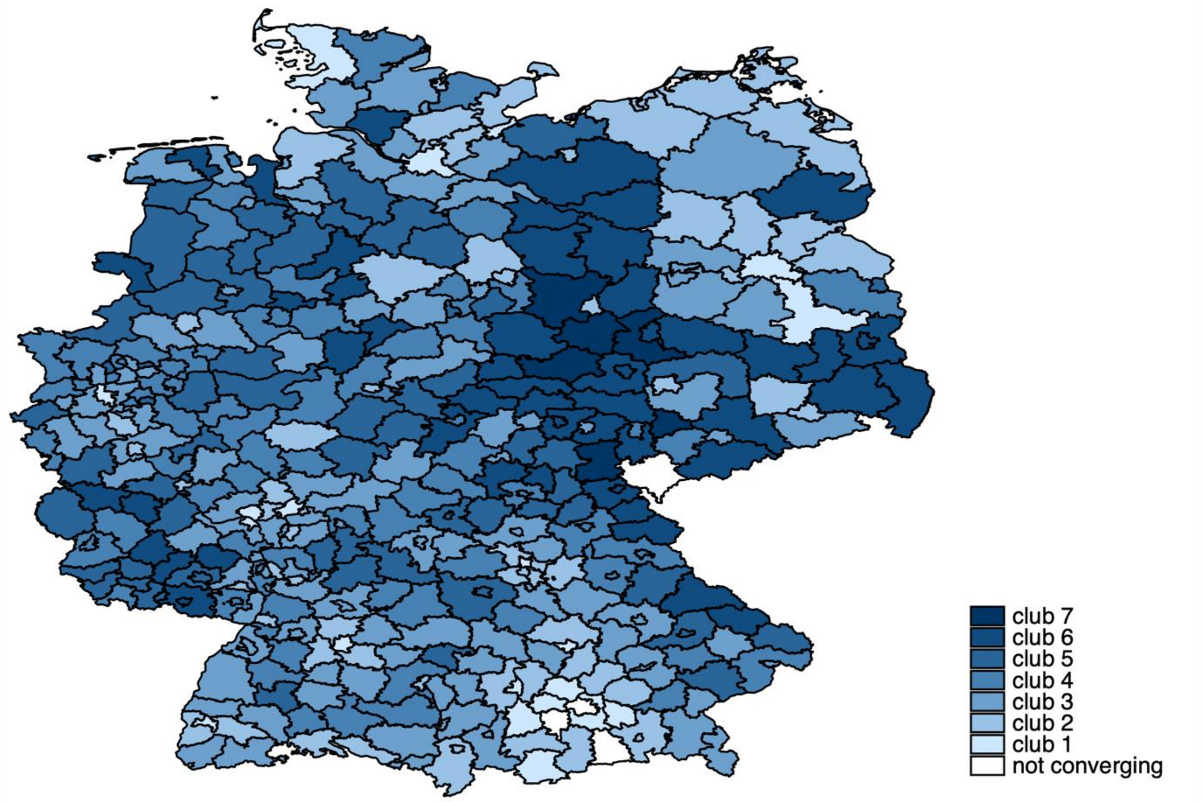


Figure 6: Convergence of Existing Flat Rents across German Districts

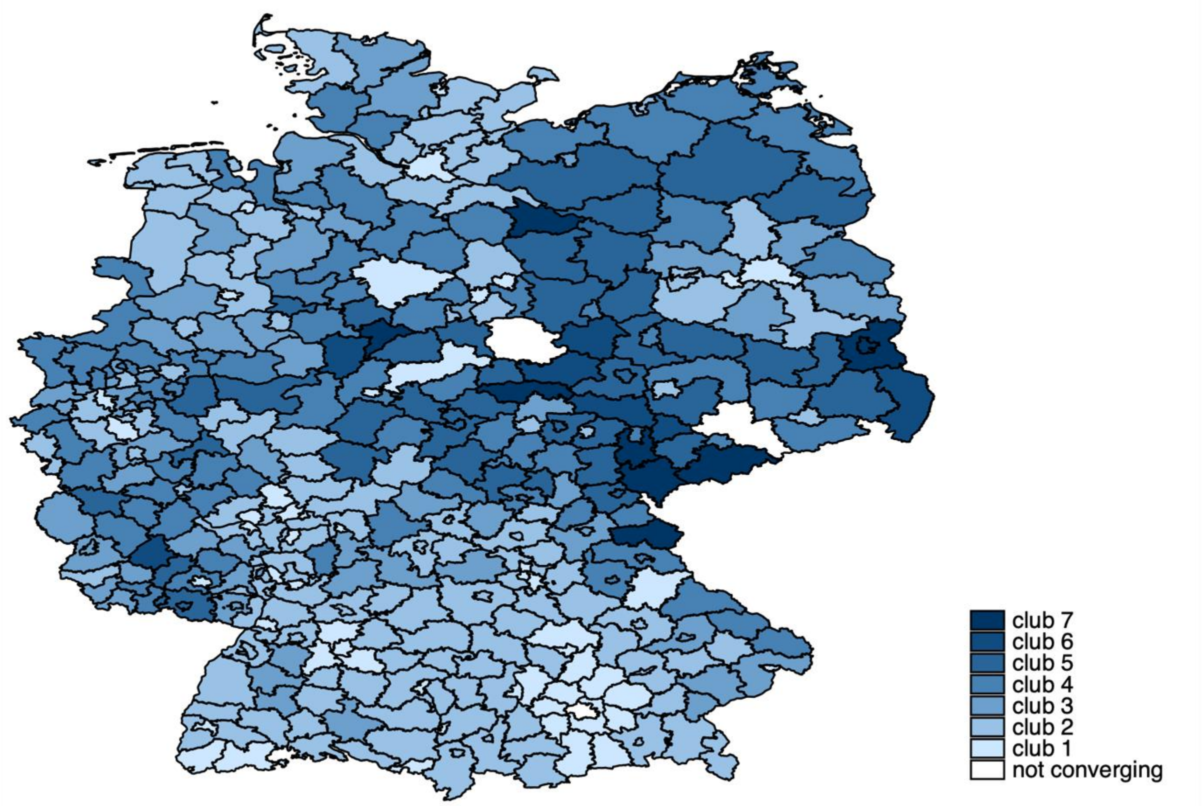
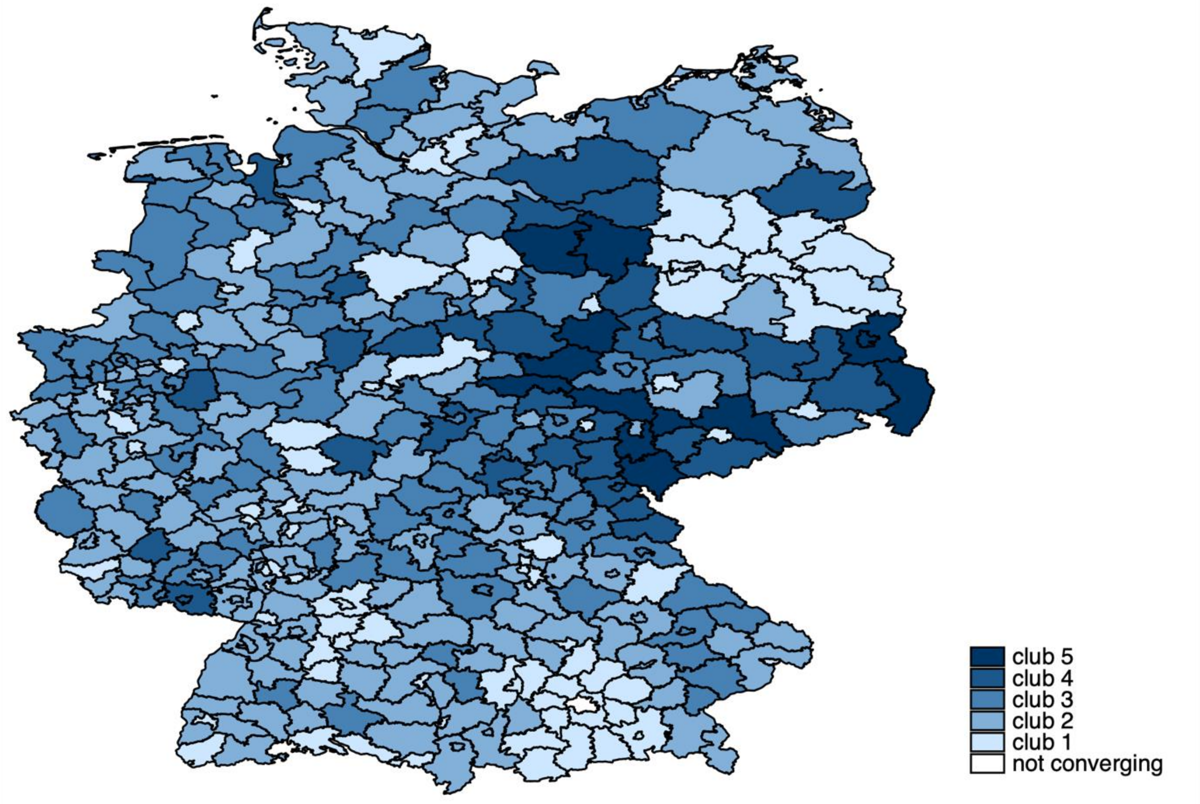


Figure 7: Convergence of New Flat Rents across German Districts



A similar trend is observed for house prices, with the exceptions of Clubs 1 and 2, where no significant influence was detected. This implies that in specific circumstances or market segments, the identified factors may not exert a strong influence on house prices. Certain regions or segments within the housing market may possess distinctive characteristics or market structures that render them less responsive to the explanatory variables considered in this analysis. For instance, Clubs 1 and 2 may exhibit unique housing supply dynamics, distinct demand catalysts, or regulatory environments that differ from the general trends observed in other districts.

4. Conclusion

When applied to Germany's administrative districts, the log *t* test (Phillips and Sul, 2007), together with the β- and σ-convergence methods, reveal no evidence of housing price convergence (except for new flat prices in Saarland). Conversely, we discover widespread divergence at the federal and state levels, as well as housing market segmentation within states in the form of convergence clubs. At the federal level, we identify the following club numbers: 11 clubs for existing flat prices, 8 clubs for house prices, 7 clubs for existing flat rents, 7 clubs for new flat prices, and 5 clubs for new flat rents. At the state level, the estimated number of clubs is generally lower, ranging from 0 to 6. Thus, regarding price convergence, we conclude that: (i) the German housing market appears to be relatively heterogeneous compared to other European countries, such as Spain (Blanco et al., 2016) or the UK (Montagnoli and Nagayasu, 2015); (ii) house prices in Germany are more likely to converge or become club members than existing and new flat prices (in contrast to the findings of Holmes et al. (2019) for England and Wales); and (iii) the members of the convergence clubs are not necessarily geographically adjacent, so we argue that administrative districts may not be the best choice for studying regional housing market dynamics.

Beyond identifying common convergence patterns, the study aims to uncover the underlying factors that shape these district clusters. Existing studies on the identification of housing price convergence clubs have revealed several determinants of membership. These include housing supply regulation and climate (Kim and Rous, 2012 for the US), regional economic and financial developments (Montagnoli and Nagayasu, 2015 for the UK), differences in population growth, rental market size, initial housing supply, and geographical location (Blanco et al., 2016 for Spain), as well as crime rates and congestion issues (Holmes et al., 2019 for England and Wales). Examining the identification of convergence clubs for rental housing in Poland, Tomal (2022) finds that the likelihood of any two cities belonging to the same club depends primarily on similarities in unemployment rate, housing stock, urban area, and student population.

To understand why housing prices rise faster in certain districts, ordered logit models are used to identify significant factors influencing the likelihood of club membership. We identify factors such as GDP per capita, population density (similar to the findings of Blanco et al., 2016 for Spain), unemployment rate (similar to the findings of Tomal, 2022 for Poland), and the shares of immigrants and asylum seekers as influential in determining club membership between 2004 and 2020. Districts with higher GDP per capita, greater population density, and a larger immigrant population are more likely to belong to a club with a higher steady state housing price level. Conversely, lower unemployment rate and a smaller share of asylum seekers are associated with higher-priced housing clubs. Moreover, it is interesting to note that differences in state-level regulation do not seem to have a strong impact on the number of estimated convergence clubs. Although we do not have a well-developed counterfactual, our analysis suggests that heterogeneous local economic dynamics are a much more influential factor for housing price convergence than current government regulation. The importance of different economic dynamics is also highlighted by the higher number of convergence clubs found for existing flats than for new flats: the latter tend to be concentrated in economically booming districts, whereas the former are more or less evenly distributed across growing and stagnating districts.

Further research could fruitfully explore in more detail the characteristics of convergent and divergent sub-groups and other possible factors driving the convergence clubs. Existing studies of housing price dynamics are often conceptualised in terms of changes in housing demand and supply (Glaeser et al., 2006; Malpezzi, 1996; and Saks, 2008), including economic (e.g., household income and the relative costs of renting versus owning), demographic and social indicators (e.g., variables that we cannot control for here, such as the composition of the population or the education level) on the demand side. Additionally, key factors on the supply side typically include construction costs, existing housing stock, and various territorial characteristics such as land availability and climate (Blanco et al., 2016). However, at this time, it is not easy to obtain suitable data on German districts accounting for all of the above factors. Moreover, it should be noted that attempting to model club membership as a function of these factors is not straightforward and may prove challenging, as spatial equilibrium models provide a theoretical justification for the endogeneity of income, population growth, and housing prices (Glaeser et al., 2006).

References:

Balcilar, M., A. Beyene, R. Gupta, & M. Seleteng (2013). 'Ripple'effects in South African house prices. *Urban Studies, 50*(5), 876–894.

Barro, R. J. and X. Sala-i-Martin (1992). Convergence. *Journal of Political Economy*, 100(2), 223–251.

Barros, C. P., L. A. Gil-Alana, & J. E. Payne (2012). Comovements among US state housing prices: Evidence from fractional cointegration. *Economic Modelling*, *29*(3), 936–942.

Blanco, F., V. Martín, & G. Vazquez (2016). Regional house price convergence in Spain during the housing boom. *Urban Studies, 53(4),* 775–798.

