The Journal of Economic Inequality
https://doi.org/10.1007/s10888-023-09616-3

Spatial earnings inequality

Christian Schluter[1,2] **· Mark Trede**[3]

Received: 6 January 2023 / Accepted: 12 December 2023

Abstract
Earnings inequality in Germany has increased dramatically. Measuring inequality locally at the level of cities annually since 1985, we find that behind this development is the rapidly worsening inequality in the largest cities, driven by increasing earnings polarisation. In the cross-section, local earnings inequality rises substantially in city size, and this city-size inequality penalty has increased steadily since 1985, reaching an elasticity of .2 in 2010. Inequality decompositions reveal that overall earnings inequality is almost fully explained by the within-locations component, which in turn is driven by the largest cities. The worsening inequality in the largest cities is amplified by their greater population weight. Examining the local earnings distributions directly reveals that this is due to increasing earnings polarisation that is strongest in the largest places. Both upper and lower distributional tails become heavier over time, and are the heaviest in the largest cities. We establish these results using a large and spatially representative administrative data set, and address the top-coding problem in these data using a parametric distribution approach that outperforms standard imputations.

Keyword Earnings inequality, spatial inequality, inequality decomposition, local earnings polarisation

1 Introduction

Earnings inequality in Germany has increased dramatically over the period 1985-2010. For instance, year-on-year increases have resulted in a staggering 60% rise in the Theil inequality measures for prime-aged male workers in full-time employment in the West. These increases far exceed inequality growth in the US for comparable workers, and have thus generated much interest among researchers (e.g. Dustmann et al. 2009; Card et al. 2013; Biewen et al.

✉ Mark Trede
mark.trede@uni-muenster.de

Christian Schluter
christian.schluter@univ-amu.fr

1 Aix-Marseille Université, CNRS, EHESS, Centrale Marseille, Aix Marseille School of Economics (AMSE) , 5 Boulevard Maurice Bourdet CS 50498, 13205 Marseille Cedex 01, France

2 Department of Economics, University of Southampton, Highfield, Southampton SO17 1BJ, UK

3 Department of Economics, Universität Münster, Am Stadtgraben 9, 48143 Münster, Germany

Published online: 25 January 2024

2018; Antonczyk et al. 2018). While these recent investigations have contributed much to our understanding of national inequality trends, conclusions about *local* earnings inequality are difficult to reach. Inequality varies across cities, and this spatial variation is unlikely to evolve uniformly over time. Casual empiricism suggests that it is *within* large cities where the largest earnings and employment discrepancies are observed, and that over time these discrepancies have worsened. Such a spatial perspective then gives rise to several questions: What is the spatial structure of earnings inequality in Germany? What are the relative contributions of large and small places, and how do they change over time? Is national inequality increasing because the rich are getting richer and the poor poorer in the largest locations? These questions and our quantifications are of direct policy relevance in view of the large resources and thus much debated place-based policies which seek to "level-up" between regions in terms of average wages. If the policy objective is the fight against inequality, then our results show that this fight needs to take place in the largest cities.

In this article, we seek to address these questions by estimating *directly* all *local* earnings distributions, comparing earnings inequalities across space and specifically in relation to city size and across time, and decomposing formally aggregate inequality into its within-location and between-location components. To this end, we use a large and spatially representative administrative data set for Germany, and a novel parametric estimation strategy that overcomes the top censoring problem in these data (and outperforms the usual Tobit imputations adopted in the papers cited above). Our estimates of the local earnings distributions give rise to our key finding: We observe an increasing trend in the *city-size inequality penalty*. This finding is robust across inequality measures. In other words, in each year larger cities tend to exhibit higher levels of inequality compared to smaller ones. Moving from the smallest to the largest places tends to double inequality locally. Over time, inequality tends to increase in all places, but relatively more so in the largest places. The cross-sectional phenomenon is well captured by annual univariate regressions of city inequality on city size, so the trend of the inequality penalty can be measured by the time trend in the slope coefficient of city size. We find that the 60% peak national inequality increase in 2010 is well matched by a 53% rise in this slope coefficient relative to the 1985 base year. Hence, the worsening inequality in the largest cities drives the observed trend in national inequality. This is further confirmed in our decomposition analysis: Overall national inequality is almost fully captured by the within-location component (its share being at least 95% of the total). This within-component increases strongly over time. In fact, the 15 largest cities contribute persistently nearly half of total national inequality in each year. The rank order of within-location inequality is also persistent, the mean of the year-to-year Spearman rank correlations being .89. Overall, the worsening inequality in the largest cities is amplified by their greater population weight.

We then show that the worsening city-size inequality penalty is due to an increasing earnings polarisation that is strongest in the largest cities: The rich are richer and the poor are poorer in the largest locations, and this gap is increasing over time. Visually, the top and bottom quantiles of the local (and aggregate) earnings distributions "fan out" over time, leading to increasingly heavier top and bottom tails, and these trends are amplified by city size. Worryingly, the poor have become poorer in the largest places: For instance, the (inflation adjusted) 15% earning's quantile in 2010 is lower than its value in 1985; by contrast, the 85% quantile has increased by a factor of 1.3. As metrics, we quantify this spatial and temporal earnings polarisation using tail indices and top earnings shares. While earnings polarisation has considerably increased across all locations, the centrifugal forces are the largest in the largest locations. For instance, the top earnings share in the largest locations is shown to have grown from about 25 to 45% according to our measures. Coinciding with this spatial earnings polarisation is a spatial job polarisation, again amplified by city size, according to which the share of workers in top-paying jobs has increased. All these changes take place locally, as the mobility of workers across locations is small. Moreover, unlike "big picture" investigations that compare outcomes between distant time points (e.g. 1985 v. 2010), our annual series reveal that the diagnosed distributional changes are fairly continuous year-on-year.

While we follow the established literature focussing first on prime-aged male workers in the West (see below), we also find the increasing city-size inequality penalty in the female wage distribution, and confirm its robustness after including the East. In a comparative benchmark exercise, we find qualitative similar (but somewhat more dispersed) results for the US.

Our paper connects and contributes to several strands of the literature. First, we contribute empirically to the literature on the rapidly risen national earnings inequality in Germany. Important contributions are, for example, Dustmann et al. (2009), Biewen et al. (2018) and Antonczyk et al. (2018) focussing on compositional changes to explain inequality trends. Card et al. (2013) document the increased assortative matching between workers and firms in West Germany using empirical two-way fixed effects models. In order to maintain comparability with this corpus of work, we use comparable administrative data and focus on the same group of workers (prime-aged full-time male dependent workers in West Germany), before considering female workers and the East. Recently, Drechsel-Grau et al. (2022) have extended the universe of analysed workers by including workers in part-time jobs, those who have only partially worked during the year, and marginal workers in social-security exempt so-called mini-jobs. In line with the above work, they observe that cross-sectional male earnings inequality rose until 2009, and slowed down thereafter. These additional subgroups, and specifically the expansion of male part-time work, are shown to have contributed to a further worsening of outcomes at the bottom of the earnings distribution.

As none of these papers adopt a spatial perspective, our principal empirical contribution is the examination of the spatial structure of inequality and its changing trend: local inequality tends to increase in location size, overall inequality is almost complete within-location inequality, and the largest cities become more important; in short, the city-size inequality penalty is increasing over time, which coincides with a worsening wage polarisation that is more severe in the largest cites. Our work is among the first to examine systematically the spatial structure of German earnings inequality[1] at the appropriate spatial scale, and all our quantifications and proposed metrics are new.

