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Uwe Neumann and Christoph M. Schmidt*

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Abstract

Inspired by the literature on social polarisation and residential segregation we draw on a probabilistic approach to pursue the evolution of household location preferences in West Germany. Using microdata from the German Socio-Economic Panel (SOEP) for the period 1984-2020 we demonstrate that structural economic change was accompanied by an increasing preference for residence in compact housing close to urban centres. Our analysis outlines that during the past two decades, intra-urban and urban-rural disparities by age and skills have begun to rise. Even for Germany, where segregation is moderate, any scenario suggesting neighbourhood-level convergence of living standards seems unlikely.

JEL-Codes: C25, R21, R23

Keywords: Household location; segregation; structural change; SOEP

December 2024

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1 German neighbourhoods in an era of polarisation

As digitisation and automation are fundamentally transforming labour markets worldwide, skills seem to be claiming an ever increasing market power and, correspondingly, unprecedented financial rewards (Autor et al. 2003, Autor 2015). In this era of global demographic change, functional elites are charmed by potential employers with tremendous career opportunities and generous income prospects and, in addition, with considerable flexibility regarding the possibilities for remote work. Low-skilled workers, by contrast, might become increasingly replaceable by machines or by competitors recruited from an effectively global human-resources reservoir.

While the focus of much of the relevant research is devoted to the US labour market, similar developments are observed in other economies such as Japan, South Korea, or the UK, illustrating their global nature. In Germany, for instance, Europe's largest economy, income disparities have traditionally been comparatively moderate, but even there they have increased in recent decades (Dao 2020). The potential persistence of and the mechanisms behind the growing remuneration of skills and widening income disparities are currently discussed intensively (Acemoglu and Restrepo 2018, Autor and Salomons 2018, Autor 2019, Acemoglu et al. 2022). Schlitte (2012) points out that workplace segregation by skills at the level of labour market regions had a negative impact on low-skilled employment growth in West Germany between 1993 and 2006.

There is hardly any question that the education system lays the foundation for the development of skills required in working life. Yet, Berlingieri et al. (2022) reveal that in Germany the opening of new institutions of tertiary education apparently has little effects on regional wages or employment. In regions with a more dynamic labour market, university openings encourage firm creation and upskilling of the workforce. Less prosperous regions, however, experience little sustained growth in high-skilled employment. Regional disparities are thus likely to persist and even threaten to be exacerbated.

Irrespective of the concrete channels working towards this polarisation of labour markets, increasing income disparities are likely to carry over to other societal facets: By and large liberated from the confines of time and space on their jobs, professional elites might use their ample financial means to reside in attractive and progressively segregated neighbourhoods. By contrast, low-skilled workers are confined to spend a large share of their narrowing household budgets on housing (Backhaus et al. 2015, Dustmann et al. 2017). Indeed, over the last quarter century, in Germany no other segment of the real estate market has expanded as rapidly as single-family homes (Destatis 2022a).

The debate about the existence and intensity of neighbourhood sorting mechanisms and the question whether modern societies might be doomed to split up into segregated neighbourhoods, has been a contentious area of enquiry for quite some time. Already in the 1980s, a number of authors argued that urban industrial societies may experience increasing international migration directed at large cities and a rise of income segregation by occupation and residential segregation within urban areas (Friedmann 1986, Sassen 1991). This "polarisation hypothesis" has been the matter of an ongoing controversial discussion (Hamnett 1994, Samers 2002, Musterd et al. 2015).

Well-established theoretical considerations underpin this discourse. Typically, they depart from the insight that access to jobs and amenities are key determinants of households' residential choices. In an early contribution Alonso (1964) extended land-use theory (von Thünen 1875, Burgess et al. (eds.) 1925) to consider how the location decisions of utility-maximising households affect urban land values. His model balances two conflicting forces, the demand for dwelling space and the desire to reduce the costs spent on commuting. Moreover, the distance to the city´s Central Business District (CBD) is a disutility affecting leisure time, since jobs and amenities concentrate in the CBD.

Current studies investigating the motivation for regional mobility decisions (e.g. Deutz and Held (2023) for Stuttgart in 2021) demonstrate that taking up a new job continues to represent the most likely motive for young persons to move into a large city and to seek residence at central locations, whereas the desire for larger housing in a "green" surrounding drives households moving from central to more peripheral urban areas.

Accordingly, housing prices and rents are predicted to be highest in and near to centres, but also in less accessible neighbourhoods, if low density or high ownership rates, for instance, are synonymous with a good (urban) environment (Richardson 1977, Hoff and Sen 2005). Furthermore, distance to the CBD loses its importance, as locations provide access to transport infrastructure, suburban shopping centres or other amenities (Pan et al. 2018). In the 2000s a renewed "city-mindedness" motivated a reurbanisation trend in Europe (Haase et al. 2010) and North America (Couture and Handbury 2017), leading to increases in urban housing prices and gentrification (Christafore and Leguizamon 2019).

Delventhal et al. (2022) argue that after the experiences made during the Covid pandemic, the share of people working from home might increase permanently, leading to a revival of suburbanisation. Ramani and Bloom (2021) describe how increasing rents and housing prices in the suburban zones of large cities in the US – the "donut effect" – might result in increased household sorting between the inner and outer zones of urban regions. In Germany net migration into large cities came to a halt during the pandemic. In 2020, the 15 largest German cities accounted for a net migration loss, after having gained from in-migration throughout the past decade up to 2019 (Destatis 2022c, Rink et al. 2021). Up to 2023, however, their population increased again by 2.1% (Destatis 2024).

Both gentrification of central areas and a revival of suburbanisation might induce a rise of segregation and provoke undesirable neighbourhood effects among poor neighbourhoods both in inner cities and outer urban zones (Wilson 1987, Asquith 2016, Van Ham et al. 2018). Correspondingly, concerns about social polarisation have inspired many place-based policy measures designed to improve living conditions in deprived areas and overcome spatial inequality (Gibbons et al. 2021). In Germany, the federal government has supported local area-based regeneration since 1999 (GCEE 2019). By 2019, this programme had supported initiatives located in 965 neighbourhoods of 544 municipalities (BMI 2021).

Yet, while concerns about increasing social polarisation are hardly challenged in the public and political discourse, it is empirically questionable whether cities have indeed been subject to significant changes in neighbourhood populations during the most recent decades. In this paper, we utilise a rich micro data set to analyse for West Germany whether the patterns by which households sort into affluent and deprived neighbourhoods have changed over the past two decades. In particular, we examine possible changes in the importance of skills and occupation as determinants of residential location decisions and their implications for any longer-term neighbourhood-level divergence processes.

We find that in West Germany over the past decades preferences regarding broad neighbourhood categories have shifted more in favour of residence close to urban centres. Accordingly, intra-urban and urban rural disparities by age, skills and education have widened significantly. These results are informative for economic policy, since attaining equivalent living conditions is one of the basic political goals in Germany, most recently supported by the agreement guiding the three-party coalition that governed Germany between 2021 and November 2024 (Wissenschaftliche Dienste des Deutschen Bundestags 2023). Our results indicate, however, that this document and previous strategies concerned with regional convergence might have instigated expectations, which overstretch the actual potential of regional policy measures.

The following section presents the empirical approach, section three provides a descriptive overview, and section four examines the evolution of household location determinants across the past decades. The study ends with a discussion of the findings in section five.

2 Empirical strategy

Analysis of sorting examines the interplay of household-specific characteristics and neighbourhood-related "pull factors" in the process leading to residential location decisions. Since individual household and average neighbourhood characteristics may be determined simultaneously, it is complicated to document empirically how households "vote with their feet" when they decide where to locate or where to leave (Tiebout 1956, Schelling 1971, Ibraimovic and Hess 2017). Similar empirical challenges arise for an evaluation of policy measures designed to improve the quality of local amenities (Chernoff and Craig 2018).