Boddin, D., te Kaat, D., Ma, C. and A. Rebucci (2023). A household housing portfolio channel of QE transmission. *Working Paper*; available at SSRN: https://ssrn.com/abstract=3782131.

Cai, Y., Y. Zhu & M. Helbich (2022). Club convergence of regional housing prices in China: evidence from 70 major Cities. *The Annals of Regional Science, 69,* 33–55.

Canarella, G., S. Miller, & S. Pollard (2012). Unit roots and structural change: An application to US house price indices. *Urban Studies, 49 (4)*, 757–776.

Chen, P. F., M. S. Chien, & C. C. Lee (2011). Dynamic modeling of regional house price diffusion in Taiwan. *Journal of Housing Economics, 20(4)*, 315–332.

Cheshire, P., C. Hilber, & H. Koster (2015). Regulating housing vacancies away? The paradoxical effects of mismatch. 55th Congress of the European Regional Science Association: 'World Renaissance: Changing roles for people and places', 25-28 August 2015, Lisbon, Portugal, European Regional Science Association (ERSA), Louvain-la-Neuve

Churchill, S. A., J. Inekwe, & K. Ivanovski (2018). House price convergence: Evidence from Australian cities. *Economics Letters, 170,* 88−90.

Cook, S. (2003). The convergence of regional house prices in the UK. *Urban Studies*, *40*(11), 2285–2294.

Cook, S. (2005). Detecting long-run relationships in regional house prices in the UK. *International Review of Applied Economics*, *19*(1), 107–118.

Cook, S. (2012). β-convergence and the cyclical dynamics of UK regional house prices. *Urban Studies*, *49(1),* 203–218.

Cook, S., & D. Watson (2016). A new perspective on the ripple effect in the UK housing market: Comovement, cyclical subsamples and alternative indices. *Urban Studies, 53(14),* 3048–3062.

Dathe, T. R. Dathe, A. Weise, I. Dathe & M. Helmold (2021). Die Regulierung des Wohnungsmarkts. In: *Berliner Mietendeckel & Co. - Staatseingriffe in den Immobilienmarkt*. Wiesbaden: Springer Gabler.

Erol, I., & Unal, U. (2022). Employment effects of immigration to Germany in the period of migration policy liberalization, 2005–2018. *Eurasian Economic Review, 12*(3), 531-565.

Ganioğlu, A. & Ü. Seven (2021), Do regional house prices converge? Evidence from a major developing economy. *Central Bank Review, 21,* 17−24.

Glaeser, E. L., J. Gyourko, & R. E. Saks (2006). Urban growth and housing supply. *Journal of Economic Geography, 6(1),* 71–89.

Gupta, R., & S. M. Miller (2012). "Ripple effects" and forecasting home prices in Los Angeles, Las Vegas, and Phoenix. *The Annals of Regional Science, 48,* 763–782.

Holmes, M. J., J. Otero, & T. Panagiotidis (2018). Climbing the property ladder: An analysis of market integration in London property prices. *Urban Studies, 55(12):* 2660–2681.

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

Holmes, M. J., J. Otero, & T. Panagiotidis (2019). Property heterogeneity and convergence club formation among local house prices. *Journal of Housing Economics, 43,* 1–13.

Kemeny, T., & M. Storper (2012). The sources of urban development: Wages, housing, and amenity gaps across American cities. *Journal of Regional Science, 52(1),* 85‒108.

Kholodilin, K. A., Michelsen, C., & Ulbricht, D. (2018). Speculative price bubbles in urban housing markets: Empirical evidence from Germany. *Empirical Economics, 55*(4), 1957–1983.

Kim, Y. S. & J. J. Rous (2012). House price convergence: evidence from US state and metropolitan area panels. *Journal of Housing Economics, 21*, 159–186.

Lau, C. K. M. (2010). New evidence about regional income divergence in China. *China Economic Review, 21*(2), 293–309.

Lean, H. H., & R. Smyth (2013). Regional house prices and the ripple effect in Malaysia. *Urban Studies, 50(5),* 895–922.

Lichtenberg, F. R. (1994). Testing the convergence hypothesis. *The Review of Economics and Statistics, 76(3),* 576–579.

Mallick, H., & M. K. Mahalik (2015). Factors determining regional housing prices: evidence from major cities in India. *Journal of Property Research, 32(2),* 123‒146.

Malpezzi, S., (1996). Housing prices, externalities, and regulation in US metropolitan areas. *Journal of Housing Research, 7(2),* 209–241.

Meen, G. (2016). Spatial housing economics: A survey. *Urban Studies, 53(10),* 1987‒2003.

Montagnoli, A. & J. Nagayasu (2015). UK house price convergence clubs and spillovers. *Journal of Housing Economics, 30,* 50−58.

Montanes, A. & L. Olmos (2013). Convergence in US house prices. *Economics Letters, 121*, 152–155.

Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section dependence. *Journal of Applied Econometrics*, *22(2)*, 265–312.

Phillips, P.C. & D. Sul (2007). Transition modeling and econometric convergence tests. *Econometrica*, *75*(6), 1771−1855.

Phillips, P.C. & D. Sul (2009). Economic transition and growth. *Journal of Applied Econometrics*, *24*(7), 1153−1185.

Quah, D. (1993). Galton's fallacy and tests of the convergence hypothesis. *The Scandinavian Journal of Economics*, *95*(4), 427−443.

Saks, R. E., (2008). Job creation and housing construction: constraints on metropolitan area employment growth. *Journal of Urban Economics, 64*, 178–195.

Tian, X., X. Zhang, Y. Zhou, & X. Yu (2016). Regional income inequality in China revisited: A perspective from club convergence. *Economic Modelling*, *56*, 50–58.

Tomal, M. (2022). Testing for overall and cluster convergence of housing rents using robust methodology: evidence from Polish provincial capitals. *Empirical Economics, 62*, 2023–2055.

Unal, U., B. Hayo, & I. Erol (2022). The effect of immigration on the German housing market. *MAGKS Joint Discussion Paper Series in Economics*, 38–2022.

Wissenschaftliche Dienste des Deutschen Bundestages (2021). Regelungen der Mietpreisregulierung in ausgewählten europäischen Staaten (https://www.bundestag.de/resource/blob/865064/cac1b33995c2c2694c580c5149120b1f/WD-7-069-21-pdf-data.pdf).

Appendix

Notes: ‘City states’ (Hamburg, Bremen, and Berlin) are excluded from the within-state analysis.

Table A1: Beta Convergence Test Results

	Germany	Baden-Wurttemberg	Bayern	Brandenburg	Hessen	Lower Saxony	Mecklenburg-Vorpommern	North Rhine Westphalia	Rhineland-Palatinate	Saarland	Saxony	Saxony Anhalt	Schleswig-Holstein	Thuringen
House Prices														
beta	0.14***	0.08	0.26***	0.27	0.19***	0.06	0.67	0.06	0.14**	-0.50	0.23	0.57	-0.19	0.27
	(0.02)	(0.05)	(0.05)	(0.16)	(0.06)	(0.12)	(0.74)	(0.07)	(0.06)	(0.19)	(0.30)	(0.28)	(0.18)	(0.29)
Constant	-1.28***	-0.51	-2.78***	-2.90	-1.90**	-0.35	-7.63	-0.42	-1.23	6.40	-2.45	-6.35	2.80	-2.81
	(0.27)	(0.69)	(0.59)	(1.93)	(0.79)	(1.50)	(8.94)	(0.91)	(0.74)	(2.35)	(3.66)	(3.37)	(2.23)	(3.52)
Observations	401	44	96	18	26	45	8	53	36	6	13	14	15	23
R-squared	0.09	0.05	0.25	0.15	0.27	0.01	0.12	0.01	0.13	0.63	0.05	0.25	0.08	0.04
Existing Flat Prices														
beta	0.64***	0.31**	0.39***	0.80***	0.42**	0.32	-0.01	0.53***	0.60**	0.86	0.75**	-0.81	0.16	0.73**
	(0.05)	(0.12)	(0.07)	(0.29)	(0.18)	(0.27)	(0.72)	(0.16)	(0.24)	(0.75)	(0.28)	(0.58)	(0.20)	(0.31)
Constant	-4.08***	-1.65	-2.12***	-5.30***	-2.56	-1.74	0.60	-3.45***	-3.80**	-5.85	-5.11**	5.65	-0.52	-5.06**
	(0.38)	(0.89)	(0.52)	(2.04)	(1.33)	(1.89)	(5.19)	(1.12)	(1.70)	(5.37)	(1.96)	(3.98)	(1.45)	(2.17)
Observations	401	44	96	18	26	45	8	53	36	6	13	14	15	23
R-squared	0.26	0.13	0.24	0.32	0.18	0.03	0.00	0.18	0.16	0.25	0.40	0.14	0.05	0.21
New Flat Prices														
beta	0.21***	0.27	0.46***	0.07	0.20	-0.48***	-0.19	0.34***	-0.26	-0.56	0.89	0.41	0.34	0.58
	(0.04)	(0.15)	(0.08)	(0.30)	(0.14)	(0.15)	(0.55)	(0.12)	(0.24)	(0.37)	(0.43)	(0.94)	(0.43)	(0.28)
Constant	-0.93***	-1.47	-2.90***	0.14	-0.85	4.16***	2.17	-1.91**	2.56	4.72	-5.86	-2.54	-1.89	-3.63
	(0.28)	(1.13)	(0.59)	(2.21)	(1.02)	(1.07)	(4.07)	(0.89)	(1.76)	(2.76)	(3.10)	(6.75)	(3.24)	(2.04)
Observations	401	44	96	18	26	45	8	53	36	6	13	14	15	23
R-squared	0.07	0.07	0.28	0.00	0.08	0.20	0.02	0.14	0.04	0.36	0.28	0.02	0.05	0.17
Existing Flat Rents														
beta	0.16***	-0.05	0.02	0.34	0.02	-0.07	0.94*	0.15	0.38***	-0.62	0.39	-0.09	-0.26	0.35
	(0.03)	(0.09)	(0.04)	(0.22)	(0.09)	(0.14)	(0.33)	(0.08)	(0.11)	(0.57)	(0.33)	(0.43)	(0.13)	(0.23)
Constant	0.10**	0.54***	0.41***	-0.25	0.33**	0.49***	-1.28*	0.06	-0.26	1.32	-0.41	0.32	0.82***	-0.30
	(0.05)	(0.15)	(0.07)	(0.36)	(0.16)	(0.22)	(0.54)	(0.13)	(0.17)	(0.93)	(0.51)	(0.64)	(0.22)	(0.36)
Observations	401	44	96	18	26	45	8	53	36	6	13	14	15	23
R-squared	0.06	0.01	0.00	0.13	0.00	0.01	0.58	0.07	0.28	0.23	0.12	0.00	0.23	0.10
New Flat Rents														
beta	0.08***	-0.05	0.07	0.24	-0.11	-0.10	0.01	-0.09	0.04	-0.85	1.67***	1.52	-0.24	0.39
	(0.03)	(0.08)	(0.05)	(0.29)	(0.08)	(0.17)	(0.21)	(0.09)	(0.13)	(0.42)	(0.33)	(0.88)	(0.14)	(0.27)
Constant	0.29***	0.54***	0.35***	0.09	0.65***	0.58**	0.46	0.56***	0.40	1.92	-2.29***	-2.07	0.90***	-0.30
	(0.06)	(0.15)	(0.09)	(0.49)	(0.16)	(0.29)	(0.35)	(0.17)	(0.23)	(0.72)	(0.54)	(1.38)	(0.25)	(0.44)
Observations	401	44	96	18	26	45	8	53	36	6	13	14	15	23
R-squared	0.02	0.01	0.02	0.04	0.07	0.01	0.00	0.02	0.00	0.51	0.69	0.20	0.20	0.09

Notes: Standard errors are in parentheses. ** and *** denote 5% and 1% significance levels, respectively.

Table A2: Sigma Convergence Test Results for Standard Deviation

	House Price			Existing Flat Price			New Flat Price			Existing Flat Rent			New Flat Rent		
	2004	2020		2004	2020		2004	2020		2004	2020		2004	2020	
Federal level															
Germany	91827	198557	+	344	1094	+	409	1158	+	1.04	1.96	+	1.19	2.21	+
State (Lander) level															
Baden-Wurttemberg	790890	151203	+	241	684	+	270	841	+	0.97	1.66	+	1.10	1.82	+
Bavaria	107220	272171	+	411	1245	+	417	1405	+	1.34	2.23	+	1.35	2.50	-
Brandenburg	45075	109162	+	232	744	+	280	855	+	0.61	1.39	+	0.81	2.00	+
Hesse	113670	222971	+	375	1055	+	404	1230	+	1.40	2.23	+	1.62	2.44	
Lower Saxony	29928	60824	+	200	694	+	252	482	+	0.60	1.07	+	0.63	1.34	+
Mecklenburg-Vorpommern	15222	65561	+	248	782	+	245	795	+	0.41	1.12	+	0.82	1.44	+
North Rhine-Westphalia	65287	122516	+	205	615	+	227	719	+	0.74	1.32	+	0.87	1.48	+
Rhineland-Palatinate	56475	111255	+	194	642	+	205	657	+	0.66	1.45	+	0.70	1.47	+
Saarland	24369	22454		106	302	+	113	179		0.24	0.38		0.35	0.46	
Saxony	32356	78426	+	240	571	+	189	872	+	0.41	0.95	+	0.47	2.13	+
Saxony-Anhalt	13120	42949	+	134	314	+	83	516	+	0.22	0.50	+	0.26	1.62	+
Schleswig-Holstein	51237	83128	+	427	1096	+	220	927	+	0.88	1.10		0.90	1.23	
Thuringia	23737	78877	+	175	503	+	176	670	+	0.43	1.04	+	0.59	1.60	+

Notes: The third column for each variable indicates the standard deviation F-test results (H_0: same standard deviation in 2004 and 2020; + = significant divergence and - = significant convergence).