Second, we contribute methodologically to the literature on earnings inequality measurement with top-coded data. Administrative earnings data are top-coded in many countries including the US and Germany. This presents a major conundrum for assessments of earnings dispersion, as the upper tail of the wage distribution is missing. For instance, German administrative earnings data are always top-coded at the year-specific social security con-

[1] The few exceptions tend to focus on West-East or urban-rural difference. For instance, Immel and Peichl (2020) study regional disparities in Germany by mapping the spatial variation of membership in the top 10% and bottom 40% earnings group. This work uses interval-censored earnings data from the microcensus for the whole of Germany and the district as the spatial unit. The authors find a large gap between the East and the West, which has lessened somewhat in recent years as top-bottom disparities within these two regions have fallen. Immel (2021) considers the effects of district-level poverty on local voting and fiscal policy outcomes, using data from the microcensus. She finds that higher local poverty increases local support for radical parties, a fall in the provision of services, and an increase in business taxes. Popp (2019) maps the Gini coefficient at the district level in 2017, and juxtaposes the aggregated time series for urban and rural districts since 2000, using wage data for full-time workers similar to ours. While urban inequality considerably exceeds inequality in rural areas, the time paths follow a similar pattern.

tribution's threshold, the mean incidence of right-censoring in our data being about 12.7% across all years. In the US CPS, Jenkins et al. (2011) report an incidence of up to 5.7%. As a substantive methodological and empirical contribution, we demonstrate how this censoring problem is convincingly overcome by a parametric approach based on the generalised beta distribution of the second kind (GB2) and a censoring-adapted maximum likelihood estimation strategy.

The outstanding goodness-of-fit resulting from this statistical approach is demonstrated in several validation exercises using internal as well as external data. Moreover, we demonstrate that this approach outperforms the usual Tobit imputations in the context of earnings inequality measurement. Empirically, a new finding is that the GB2 models provides outstanding fits for all *local* earnings distributions irrespective of city size. The estimated location-specific distribution models then permit the computation of local earnings quantiles, moments, and inequality measures. We further innovate by showing how the tail indices of the earnings distribution can be used as indicators of earnings polarisation.

Third, we fuse strands in the inequality and urban economics literature by emphasising the importance of the spatial structure in the former, and of inequality in the latter. As argued above, the inequality literature tends to focus on the national earnings distribution, ignoring thus the spatial dimension of inequality. By contrast, spatial variation is a core concern in urban economics, but the usual focus is on the spatial difference of mean wages, often referred to as the "urban wage premium" (see, e.g. Glaeser and Mare 2001, using data for the US or Combes et al. 2008, for the case of France). Dauth et al. (2021) extend the empirical two-way worker-firm fixed effect model of Card et al. (2013) by decomposing further the firm-worker covariance by city size. This sorting measure increases in city size, but is quantitatively small (their footnote 27). This worker sorting, however, is taking place within rather than across cities, since we show that the spatial mobility of workers is relatively low. In contrast to this focus on mean wages, Baum-Snow and Pavan (2013) were among the first to examine systematically the link between location size and local wage inequality in the US. While we address this question as well using administrative data for Germany, we go beyond their spatial variance decomposition and consider explicitly and directly the role of job and earnings polarisation, in a coherent distributional framework. The quantitative importance of the city-size inequality penalty becomes even more evident when benchmarked against the size of the urban wage premium. We show that the city-size earnings inequality penalty is substantially larger and the statistical relation is considerably tighter. Specifically, for the year 2010, the city-size elasticity is about 3.6 times larger and the R^2 statistics is about 3.3 times larger.

The outline of the paper is as follows. In Section 2 we detail the treatment of our administrative data, the empirical challenges, and explain our estimation method for top-coded earnings data. Our empirical analyses are carried out in Sections 3 and 4, where we show robustly that inequality growth in the largest locations drives the overall inequality trend. While the focus is on male workers in the West, qualitatively similar conclusions obtain for female workers and the East (Sections 3.4 and 3.5). In Section 4 we dig deeper, and reveal how locally increased inequality is a manifestation of increased earnings polarisation and local job polarisation. Section 5 places the evidence for Germany in an international context by benchmarking the changes against US data. While throughout our analysis focuses mainly on the period 1985-2010 in which inequality rose spectacularly, the Concluding Comments of Section 6 discuss the trends after the inequality turning point 2010. All technical material is collected in the (Web-) Appendix, which also provides extensive robustness evidence as well as further graphical analysis.

2 Data and estimation

Our analysis of the evolution of spatial inequalities uses German administrative data for the years 1985-2017 (SIAB) which is a 2% sample of all dependent (i.e. not self-employed or civil servant) employees who are subject to social security contributions. The sampled population covers about 80% of German employees. Two reasons motivate this choice: First, in order to bring the spatial perspective to the established literature, we want to stay close to it in terms of data source and sample selection.[2] Second, our administrative data set is sufficiently large to allow a spatially representative analysis at the appropriate spatial scale (which is not feasible using standard survey data such as the socio-economic panel, SOEP).

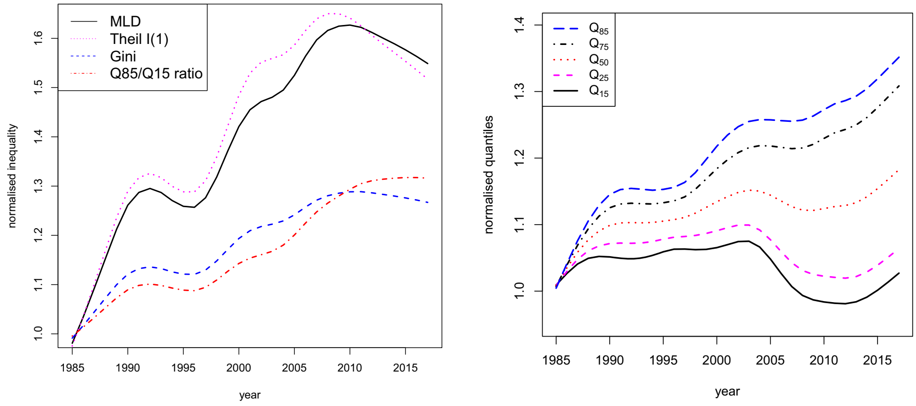
As this data set is well known, we refer to the established literature for detailed descriptions, such as Biewen et al. (2018) who also survey the literature on the evolution of German wage inequality. Our analysis starts in 1985 since a structural break in the reporting of the data in 1984 implies that wages from earlier years are not fully comparable to subsequent ones. In order to maintain comparability with the established literature, we consider the population of prime aged (20-60) full-time male dependent workers in West Germany. However, we also consider females in Section 3.4 and East Germany in Section 3.5. Our unbalanced panel contains about 8 million year-person observations. For the last year 2017, the cross-section counts 214,255 observations. Earnings refers to real annual wage earnings after standard CPI deflation. Alternative definitions, such as daily wages (noting that hours of work are not recorded in the data), or daily wages of the longest firm-worker spell in a given year, yield similar results and are not reported below.

We depict in Fig. 1 the national trends in earnings inequality that we seek to decompose spatially. In particular, Panel (a) depicts the smoothed time trend for several inequality measures. Year-on-year increases have resulted in a staggering 25-60% rise. Different inequality measures agree on the trend but quantify the distributional changes differently depending on their top-sensitivity (see Web-Appendix Section A.2.2 for a detailed technical analysis.). Panel (b), depicting the trends in bottom and top quantiles, reveals that this inequality increase is due to the aggregate distribution fanning out over time. This fanning out suggests an earnings polarisation at the national level, that we will also find locally, and more severely in the largest locations. In particular, the lowest earnings quantiles deteriorated in the years since about 2001, falling even below their 1985 level, while the upper quantiles display remarkable year-on-year increases.