Our theoretical framework derives from a probabilistic approach to study household location. Bayer et al. (2004) define an equilibrium model of a self-contained urban housing market, in which households sort themselves among the available types of housing and location. In contrast to "vertical" sorting models, which assume common preferences over neighbourhood amenities (Epple and Sieg 1999), this "horizontal" model allows households to hold heterogeneous preferences defined over housing and neighbourhood attributes.

The residential location decision is modelled as a discrete choice among a set of housing types available in the market. In our analysis we draw on this approach using rich German panel data providing comprehensive information on household characteristics. We consider a sorting equilibrium in which each household i chooses residence h to solve the utility maximisation problem (abstracting from time indices)

$$\max_h \mathrm{V}_h^i = a_X^i X_h + a_Z^i Z_h - a_p^i p_h - a_d^i d_h + \xi_h + \varepsilon_h^i. \qquad (1)$$

In equation (1) the error structure is divided into a residence-specific component that is valued equally by all households, ξ_h, and a household-specific term ε_h^i. It is assumed that ξ_h is exogenous to sorting, i.e. all relevant neighbourhood amenities affected by household sorting are included as observables. The X_h represent the observable characteristics of the housing choice, including characteristics of the house itself (e.g., size, age, and type) and its neighbourhood (e.g., schools, crime, land use, topography). The Z_h represent average sociodemographic features of the corresponding neighbourhood, p_h denotes the price and d_h the distance to jobs and amenities[1].

Each household´s valuation of choice characteristics varies with its own characteristics z_k^i. Every parameter associated with housing and neighbourhood characteristics and price a_j^i, $j \in \{X, Z, p, d\}$, varies according to a household´s own features with

$$a_j^i = a_{0j} + \sum_{k=1}^{K} a_{kj} z_k^i. \qquad (2)$$

Equation (2) describes household i´s preference for choice characteristic j. The flexibility of the horizontal model is relevant when modelling preferences over neighbourhood characteristics, since it can be expected that the ranking of neighbourhoods varies by household characteristics k. In order to operationalise the analysis of the residential location decision we assume that the housing market can be fully described by a set of housing types, which distinguishes basic features of the total set of available dwellings.

The probability that a household chooses any particular option depends on the characteristics of the full set of all possible housing choices, i.e. it can be formalised as a function of the full vectors of housing and neighbourhood characteristics, prices and the household´s own traits. Aggregating the probabilities over all observed households yields the predicted demand for each housing category. In order for the housing market to clear, the demand for houses of type h must equal its supply. Prices are assumed to adjust to the relation between supply and demand in order for the market to clear.

Following Bayer et al. (2004) we rewrite the indirect utility function as

$$\max_h V_h^i = \delta_h + \lambda_h^i + \varepsilon_h^i. \qquad (3)$$

[1] The horizontal sorting model draws on the location choice model by Alonso (1964) (see above). In Bayer et al. (2004) distance to the household´s primary working location replaces distance to the CBD as the main commuting destination. In the household-specific weighting scheme between the conflicting preferences for dwelling space and leisure time, however, both aspects may play a role.

In equation (3), the indirect utility of location choice V_h^i , divides into, first, mean preferences δ_h, which are common to all households (equation (4)),

$$\delta_h = a_{0X}X_h + a_{0Z}Z_h - a_{0p}p_h - a_{0d}d_h + \xi_h \quad (4)$$

and, second, household-specific preferences λ_h^i with

$$\lambda_h^i = \left[\sum_{k=1}^{K} a_{kX}\, z_k^i\right]X_h + \left[\sum_{k=1}^{K} a_{kZ}\, z_k^i\right]Z_h - \left[\sum_{k=1}^{K} a_{kp}\, z_k^i\right]p_h - \left[\sum_{k=1}^{K} a_{kd}\, z_k^i\right]d_h. \quad (5)$$

In (5), household characteristics are indexed by k. As explained, the unobservable component of δ_h, ξ_h, captures the portion of unobserved preferences that is correlated across households while ε_h^i represents the impact of the unobserved idiosyncratic preferences in addition to this shared component. Maximisation of the likelihood that each household chooses its appropriate house conditional on prices, housing and neighbourhood attributes – given its own characteristics (equation (5)) – is computationally demanding. In our analysis the computational burden will be reduced as the set of choice options is limited to basic categories of the housing environment.

In the estimation, mean indirect utilities represent the average valuation given observable characteristics of housing choice h, neighbourhood attributes and the housing price. Individual and choice-specific average preferences will be estimated in terms of a multinomial logit (MNL) model[2], representing choice h among a given set of n = 1, …, 6 housing environment categories (see below) for each year t = 1984, 1986, …., 2020. For any combination of k = 1, …, 10 household parameters $z_{k,t}^i$ household-specific preferences $\lambda_{h,t}^i$, and mean indirect utilities $\delta_{h,t}$, the model predicts the probability that household i chooses option h in any given year t.

The MNL model (equation 6) describes the probability that the response for the ith observation is equal to outcome h among our housing environment categories,

$$\Pr(y_i = h) = \exp(x_i\, ß_h) \;/\; 1 + \sum_{n=1}^{N} \exp(x_i\, ß_n) \quad (6)$$

where x_i is the row vector of observed values of explanatory variables for the ith observation. A variety of studies have found the MNL model to be an appropriate empirical framework for analysing housing choice from a cross-sectional perspective (Gabriel and Rosenthal 1999, Tra et al. 2013). Since all covariates are constructed to have mean zero, the mean indirect utility derives directly from n alternative-specific individual constants. Household characteristics include income, household size and a set of further demographic household

[2] In the MNL model, the “independence of irrelevant alternatives” (IIA) property implies that the unmeasured attributes of alternative choices are uncorrelated. Test results based on Chi-Square statistics as proposed by Hausman and McFadden (1984) confirm the applicability of the MNL model to the neighbourhood choice options for all annual cross-sections comprising the period 1985-2020 except for 2013 and 2015, when the IIA assumption is violated. We test the IIA null hypothesis by comparing the full model to a restricted model excluding rural regions. We exclude 1984, since no urban-rural distinction is possible for this first year (see below). In line with a broadening of disparities between urban and rural regions (see below) during the past decades households appear to have widened their catchment area when searching for accommodation. Whereas choice among urban housing options was hardly affected by rural alternatives in previous decades, today a higher share of location choices might result from a process, in which both urban and rural options are considered as suitable alternatives. Nevertheless, for most years of the past decade the analysis suggests that an urban-rural distinction still represents important location attributes.

attributes (age, education and occupation of household members, migration background) (Table 1, see below).

The first step of the analysis estimates equation (3) for our complete sample, which is representative of West Germany as a whole. Since living conditions in East Germany differed from those in the West for a long time after reunification, we restrict our analysis to West Germany. Regarding household preferences λ_h^i the estimation will capture the average value for each of the parameters $z_{k,t}^i$ regarding housing and neighbourhood characteristics a_j^i, as described by (2) and (5). Given that the analysis is motivated by widespread concern regarding an increase in sorting by income, skills and occupation, the household-specific parameters $z_{k,t}^i$ will be the main focus of this first step. In particular, we will study the evolution of the cross-sectional estimations of parameters a_j^i and mean preferences $\delta_{h,t}$. Standard errors are clustered by macro-regions comprising German federal states (Baden-Württemberg, Bavaria, Berlin, North Rhine-Westphalia) or groups of states (North, i.e. Bremen, Hamburg, Lower Saxony, Schleswig-Holstein; Mid-South, i.e. Hesse, Rhineland-Palatinate and Saar, Figure 1).