Table A3: Sigma Convergence Test Results for Coefficient of Variation

	House Prices			Existing Flat Prices			New Flat Prices			Existing Flat Rents			New Flat Rents		
Federal level															
Germany	0.36	0.49	+	0.26	0.47	+	0.22	0.33	+	0.20	0.25	+	0.20	0.23	+
State (Lander) level															
Baden-Wurttemberg	0.25	0.30		0.15	0.23	+	0.12	0.21	+	0.16	0.18		0.16	0.17	
Bavaria	0.36	0.51	+	0.27	0.40	+	0.20	0.33	+	0.24	0.26		0.21	0.25	
Brandenburg	0.25	0.39		0.19	0.42	+	0.19	0.29	+	0.12	0.20	+	0.15	0.22	
Hesse	0.38	0.47		0.25	0.41	+	0.21	0.31	+	0.23	0.26		0.24	0.23	
Lower Saxony	0.15	0.20		0.18	0.36	+	0.16	0.17		0.13	0.15		0.11	0.16	+
Mecklenburg-Vorpommern	0.08	0.23	+	0.19	0.32		0.15	0.23		0.08	0.16		0.15	0.16	
North Rhine-Westphalia	0.23	0.31	+	0.15	0.31	+	0.12	0.21	+	0.14	0.18		0.14	0.16	
Rhineland-Palatinate	0.24	0.30		0.16	0.32	+	0.12	0.20	+	0.13	0.20	+	0.12	0.16	
Saarland	0.55	0.08		0.20	0.18		0.17	0.06	-	0.10	0.06		0.13	0.05	
Saxony	0.18	0.29		0.22	0.43	+	0.13	0.32	+	0.09	0.16	+	0.09	0.28	+
Saxony-Anhalt	0.09	0.19	+	0.14	0.29	+	0.06	0.24	+	0.05	0.09	+	0.05	0.24	+
Schleswig-Holstein	0.20	0.20		0.31	0.42		0.12	0.25	+	0.15	0.13		0.14	0.12	
Thuringia	0.15	0.32	+	0.16	0.43	+	0.13	0.29	+	0.09	0.17	+	0.12	0.22	+

Notes: The third column for each variable indicates the coefficient of variation *t*-test results (H_0: same coefficient of variation in 2004 and 2020; + = significant divergence and - = significant convergence).

Table A4: Conditional Convergence Test Results with Further Control Variables

	Germany	Baden-Wurttemberg	Bayern	Brandenburg	Hessen	Lower Saxony	Mecklenburg-Vorpommern	North Rhine Westphalia	Rhineland-Palatinate	Saarland	Saxony	Saxony Anhalt	Schleswig-Holstein	Thuringen
							House Prices							
beta	0.025	-0.499***	0.026	-0.566***	-0.088	0.115*	-0.015	-0.337	-0.187	0.015	0.122	-0.425***	0.004	-0.565
	(0.043)	(0.000)	(0.078)	(0.000)	(0.107)	(0.065)	(0.498)	(0.210)	(0.115)	(0.077)	(0.236)	(0.131)	(0.076)	(0.387)
Log GDP per capita	0.000***	0.000***	0.000***	0.000***	0.000	0.000	0.000	-0.000*	-0.000**	-0.000**	-0.000**	-0.000	0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Population density	0.051**	*(omitted)*	0.018	*(omitted)*	-0.017	-0.029	-0.003	0.707**	0.241***	0.171**	0.125	0.373***	-0.029	0.713**
	(0.022)		(0.030)		(0.085)	(0.034)	(0.570)	(0.286)	(0.067)	(0.065)	(0.104)	(0.055)	(0.039)	(0.272)
Unemployment rate	-0.016***	-0.094***	-0.013	-0.024***	-0.034	-0.019	0.013	-0.049*	-0.043***	-0.013**	-0.022	-0.073***	0.012	0.012
	(0.004)	(0.000)	(0.012)	(0.000)	(0.029)	(0.013)	(0.050)	(0.025)	(0.011)	(0.006)	(0.013)	(0.015)	(0.021)	(0.019)
Share of immigrants	-0.004	-0.042***	-0.006	-0.006***	0.015**	0.017**	0.019	0.069	-0.013	-0.003	-0.019	0.045**	-0.004	0.061
	(0.003)	(0.000)	(0.006)	(0.000)	(0.007)	(0.007)	(0.210)	(0.089)	(0.010)	(0.008)	(0.040)	(0.015)	(0.007)	(0.047)
Share of Asylum seekers	-0.015	-0.592***	-0.044	0.008***	0.083	0.003	0.223	-0.245	0.103*	0.044	0.211	-0.458***	0.024	-0.463**
	(0.017)	(0.000)	(0.050)	(0.000)	(0.054)	(0.026)	(0.175)	(0.141)	(0.055)	(0.059)	(0.121)	(0.088)	(0.032)	(0.168)
Observations	788	12	106	12	52	192	24	36	90	72	28	30	88	46
R-squared	0.177	1.000	0.483	1.000	0.485	0.304	0.565	0.607	0.403	0.297	0.854	0.873	0.304	0.488
							Existing Flat Prices							
beta	0.197***	-0.142***	0.054	*(omitted)*	-0.411	0.067	1.173**	-0.321	0.201	-0.196	-0.921***	0.324*	0.098	-0.322
	(0.066)	(0.000)	(0.216)		(0.262)	(0.092)	(0.471)	(0.394)	(0.293)	(0.300)	(0.244)	(0.177)	(0.146)	(0.244)
Log GDP per capita	0.000***	0.000***	0.000	0.000***	0.000	0.000	0.000	-0.000	0.000**	-0.000	-0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Population density	0.120***	*(omitted)*	0.078*	-2.970***	0.008	0.073	0.362	0.255	0.358***	0.067	0.293	0.410***	0.075	0.498*
	(0.027)		(0.044)	(0.000)	(0.101)	(0.049)	(0.244)	(0.393)	(0.124)	(0.152)	(0.314)	(0.136)	(0.064)	(0.262)
Unemployment rate	-0.048***	-0.227***	-0.042**	0.276***	-0.096**	-0.066***	0.120	-0.065**	-0.067**	-0.072***	-0.048	-0.021	-0.008	-0.008
	(0.006)	(0.000)	(0.018)	(0.000)	(0.045)	(0.017)	(0.070)	(0.026)	(0.027)	(0.021)	(0.038)	(0.016)	(0.028)	(0.019)
Share of immigrants	-0.001	-0.119***	0.010	0.017***	0.039***	0.017**	-0.419*	0.162	-0.024	0.036*	0.024	0.065**	0.000	0.131**
	(0.004)	(0.000)	(0.011)	(0.000)	(0.012)	(0.008)	(0.211)	(0.155)	(0.023)	(0.020)	(0.124)	(0.027)	(0.008)	(0.055)
Share of Asyl seekers	0.070***	-1.226***	-0.001	0.294***	0.228***	0.070	0.802**	-0.293	0.199	0.442***	0.162	-0.697***	0.026	-0.324
	(0.025)	(0.000)	(0.112)	(0.000)	(0.040)	(0.046)	(0.304)	(0.306)	(0.133)	(0.125)	(0.373)	(0.149)	(0.061)	(0.198)
Observations	788	12	106	12	52	192	24	36	90	72	28	30	88	46
R-squared	0.479	1.000	0.340	1.000	0.754	0.487	0.737	0.612	0.298	0.471	0.792	0.618	0.427	0.810
							New Flat Prices							
beta	-0.008	-1.507***	0.157	-0.402***	-0.411**	0.165*	0.382	-0.652**	-0.628***	-0.787***	0.450	0.339	-0.200	-1.113***
	(0.067)	(0.000)	(0.176)	(0.000)	(0.175)	(0.095)	(0.404)	(0.287)	(0.136)	(0.145)	(0.412)	(0.376)	(0.158)	(0.288)
Log GDP per capita	0.000***	0.000***	0.000**	-0.000***	0.000***	0.000*	0.000	-0.000	0.000*	-0.000**	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Population density	0.077***	*(omitted)*	-0.047	*(omitted)*	-0.011	0.066	0.599*	0.210	0.195***	0.269***	-0.096	0.159	0.167**	0.460**
	(0.020)		(0.034)		(0.074)	(0.048)	(0.289)	(0.316)	(0.065)	(0.091)	(0.204)	(0.168)	(0.067)	(0.205)
Unemployment rate	-0.009**	-0.225***	0.009	0.014***	-0.029	-0.031**	0.061	-0.071***	-0.032***	-0.050***	0.002	0.009	-0.062*	-0.024**
	(0.004)	(0.000)	(0.010)	(0.000)	(0.028)	(0.014)	(0.067)	(0.022)	(0.011)	(0.010)	(0.021)	(0.031)	(0.032)	(0.011)
Share of immigrants	0.000	-0.280***	0.006	-0.014***	0.015**	0.010	-0.269	0.030	-0.018	0.009	0.107**	0.041	0.009	0.071**
	(0.002)	(0.000)	(0.008)	(0.000)	(0.006)	(0.006)	(0.186)	(0.090)	(0.011)	(0.010)	(0.046)	(0.033)	(0.007)	(0.032)

Share of Asyl seekers	0.012	-0.584***	-0.044	0.073***	0.037	-0.009	0.256	-0.026	0.135*	0.231***	0.086	-0.656*	0.045	0.047
	(0.020)	(0.000)	(0.047)	(0.000)	(0.047)	(0.033)	(0.169)	(0.167)	(0.072)	(0.075)	(0.282)	(0.362)	(0.058)	(0.125)
Observations	788	12	106	12	52	192	24	36	90	72	28	30	88	46
R-squared	0.227	1.000	0.298	1.000	0.703	0.454	0.573	0.590	0.421	0.675	0.863	0.360	0.568	0.769
Existing Flat Rents														
beta	-0.167***	*(omitted)*	-0.039	*(omitted)*	-0.431**	-0.245***	-0.044	-0.471*	-0.375***	0.041	-0.706***	-0.275***	-0.327***	-0.945***
	(0.032)		(0.088)		(0.156)	(0.049)	(0.167)	(0.243)	(0.125)	(0.134)	(0.100)	(0.053)	(0.107)	(0.260)
Log GDP per capita	0.000***	-0.000***	0.000	0.000***	0.000**	0.000	0.000	-0.000	0.000***	-0.000	0.000*	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Population density	0.056***	0.628***	0.026	-1.844***	-0.023	0.045	0.036	0.164	0.167***	-0.012	-0.001	0.175***	0.086**	0.344***
	(0.012)	(0.000)	(0.018)	(0.000)	(0.057)	(0.028)	(0.097)	(0.171)	(0.047)	(0.059)	(0.047)	(0.037)	(0.036)	(0.106)
Unemployment rate	-0.022***	-0.049***	-0.016*	0.188***	-0.028	-0.026***	-0.001	-0.035***	-0.037***	-0.022*	-0.004	-0.008	-0.039**	-0.001
	(0.002)	(0.000)	(0.008)	(0.000)	(0.025)	(0.009)	(0.024)	(0.009)	(0.010)	(0.011)	(0.004)	(0.007)	(0.019)	(0.010)
Share of immigrants	0.004**	-0.151***	0.003	0.015***	0.018**	0.014***	0.024	0.069	-0.006	0.014**	0.021*	0.018**	0.009	0.036*
	(0.002)	(0.000)	(0.005)	(0.000)	(0.007)	(0.004)	(0.070)	(0.067)	(0.007)	(0.007)	(0.012)	(0.006)	(0.007)	(0.018)
Share of Asyl seekers	0.014	0.279***	0.073	0.118***	0.072***	0.013	-0.044	-0.117	0.095*	0.142	0.083	-0.320***	0.055	-0.266*
	(0.012)	(0.000)	(0.045)	(0.000)	(0.024)	(0.026)	(0.050)	(0.106)	(0.054)	(0.088)	(0.070)	(0.052)	(0.037)	(0.129)
Observations	788	12	106	12	52	192	24	36	90	72	28	30	88	46
R-squared	0.485	1.000	0.313	1.000	0.634	0.442	0.812	0.513	0.498	0.520	0.949	0.883	0.436	0.696
New Flat Rents														
beta	-0.175***	*(omitted)*	-0.365***	*(omitted)*	-0.404***	-0.239***	1.499**	-0.101	-0.427***	-0.374***	-0.484**	-0.386*	-0.330***	-1.006**
	(0.038)		(0.123)		(0.126)	(0.068)	(0.595)	(0.229)	(0.155)	(0.110)	(0.219)	(0.186)	(0.094)	(0.382)
Log GDP per capita	0.000**	-0.000***	0.000	0.000***	0.000	0.000	-0.000**	-0.000***	0.000*	0.000	0.000*	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Population density	0.065***	1.781***	0.025	-2.007***	0.043	0.053	0.180	-0.229	0.167***	0.034	0.119	0.124*	0.086**	0.547**
	(0.015)	(0.000)	(0.025)	(0.000)	(0.054)	(0.033)	(0.217)	(0.242)	(0.060)	(0.059)	(0.141)	(0.059)	(0.038)	(0.238)
Unemployment rate	-0.016***	0.069***	-0.023**	0.200***	-0.015	-0.029***	-0.043	-0.040***	-0.035***	-0.032***	-0.027	-0.012	-0.026	-0.009
	(0.003)	(0.000)	(0.010)	(0.000)	(0.020)	(0.011)	(0.027)	(0.006)	(0.010)	(0.005)	(0.017)	(0.018)	(0.019)	(0.012)
Share of immigrants	0.000	-0.454***	0.009	0.016***	0.007	0.012***	0.063	0.095	-0.005	0.010	-0.058	0.016	0.010*	0.015
	(0.002)	(0.000)	(0.007)	(0.000)	(0.006)	(0.004)	(0.102)	(0.075)	(0.009)	(0.006)	(0.042)	(0.014)	(0.006)	(0.035)
Share of Asyl seekers	0.039**	1.757***	0.082*	0.096***	0.073**	0.003	0.040	-0.001	0.112**	0.146**	0.376***	-0.159	0.024	0.014
	(0.016)	(0.000)	(0.044)	(0.000)	(0.031)	(0.029)	(0.090)	(0.156)	(0.049)	(0.058)	(0.122)	(0.098)	(0.029)	(0.145)
Observations	788	12	106	12	52	192	24	36	90	72	28	30	88	46
R-squared	0.218	1.000	0.256	1.000	0.578	0.330	0.839	0.675	0.428	0.552	0.917	0.452	0.485	0.649

Notes: Clustered standard errors are in parentheses. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively.