These inequality and polarisation trends correlate partly with changing general economic conditions, such as the recession in 2001 and the Great Recession 2008-09, and partly with changing labour market institutions. In particular, while union membership declined, the biggest change was an increased adoption of localised and decentralised firm-level wage settlements (as opposed to the traditional industry-wide agreements resulting in wage compression[3]) in the mid 1990s to combat rising unemployment levels, and credible threats of relocating manufacturing to cheaper sites in Eastern Europe after 2000. See e.g. Jäger

[2] As is usual in this literature, the wage considered is before tax, and the analysis does therefore not take into account the (location-invariant) redistribution of the tax-benefit system. We also note that the self-employed are not sampled. A recent literature examines top wealth and earnings in Germany (Bartels 2019; König et al. 2022), and finds that in recent years the richest 1% tend to be self-employed entrepreneurs. As they are located mostly in larger cities, this would constitute a further factor driving inequality and polarisation in the largest places.

[3] From 1996 to 2019, the share of employees covered by industry-wide agreements fell from 70 to 45%, while the fall of the coverage share of work councils fell more moderately from 55 to 45%. By 2020 about 29% of workers are not covered by any bargaining agreement. Reinforcing these tendencies, the proliferation of "opening clauses" in collective agreements have become more important, permitting an opting out or deviating



(a) Inequality trends (b) Quantile trends

Fig. 1 Time trends of West German earnings inequality 1985-2017. Notes. Plotted are spline-smoothed inequality measures and selected quantiles Q_p of the German earnings distribution, divided by the value in 1985. MLD is the mean logarithmic deviation. Sample of prime-aged male workers in full-time employment in West Germany, using administrative SIAB data

et al. (2022) for a detailed up-to-date description and analysis of the German system of collective bargaining and firm-level worker codetermination. The resulting increased flexibility of labour market institutions, coupled with falling participation of smaller firms, partly explains the losses at the bottom of the distribution and an increase in competitiveness which transformed Germany, according to some commentators, from "sick man" of Europe to a "superstar" (Dustmann et al. 2014) by 2010. Similarly, Biewen and Seckler (2019) conclude that the dramatic decline in union coverage is reponsible for the observed inequality trends, coupled with a shrinking of sectors in which collective settlements were used. At the same time, many large firms have outsourced their lowest paid work (such as cleaning, security, logistics and food jobs) to uncovered firms (Goldschmidt and Schmieder 2017). Yet robotisation in German manufacturing, while highly advanced, has not led to employment declines (Dauth et al. 2021). Within this context, Card et al. (2013) argue that the heterogeneity of pay across German firms has increased, while Hirsch and Mueller (2020) argue that the former's firm wage premium is higher in firms with work councils, reflecting greater worker bargaining power. Germany's first federal minimum wage came into existence only in 2015 as a response to the perceived wage losses at the bottom.

This cited literature focuses, as we do consequently, on the core group of prime-aged workers in full-time dependent employment. Recently, using similar administrative annual earnings data for the period 2001-2016, Drechsel-Grau et al. (2022) have extended the universe of considered workers by including workers with lower labour market attachment: part-time jobs, those who have only partially worked during the year, and marginal workers in social-security exempt so-called mini-jobs. They conclude that an increase in part-time work (from about 3% to 10% for men and from about 30% to 45% for women) has contributed to a further worsening of outcomes at the bottom of the earnings distribution. In a

downwards if a firm's work council agrees. In 2005 about 75% of firms with collective agreements use such clauses. Coverage rates of collective agreements increase strongly in establishment size. In 2019, 66% of firms with more than 500 employees are covered by a sectoral agreement and 86% have work councils, compared to 36% and 6% respectively of firms with fewer than 50 employees. See e.g. Ellguth and Kohaut (2020) for detailed tabulations.

further innovative departure, observations at the censoring threshold are replaced, using a non-parametric matching technique, by uncensored data from the German Taxpayer Panel (TPP). This enables the authors to consider, in addition, entrepreneurs (the self-employed, business owners, and landlords whose 2008 population shares by main earnings source are 2.6%, 8.2% and 1% respectively) and thus to extend the perspective from labour to total earnings. The authors find that the top percentiles increased significantly more for total earnings than for earnings, contributing to a further worsening of inequality. Overall, they conclude that total inequality increased significantly more than earnings inequality. The effect of these two additonal groups of part-time workers and entrepreneurs, impacting the bottom and the top of the distribution, varies slightly but systematically with the size of the local labour market,[4] thus amplifying further inequality and polarisation in the largest places relative to the core group of workers.

2.1 Travel-to-work areas

Our spatial unit is the travel-to-work area (TTWA), in order to operationalise the idea of local labour markets, which are obtained by spatially aggregating smaller administrative NUTS-3 units (districts or *Kreise*) which do not necessarily reflect the local spatial economic organisation. The district is the smallest spatial unit in SIAB for reasons of data protection.[5] This spatial aggregation follows the classification of Eckey et al. (2006), which is based on a detailed factor analysis of actual commuting flows within radii of up to 60 minutes travel time, and results in mapping about 326 districts into 106 TTWAs, none of which is smaller than 100,000 inhabitants. Our results reported below are robust to alternative definitions of commuting zones, as such alternative spatial units and our TTWAs are highly correlated (the results are therefore not reported below). The scale of these spatial units is similar to the 741 Commuting Zones or 283 Metropolitan Areas in US studies, after noting that the US population is about 4 times that of Germany. We follow common practice in urban economics of referring interchangeably to TTWAs, cities or locations.

We provide further data descriptives and summary statistics in (Data) Web-Appendix C, and demonstrate that the characteristics of our data are in line with results reported in the literature. The Data Web-Appendix then proceeds to illustrate and map extensively spatial variations in earnings outcomes, skills and occupations focussing on the largest and smallest TTWAs. We also examine the trends in the spatial mobility of workers across these TTWAs. It turns out that spatial mobility is fairly low, ranging from 2.9% in the 1980s to 5% in the 2010-17 window.[6] In and out movements are typically very similar, rates for large locations being similar to overall rates. This spatial immobility implies that inequality within and between locations will be persistent, and overall inequality trends likely to be driven by within-location changes.

4 In Data Web-Appendix Table C2 we report, using census data, local employment shares. The incidence of self-employment is slightly higher in the largest locations, which we interpret as being driven by a larger share of entrepreneurs.

5 We note that there is a growing literature on residential segregation, which focuses on the growing disparities across neighbourhoods in US cities (see e.g. Fogli and Guerrieri 2019, for a recent contribution), and a technical literature on racial segregation that seeks to quantify the spatial-scale dependency of within and between segregation measures (Reardon et al. 2008). While increased residential segregation undoubtedly leads to an increase in within-city inequality, our focus is on the local labour market as a whole. Nonetheless, we show in Web-Appendix Section D.2 that our results also hold at the level of the district.

6 Nanos and Schluter (2020) and Schluter and Wilemme (2023) explain these patterns of spatial mobility using structurally estimated models of job search within and across local labour markets.

2.2 Estimation of earnings distribution models in the presence of top-coding

As is well known, earnings in German administrative data are top-coded at the year-specific social security contribution's threshold, resulting in a mean censoring incidence of about 12% in the yearly cross-section. The resulting absent earnings variation in the right tail of the estimation sample presents a vexing problem for inequality analysis.[7] To address this issue, we add structure by modelling local and national earnings distributions parametrically, i.e. the unit of analysis is modelled and estimated directly (unlike the indirect micro-econometric approach of wage regressions). A natural choice of departure then is the four-parameter generalised beta distribution of the second kind (GB2) which in the earnings distribution literature has been used very successfully to model national distributions.[8] The GB2 density is given by

$$f(x; a, b, c, p) = \frac{bx^{pb-1}}{a^{bp}B(p, c)[1 + (x/a)^b]^{c+p}}$$

where B denotes the beta function. The model nests several other well-known distributions as special cases (e.g. the Singh-Maddala / Burr distribution, the Dagum, lognormal, gamma, Weibull, Lomax and Fisk distributions). See Kleiber and Kotz (2003) for a general textbook exposition, and Web-Appendix Section A for further technical details.