In order to consider a plausible degree of regional variation, in the second step of our analysis mean indirect utilities will derive from separate estimations of equation (3) by macro-regions. In the analysis according to equation (7),

$$\delta_{h,r,t} = ß_0 + ß_1 X_{h,r,t} + ß_2 Z_{h,r,t} - ß_3 p_{h,r,t} + \mu_{h,r} + \xi_{h,r,t} \,, \quad (7)$$

the $\delta_{h,r,t}$ thus refer to the mean indirect utilities of choosing option h by macro-region r in year t. Housing characteristics $X_{h,r,t}$ will be represented by the average of residential floorspace per dwelling at option h by macro-region r in year t, price $p_{h,r,t}$ by the average monthly rent or mortgage payments per m², and neighbourhood attributes $Z_{h,t}$ by the mean age of the residential population. The term ξ_h comprises the region-specific proportion of unobserved preferences for housing. Households sort across neighbourhoods at least partly by "pull factors" unobservable to the researcher, and households with similar characteristics may respond to these factors in a similar way. Housing prices and sociodemographic characteristics are thus presumably correlated with the ξ_h. The application of instrumental variables therefore has become a key feature of the empirical framework with respect to sorting models (Kuminoff et al. 2013).

In our analysis longitudinal data provide us with an alternative opportunity to overcome the endogeneity problems confronting the second step. In equation (7) the fixed effect $\mu_{h,r}$ accounts for unobservable heterogeneity between macro-regional housing environment options h. The commuting distance d_h is excluded as it is expected to be (presumably inversely) correlated with residential floorspace, which is controlled for as a housing characteristic, and therefore of comparatively greater concern in the context of our study.

Of course, the analysis differs from other studies inspired by Bayer et al. (2004) in its regional layout. It will be the purpose to utilise the full magnitude of micro-level information on household, housing and neighbourhood characteristics arising from a large panel study. While the information deriving from this data base is representative of the population of

Germany as a whole and at the level of federal states, it would go beyond its capability to serve as a source for case studies with reference to specific localities (see below).

In a third and final step, however, we utilise a further territorial category provided by the panel study. We examine the likelihood to reside in one of the deprived neighbourhoods, which have been supported by a nation-wide urban regeneration programme over the past two decades. For this purpose, we draw on a logit estimation using the same set of indicators as in equation (1). The dependent variable in this case is binary, indicating whether household i resides in a programme area in year t = 2000, 2001, …., 2020.

3 The SOEP as data source

In Germany, restricted access to neighbourhood-related information in microdata imposes considerable constraints on segregation analysis. It is all but impossible to use neighbourhood identifiers to augment household records by the characteristics of their residential location. In principle, this also holds for the German Socio-Economic Panel (SOEP) which has become a standard data source for individual and household-level analysis: Started in 1984, the SOEP is an annual representative study of private households in Germany (see Table A1 in the appendix)[3], comprising various topics, e.g. household composition, residence, earnings, education and occupation of household members. While the information about households and individuals can be linked to regional identifiers (Eilers et al. 2021), due to small sizes of regional clusters, it would be difficult to construct a representative sample of any specific city or region (Giesselmann et al. 2019).

Nevertheless, the SOEP may be used in order to study the regional context, e.g. with respect to broader regional categories (Goebel and Zimmermann 2021). Furthermore, it offers valuable information on the nature of the respondents' housing and neighbourhood (Knies and Spiess 2007)[4]. Moreover, in 2018 a new refreshment sample "O" was specifically designed to increase the number of households from deprived neighbourhoods supported by the Social City programme, an urban policy initiative cofunded by the federal government, the federal states and municipalities, which was established in 1999 (Steinhauer et al. 2020). Consequently, the SOEP-Core v38 from 2021, which will be the base of the following study, comprises information about nearly 1,000 households from programme areas in 2016.

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[3] The SOEP is a research-based infrastructure facility at DIW Berlin funded by the German Federal Ministry of Education and Research (BMBF) and federal state governments. Having started with the first Samples A (Residents in the Federal Republic of Germany) and B (Foreigners in the Federal Republic of Germany) in 1984, the SOEP has been expanded by various samples since then, e.g. "Residents in the German Democratic Republic" (Sample C) in 1990, "Immigrants" (Sample D) in 1994/95, "Refreshments I/II" (Samples E/F) in 1998/2000,"High income" (Sample G) in 2002,"Refreshment III" (Sample H) in 2006 and "Innovation" (Sample I) in 2009 (Kroh et al. 2018). The most recent expansions comprise Samples P ("Top Shareholders") and Q ("LGBTIQ") from 2019. The SOEP surveys not only households from the first wave per sample, but also households and persons that enter at later points in time, e.g. when households split or expand by persons moving in or by birth. Table A1 in the appendix reports the development of the total West German survey population from 1984-2020.

[4] Information on housing and neighbourhood characteristics is generated on the basis of information households provide in the wave-specific household questionnaire when they enter the survey or relocate.

Furthermore, a question reaching back to the year 2000 even identifies over 700 households as residents of Social City areas in 2000 (SOEP Group 2020).

Due to this ample information, the SOEP provides a sound basis for the study of sorting across neighbourhood categories. Taking households as the basic units of observation, Table 1 displays the household-level indicators used in the analysis.

Table 1
Description of variables

Variable	Description
net household income	average monthly net household income in €, current prices
household size	number of persons in the household
mean age	mean age of household members
floorspace	total residential floorspace, in m²
cost/m²	monthly rent (without heating) or mortgage repayment in €
$\delta_{h,t}$	probability of households with mean characteristics to reside at any housing environment type h in year t
dummy variables (1 if characteristic applies to at least one household member, 0 otherwise)	
migrant background	immigrated (direct migration background) or born in Germany, but of migrant origin (indirect migration background)
age 60+	aged 60 or over
upper secondary school	upper secondary school certificate
type of occupation[1] (reference category: ISCO88/08 <3,000, i.e. managerial and professional occupations) (1 if characteristic applies to at least one household member, 0 otherwise)	
technician	1 if ISCO88/08 = 3,000-4,000
white-collar worker (clerical, service, sales)	1 if ISCO88/08 = 4000-6000
farming, agricultural worker	1 if ISCO88/08 = 6000-7000
skilled blue-collar worker (mining, construction, manufacturing)	1 if ISCO88/08 = 7000-9000
unskilled worker	1 if ISCO88/08 = 9000 or over
household characteristics (1 if characteristic applies to household, 0 otherwise)	
Social City	household resides in Social City programme area

[1]up to 2017, occupations are categorised by ISCO88 codes, from 2018 by ISCO08 codes

Central to our analysis, six types of housing environment will be distinguished, which have been constructed explicitly to capture the amalgamation of the various factors presumed to reflect the location choice (Boehm et al. 1991, Knox and Pinch 2010):

1. one- and two-family homes in residential areas of urban regions,
2. multi-family homes in urban residential areas with mainly post-war housing,
3. multi-family homes in urban residential areas with mainly pre-war housing,
4. mixed residential / commercial and commercial areas of urban regions,

5. one- and two-family homes in rural regions, and
6. multi-family homes in rural regions[5].

Figure 1 illustrates for the year 2015 the classification provided by the Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR) of West German regions into urban and rural regions (BBSR 2017).

For a certain share of households in each year (usually around 5%) there is no adequate information about the housing environment. These households are much more likely than other households to subsequently drop out of the survey. While some of the information about household location preferences will therefore be lost, the SOEP providers at DIW Berlin study the reasons for panel attrition in each year: Only a small fraction of households (under 1% per year) tend to leave the survey due to an unsuccessful follow-up. The main reason to drop out of the survey is outright refusal to participate once more (Siegers et al. 2020). To facilitate intertemporal comparisons, we utilise cross-sectional weights provided by the SOEP, which compensate for dropouts.

The descriptive statistics in Table 2 document the severe structural changes experienced by the entirety of West German households over the last four decades. In the early years after German reunification in 1990, the number of households has increased drastically, and it has remained elevated ever since.

Nominal net household income has more than doubled, outpacing inflation by far. During the same period, average household size has been shrinking and mean age has increased remarkably. Both floorspace and residential quality, at least to some extent being reflected in the increase of floor-prices by almost 150%, have increased.