Table A5: **Log *t* test results**

	Variable	*b*-coefficient	*t-statistic*
Germany	House price	-1.142	-381.256***
	Existing flat price	-1.819	-123.889***
	New flat price	-1.204	-257.406***
	Existing Flat Rent	-1.076	-404.518***
	New Flat Rent	-0.868	-53.648***
Baden-Wurttemberg	House price	-1.053	-81.641***
	Existing flat price	-1.426	-85.419***
	New flat price	-1.540	-595.240***
	Existing Flat Rent	-0.813	-58.701***
	New Flat Rent	-0.637	-22.958***
Bavaria	House price	-1.340	-1048.007***
	Existing flat price	-1.497	-673.528***
	New flat price	-1.527	-235.307***
	Existing Flat Rent	-0.715	-31.794***
	New Flat Rent	-0.769	-31.082***
Brandenburg	House price	-1.373	-135.632***
	Existing flat price	-2.098	-49.281***
	New flat price	-1.395	-43.617***
	Existing Flat Rent	-1.471	-508.574***
	New Flat Rent	-1.234	-67.391***
Hesse	House price	-1.069	-93.347***
	Existing flat price	-1.579	-112.142***
	New flat price	-1.202	-236.833***
	Existing Flat Rent	-0.762	-41.167***
	New Flat Rent	-0.562	-18.899***
Lower Saxony	House price	-1.601	-99.486***
	Existing flat price	-2.253	-191.328***
	New flat price	-0.867	-28.631***
	Existing Flat Rent	-1.234	-181.792***
	New Flat Rent	-1.182	-231.757***
Mecklenburg-Vorpommern	House price	-2.473	-95.834***
	Existing flat price	-1.991	-76.770***
	New flat price	-1.518	-112.588***
	Existing Flat Rent	-1.881	-505.035***
	New Flat Rent	-0.648	-34.837***
North Rhine – Westphalia	House price	-0.990	-70.345***
	Existing flat price	-1.768	-185.235***
	New flat price	-1.227	-187.280***
	Existing Flat Rent	-0.955	-54.963***
	New Flat Rent	-0.605	-15.281***
Rhineland-Palatinate	House price	-1.117	-155.560***
	Existing flat price	-1.961	-115.906***
	New flat price	-1.740	-95.559***
	Existing Flat Rent	-1.195	-92.955***
	New Flat Rent	-1.004	-31.915***
Saarland	House price	-0.747	-32.221***
	Existing flat price	-1.594	-36.186***
	New flat price	0.283	3.092
	Existing Flat Rent	-1.380	-26.738***
	New Flat Rent	-1.431	-15.912***
Saxony	House price	-1.761	-53.282***
	Existing flat price	-2.109	-48.624***
	New flat price	-1.779	-776.116***
	Existing Flat Rent	-1.782	-404.466***
	New Flat Rent	-1.837	-114.003***
Saxony-Anhalt	House price	-1.623	-384.122***
	Existing flat price	-3.343	-19.898***
	New flat price	-3.005	-325.983***
	Existing Flat Rent	-2.206	-29.014***
	New Flat Rent	-2.767	-118.926***

Schleswig-Holstein	House price	-0.888	-79.225***
	Existing flat price	-1.231	-194.716***
	New flat price	-1.355	-110.177***
	Existing Flat Rent	-0.657	-74.747***
	New Flat Rent	-0.324	-8.276**
Thuringia	House price	-1.770	-78.286***
	Existing flat price	-2.318	-144.696***
	New flat price	-1.624	-113.980***
	Existing Flat Rent	-1.633	-399.594***
	New Flat Rent	-1.520	-231.050***

Notes: ** and *** indicate the rejection of H_0 = convergence at the 5% and 1% significance levels, respectively.

Table A6: Log *t* test - Initial Convergence Clubs

		House Price		Existing flat price		New flat price		Existing Flat Rent		New Flat Rent	
		b-coefficient	*t-statistic*	*b*-coefficient	*t-statistic*	*b*-coefficient	*t-statistic*	*b*-coefficient	*t-statistic*	*b*-coefficient	*t-statistic*
Germany	Club 1	2.037	7.776	0.219	3.223	0.091	1.296	0.267	4.091	0.145	1.948
	Club 2	0.03	0.307	0.287	4.218	1.119	0.743	0.34	4.51	0.17	2.121
	Club 3	0.648	5.374	0.326	3.155	0.116	1.235	0.266	3.794	0.116	1.578
	Club 4	0.346	2.893	0.082	1.037	0.382	5.71	0.136	2.032	-0.068	-1.209
	Club 5	0.281	3.333	0.158	2.61	0.272	3.535	0.21	2.883	-0.014	-0.589
	Club 6	0.127	1.729	0.361	3.899	0.151	2.166	0.163	1.932	1.315	8.762
	Club 7	0.293	2.754	-0.032	-1.204	0.314	3.269	0.236	2.34	1.487	4.071
	Club 8	0.235	2.676	0.771	5.541	0.329	3.278	0.142	1.622		
	Club 9	0.125	1.633	0.48	3.451	0.224	1.929	0.112	1.466		
	Club 10	0.163	1.594	0.391	8.791	0.435	4.999	0.296	2.603		
	Club 11	0.269	3.649	0.322	4.849	0.457	4.317	0.489	3.737		
	Club 12	0.552	3.954	0.285	5.923	0.084	1.028	0.17	2.275		
	Club 13	1.085	7.403	-0.024	-0.094	0.693	5.57	0.742	3.007		
	Club 14	-1.342	-333.729+	-1.666	-132.968+	-1.566	-488.279+	0.051	0.711		
	Club 15							-1.321+	-759.838+		
Baden-Wurttemberg	Club 1	0.583	5.834	-0.016	-0.331	0	-0.007	0.06	2.259	-0.065	-1.356
	Club 2	2.78	4.931	0.732	9	-0.021	-0.257	0.503	8.436	0.13	1.809
	Club 3	0.302	2.911	-2.146	-1.381	0.041	0.304	7.405	4.262	0.416	4.108
	Club 4	0.006	0.077	0.856	6.366	0.1	1.566	3.194	9.74	-0.443	-38.248+
	Club 5	0.334	2.901	0.5	6.175	0.352	4.214	1.001	3.576		
	Club 6	0.308	4.087	0.938	1.885	-1.752	-710.064+	2.227	52.947+		
	Club 7	1.724	5.585	1.688	5.649						
	Club 8	-1.246	-156.627+	-1.639	-122.306+						
Bavaria	Club 1	2.037	7.776	0.132	2.551	0.194	2.274	0.188	3.328	0.31	6.474
	Club 2	0.03	0.307	0.182	2.571	-0.079	-1.626	0.14	1.938	0.136	1.96
	Club 3	-0.078	-1.116	0.073	0.982	0.451	12.25	0.15	2.05	0.087	1.485
	Club 4	0.068	1.147	0.045	0.923	1.527	9.572	0.213	3.478	0	-0.005
	Club 5	-0.003	-0.048	0.233	1.386	0.245	2.267	0.143	1.624	0.221	3.031
	Club 6	0.146	1.441	-0.071	-1.096	1.068	10.534	0.244	2.604	0.198	8.584
	Club 7	0.201	1.414	0.002	0.038	0.418	4.475			0.987	8.954
	Club 8	0.132	1.296	1.575	5.18	0.798	5.427			-0.925	-14.649+
	Club 9	0.323	2.734	1.117	2.931	0.4	5.305				
	Club 10	-0.073	-1.562	-1.804	-259.708+	-1.953	-379.337+				
	Club 11	0.515	7.026								
	Club 12	0.949	3.958								

Brandenburg	Club 1	0.189	3.924	0.35	2.662	0.003	0.062	1.655	4.382	0.097	1.726
	Club 2	4.631	2.081	0.038	0.314	0.595	10.076	0.974	5.115	0.529	6.407
	Club 3	0.481	4.87	2.266	5.42	-6.554	-5.693+	0.506	8.805	-1.04	-70.59+
	Club 4	1.364	5.558	0.708	6.535			0.112	0.2		
	Club 5	-1.916	-354.284+	-1.905	-118.455+			-1.603	-176.592+		
Hesse	Club 1	1.815	6.201	0.023	0.61	0.822	5.543	0.155	2.287	0.06	1.307
	Club 2	-0.027	-1.181	-4.569	-1.493	0.744	13.803	0.244	3.886	0.354	3.998
	Club 3	0.25	5.733	0.378	4.248	0.476	13.177	0.31	3.601	0.189	4.435
	Club 4	0.094	1.558	0.048	0.811	0.438	3.367	0.375	5.324	-0.789	-26.125
	Club 5	0.183	2.522	4.672	2.902	0.747	5.521				
	Club 6	0.524	3.469	0.15	0.424	-0.665	-13.423+				
	Club 7	-1.164	-62.732+	0.352	5.302						
	Club 8			-1.527	-180.134+						
Lower Saxony	Club 1	0.236	10.188	-0.109	-0.676	1.036	9.901	-0.025	-1.619	0.328	5.261
	Club 2	-0.042	-0.638	-1.325	-0.794	0.245	3.736	0.53	7.595	0.921	7.157
	Club 3	0.05	0.627	-0.391	-1.176	1.672	8.6	1.309	4.391	0.935	4.566
	Club 4	0.879	7.176	3.623	6.799			1.239	2.511	0.144	3.383
	Club 5	0.165	2.904	1.31	0.918			-0.286	-0.137	0.472	7.964
	Club 6	1.412	3.177	0.495	3.201			4.893	3.634	-1.333	-129.951+
	Club 7	-1.234	-28.906+	0.059	1.383			0.939	9.715		
	Club 8			0.206	2.317			-2.283	-64.118+		
	Club 9			-2.047	-138.708+						
Mecklenburg-Vorpommern	Club 1	-0.879	-0.318	2.984	6.481	0.043	1.467	1.197	8.421	0.032	0.388
	Club 2	2.496	8.103	2.57	7.765	0.64	3.354	1.685	1.177	0.23	2.192
	Club 3	-2.911	-72.107+	-4.685	-48.327+	3.111	1.973	-1.9	-733.692+	-1.74	-164.749+
	Club 4										
North Rhine - Westphalia	Club 1	5.422	3.648	1.281	6.606	0.337	2.215	-0.25	-1.112	0.185	2.024
	Club 2	0.9	4.338	0.218	5.517	0.489	3.389	0.26	2.345	0.077	0.83
	Club 3	0.066	0.739	-0.011	-0.221	0.42	3.39	0.202	2.6	0.319	3.462
	Club 4	0.286	3.043	0.587	4.245	0.2	2.509	0.182	1.736	0.297	3.15
	Club 5	0.162	1.782	0.689	3.511	0.121	1.477	0.277	2.807	0.663	1.766
	Club 6	-0.783	-9.017+	0.37	2.342	0.056	1.527	0.106	0.787	-1.166	-22.86+
	Club 7			-1.715	-175.133+	1.087	4.945	0.606	6.336		
	Club 8					-3.265	-0.882	0.205	6.957		
	Club 9					-1.484	-57.611+	0.515	4.298		
	Club 10							-1.505	-40.601+		

Rhineland-Palatinate	Club 1	1.024	7.112	0.002	0.009	0.03	0.537	1.273	11.511	1.342	44.435
	Club 2	0.312	3.739	0.597	10.009	1.025	6.292	0.919	8.887	0.948	1.021
	Club 3	0.81	3.548	1.134	2.707	0.19	4.52	0.196	12.329	0.254	2.139
	Club 4	-0.036	-0.85	3.05	2.146	-2.366	-59.011+	0.855	6.817	1.659	5.186
	Club 5	0.585	3.991	0.227	0.624			0.294	3.825	0.54	4.536
	Club 6	0.562	1.998	5.154	3.952			0.557	4.162	0.725	6.164
	Club 7	-0.824	-35.329+	-2.25	-140.755+			1.808	1.75	-0.277	-0.581
	Club 8							-0.132	-0.319	-1.928	-60.163+
	Club 9							-0.979	-25.064+		
Saarland	Club 1	2.051	1.282	0.267	2.229	0.283	3.092	5.53	2.976	0.542	1.026
	Club 2	1.181	2.756	-2.898	-140.89+			1.244	5.997+	-7.72	-11.354+
	Club 3	-0.593	-9.188+								
Saxony	Club 1	0.563	5.441	1.826	6.018	0.297	2.799	0.139	0.926	3.674	2.258
	Club 2	0.536	3.338	0.699	4.672	-2	-0.708	1.397	7.904	-0.212	-0.079
	Club 3	4.007	0.753	1.579	1.134	0.688	4.074	2.663	4.137	0.434	3.953
	Club 4	0.521	5.877	0.328	2.665	2.545	1.977	0.26	1.445	-3.172	-91.926+
	Club 5					-2.337	-50.976+	-0.024	-0.154		
Saxony-Anhalt	Club 1	6.504	5.532	2.125	16.146	0.369	1.386	0.361	5.372	1.952	0.708
	Club 2	2.013	4.456	0.022	0.03	0.875	5.646	0.475	2.296	0.196	1.717
	Club 3	0.997	3.616	0.69	2.444	4.669	1.62	-3.286	-141.959+	-0.366	-1.193
	Club 4	4.278	4.302	-3.91	-35.671+	0.909	0.392			0.882	0.675
	Club 5	0.737	3.337			-3.342	-63.259+			0.687	5.458
	Club 6									-5.041	-12.583+
Schleswig-Holstein	Club 1	0.137	1.797	0.265	3.492	1.114	4.863	0.598	12.617	0.067	0.705
	Club 2	2.314	21.861	0.337	3.274	0.045	1.313	0.307	3.492	0.285	3.269
	Club 3	0.495	6.863	-1.316	-127.55+	1.5	6.816	0.107	4.975	-0.054	-1.463
	Club 4	-1.292	-167.45+			-1.88	-48.834+	0.547	3.864	0.337	12.118
Thuringia	Club 1	1.841	10.048	0.171	1.176	2.759	5.937	1.881	8.034	0.011	0.064
	Club 2	0.009	0.046	1.819	6.447	0.193	1.605	0.203	3.031	1.014	15.604
	Club 3	-0.099	-1.379	1.932	12.048	0.444	8.507	0.204	1.544	1.201	7.67
	Club 4	-4.342	-83.259+	0.802	0.359	1.757	8.261	1.197	8.809	-2.529	-93.929+
	Club 5			0.565	3.966			0.022	0.143		
	Club 6			1.143	6.888			-1.642	-33.241+		
	Club 7										

Notes: The clubs are obtained by applying the algorithm proposed by Phillips and Sul (2007), which is based on finding groups of districts with similar convergence speeds. *t-statistic* is the convergence test statistic, which is distributed as a one-sided *t*-test with a critical value of −1.65 at the 5% significance level. "+" indicates a non-convergent group rather than a club in the respective row.