The top-coding is then addressed within a maximum likelihood estimation framework. The log-likelihood for each location l is

$$\sum_{i\text{:not censored}} \log f_l(y_i) + N_{c,l} \times \log(1 - F_l(c))$$

where y_i denotes the earnings of worker i (in location l), l indexes the location, F_l is the local GB2 CDF, c the right-censoring earnings threshold, and $N_{c,l}$ the number of censored cases locally. In short, $f_l \equiv f(.; a_l, b_l, c_l, p_l)$ is estimated for each location.

The appropriateness of this distributional model for our top-censored data is extensively verified in the Web-Appendix. In particular, we show first in Web-Appendix Section A.3 in simulation experiments that the quality of the distributional parameter estimates is not unduly affected by the incidence of right-censoring similar to that encountered in our actual administrative data. In Web-Appendix Section B.4 we confirm in a further validation using external data (uncensored and censored administrative earnings data from the SOEP-RV project), the superb performance of the GB2 model. Second, and as a substantive empirical contribution, we then show that the GB2 distribution not only provides an outstanding fit in the German case nationally, but also *locally* for our TTWAs. The outstanding goodness-of-fit is illustrated in many examples covering the largest and smallest locations in Web-Appendix Section B. Finally, we also demonstrate in Web-Appendix Section B.4 that our parametric approach outperforms the usual Tobit imputations in the context of inequality measurement.

[7] To date, the distributional literature has often dealt with this censoring problem by restricting the inequality analysis to non-decomposable measures that exclude distribution tails, such as the Q_{75}/Q_{25} quantile ratio. By contrast, the micro-econometric literature frequenly uses Tobit imputations. We show in Web-Appendix Section B.4, using results from the companion paper König and Schluter (2022), that our proposed parametric approach outperforms Tobit imputations for the purpose of inequality measurement. In particular, Tobit imputations tend to over-estimate censored earnings, leading to a substantial over-estimate of inequality.

[8] For instance, Jenkins et al. (2011) advocate the use of the GB2 model for the aggregate US CPS data, and show by juxtaposing the fits for the censored public use CPS data and the internal confidential CPS data that this distributional model considerably reduces the censoring problem. In related work Armour et al. (2016) use a simpler Pareto model to impute the right-censored tail.

Finally, we also note that unlike the Tobit approach, in which usually location-invariant Mincerian earnings functions are estimated, our estimation approach does not impose cross-location restrictions since we estimate each local earnings distribution independently from other locations. Having thus estimated the local earnings distribution, inequality and polarisation measures (based on tail indices) are directly computable.

3 Time trends and the changing structure of spatial inequality

For our subsequent analysis, we focus on the mean logarithmic deviation (MLD) given by $I(0) = \log(E(Y)) - E(\log Y)$ for earnings random variable Y with distribution F. We have already seen in Fig. 1.(a) that the use of alternative inequality measures yields the same characterisation of the trend in German earnings inequality. In view of this similarity, we use the MLD as the inequality index that provides the greatest transparency for our purposes. All our subsequent results are robust across inequality measures (see e.g. Web-Appendix Section D.1 for further evidence).

3.1 Spatial inequality decompositions 1985-2017: Dominance of the within-location component

We turn to the spatial dimension of the inequality evolution. First, we decompose directly inequality by contrasting inequality within local labour markets with inequality between them, examine the time trends, and then quantify the increased importance of large cities. In the spatial context, scale-independent measurement of inequality is especially important, since otherwise larger places may mechanically exhibit larger earnings dispersion if earnings in larger places are scaled up compared to smaller places. The variance, of course, is not scale independent. As all generalised entropy indices $I(\alpha)$ are decomposable (see Web-Appendix Section A.2 for formal definitions), so is the MLD, the resulting decomposition generically being

$$I(0) = I_{within}(0) + I_{between}(0). \tag{1}$$

For our spatial decomposition the "between" component specialises to the inequality index applied across locations whose members receive the mean earnings in that location, while the "within" component specialises to the population weighted sum of local inequalities I_l. We estimate these using our maximum likelihood estimated earnings models thereby accounting for the discussed right-censoring of earningss.

Figure 2 depicts the trend of overall inequality measured by MLD, in particular its sharp increase from the mid 1990s to about 2010. Also plotted in this figure is the within-locations component, which closely tracks the overall trend. It is also clear that most inequality is due to this within-component, its share in total inequality being no less than 95% throughout.[9] This is one quantification of the city-size inequality penalty (depicted in Fig. 4 for the MLDs), which leads us to our first important conclusion: Spatial inequalities are predominantly within locations, not across locations.

[9] Fogli and Guerrieri (2019, Figure 1) provide a similar spatial decomposition of the Theil index for US Metro areas using census data 1980-2010 and family earnings. At the national level, the Theil index is about .23 in 1980 and increases steadily to .3 in 2010. The share of the within-location component is about 83% in 1980 and about 70% in 2010. The levels of German inequality globally and within locations are thus considerably smaller, but inequality growth is larger than in the US; the share of the German across-locations component is considerably smaller than in the US.

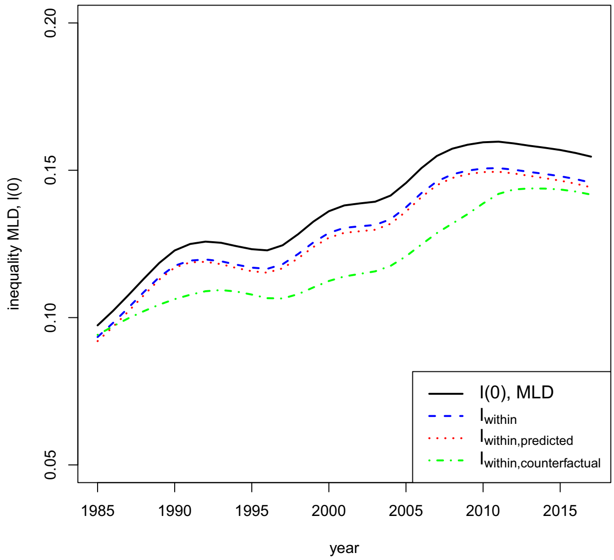
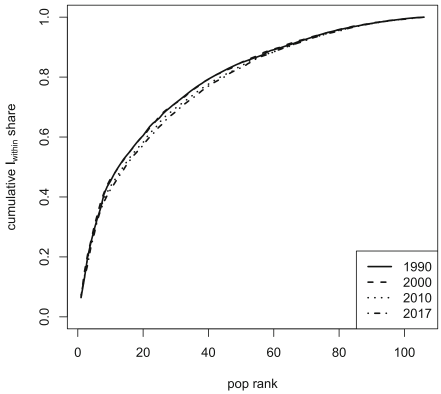


Fig. 2 Spatial inequality decompositions 1985-2017. Notes. Plotted are the overall mean logarithmic deviations (MLD) or Theil measures $I(0)$ (solid black line) and the within-location component $I_{within}(0)$ (dashed blue line). The direct spatial inequality decomposition is $I(0) = I_{within}(0) + I_{between}(0)$, where $I_{within} = \sum_{l=1}^{L} s_l I_l(0)$, I_l denoting the inequality measure applied to location l and s_l the local population share. See Web-Appendix Section A.2 for formal definitions. Note that neither the Gini nor the Q85/Q15 ratio are decomposable. The method for obtaining the predicted within-component (dotted red line) is explained below in Section 3.3, as is the counterfactual (dashed-dotted green line) which is constructed on the assumption that the spatial structure of inequality of 1985 prevails

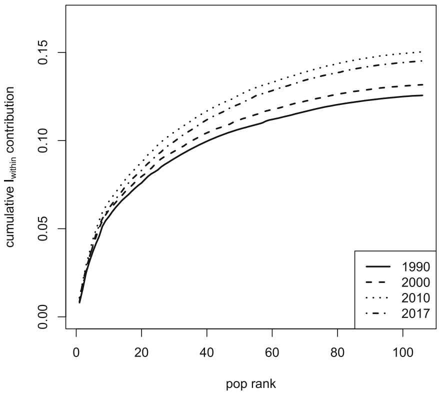
Already included in the figure is the prediction of the dominant within-location component. The method is explained below in Section 3.3, exploiting the tight relation between local inequality and local population size. For now, we simply observe that the method provides a superb prediction of the dominant within-component, which then serves as a good approximation of the overall level of inequality. In that section we also use the method to construct the plotted counterfactual, based on the assumption that the spatial structure of 1985 prevails. For now, we simply observe that overall inequality would have been substantially smaller in the absence of changes to the spatial structure.