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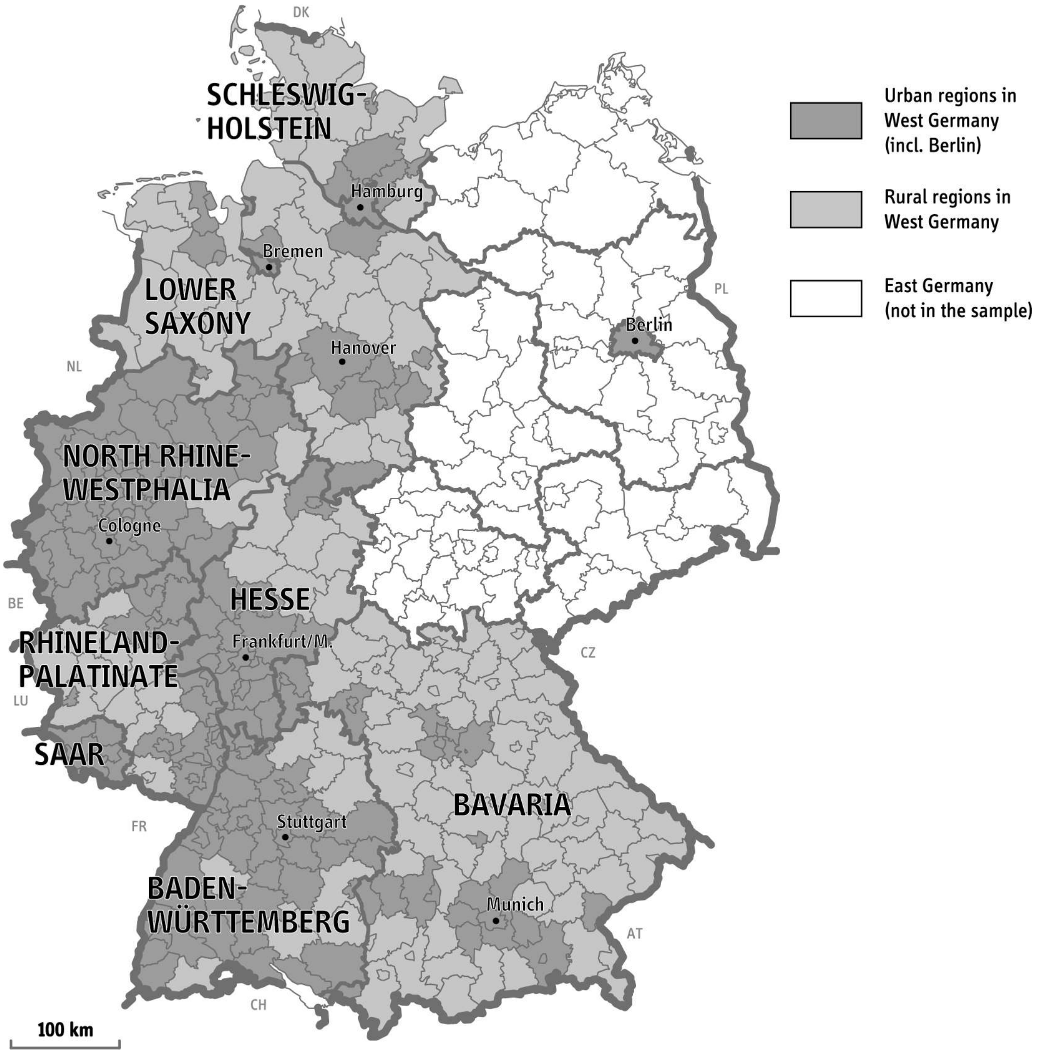
[5] A broad regional classification by the Federal Institute for Research on Building, Urban Affairs and Spatial Development categorises SOEP households by residence in “urban” or “rural” municipal districts for all years from 1985 (Kreise and kreisfreie Städte, NUTS 3 region) (BBSR 2017) (Figure 1). Our typology draws on the concept of monocentric cities that derives from land-use theory (Burgess et al. 1925, Alonso 1964), but as type 4 comprises city and neighbourhood centres, the typology accounts for the subdivision of urban regions into areas served by various local centres. Since our analysis is concerned with change over time in the appreciation of neighbourhood characteristics, it is important that the main features determining the distinction between neighbourhood categories remain steady over the study period. Concern may arise particularly regarding the urban types 2-4, since the distinction by the overall age of the housing stock and according to land use (residential versus mixed residential and commercial) might be less obvious than the differences between these and the other types. Due to household mobility and various sample extensions the housing environment represented by each of these categories might therefore have changed over time. However, as far as basic housing characteristics are concerned (average floorspace per dwelling, year of construction, number of rooms), the available statistics suggest that the distinctions between our categories hold across the study period. Figure 3 (see below) demonstrates that as far as rents are concerned, the ranking of types 2-4 has remained stable during the past two decades. As part of a research project funded by the Leibniz Association (Bügelmeyer et al. 2015), we examined how neighbourhood types of SOEP households are distributed across postal districts. Apparently, while there is a plausible degree of heterogeneity in this spatial distribution, households of the same type tend to cluster considerably. In 2019 and 2020, only a comparatively small share of households providing housing and neighbourhood information can be assigned to rural regions. For these years, characteristics of the housing environment were therefore only assigned to those households, which had already taken part in 2018 and had not changed their location since then. While the annual share of missing values concerning the housing environment only amounts to 2.8% on average before 2019, it increases to 17.5% in 2019 and 20% in 2020. As an urban/rural-distinction was introduced in 1985, only types 1-4 are distinguished in 1984.

Figure 1
Urban and rural municipal districts in Germany (2015)



Authors´ illustration. – Data Source: BBSR (2017). East Berlin is excluded from the sample.

The figures impressively document the ongoing demographic change, which has been holding Germany in its grip for quite some time and is now accelerating: While the average number of children per household has been shrinking, the share of senior persons in West German households has grown. At the same time, a migrant background has become a mainstream characteristic.

Our descriptive results also document tendencies for polarisation on the labour market: While the share of skilled blue-collar workers´ households decreased from more than a fifth in 1985 to slightly less than 10% in 2020, the share of white-collar workers´ (comprising clerical, services and sales personnel without a college degree) households remained constant at around 17-20%[6].

Table 2

Descriptive statistics for West Germany (incl. West Berlin), (in %, except as indicated)

	1985	1995	2005	2015	2020
number of households represented	*23,420,244*	*25,971,433*	*27,646,447*	*28,322,014*	*27,689,703*
net household income (median)[1]	1,125	1,534	1,800	2,100	2,400
household size (mean)	2.1	2.0	1.9	1.8	1.8
mean age (mean)	48.9	49.3	51.4	54.6	55.5
floorspace (mean)	81.0	76.6	89.6	93.8	95.0
cost/m² (median)[1]	3.19	5.93	6.18	7.92	7.91
dummy variables = 1 (in %)					
migrant background	10.9	16.7	17.2	22.5	23.7
child < 14	12.7	13.6	11.3	8.1	9.0
age 60+	43.6	41.6	44.9	49.2	52.9
upper secondary school	20.2	23.7	28.6	33.4	35.6
Social City	-	-	7.1	6.3	6.2
type of occupation (in %, reference category: highly qualified (degree-level) occupations)					
technician	14.6	16.9	16.7	18.3	17.7
white-collar worker	18.5	20.0	17.2	18.2	16.6
agricultural worker	1.4	0.9	0.8	0.7	0.6
skilled blue-collar worker	21.9	19.1	14.9	12.3	9.5
unskilled worker	13.7	11.3	11.4	9.2	7.0
residence in housing environment type…(in %)[2]					
1	23.7	25.6	25.9	26.0	26.1
2	16.4	16.5	15.6	8.7	8.7
3	12.3	10.9	11.6	19.2	20.3
4	22.3	22.3	22.1	20.7	20.7
5	10.8	10.3	12.0	12.4	12.8
6	11.0	10.7	9.8	11.7	11.4

Authors´ calculations. – Data source: SOEP – weighted using weights provided by the SOEP; for explanation of variables cf. Table 1; [1]current prices, in euro; [2]types: 1 = one- and two-family homes in residential areas of urban regions, 2 = multi-family homes in residential areas of urban regions with mainly post-war housing, 3 = multi-family homes in residential areas of urban regions with mainly pre-war housing, 4 = mixed residential / commercial and commercial areas of urban regions, 5 = one- and two-family homes in rural regions, 6 = multi-family homes in rural regions; values for residence in housing environment types in 2020 corrected for larger share of missing values (see above).