Table A7: Log *t* test - Club Merging

		House Price		Existing flat price		New flat price		Existing Flat Rent		New Flat Rent	
		b-coefficient	*t*-statistic	*b*-coefficient	*t*-statistic	*b*-coefficient	*t*-statistic	*b*-coefficient	*t*-statistic	*b*-coefficient	*t*-statistic
Germany	Club 1	2.037	7.776	0.219	3.223	-0.08	-0.941	0.043	0.915	0.158	2.154
	Club 2	0.03	0.307	0.049	0.737	0.027	0.477	-0.03	-0.573	0.116	1.578
	Club 3	0.129	1.919	0.054	0.968	0.092	1.253	0.163	1.932	-0.068	-1.209
	Club 4	0.281	3.333	0.361	3.899	0.224	1.929	-0.024	-0.352	-0.014	-0.589
	Club 5	-0.075	-1.182	-0.032	-1.204	0.435	4.999	0.133	2.314	-0.014	-0.311
	Club 6	0.235	2.676	0.771	5.541	-0.033	-0.544	0.742	3.007	-1.261	-155.690+
	Club 7	-0.09	-1.542	0.48	3.451	0.693	5.57	0.051	0.711		
	Club 8	-0.076	-1.526	0.391	8.791	-1.566	-488.279+	-1.321	-759.838+		
	Club 9	-1.342	-333.729+	0.322	4.849						
	Club 10			0.285	5.923						
	Club 11			-0.024	-0.094						
	Club 12			-1.666	-132.968+						
Baden-Wurttemberg	Club 1	0.583	5.834	-0.016	-0.331	No clubs can be merged		0.06	2.259	No clubs can be merged	
	Club 2	2.78	4.931	0.909	7.989			0.448	6.295		
	Club 3	0.235	2.626	0.856	6.366			0.126	2.01		
	Club 4	0.334	2.901	0.5	6.175			2.227	52.947		
	Club 5	-0.047	-0.907	0.31	5.902			-1.096	-67.692+		
	Club 6	-1.246	-156.627+	-1.639	-122.306+						
Bavaria	Club 1	2.037	7.776	0.132	2.551	0.194	2.274	0.188	3.328	-0.001	-0.028
	Club 2	0.03	0.307	0.182	2.571	-0.079	-1.626	-0.164	-0.279	0	-0.005
	Club 3	-0.078	-1.116	-0.039	-0.672	-0.017	-0.266	0.213	3.479	0.221	3.031
	Club 4	0.068	1.147	0.233	1.386	0.021	0.263	0.143	1.624	0.198	8.584
	Club 5	-0.017	-0.211	-0.071	-1.096	0.383	4.678	0.244	2.604	0.987	8.954
	Club 6	0.168	1.694	0.002	0.038	0.4	5.305			-0.925	-14.649+
	Club 7	-0.073	-1.562	1.575	5.18	-1.953	-379.337+				
	Club 8	0.515	7.026	1.117	2.931						
	Club 9	0.949	3.958	-1.804	-259.708+						
Brandenburg	Club 1	No clubs can be merged		No clubs can be merged		No clubs can be merged		No clubs can be merged		No clubs can be merged	
	Club 2										
	Club 3										
	Club 4										
	Club 5										
Hesse	Club 1	1.815	6.201	0.168	4.273	0.822	5.543	-0.037	-0.786	No clubs can be merged	
	Club 2	-0.027	-1.181	-0.069	-1.352	0.119	2.475	0.31	3.601		
	Club 3	0.25	5.733	4.672	2.902	0.017	0.269	0.375	5.324		
	Club 4	0.094	1.558	0.15	0.424	-0.665	-13.423+	-1.034	-52.551+		

	Club 5	0.233	2.985	0.352	5.302						
	Club 6	-1.164	-62.732+	-1.527	-180.134+						
Lower Saxony	Club 1	0.236	10.188	-0.109	-0.676	No clubs can be merged		-0.025	-1.619	0.328	5.261
	Club 2	-0.042	-0.638	-1.325	-0.794			0.217	5.952	0.894	6.617
	Club 3	-0.05	-1.38	-0.391	-1.176			0.906	6.246	0.144	3.383
	Club 4	0.165	2.904	1.188	4.712			0.939	9.715	0.472	7.964
	Club 5	1.412	3.177	0.495	3.201			-2.283	-64.118+	-1.333	-129.951+
	Club 6	-1.234	-28.906+	0.059	1.383						
	Club 7			0.206	2.317						
	Club 8			-2.047	-138.708+						
Mecklenburg-Vorpommern	Club 1	No clubs can be merged		No clubs can be merged		No clubs can be merged		No clubs can be merged		-0.078	-1.283
	Club 2									-1.74	-164.749
	Club 3										
	Club 4										
North Rhine - Westphalia	Club 1	No clubs can be merged		1.281	6.606	0.337	2.215	-0.25	-1.112	-0.028	-0.379
	Club 2			0.218	5.517	-0.051	-0.684	0.26	2.345	-0.062	-1.168
	Club 3			-0.011	-0.221	0.121	1.477	0.162	2.09	-1.166	-22.86+
	Club 4			0.083	1.028	0.254	3.62	0.106	0.787		
	Club 5			0.37	2.342	-3.265	-0.882	0.377	5.873		
	Club 6			-1.715	-175.133+	-1.484	-57.611+	0.515	4.298		
	Club 7							-1.505	-40.601+		
Rhineland-Palatinate	Club 1	No clubs can be merged		No clubs can be merged		No clubs can be merged		1.273	11.511	1.342	44.435
	Club 2							0.919	8.887	0.293	3.198
	Club 3							0.196	12.329	-0.084	-1.205
	Club 4							0.855	6.817	-0.277	-0.581
	Club 5							0.294	3.825	-1.928	-60.163+
	Club 6							0.127	1.101		
	Club 7							-0.132	-0.319		
	Club 8							-0.979	-25.064+		
Saarland	Club 1	No clubs can be merged		No clubs can be merged		No clubs can be merged		No clubs can be merged		No clubs can be merged	
	Club 2										
	Club 3										
Saxony	Club 1	No clubs can be merged		No clubs can be merged		No clubs can be merged		No clubs can be merged		No clubs can be merged	
	Club 2										
	Club 3										
	Club 4										
	Club 5										

Saxony-Anhalt	Club 1	6.504	5.531	No clubs can be merged		No clubs can be merged		-0.018	-0.749	No clubs can be merged	
	Club 2	2.012	4.455					-3.286	-141.958+		
	Club 3	0.250	1.991								
	Club 4	0.737	3.336								
	Club 5										
	Club 6										
Schleswig-Holstein	Club 1	-0.039	-0.613	No clubs can be merged		No clubs can be merged		0.272	7.606	0.06	0.819
	Club 2	0.495	6.863					0.107	4.975	-0.054	-1.463
	Club 3	-1.292	-167.45+					0.547	3.864		
	Club 4							1.287	-61.843+		
Thuringia	Club 1	No clubs can be merged		No clubs can be merged		No clubs can be merged		No clubs can be merged		No clubs can be merged	
	Club 2										
	Club 3										
	Club 4										
	Club 5										
	Club 6										

Notes: The clubs are obtained by applying the algorithm proposed by Phillips and Sul (2007), which is based on finding groups of districts with similar convergence speeds. *t-statistic* is the convergence test statistic, which is distributed as a one-sided *t*-test with a critical value of -1.65 at the 5% significance level. "+" indicates a non-convergent group rather than a club in the respective row.

Table A8: Estimation Results from Ordered Logit Model – Average Marginal Effects

		Club 1	Club 2	Club 3	Club 4	Club 5	Club 6	Club 7	Club 8	Club 9	Club 10	Club 11
House Prices	Log GDP per capita	0.001	0.003	0.022***	0.062***	0.218***	-0.058**	-0.222***	-0.028***			
		(0.001)	(0.002)	(0.008)	(0.021)	(0.067)	(0.026)	(0.066)	(0.010)			
	Population density	0.001	0.002	0.018***	0.052***	0.184***	-0.049**	-0.187***	-0.023***			
		(0.001)	(0.001)	(0.006)	(0.013)	(0.043)	(0.019)	(0.041)	(0.007)			
	Unemployment rate	0.000	-0.001	-0.004***	-0.013***	-0.045***	0.012***	0.046***	0.006***			
		(0.000)	(0.000)	(0.001)	(0.003)	(0.008)	(0.004)	(0.008)	(0.001)			
	Share of immigrants	0.000	0.000	0.003***	0.007***	0.026***	-0.007**	-0.026***	-0.003***			
		(0.000)	(0.000)	(0.001)	(0.002)	(0.006)	(0.003)	(0.006)	(0.001)			
	Share of Asylum seekers	-0.001	-0.002	-0.013***	-0.036***	-0.128***	0.034***	0.131***	0.016***			
		(0.001)	(0.001)	(0.004)	(0.007)	(0.021)	(0.012)	(0.020)	(0.004)			
Existing Flat Prices	Log GDP per capita	0.011**	0.052***	0.203***	0.107***	-0.034	-0.099***	-0.110***	-0.050***	-0.028***	-0.048***	-0.006*
		(0.005)	(0.013)	(0.044)	(0.027)	(0.027)	(0.025)	(0.026)	(0.014)	(0.010)	(0.005)	(0.003)
	Population density	0.007**	0.035***	0.138***	0.072***	-0.023	-0.067***	-0.074***	-0.034***	-0.019***	-0.033***	-0.004**
		(0.003)	(0.010)	(0.029)	(0.018)	(0.018)	(0.016)	(0.018)	(0.010)	(0.007)	(0.002)	(0.002)
	Unemployment rate	-0.002**	-0.011***	-0.045***	-0.024***	0.007	0.022***	0.024***	0.011***	0.006***	0.011***	0.001**
		(0.001)	(0.003)	(0.006)	(0.005)	(0.006)	(0.004)	(0.005)	(0.003)	(0.002)	(0.002)	(0.001)
	Share of immigrants	0.001*	0.003***	0.013***	0.007***	-0.002	-0.006***	-0.007***	-0.003***	-0.002**	-0.003***	-0.000*
		(0.000)	(0.001)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.000)	(0.000)
	Share of Asylum seekers	-0.005**	-0.022***	-0.086***	-0.045***	0.014	0.042***	0.046***	0.021***	0.012***	0.020***	0.002**
		(0.002)	(0.005)	(0.013)	(0.010)	(0.011)	(0.009)	(0.010)	(0.006)	(0.004)	(0.000)	(0.001)
New Flat Prices	Log GDP per capita	0.026***	0.134***	0.136***	-0.077***	-0.119***	-0.095***	-0.008**				
		(0.009)	(0.038)	(0.043)	(0.025)	(0.035)	(0.028)	(0.004)				
	Population density	0.029***	0.149***	0.151***	-0.085***	-0.132***	-0.105***	-0.009**				
		(0.008)	(0.031)	(0.035)	(0.022)	(0.027)	(0.020)	(0.004)				
	Unemployment rate	-0.005***	-0.025***	-0.025***	0.014***	0.022***	0.018***	0.001**				
		(0.001)	(0.004)	(0.006)	(0.003)	(0.004)	(0.003)	(0.001)				
	Share of immigrants	0.001**	0.007**	0.007**	-0.004**	-0.006**	-0.005**	-0.000*				
		(0.001)	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.000)				
	Share of Asylum seekers	-0.009***	-0.048***	-0.049***	0.028***	0.043***	0.034***	0.003**				
		(0.003)	(0.009)	(0.012)	(0.007)	(0.009)	(0.007)	(0.001)				
Existing Flat Rents	Log GDP per capita	0.153***	0.360***	-0.123***	-0.269***	-0.103***	-0.011**	-0.009**				
		(0.031)	(0.068)	(0.032)	(0.052)	(0.022)	(0.005)	(0.004)				
	Population density	0.090***	0.212***	-0.073***	-0.158***	-0.061***	-0.006**	-0.005**				
		(0.021)	(0.045)	(0.021)	(0.035)	(0.014)	(0.003)	(0.002)				
	Unemployment rate	-0.020***	-0.047***	0.016***	0.035***	0.013***	0.001**	0.001**				
		(0.004)	(0.008)	(0.004)	(0.007)	(0.003)	(0.001)	(0.000)				
	Share of immigrants	0.010***	0.024***	-0.008***	-0.018***	-0.007***	-0.001**	-0.001**				
		(0.003)	(0.006)	(0.003)	(0.005)	(0.002)	(0.000)	(0.000)				
	Share of Asylum seekers	-0.056***	-0.131***	0.045***	0.098***	0.037***	0.004**	0.003**				
		(0.009)	(0.022)	(0.011)	(0.016)	(0.007)	(0.002)	(0.001)				
New Flat Rents	Log GDP per capita	0.200***	0.096**	-0.212***	-0.070***	-0.014**						
		(0.060)	(0.040)	(0.064)	(0.022)	(0.006)						
	Population density	0.231***	0.111***	-0.245***	-0.081***	-0.017***						
		(0.049)	(0.037)	(0.050)	(0.019)	(0.005)						
	Unemployment rate	-0.036***	-0.017***	0.038***	0.013***	0.003***						

	(0.006)	(0.007)	(0.008)	(0.003)	(0.001)
Share of immigrants	0.013***	0.006**	-0.014***	-0.004**	-0.001**
	(0.005)	(0.003)	(0.005)	(0.002)	(0.000)
Share of Asylum seekers	-0.071***	-0.034***	0.075***	0.025***	0.005***
	(0.012)	(0.012)	(0.015)	(0.005)	(0.002)

Notes: The dependent variables takes value 1 for series in Club 1, and so on, until value 11 for price series in Club 11. Marginal effects are calculated at mean values. Clustered standard errors in parentheses. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively.