3.2 The stable population structure in locations

Next, we take a first look at the role of city size for the overall inequality trend by examining the contributions to the dominant within-locations component of the largest cities. To this end, we plot in Fig. 3 for selected years the cumulative within-locations component $\sum_l^r s_l I_l(0)$ contributions against the ordered local population sizes represented here by the rank r of the city (rank 1 being the largest and 106 the smallest city), expressed first as inequality shares and then levels. Panel (a) of the figure (being similar to a Lorenz curve) not only shows that the 15 largest TTWAs contribute about 50% to the total I_{within} measure, but also that the hierarchical city-size structure in terms of ranks is remarkably stable over time. Panel (b) shows that the trends in overall inequality are principally driven by changes in local inequality I_l in the largest cities. We thus conclude that the changes in spatial inequalities are predominantly due to inequality changes *within* the largest locations.



(a) shares



(b) levels

Fig. 3 Cumulative within-locations inequalities. Notes. x-axis: ordered population shares, ranging from the largest (rank 1) to the lowest (rank 106). y-axis: cumulative within-inequality $\sum_{l=1}^{r} s_l I_l(0)$ for ranks $r = 1, \ldots, 106 = R$, unnormalised (right panel) and as share of total within-inequality I_{within} (left panel). For instance, the left panel shows that the 15 largest TTWAs contribute about 50% to the total I_{within} measure; the population share of these 15 TTWAs is about 45%

Further evidence of this stability is provided by the Spearman rank correlation between local inequality. The mean of the year-to-year rank correlations is .89. Even in longer run, these a fairly stable: The Spearman rank correlation between local inequality in 1985 and 2000 is .72; adding another 10 years, this correlation falls only slightly to .68 for 1985 and 2010. For 2000 and 2010 it is .85, and .84 for 2010 and 2017.

3.3 The time trend of the city-size inequality penalty

Next, we examine directly to what extent the local earnings inequalities (I_l) relate to the size of the local population. To this end, the key Fig. 4 depicts simple scatter plots for several years of local inequality against local log population size, as well as the fitted (population-weighted) OLS regression line and a non-parametric fit (using a local polynomial regression, "loess"). The figure reveals a qualitative positive relation that becomes over time increasingly better described by a linear relation. In particular, the plot for year 2010 reveals a remarkable OLS fit (with R^2=.56) for a univariate regression, and a non-parametric local regression fit that is approximately linear for larger locations. Over the depicted size range, the regression line implies that inequality increases by about 71% in that year, going from the smallest to the largest locations.

A scalar measure of the city-size inequality penalty is thus the slope coefficient $\beta_{1,t}$ of the regression of local inequality on log city size in year t

$$I_l^{(t)} = \beta_{0,t} + \beta_{1,t} \log(size_{l,t}) + error_{l,t} \tag{2}$$

Figure 5 depicts the trend of the slope coefficient across all years. The slope coefficients exhibit an almost 60% increase during the period 1985-2010 in which overall inequality has significantly increased, which implies a substantial increase of the city-size inequality penalty. This in turn drives the increase in inequality at the national level. In line with the overall inequality trend, the penalty is, however, declining post 2010 (which is explained below in Section 4 and Fig. 6).

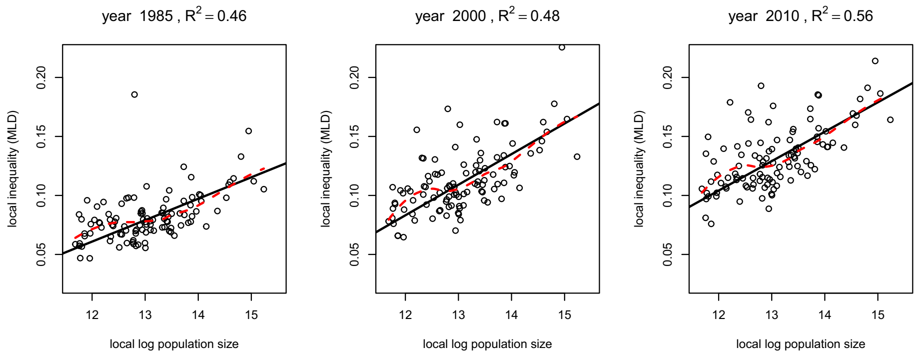


Fig. 4 The city-size inequality penalty. Notes. Solid line: fit of univariate population weighted OLS regression of local inequality on log population size whose R^2 is reported in the panel title. Dashed red line: non-parametric fit using a local polynomial regression (loess) on the bivariate relation. In Web-Appendix Section D.1 we show that the findings are robust across inequality measures, such as the Gini coefficient or the Q_{85}/Q_{15} ratio. For a fusion of the temporal and spatial cross-sectional perspective, see Web-Appendix Section D.10. See Web-Appendix Section D.4.1 for tables focussing on the 5 largest and smallest TTWAs and further visualisations. The 5 largest TTWAs are Berlin, Hamburg, Munich, Frankfurt, and Düsseldorf. Location sizes based on population data from the Federal Statistical Office

In Web-Appendix Section D.1 we show that these findings are robust across inequality measures, and in Web-Appendix Section D.2 robust to changing the spatial scale from TTWAs to the smaller administrative districts. In Web-Appendix Section D.3 we benchmark the city-size inequality penalty against the urban wage-premium in order to gain a better

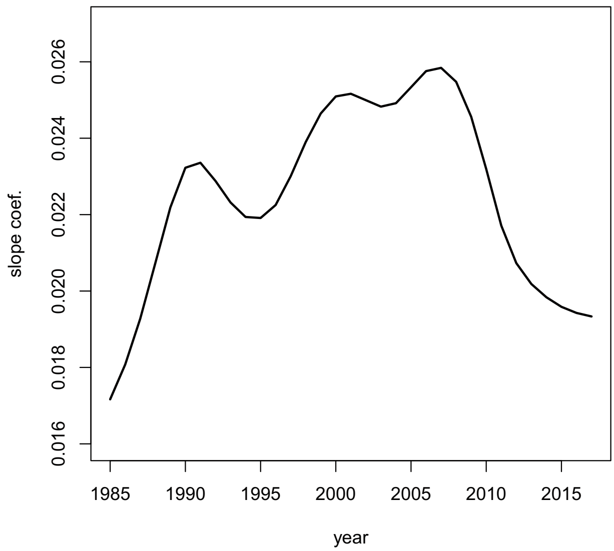


Fig. 5 The changing size of the city-size inequality penalty. Notes. Plotted is the time series of slope coefficients obtained from population-weighted OLS regression of the local inequality, measured by MLD, on log population size, as given by equation (2). See Web-Appendix Section D1 for evidence that the city-size inequality penalty is robust across inequality measures; see e.g. Figure D2 for quantitatively similar trends based on the Gini coefficient