[6] In 2018, the occupational classification changed from ISCO-88 to the revision of the International Standard Classification of Occupations from 2008, the ISCO-08. Due to considerable change in occupational characteristics over the past decades, it had become necessary to adapt the classification in order to provide a more accurate representation of today´s working life. Any change in the statistical nomenclature, however, makes it more difficult to construct occupational categories that remain constant and represent the same type of occupations over several decades. In our analysis, the categorisation by ISCO-08 has been applied only to annual cross-sections from 2018, when the ISCO-88 code was no longer maintained.

Apparently, over the past decades there has been a certain shift of the residential population from type 2 (urban areas, post-war housing) to 3 (urban areas with mainly pre-war housing); type 3 tends to be more characteristic of larger cities. Since it can – as we have explained above – be ruled out that some kind of change would have affected the distinction between neighbourhood categories in the course of various SOEP survey extensions, this shift among location choices indicates a true change in preferences, which will be examined in greater detail in the following sections. With respect to sorting across neighbourhood categories, it is not surprising that average household income is highest among one- or two-family homes and that average income is particularly high in such housing within urban areas (type 1), where the price of land exceeds that in rural regions (Figure 2).

Over the past two decades the divergence in rents between "urban" neighbourhood types 2, 3, and 4 on the one hand, and types 1, 5 and 6 on the other has increased (Figure 3). From around 2005, households have apparently been willing to pay a rent premium for residence at urban locations. A steady gap between the somewhat higher rents in urban post-war residential areas (type 2) than in those of type 3 implies that basic characteristics distinguishing these two kinds of housing environment remained effective throughout the past two decades. Changes in preferences regarding both types of neighbourhood would thus truly reflect the desirability of the respective location characteristics rather than some unobservable change in basic attributes assigned to neighbourhoods in the survey.

4 Analysis

4.1 Household-specific location preferences

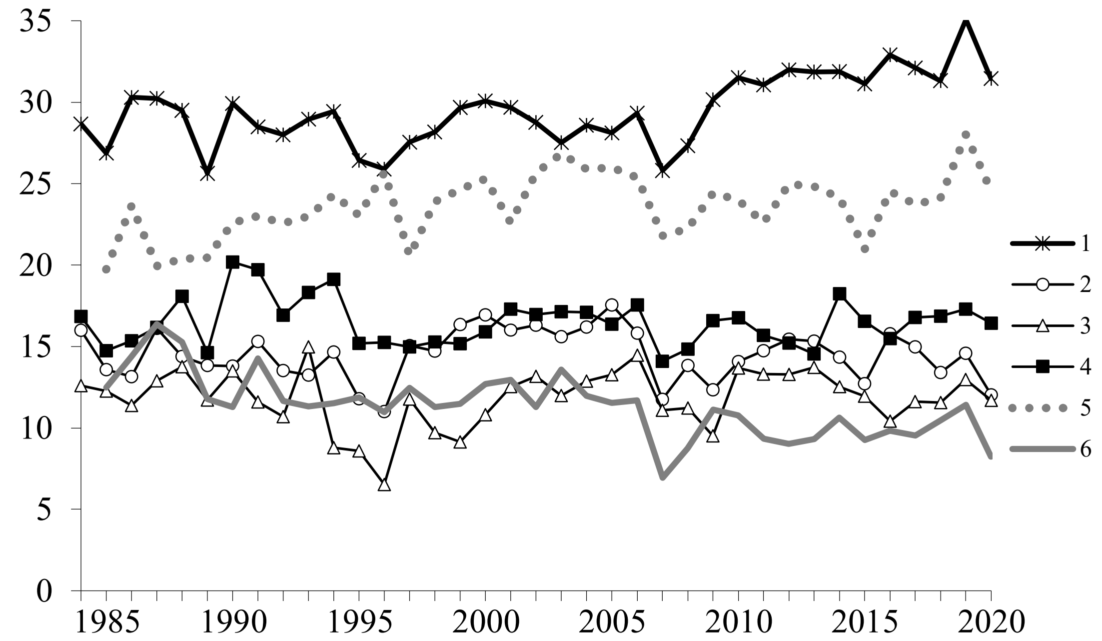
For three basis years, 1985, 2005, and 2020, Table 3 documents our MNL estimates (log odds) of the development of the forces determining location choices over time[7]. Throughout, a large share of the household-specific variation in choice probabilities among basic neighbourhood categories is significantly related to household income and household size. High-income households clearly tend to favour neighbourhoods characterised by one- or two-family homes in urban regions (type 1) over all other options. Larger households tend to reside more often in regions dominated by one- or two-family homes (types 1 and 5), although the preference for rural (type 5) regions has declined over time.

Migrant households, i.e. households comprising at least one member with a direct or an indirect migration background, are more likely to live in an urban environment dominated by multi-family homes (types 2 to 4) than in an urban one- or two-family home environment (type 1), and are particularly unlikely to reside in rural regions characterised by one- or two-family homes (type 5).

[7] Results for other yearly cross-sections are available from the authors on request.

Figure 2

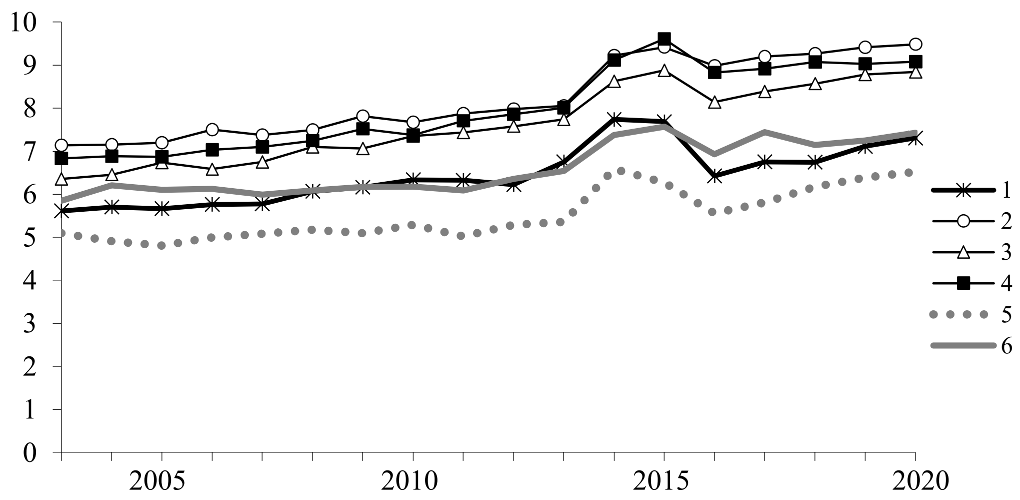
Households in each year´s top quintile of net household income (1984-2020, in %), by housing environment types in West Germany[1]



Authors´ calculations. – Data source: SOEP; weighted using weights provided by the SOEP; [1]types: 1 = one- and two-family homes in residential areas of urban regions, 2 = multi-family homes in residential areas of urban regions with mainly post-war housing, 3 = multi-family homes in residential areas of urban regions with mainly pre-war housing, 4 = mixed residential/commercial and commercial areas of urban regions, 5 = one- and two-family homes in rural regions, 6 = multi-family homes in rural regions; values for 2019 and 2020 corrected for larger shares of missing values (see above); in 1984, only types 1-4 are distinguished.