Figure A1: Convergence Maps for Baden-Wurttemberg

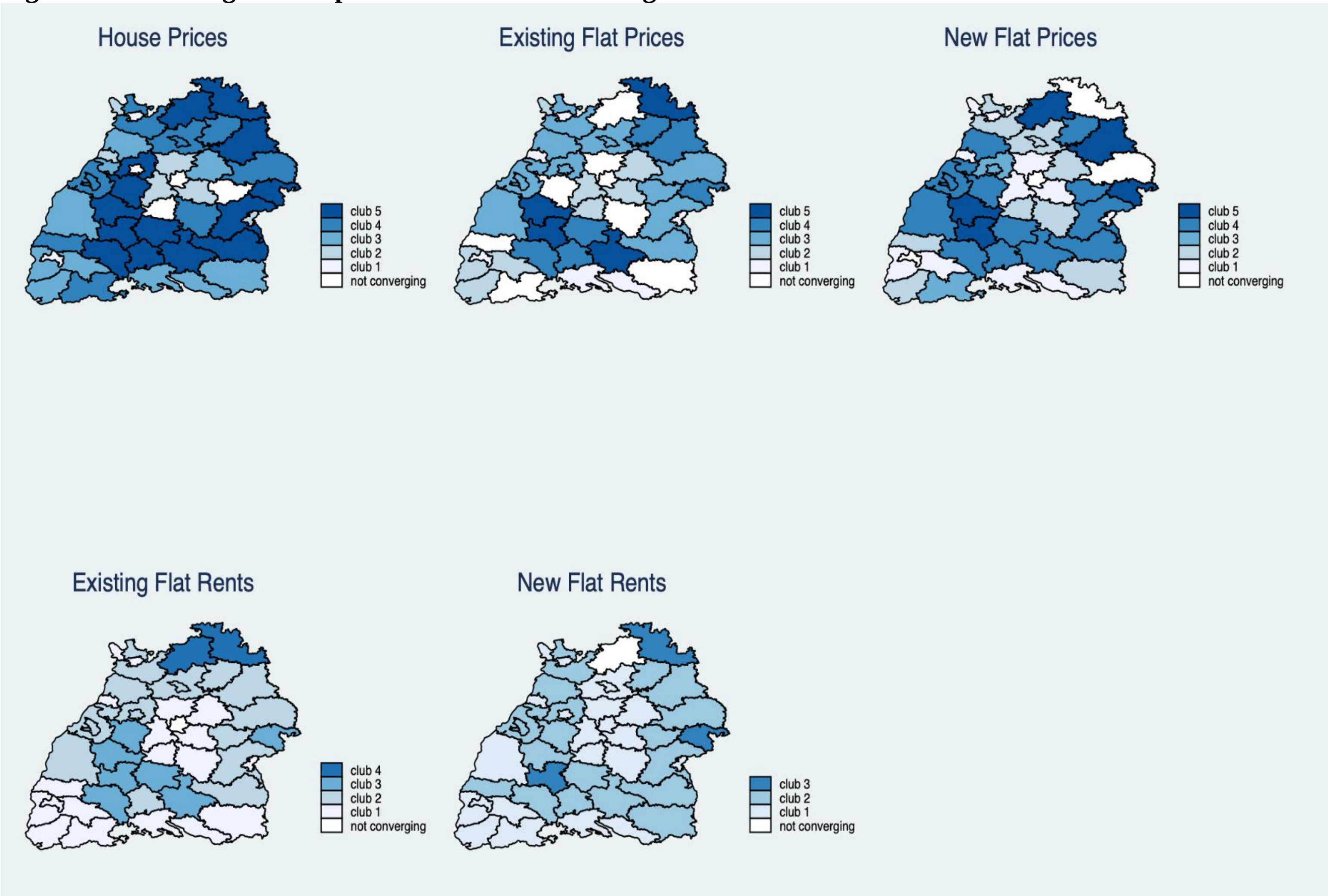


Figure A2: Convergence Maps for Bavaria

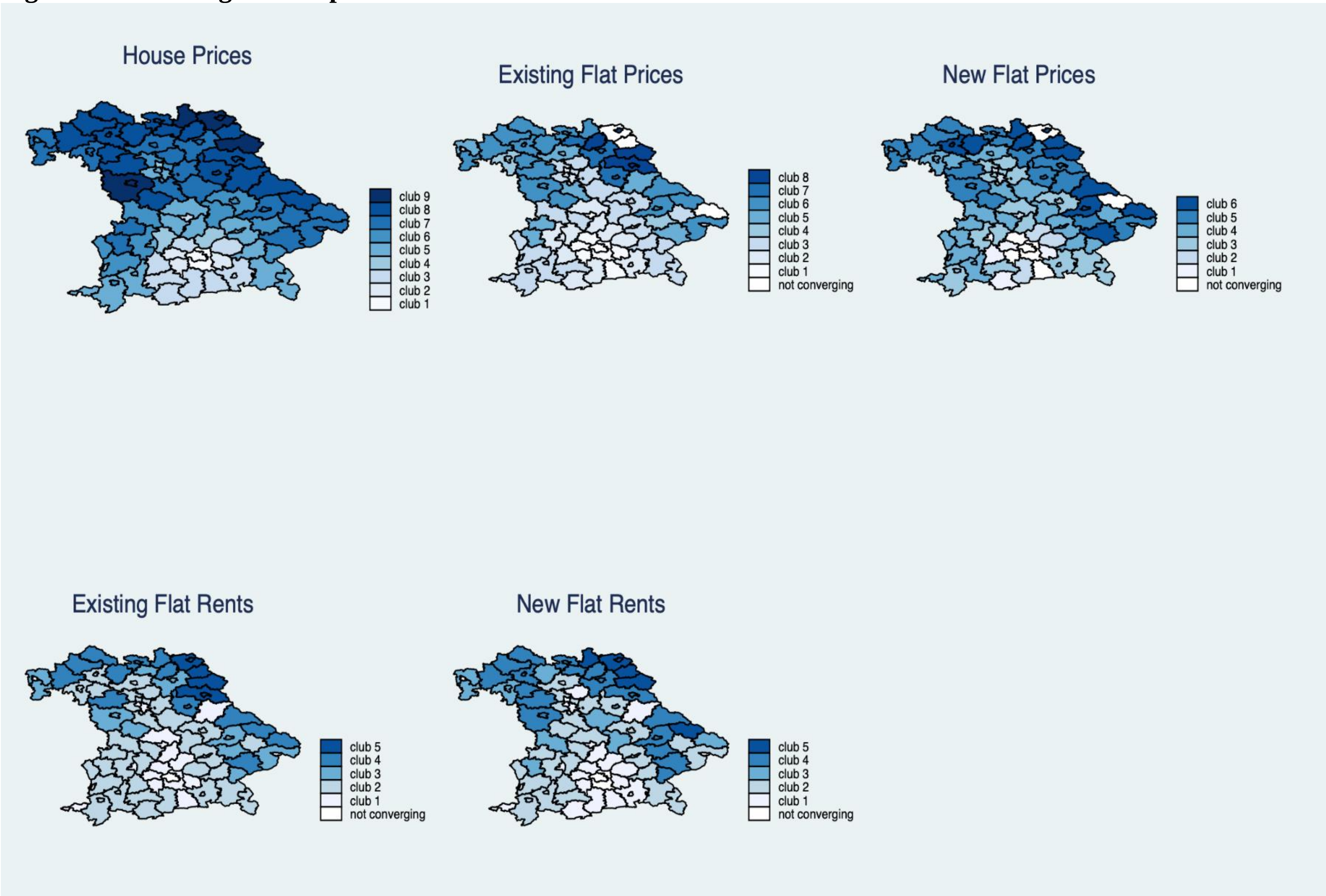


Figure A3: Convergence Maps for Brandenburg

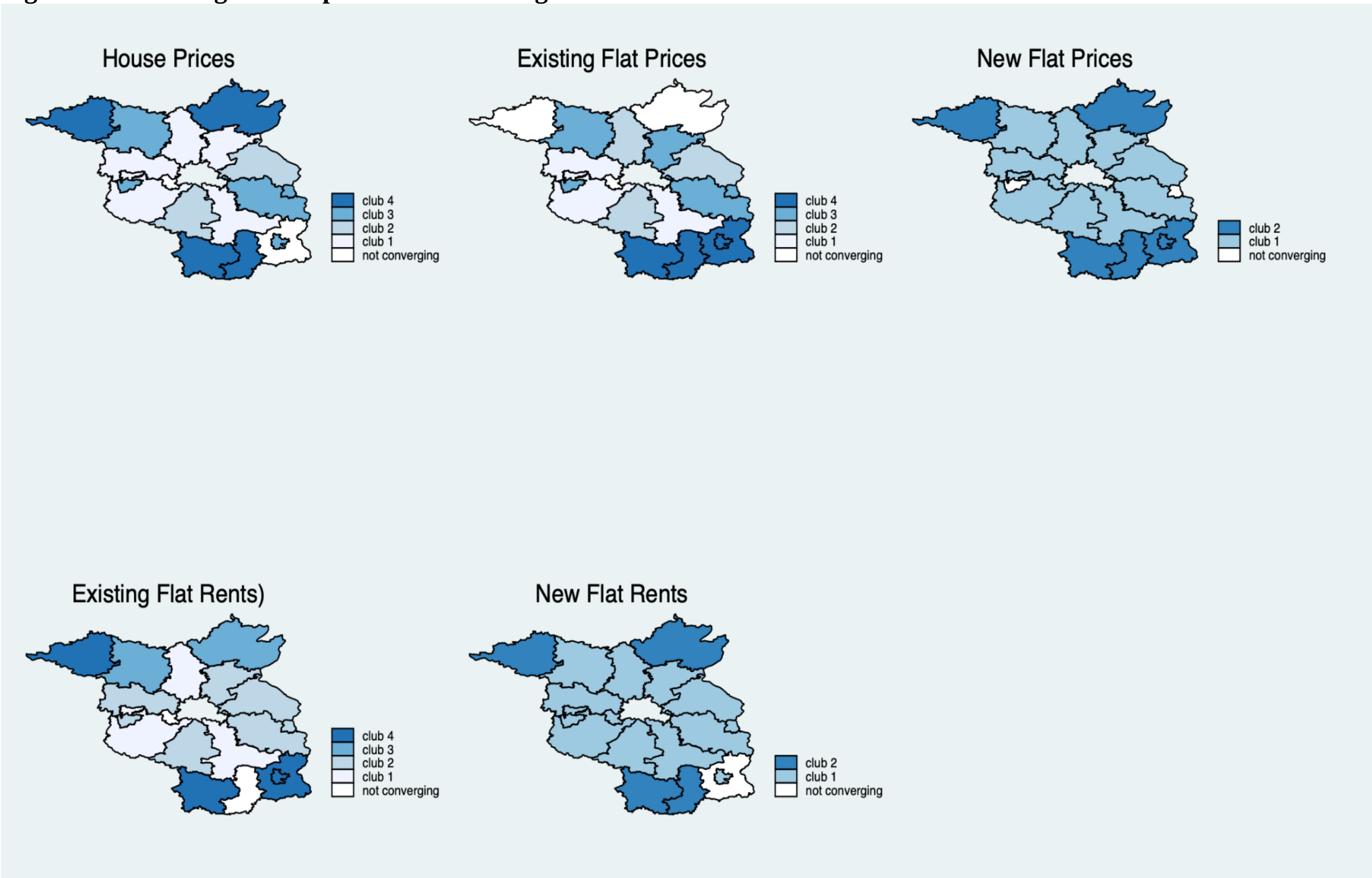


Figure A4: Convergence Maps for Hesse

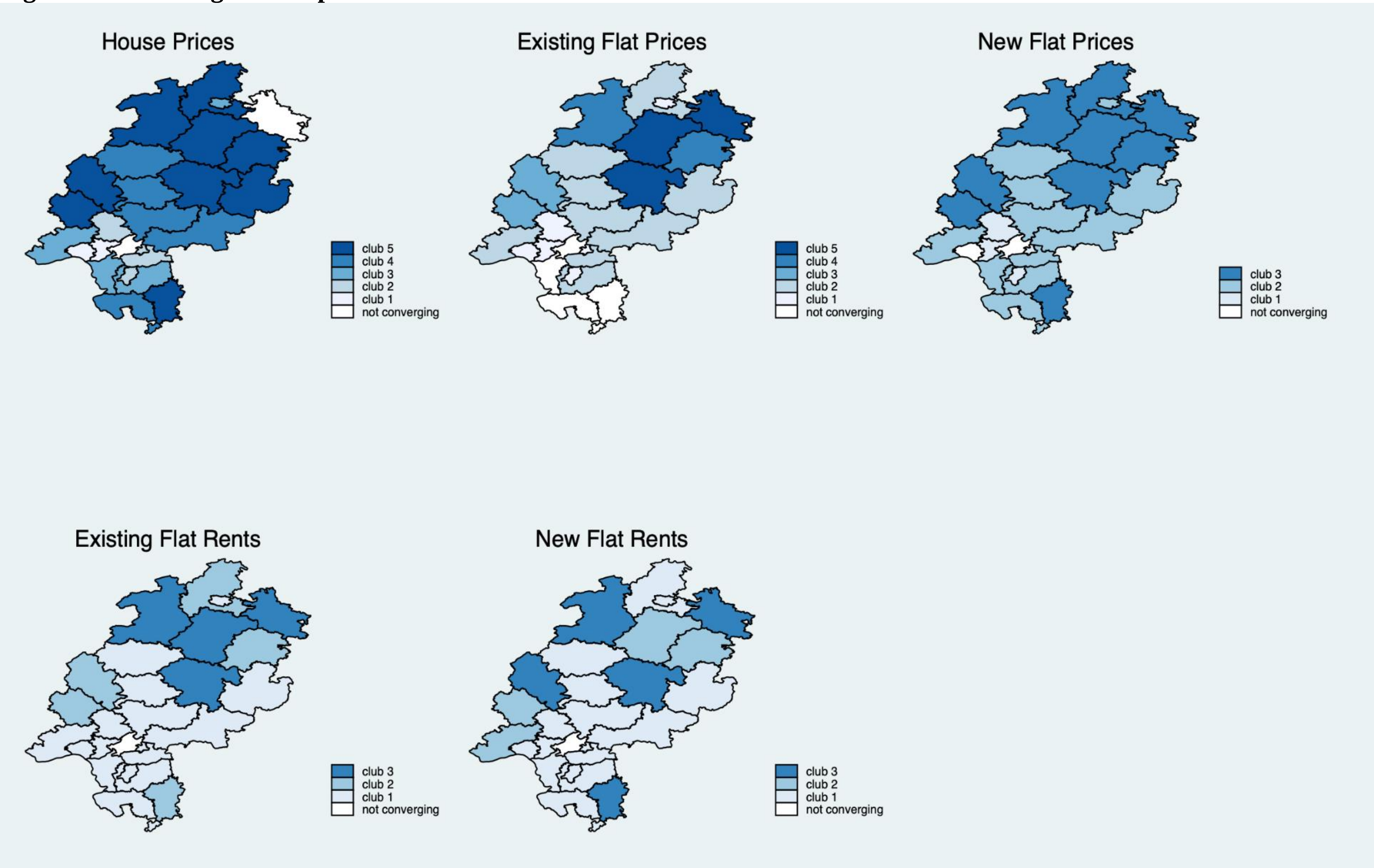