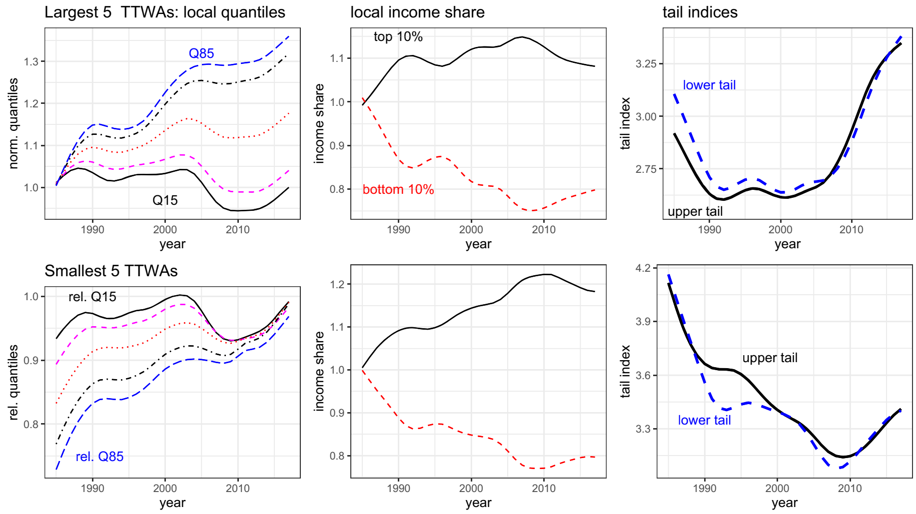


Fig. 6 Local earnings polarisation. Notes. Left panel: Selected quantiles: Q_{15} (black solid line), Q_{25} (magenta dashed line), Q_{50} (red dotted lines), Q_{75} (black dashed dotted line), Q_{85} (blue dashed line). For the smallest TTWAs, the local quantiles are normalised by the respective quantiles in the largest TTWAs in 1985. Middle panel: The top 10% earnings share in 1985 in the largest places is 24%, and the bottom 10% is 4%. For the smallest 5 places the respective shares are 18% and 5%. Right panel: For a formal definition of the tail indices, see Web-Appendix Section A.1.2

understanding of the observed magnitudes. There we also control for local housing costs. We show that the city-size inequality penalty is substantially larger and the statistical relation is considerably tighter than for the urban wage-premium. Specifically, for the year 2010, the city-size elasticity is about 3.6 times larger and the R^2 statistcis is about 3.3 times larger.

The good fit of the regression also implies that year-t within-locations component of inequality, $I^{(t)}_{within} = \sum_l s_l^{(t)} I_l^{(t)}$ is well approximated by

$$\beta_{0,t} + \beta_{1,t} \sum_l s_l^{(t)} \log(size_l) \approx I^{(t)}_{within} \approx I^{(t)}.$$

In Fig. 2 above we have already encountered the superb prediction of the within-location component: The predicted within component is almost indistinguishable from the actual within-locations inequality component. Since in the spatial decomposition of the inequality measure we discovered that the between-locations component is negligible, it follows that the above regression-based prediction is also a very good approximation of overall inequality. The regression based prediction allows us to construct counterfactuals, in order to quantify the consequences of the changing spatial structure. For Fig. 2 above we fix the spatial structure to 1985 by fixing the slope coefficient of the regression. The plot shows that overall inequality would have been substantially smaller in the absence of changes to the spatial structure. For instance, inequality in the peak year of 2010 would have been about 10% lower.

We conclude this section by observing that the 60% peak growth in inequality in Germany (when measured by the MLD) coincides with a growth of 53% of the city-size gradient: The large national inequality increase is driven by the large inequality increases in the largest cities, and these largest cities have come to play an increased quantitative importance. In Section 4 we show that this increased local inequality in the largest cities is driven by increasing polarisation.

3.4 The female earnings distribution

The established literature focusses on prime-aged males in full-time employment. The exclusion of female workers is partly justified by appeals to selectivity biases and discrimination. Nonetheless, we summarise here our evidence for the female earnings distribution which is presented in detail in Web-Appendix D.7. As for males, we consider prime-aged female workers in full-time employment in West Germany. While the reduction of the employment and wage gender gap undoubtedly explain, over the period 1985-2017, major improvements in the quantiles of the female earnings distribution, when focussing on inequality, we find that, qualitatively, many features of the male earnings distribution discussed so far also apply to the female distribution. In particular: (i) inequality in the national distribution rises steeply over the period across all inequality measures, the MLD registering a 50% increase (compared to a 60% increase for males). The time series of the quantiles also displays a fanning out, which results in increased tail thickness in the earnings distribution and thus explains the concomitant increase in inequality. (ii) The spatial decomposition of the inequality index shows, once again, that inequality is predominately within locations. The city-size inequality penalty is also present: Local inequality tends to increase in local population size. Compared to the male spatial structure, the size gradient is considerably smaller as is the R^2 measure; yet the latter remains sizeable, being .29 in 2010 compared to .56 for males. However, over the observation window, the slope coefficient has doubled which is a simliar relative increase compared to the male distribution.

3.5 The West and East combined

It is well known that even after unification, the economic transformation of the East has been slow and is still ongoing, to the extent that stark regional differences persist even 30 years after the fall of the Berlin Wall. For this reason, most of the papers cited above focus principally on the West. Nonetheless, we consider spatial inequality in the East in Web-Appendix Section D.8 in some detail, focussing again on prime aged male workers in full time work. This region has fewer TTWAs, i.e. 30 compared to 106 in the West, and the largest places are located in the West. In the aggregate, inequality in the East is lower than in the West, but the time trends are very similar. The spatial decomposition indicates that the share of the within-location component of inequality is even larger than in the West (in excess of 98%). Turning to the city-size-inequality relation, we demonstrate that the inclusion of the East has only a marginal effect when we consider now the whole of Germany; for instance, for the year 2010, the quality of the bivariate relation remains outstanding (with R^2 .54), since the TTWAs in the East cluster around the fitted regression line in the lower half of the scatter plot.

4 Local earnings polarisation

Inequality in large cities is larger than in small cities, and the within-location earnings inequality has increased dramatically in Germany reaching its peak around 2010, being driven by the largest cities. Are there systematic changes in the local earnings distributional that can explain these increases in local inequality? It turns out that locally these distributions become, up to around 2010, increasingly polarised: Both lower and upper tails increase in size, but the speed is larger in the largest locations.

We begin by examining the local distributions directly, focussing on the 5 largest and smallest TTWAs. In the top left panel of Fig. 6 we depict the time trend of selected upper and lower quantiles in the largest 5 places relative to their values in 1985. It is evident that these quantiles are fanning out, the cone widening steadily. More specifically, the upper quantiles have increased year-on-year since 1985, the growth in Q_{85} even outstripping the growth in Q_{75}, reaching 30% at the end of the observation window. In line with the national picture of Fig. 1, we see two periods of very steep growth. By contrast, such earnings gains are not enjoyed at the bottom of the distribution. While the upper quantiles exhibit a spectacular increase, Q_{15} remains fairly stable until about 2003, before it actually falls below the 1985 value. Only in 2017 has it recovered to its initial level. In order to quantify the implied distributional gains and losses, we report trends in the top and bottom 10% earnings shares. Up to 2010, the richest 10% have seen year-on-year gains of up to 15%, before their earnings share falls in line with the fall in earnings inequality. As a mirror image, the earnings share of the bottom 10% has fallen year-on-year until 2010. In other words, the rich are richer and the poor are poorer in the largest locations. Both quantile and earnings share plots clearly put in evidence the increasing polarisation until about 2010. In the rightmost panel, we consider another aspect of this polarisation, by depicting the upper and lower tail indices[10] of the earnings distribution. A distributional tail gets thicker or heavier if the tail index falls in magnitude. Overall, the U-like shape of both tail indices complements the evidence: Initially, both upper and lower tails increase in heaviness, then remain fairly constant,[11] and improve in the recent periods.