Figure 3

Average monthly rent (without heating) in Euro per m² (in current prices), by housing environment types[1] in West Germany, 2003-2020



Authors´ calculations. - Data source: SOEP; weighted using weights provided by the SOEP; [1]types: cf. Figure 2.

Table 3

Household characteristics, by choice of housing environment type…(log odds, base category is type 1 in all years)), selected years

	Urban regions, multi-family homes			Rural regions	
Housing environment type….	2	3	4	5	6
	post-war	pre-war	central	one- or two-family homes	multi-family homes
1985					
income (log)	-0.198**	-0.395***	-0.357***	-0.256***	-0.459***
	(0.108)	(0.090)	(0.057)	(0.089)	(0.127)
household size	-0.518***	-0.547***	-0.427***	0.190***	-0.115***
	(0.087)	(0.055)	(0.091)	(0.050)	(0.041)
dummy variables					
migrant	0.147***	0.135***	0.063	-0.146***	-0.006
	(0.045)	(0.034)	(0.061)	(0.034)	(0.019)
age 60^{+}	-0.300***	-0.303***	-0.221***	0.020	0.027
	(0.069)	(0.058)	(0.041)	(0.060)	(0.064)
upper secondary school	-0.052	0.129	0.154***	-0.089	-0.039
	(0.059)	(0.093)	(0.049)	(0.070)	(0.076)
dummy variables representing occupations (reference: managerial and professional occupations)[1]					
technician	-0.039	-0.183*	0.041	-0.112*	-0.020
white-collar worker	-0.019	-0.022	0.059	0.008	0.018
agricultural worker	-0.132	-0.160**	-0.202***	0.009	-0.243***
skilled manual worker	0.016	-0.020	0.038	0.031	0.105**
unskilled worker	0.009	0.027	0.098*	0.029	-0.001
$\delta_{h.t}$	-0.348*	-0.650***	-0.074	-0.825	-0.765
	(0.189)	(0.184)	(0.197)	(0.516)	(0.518)
observations			3,898		
p^2_{MF}			0.0347		
2005					
income (log)	-0.202***	-0.393***	-0.353***	-0.179**	-0.587***
	(0.054)	(0.036)	(0.046)	(0.088)	(0.072)
household size	-0.471***	-0.455***	-0.400***	0.119***	-0.133***
	(0.061)	(0.055)	(0.092)	(0.035)	(0.057)
dummy variables					
migrant	0.305***	0.274***	0.184***	-0.216***	-0.007
	(0.045)	(0.036)	(0.044)	(0.094	(0.060)
age 60^{+}	-0.362***	-0.485***	-0.270***	-0.083	-0.245***
	(0.075)	(0.046)	(0.065)	(0.122)	(0.062)
upper secondary school	-0.041	0.059	0.145**	-0.175**	-0.140*
	(0.074)	(0.087)	(0.058)	(0.069)	(0.080)
dummy variables representing occupations (reference: managerial and professional occupations)[1]					
technician	-0.026	0.038	0.020	-0.008	0.028**
white-collar worker	-0.047	-0.099**	0.043	0.047	0.033
agricultural worker	0.020	0.056*	0.034	0.065	0.089*
skilled manual worker	-0.014	-0.110***	-0.003	-0.050*	0.020
unskilled worker	0.042	0.179***	0.098	0.087	0.179*
$\delta_{h.t}$	-0.420***	-0.778***	-0.085	-0.764	-0.938*
	(0.109)	(0.211)	(0.147)	(0.535)	(0.554)
observations			6,472		
p^2_{MF}			0.0361		

Table 3 continued

Housing environment type….	Urban regions, multi-family homes 2 post-war	3 pre-war	4 central	Rural regions 5 one- or two-family homes	6 multi-family homes
2020					
income (log)	-0.403***	-0.455***	-0.477***	-0.092	-0.498***
	(0.115)	(0.086)	(0.084)	(0.066)	(0.0661)
household size	-0.648***	-0.462***	-0.335***	-0.035	-0.359***
	(0.095)	(0.094)	(0.078)	(0.064)	(0.019)
dummy variables					
migrant	0.173	0.228**	0.240*	-0.231***	0.052
	(0.105)	(0.109)	(0.122)	(0.096)	(0.122)
age 60^{+}	-0.330***	-0.474***	-0.473***	-0.183***	-0.402***
	(0.101)	(0.034)	(0.042)	(0.026)	(0.042)
upper secondary school	-0.013	-0.067	0.075	-0.206***	-0.297***
	(0.038)	(0.066)	(0.053)	(0.060)	(0.060)
dummy variables representing occupations (reference: managerial and professional occupations)[1]					
technician	0.111	0.006	0.047	0.067**	0.114***
white-collar worker	0.026	0.029	0.018	0.010	-0.052
agricultural worker	0.067	-0.091*	0.046	0.081**	0.048
skilled manual worker	-0.013	-0.059	-0.047	0.080***	-0.026
unskilled worker	0.019	0.072**	0.029	0.167***	0.206***
$\delta_{h.t}$	-1.031***	-0.137	-0.082	-0.662	-0.767
	(0.164)	(0.134)	(0.155)	(0.593)	(0.611)
observations			6,118		
p^2_{MF}			0.0425		

Authors´ calculations. - Data source: SOEP; multinomial logit estimation, weighted using weights provided by the SOEP; robust standard errors (clustered by macro-region) in parentheses; ***/**/* =significant at 0.01/0.05/0.1-level, p^2_{MF} = McFadden´s Pseudo-R^2; for explanation of variables cf. Table 1; [1]among occupational characteristics, multiple entries per household are possible; since all variables are constructed to have mean zero, the constants δ_h represent mean utilities, i.e. the probability of households with mean characteristics to reside at each housing environment type.

Households with members being 60 years or older are, by contrast, less likely to reside in urban regions dominated by multi-family homes (types 2 to 4) than in urban areas characterised by one- or two-family homes (type 1) or in rural regions (types 5 and 6). Over time, they have also tended to display a lower preference for rural environments vis-á-vis their most preferred type 1 environment.

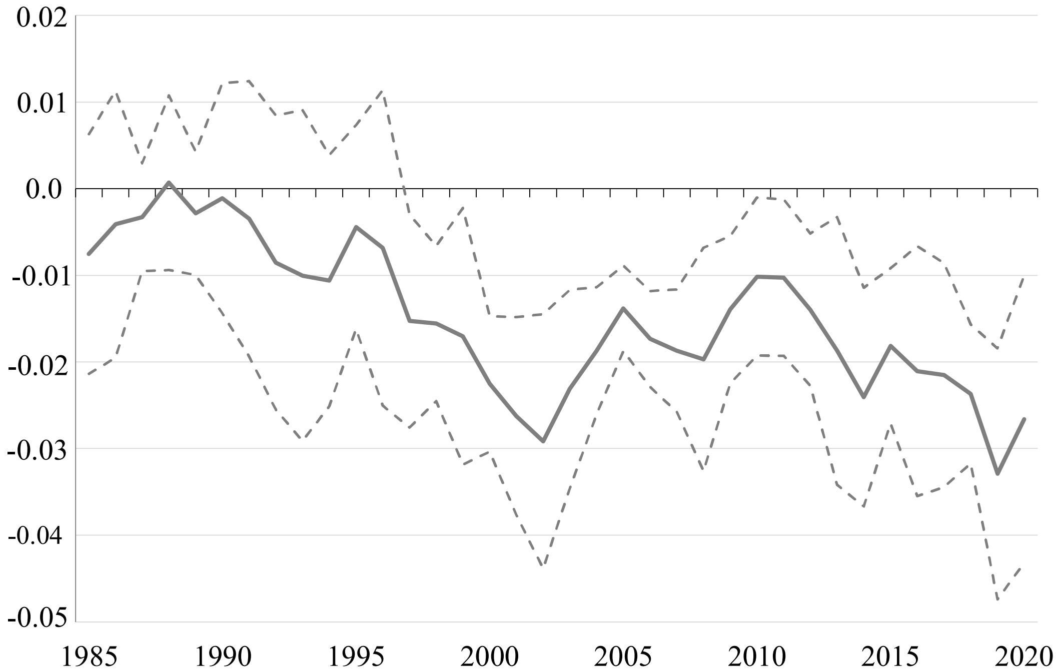
It is somewhat more difficult to discern a pattern of locational choices with respect to the educational and occupational structure of households. Yet one trend seems to emerge: More educated households, i.e. those households comprising at least one member who graduated from upper secondary school, have tended over time to shy away from rural environments. Figure 4 provides a graphical account of this transition on the basis of our annual estimates.