Figure A5: Convergence Maps for Lower Saxony

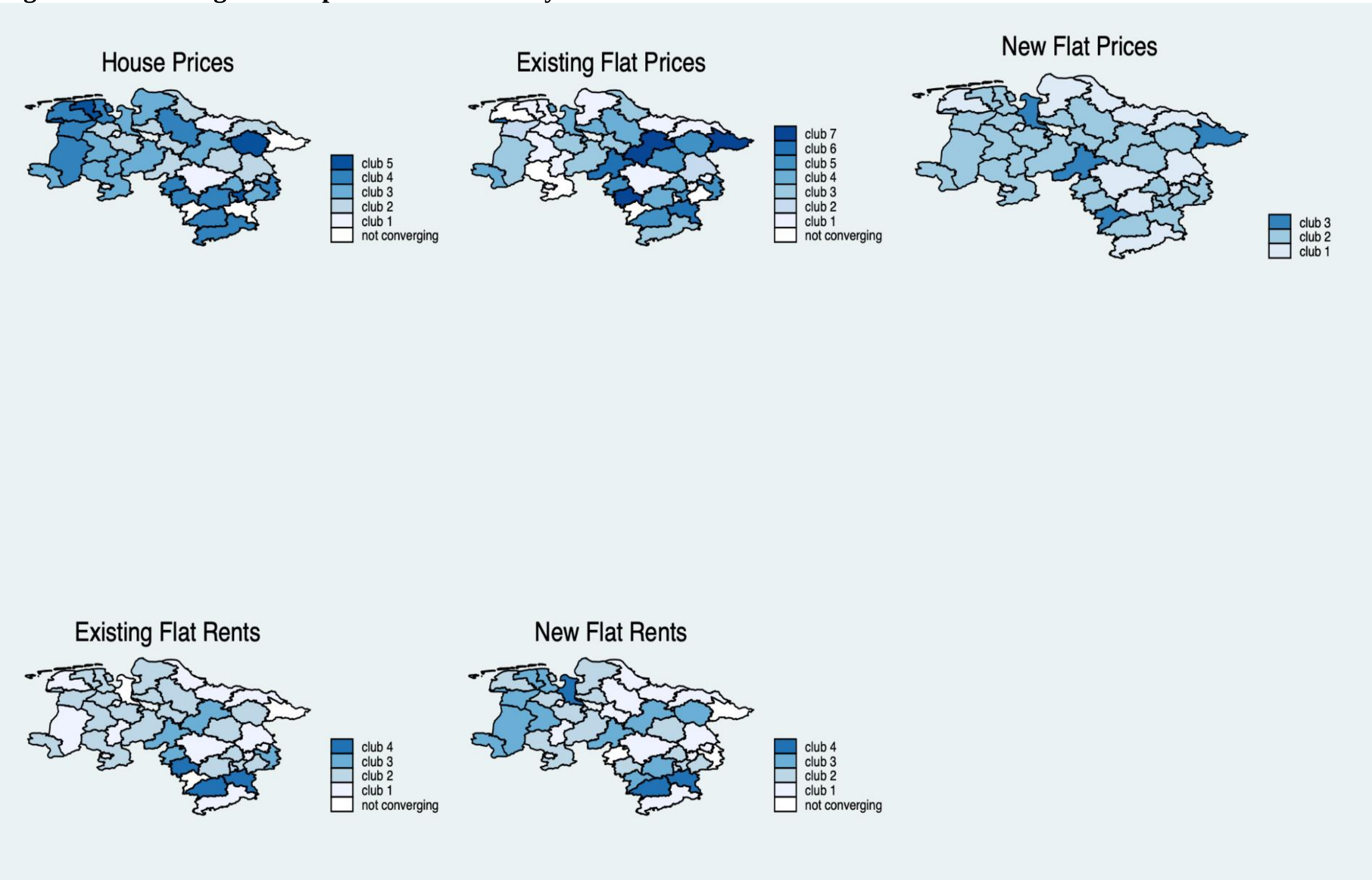


Figure A6: Convergence Maps for Mecklenburg-Vorpommern

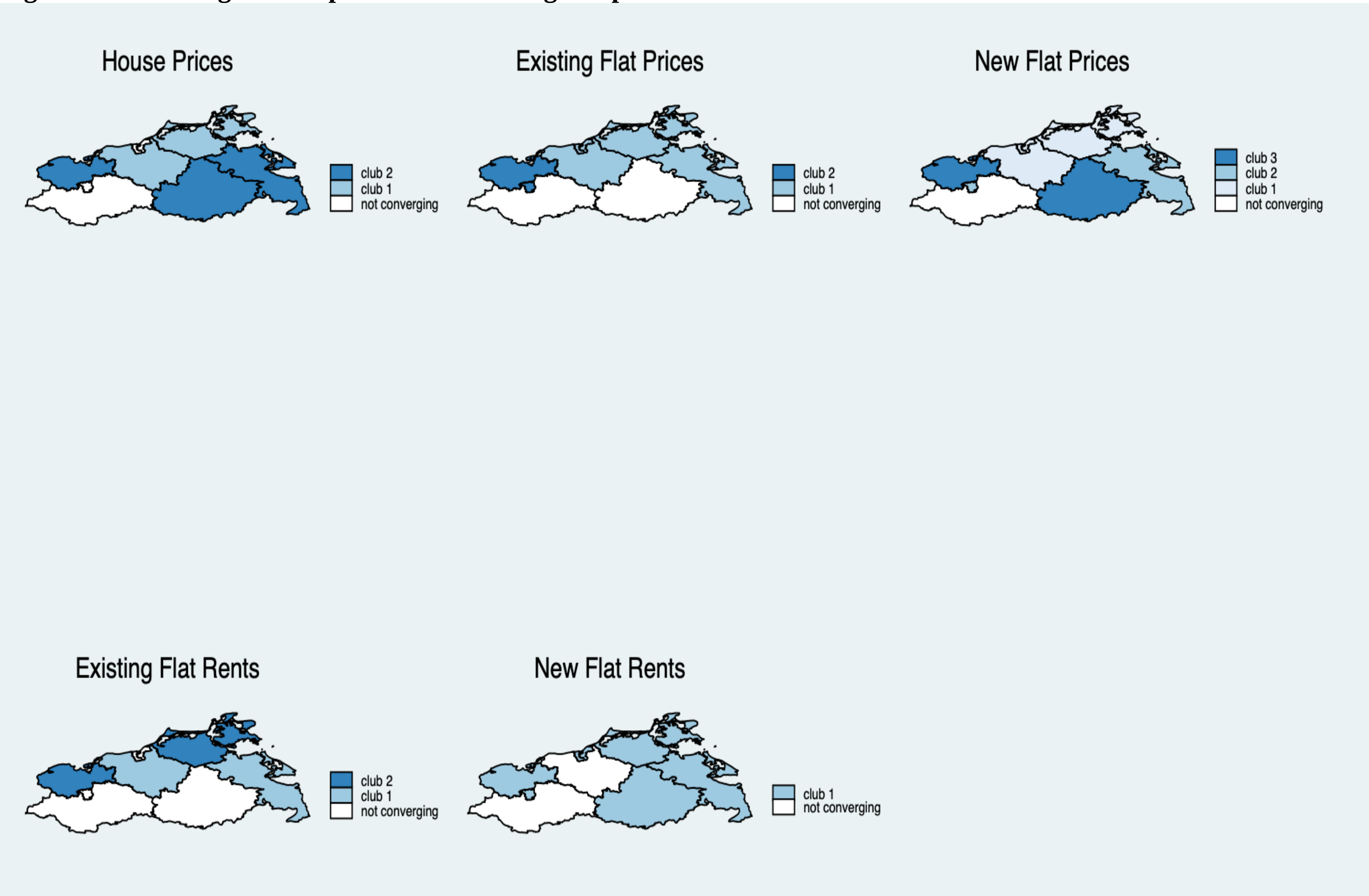


Figure A7: Convergence Maps for North Rhine-Westphalia

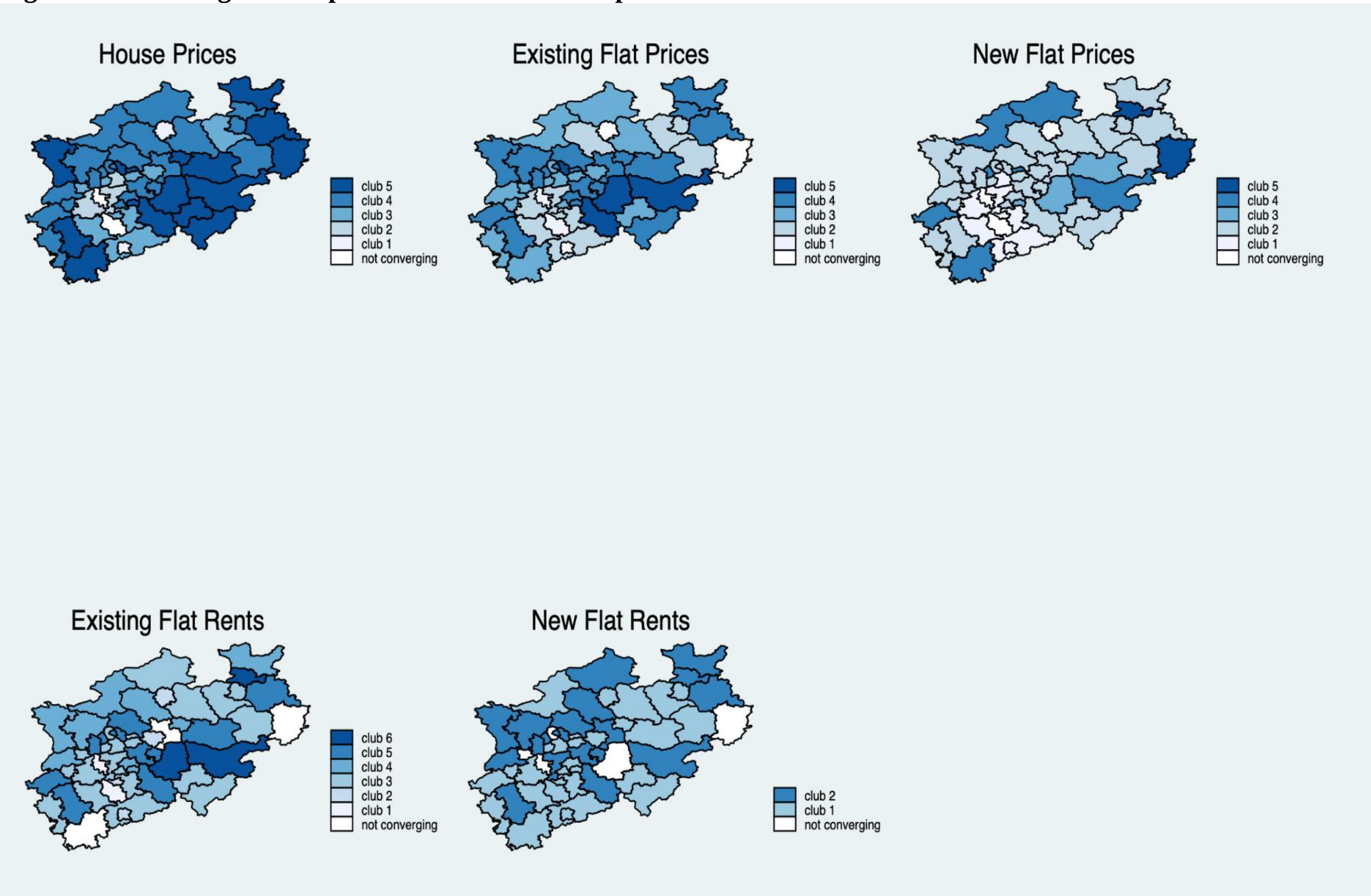


Figure A8: Convergence Maps for Rhineland-Palatinate

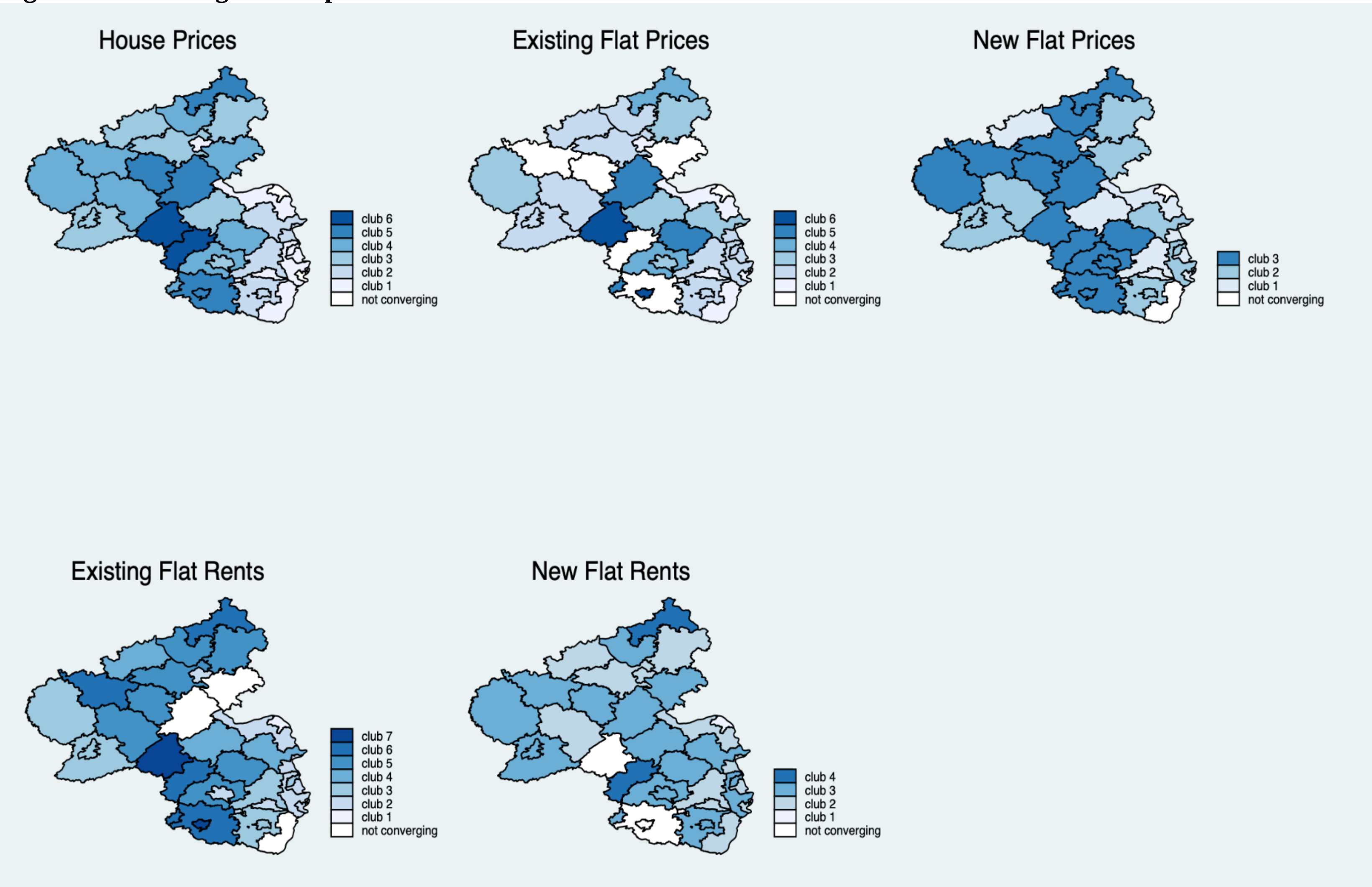