The 5 smallest TTWAs are considered in the lower part of the Figure. In the leftmost panel, we normalise the local quantiles by the respective quantiles in the 5 largest locations in 1985 in order to enable also an across-places comparison. For the 1985 base year, this panel clearly shows that in the smallest places the distribution is much compressed relative to that in the largest locations. For instance, Q_{15} is smaller by a factor of about .95 whereas Q_{85} is smaller by a factor of nearly .7. As a result, inequality in the largest places measured by the MLD is about twice as large as in the smallest places in that year (see also further comparisons in Web-Appendix Section D.4.1). Since these relative quantiles are increasing, this implies that the local earnings distribution is also fanning out, resulting in earnings polarisation. However, the width of the cone is smaller than that for the largest places. In the middle panel, we depict the implied earnings shares. The earnings shares of the top and bottom 10% move into opposite directions. Turning to the tail indices, we see again an U-like pattern. However, both distributional tails become increasingly heavy until about 2010, thereafter improving a bit. In line with the depicted relative quantiles, the tails of the earnings distribution in the smallest places are considerably less heavy than those in the largest places.

4.1 The role of large firms

Figure 6 has shown that the local earnings distributions exhibit qualitatively an earnings polarisation already observed and discussed in the national distribution. The new finding is that these tendencies are much stronger in the largest locations. If de-unionisation and

[10] As explained in Web-Appendix Section A.1.2, the tails of the GB2 distribution are Pareto-like, i.e. $1 - F(x) = x^{-\alpha} l_U(x)$ as $x \to \infty$ where $\alpha > 0$ is known as the upper tail index, and $F(x) = x^{-\beta} l_L(x)$ as $x \to 0$ with lower tail index $\beta > 0$; l_U and l_L are slowly varying functions, converging to constants asymptotically. The upper and lower tail index are simple functions of the GB2 distribution's shape parameters.

[11] This behaviour in the middle of the the observation window does not contradict the conclusions drawn from the quantile and earnings share trends, since a tail index focuses on the *extreme* tail.

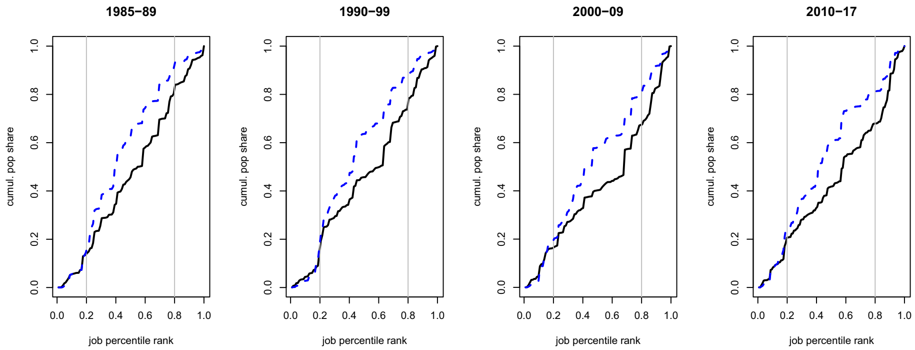


Fig. 7 The distribution of all jobs. Notes. Job ranking by mean earnings of job in the 5 largest (solid line) and 5 smallest TTWAs (dashed line). In this percentile ranking, the hightest paid job has rank 1

localisation of wage settlements are partly explaining the losses at the bottom and a wage decompression, are these forces stronger in the largest locations?

To address this question, we examine whether the size of firms correlates with city size. In particular, a firm-level regression of log firm size on log city size and time fixed effects yields a statistically significant elasticity estimate of 0.0217 (with SE .0009). Focussing directly on the largest firms, we also estimate firm-level linear probability models for the event that the firm size exceeds a fixed threshold, and regress the event indicator on log city size and time fixed effects. For a threshold size of 50 employees, corresponding to about 12% of all firms, the city size coefficient is 0.007 (with SE .00027); for a threshold size of 100 employees, corresponding to about 6% of all firms, the coefficient is 0.0057 (with SE .00019). Hence mean firm size tends to increase moderately with city size, and the largest firms tend to locate in large cities.

We conclude that the centrifugal forces already evident in the national earnings distribution are amplified in the largest cities since they tend to host the largest firms.

4.2 Job polarisation

Finally, having observed until about 2010 the increasing earnings polarisation that is stronger in the largest places, we examine whether this could be driven by local job polarisation. To answer directly the question of thicker distributional tails in larger cities we consider the distribution of *all jobs* in the 5 largest and smallest cities.[12] To this end, we rank all 126 job titles enumerated in the SIAB by their mean earnings. In this percentile ranking, the highest paid job has rank 1.0. Turning to the top ranked jobs, although the incidence of right censoring of earnings is substantial, it is affecting the ranking of top jobs at worst only marginally. We then juxtapose the empirical CDFs of the job distribution for the 5 largest and smallest cities. Interpreting the percentile job rank as a measure of skill enables us to compare directly the lower and upper tail areas of the distribution of all jobs; specifically, in order to guide the cross-location comparison, we consider percentile ranks below .2 and above .8.

The CDFs are depicted in Fig. 7 by decade. In terms of a "big picture" comparison between distant points in time, here 1985-89 v. 2010-17, we observe an increased job polarisation. The share of bottom rankings (full-time male) jobs has increased, while the difference between

[12] In Web-Appendix D.6 we swap the perspective and consider *all locations*, juxtaposing several low-skill low-pay and high-skill high-pay jobs.

the largest and smallest locations is negligible. For instance, during 1985-2009, about 15% of male workers occupy the 20% worst paid jobs in the largest cities and 17% in the smallest cities. By contrast, the share of top-paid jobs has increased substantially, and it is here that we also see a large difference between the largest and smallest locations. This substantially greater proportion of male workers in top jobs in the largest cities is consistent with the observed differences in the upper tails of the local earnings distribution and the ensuing higher local inequalities and city-size inequality penalty. For instance, in the most recent decade, 33% of workers in the largest cities occupy the top 20% jobs whereas the corresponding proportion in the smallest cities is 19%. The plots for the intermediate periods show that these shares have grown steadily over time, their respective values during 1985-89 being 20% and 9%.

5 Some comparative US evidence

In order to place our analysis of the spatial structure of inequality in Germany in a comparative context, we consider briefly the case of the US. The latter exhibits, as does Germany, a significant city-size inequality penalty. However, given the well-known fact that inequality in the US is considerably larger than in Germany, and the discussed rapid inequality growth in Germany from a much lower level, it is not surprising that the effects differ somewhat quantitatively since inequality measures are not linear. However, for a re-analysis of the US data, time trends are similar to the German case as are the order of magnitudes.

More precisely, Baum-Snow and Pavan (2013) were among the first to examine systematically the link between location size and local inequality, using US decadal census data for white male prime-aged full-time full-year workers, log hourly wages, and metropolitan areas as the spatial unit. At the national level, the variance of log hourly wages has increased from 0.21 in 1979 to 0.39 in 2004-7. Coinciding with this overall inequality growth is the increasingly growing inequality across city-size deciles, i.e. the city-size inequality penalty. For instance, by 2004-2007, the variance of log hourly wages differed by .25 between rural areas and the largest metropolitan areas, whereas in the 1980 census the difference is negligible. In a follow up, Baum-Snow et al. (2018) examine the trend in city-size related inequality in terms of the gap in local mean wages between skilled and unskilled workers. Fogli and Guerrieri (2019) consider family earnings and an unrestricted sample of households. Using the Theil index as an inequality measure, they report that, at the national level, inequality is about .23 in 1980 and increases steadily to .3 in 2010. Using metropolitan areas as the spatial unit, they then decompose, as we do, the inequality measure spatially. As in the German case, the within-location component dominates, being about 83% in 1980 and about 70% in 2010.