By contrast, in addition to basic determinants such as income, household size, age, education and the migrant background, the occupational structure of households does not seem to have a similarly significant bearing on the choice of the housing environment. Yet, manual and unskilled workers have become more inclined to settle in rural regions.

As all covariates are constructed to have mean zero, constants $\delta_{h,t}$ represent the choice probabilities of households with average characteristics for each neighbourhood type in relation to the base category type 1, urban regions dominated by one- or -two-family homes.

As mean households´ probability to locate in any other type cannot exceed 0.5, the value of δ_h (which is measured in log odds) necessarily falls short of 0.

Figure 4
Annual likelihood of holders of an upper secondary school certificate to reside in type 6 (multi-family homes of rural regions) among 6 types of housing environment[1], 1985-2020, MNL estimation, marginal effects

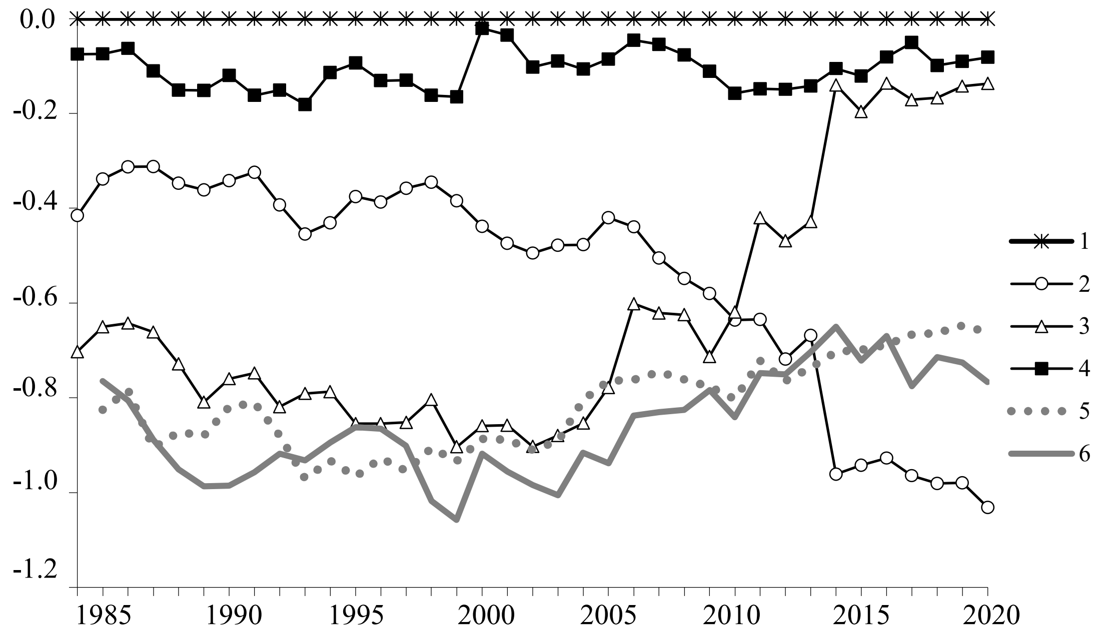


Authors´ calculations. - Data source: SOEP; weighted using weights provided by the SOEP; [1]types: cf. Figure 2; solid lines display annual marginal effects of MNL estimation (standard errors clustered by macro-region), dashed lines display lower and upper bounds of 95% confidence interval; no information available for 1984.

Three principal insights emerge from an inspection of our estimates. First, over the whole sample period type 4 environments, i.e. urban central regions with mixed housing structure, roughly enjoy the same average appreciation as urban environments dominated by one- or two-family homes (type 1). Second, rural environments (types 5 and 6) receive a substantially lower appreciation, albeit with the slight qualification that for type 5 environments, i.e. rural regions dominated by one- or two-family-homes, the discrepancy with type 1 environments is measured with a large degree of imprecision and according to point estimates has tended to decline somewhat.

Third, while the urban multi-home environments which are either dominated by post-war (type 2) or pre-war (type 3) housing both enjoy a lower appreciation than type 1 environments throughout the sample period, we observe noteworthy shifts in the relative attractiveness of these two types of environment: Type 3 housing which is most typical of the more central parts of large cities, has closed the gap to type 1 housing in recent years. By contrast, type 2 housing, which is most typical of post-war urban residential areas located in some distance to centres, drastically has been falling out of favour over time. Effectively, both urban housing types have completely changed their roles in the preference ranking of housing environments. This transition is displayed on an annual basis in Figure 5. Obviously, it has taken off in the early 2000s, coinciding with the long-lasting economic recovery and labour market boom instigated by the Agenda 2010 reforms.

Figure 5
Annual mean location preferences, MNL estimation, log odds δ_h, by housing environment types in West Germany, 1984-2020



Authors´ calculations. - Data source: SOEP; weighted using weights provided by the SOEP; standard errors clustered by macro-regions; types: cf. Figure 2; δ_h = annual log odds of households with mean characteristics to choose housing environment type 1, …, 6 (cf. Table 3); all variables are constructed to have mean zero, type 1 remaining the most probable base category with δ_h = 0; in 1984, only types 1-4 are distinguished.

In a second step of analysis, we utilise the variation of average housing and neighbourhood characteristics across macro regions to explore the driving forces behind mean indirect utilities $\delta_{h,r,t}$. As explained above, the federal states are the smallest regional entity for which the SOEP provides representative statistical information (Bügelmeyer et al. 2015), and some of them need to be grouped to larger entities to engage in a statistically viable analysis. Separating the six types of housing environment h by the constructed six macro-regions (see above) consequently results in 34 type-region combinations (two less than 36, since Berlin comprises only the four urban environments). Our regressions include decade fixed effects, in accordance with equation (7). Alternatively in estimation 2, we pool choice options per decade.

The estimation results documented in Table 4 suggest that those neighbourhoods tend to enjoy a significantly higher appreciation where costs per m² have increased at above-average rates. Over time mean preferences have apparently boosted housing choices in macro regions where housing costs per m² have increased at a comparatively fast rate during the past decades.