Figure A9: Convergence Maps for Saarland

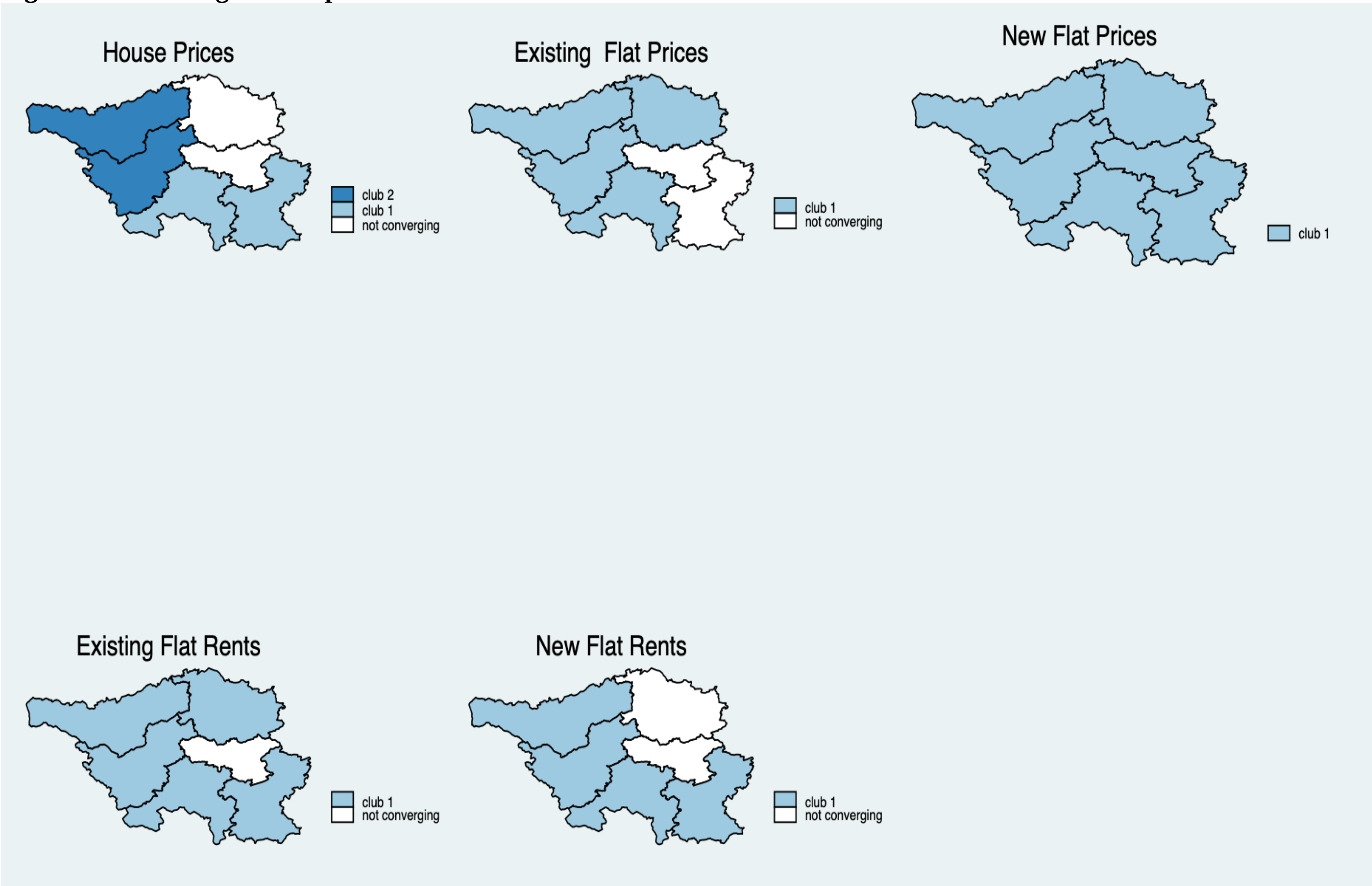


Figure A10: Convergence Maps for Saxony

Figure A11: Convergence Maps for Saxony-Anhalt

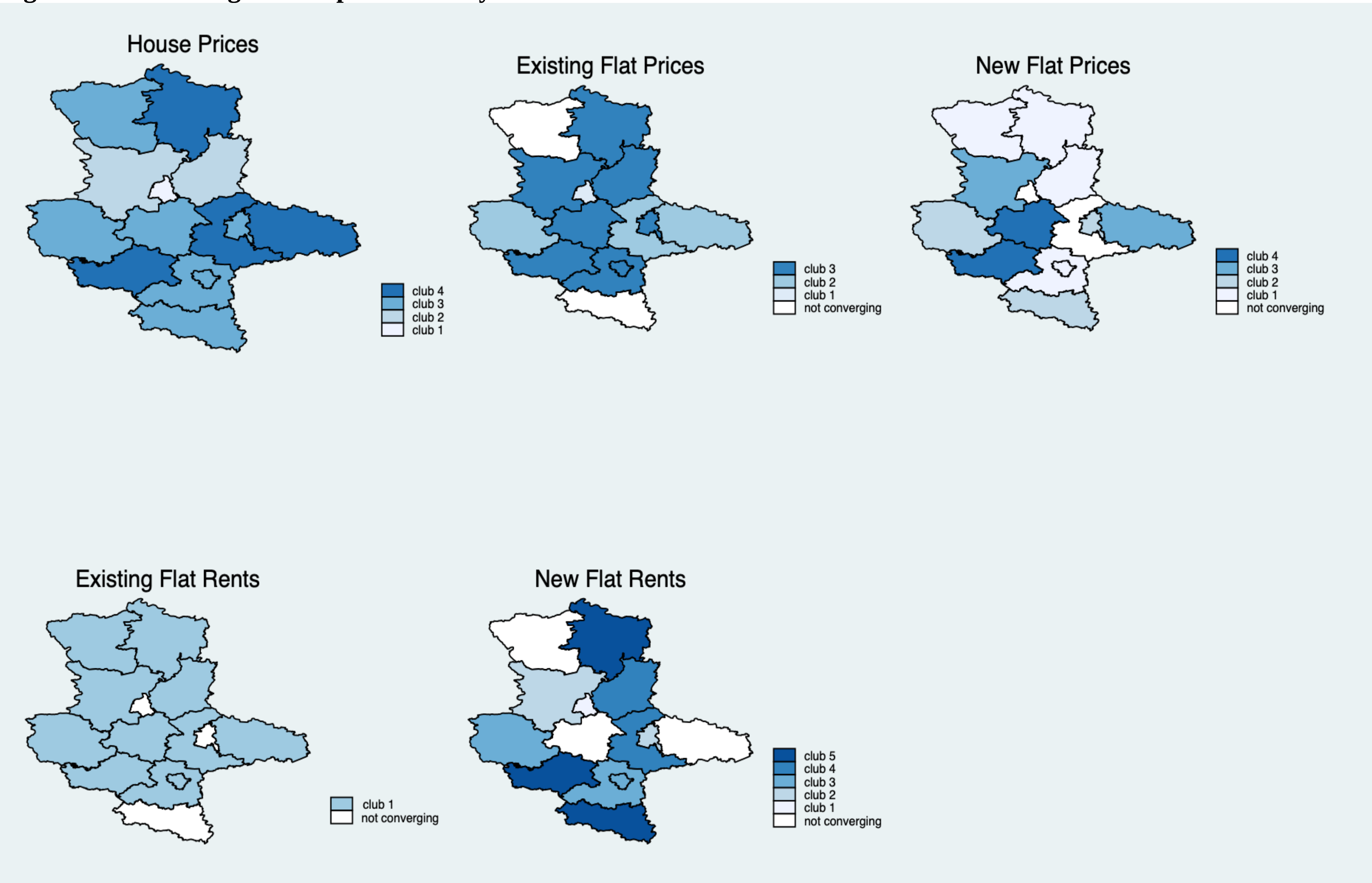


Figure A12: Convergence Maps for Schleswig-Holstein

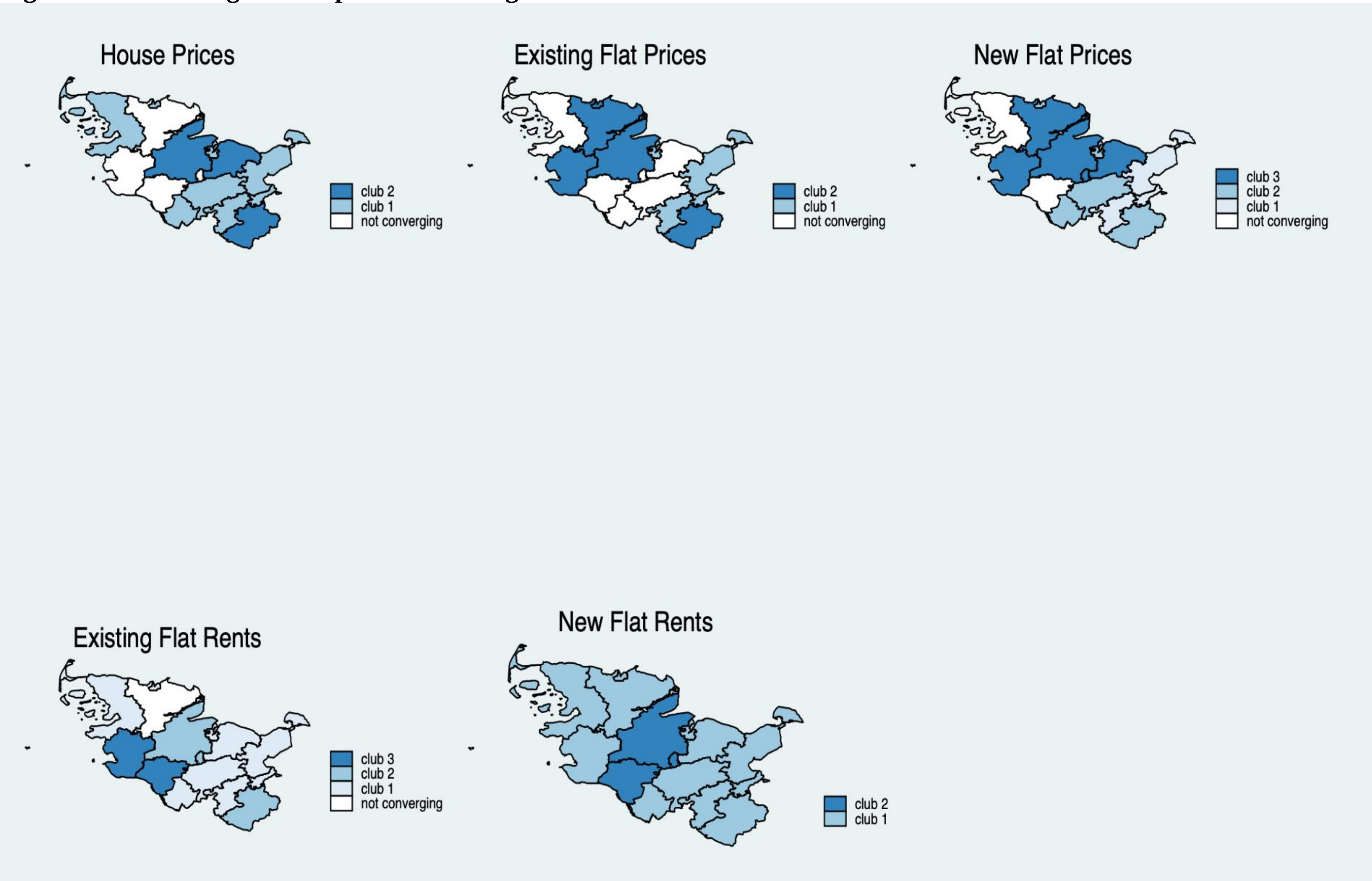


Figure A13: Convergence Maps for Thuringia