Table 4

Mean preferences, by housing environment type and macro-region, fixed effects

model	FE	FE
time interval	years	decades
estimation	(1)	(2)
floorspace (log)	0.011	0.039
	(0.182)	(0.177)
cost/m² (log)	0.258**	0.365***
	(0.066)	(0.086)
mean age	0.139	0.195*
	(0.080)	(0.114)
fixed effect 1984-1990	0.319	-
	(0.155)	
fixed effect 1991-2000	0.416**	-
	(0.120)	
fixed effect 2001-2010	0.012	-
	(0.018)	
constant	-1.514***	-1.345***
	(0.056)	(0.005)
observations	1,201	1201
macro region-type interactions	34	340
R^2 (within)	0.069	0.055

Authors´ calculations. - Data source: SOEP; FE: fixed effects estimation; weighted using a longitudinal weight derived from the annual cross-sectional weights per housing environment and macro-region provided by the SOEP; robust standard errors in parentheses;; ***/**/* =significant at 0.01/0.05/0.1-level; for explanation of variables cf. Table 1

Table 5

Residence in "Social City" programme areas among urban housing environment types 2-4, logit estimation, average marginal effects

year	2000	2005	2015	2020
estimation	(1)	(2)	(3)	(4)
	dy/dx	dy/dx	dy/dx	dy/dx
income (log)	-0.034***	-0.035***	-0.039***	-0.040***
	(0.008)	(0.008)	(0.013)	(0.005)
household size	0.016	0.021***	0.017**	0.020***
	(0.010)	(0.010)	(0.008)	(0.004)
dummy variables				
migrant	-0.002	-0.005*	0.016	0.020***
	(0.005)	(0.003)	(0.012)	(0.007)
age 60+	-0.022***	-0.006	-0.024**	-0.015
	(0.004)	(0.008)	(0.010)	(0.009)
upper secondary school	-0.001	-0.001	-0.002	0.000
	(0.007)	(0.011)	(0.006)	(0.011)
dummy variables representing selected occupations (reference: highly qualified (degree-level) occupations)				
technician	-0.018**	-0.000	-0.014*	-0.007
white-collar worker	0.000	-0.011	-0.002	0.002
agricultural worker	-0.009	-0.011	-0.003	-
skilled blue-collar worker	-0.005	-0.007	-0.015	-0.007
unskilled worker	0.005	0.016**	0.005	-0.003
observations	3,566	3,025	4,200	3,047
p^2_{MF}	0.018	0.018	0.043	0.042

Authors´ calculations. - Data source: SOEP; robust standard errors (clustered by macro-region) in parentheses; ***/**/* =significant at 0.01/0.05/0.1-level, p^2_{MF} = McFadden´s Pseudo-R²; for explanation of variables cf. Table 1

Thus, these findings correspond with the results of our first-stage MNL estimations which imply a trend towards housing in central urban residential areas, where rents have risen faster than in urban low-density areas and rural regions (see Figures 3 and 5 above).

Alternatively, an estimation using pooled data for each decade (and therefore observing only three differences over time) corroborates these results (estimation 2).

4.2 Households in deprived urban areas

The cross-sectional logit estimations of the likelihood to reside in a programme area of the "Social City" for t = 2000, 2005, 2015 and 2020 display that basic household characteristics distinguishing households in deprived neighbourhoods from those in other urban areas (lower income, larger household size, lower age) have remained relatively stable over the past two decades (Table 5). The migrant status has changed the coefficient sign from negative (and significant at the 0.01-level) in 2005 to positive and significant in 2020, i.e. other things equal is has become more likely for migrant households to reside in programme areas. Low income is obviously the main determinant of housing in a deprived area, while skills and occupation apparently do not exert any significant additional effect.

5 Discussion and conclusions

Our analysis pursues the dynamics of household sorting among neighbourhood categories in West Germany. We examine whether sorting by skills and occupation has increased in line with structural economic change over the past decades. We find that while basic location preferences have persisted, location choices have begun to diverge by age, skills and education. The overall reduction in the number of skilled manual workers, however, has not been accompanied by a stronger clustering of this group within a specific neighbourhood type among our broad classification.

Our results on widening rural-urban disparities tend to corroborate the polarisation hypothesis from the 1980s and 1990s, which expected residential segregation to increase in line with structural economic change. Furthermore, the polarisation hypothesis projected segregation to increase as a consequence of continuing urbanisation, as the shift of economic activity from manufacturing to services was envisaged to attract more regional and international migrants to cities. Our analysis suggests that location preferences have indeed turned towards more central urban locations. In addition, as a reflection of the strong preference of younger households for residence near to urban centres, which is prone to be linked to longer-term structural economic change, intra-urban disparities of demographic ageing have been on the rise for some time. This may imply very heterogeneous effects across local economies, for example regarding housing markets and consumer services.

Since the beginning of the Covid pandemic the impact of rapidly improving information and communication technology on personal interaction has experienced a considerable spur. It has now become possible for an even greater share of the workforce to disperse to more peripheral locations. In the US, a revival of suburbanisation has already been detected among the largest cities. In the German housing market, rural regions had caught up with large cities at least in the pace of price increases in 2022 (Destatis 2022b). However, the continuing necessity for face-to-face contacts – albeit perhaps at a reduced frequency, depending on the type of economic activity – and further persisting advantages of housing at urban locations might in turn work against this “donut effect” in Germany.

Following a slump in migration to Germany´s largest 15 cities in 2020, between 2020 and 2023 their population increased again by over 2%. An ailing transport and communications infrastructure (including a considerable backlog in the provision of rural broadband access) may continue to generate further disincentives regarding (primary) residence at remote locations and thus reinforce the apparent long-term prevalence of agglomeration for quite some time.

While up to 2020 average preferences had shifted in favour of more central urban areas, cities have also remained the main place of residence for most poor households. It has been the objective of urban regeneration policy in many countries for decades to improve living conditions in deprived areas, where the poor agglomerate. Yet, place-based policies alone will not be able to improve the prosperity of low-income households. With respect to sorting into West German programme areas of the “Social City”, for instance, there have only been limited changes among basic determinants during the past two decades. After all, most of the programme areas still rank high on deprivation indicators today.

While it is difficult to foresee the evolution of location preferences, the analysis makes it possible to derive probable scenarios for the near future. First, rather than provoking further polarisation regarding income inequality amongst neighbouring city districts as predicted by the polarisation hypothesis, it seems that spatial agglomeration forces attracting more well-off households may continue to edge out poorer households from the desirable central parts of cities altogether. For the UK, for example, Bailey and Minton (2018) demonstrate that suburbanisation of poverty has been well underway during the past two decades.

Second, it is plausible to assume that the “donut effect” arising from a higher flexibility of many households in their location choices implies greater residential segregation among the outer zones of urban regions. From different countries, e.g. the UK and France (Malterre-Bartes 2022), it is well-known that isolation of deprived areas on urban fringes may exacerbate the detrimental neighbourhood effects arising for the local population.

Due to continuing segregation at the regional and neighbourhood level, a serious effort to overcome these undesirable context effects will seek to synchronise place-based policy with various other fields of policy, e.g. housing, environment, labour and education. In turn, as spatial inequality is obviously here to stay, it is time to reinterpret the objective of converging living standards.

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Appendix

Table A1

Development of SOEP household-level observations, West Germany (incl. West Berlin), 1984-2020

	unweighted	weighted*
1984	10,363	22,974,202
1985	6,142	23,420,244
1986	5,879	23,731,403
1987	5,513	24,107,552
1988	5,404	24,456,296
1989	5,214	24,608,118
1990	5,091	24,860,661
1991	5,106	25,171,044
1992	5,127	25,154,055
1993	5,184	25,539,304
1994	5,391	25,791,433
1995	5,598	26,395,685
1996	5,527	26,615,027
1997	5,431	26,521,911
1998	6,253	26,214,943
1999	6,172	26,543,256
2000	10,790	26,886,359
2001	10,759	27,145,613
2002	11,137	27,068,697
2003	10,608	27,382,870
2004	10,055	27,576,686
2005	9,827	27,646,447
2006	10,771	27,642,647
2007	10,267	27,794,841
2008	9,648	28,057,873
2009	10,244	28,138,205
2010	13,638	28,370,855
2011	14,781	27,827,278
2012	15,021	27,898,047
2013	16,651	27,579,216
2014	15,682	27,787,221
2015	15,485	28,322,014
2016	16,930	28,478,335
2017	23,062	28,888,160
2018	23,130	28,558,168
2019	35,897	28,397,929
2020	49,932	27,689,703

Authors´ calculations. - Data source: SOEP; *weighted using weights provided by the SOEP