Given the differences in research design across these studies, we consider in Web-Appendix D.9 explicitly the core sample of workers examined in Baum-Snow and Pavan (2013), using census data from IPUMS-USA (1990, 2000, 2007, 2010), and two geographies (metropolitan areas (MSAs) and commuting zones). For this core group of workers annual earnings inequality, measured by the MLD, has increased from .19 in 1990 to .248 in 2010 nationally, an increase of 27%. At the level of the MSA, the scatter plots of local inequality on population size are similar to Fig. 4: the slope of the regressions, capturing the city-size inequality penalty, is substantial, exhibiting the same order of magnitude, and more than doubles over time, being .021 in 2010. The fit of the bivariate regression also improves substantially, from $R^2 = .28$ in 1990 to .47 in 2010. The non-parametric loess regression suggests that the linear model is a good approximation. Overall, we conclude that the patterns of spatial earnings inequality in the US and Germany are rather similar.

6 Concluding comments

Our discussion of the changing nature of, and specifically the spectacular increase in German earnings inequality has focussed on the years up to 2010, in line with current literature. For this period we have documented the increasing importance of the largest locations, i.e. the increasing city-size earnings inequality penalty. At the same time we have documented the increased local job and earnings polarisation. Overall, our quantitative spatial decomposition has shown that inequality is predominantly within locations. The spatial structure of inequality is also fairly stable even in the long term, the mean of the year-to-year rank correlations of local inequalities being .89.

What about the years after 2010? Here, we observe a reversal of the previous trends: national inequality falls as the city-size inequality penalty falls, while locally earnings become less polarised (as the top and bottom tails of the local earnings distributions become less heavy, and the earnings shares at the top fall while those at the bottom improve). In Web-Appendix Section D.10 we combine the temporal and spatial cross-sectional perspectives to elucidate further the systematic local reversals after 2010. Overall, we conclude that the fall in German earnings inequality after 2010 is a coherent reversal of the pre-2010 local narratives.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s10888-023-09616-3.

Acknowledgements We thank M. Biewen, C. Garcia-Penalosa, S. Jenkins, and C. Schröder for helpful discussions.

Author Contributions The authors contributed equally to this work.

Funding Open Access funding enabled and organized by Projekt DEAL. Financial support from ANR-DFG (grants ANR-15-FRAL- 0007-01 and ANR-19-FRAL-0006-01, DFG-TR709/5-1) and ANR-17-EURE-0020 is gratefully acknowledged.

Availability of data and materials The data are available for scientific researchers at the research data centre of the German Federal Employment Agency at the Institute for Employment Research.

Declarations

Ethical Approval Not applicable.

Competing interests The authors declare no competing interests.

References

Antonczyk, D., DeLeire, T., Fitzenberger, B.: Polarization and Rising Wage Inequality: Comparing the U.S. and Germany. Econometrics. **6**(2), 1–33 (2018)

Armour, P., Burkhauser, R.V., Larrimore, J.: Using the Pareto Distribution to Improve Estimates of Topcoded Earnings. Econ. Inq. **54**(2), 1263–1273 (2016)

Autor, D., Dorn, D.: The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market. Am. Econ. Rev. **103**(5), 1553–1597 (2013)

Bartels, C.: Top Incomes in Germany, 1871–2014. J. Econ. Hist. **79**(3), 669–707 (2019)

Baum-Snow, N., Pavan, R.: Inequality and City Size. Rev. Econ. Stat. **95**(5), 1535–1548 (2013)

Baum-Snow, N., Freedman, M., Pavan, R.: Why has Urban Inequality Increased? American Economic Journal: Applied Economics. **10**(4), 1–42 (2018)

Biewen, M., Fitzenberger, B., de Lazzer, J.: The Role of Employment Interruptions and Part-time Work for the Rise in Wage Inequality. IZA J. Labor Econ. **7**, 10 (2018)

Biewen, M., Seckler, M.: Unions, Internationalization, Tasks, Firms, and Worker Characteristics: A Detailed Decomposition Analysis of Rising Wage Inequality in Germany. J. Econ. Inequal. **17**, 461–498 (2019)

Card, D., Heining, J., Kline, P.: Workplace Heterogeneity and the Rise of West German Wage Inequality. Q. J. Econ. **128**, 967–1015 (2013)

Cerina, F., Dienesch, E., Moro, A., Rendall, M.: Spatial Polarisation. Econ. J. (2022). https://doi.org/10.1093/ej/ueac040

Combes, P.-Ph., Duranton, G., Gobillon, L.: Spatial Wage Disparities: Sorting matters! J. Urban Econ. **63**(2), 723–742 (2008)

Cowell, F.A.: Measuring Inequality, 3rd edn. Oxford University Press, Oxford (2011)

Dauth, W., Findeisen, S., Moretti, E., Suedekum, J.: Matching in Cities. NBER Working Paper 25227 (2021). https://doi.org/10.3386/w25227

Dauth, W., Findeisen, S., Suedekum, J., Woessner, N.: The Adjustment of Labor Markets to Robots. J. Eur. Econ. Assoc. **19**(6), 3104–3153 (2021)

Drechsel-Grau, M., Peichl, A., Schmid, K.D., Schmieder, J.F., Walz, H., Wolter, S.: Inequality and Income Dynamics in Germany. Quant. Econ. **13**, 1593–1635 (2022)

Dustmann, C., Fitzenberger, B., Schönberg, U., Spitz-Oener, A.: From Sick Man of Europe to Economic Superstar: Germany's Resurgent Economy. J. Econ. Perspect. **28**, 167–88 (2014)

Dustmann, C., Ludsteck, J., Schönberg, U.: Revisiting the German Wage Structure. Q. J. Econ. **124**, 843–881 (2009)

Eckey, H.-F., Kosfeld, R., Tuerck, M.: Delineation of German Labour Market Regions. Raumforschung und Raumordnung **4**, 299–309 (2006)

Eeckhout, J., Pinheiro, R., Schmidheiny, K.: Spatial Sorting. J. Polit. Econ. **122**, 555–620 (2014)

Ellguth, P., Kohaut, S.: Tarifbindung und betriebliche Interessenvertretung: Aktuelle Ergebnisse aus dem IAB-Betriebspanel 2019. WSI-Mitteilungen. **73**(4), 278–285 (2020)

Fogli, A., Guerrieri, V.: The End of the American Dream? Inequality and Segregation in US Cities. NBER Working Paper 26143 (2019)

Glaeser, E.L., Mare, D.C.: Cities and Skills. J. Labor Econ. **19**(2), 316–342 (2001)

Goldschmidt, D., Schmieder, J.F.: The Rise of Domestic Outsourcing and the Evolution of the German Wage Structure. Q. J. Econ. **132**(3), 1165–1217 (2017)

Hirsch, B., Mueller, S.: Firm Wage Premia, Industrial Relations, and Wage Sharing in Germany. ILR Rev. **73**(5), 1119–1146 (2020)

Immel, L.: *The Regional Distribution of Income and Wages: Causes and Consequences.* Ifo Beitraege zur Witschafsforschung, no. 94. (2021)

Immel, L., Peichl, A.: Regionale Ungleichheit in Deutschland: Wo leben die Reichen und wo die Armen? ifo Schnelldienst, 73, 05/2020 (2020)

Jäger, S., Noy, S., Schoefer, B.: The German Model of Industrial Relations: Balancing Flexibility and Collective Action. NBER Working Paper No. 30377 (2022)

Jenkins, J., Burkhauser, R.V., Feng, S., Larrimore, J.: Measuring Inequality using Censored Data: a Multiple-imputation Approach to Estimation and Inference. J. R. Stat. Soc. A. **174**(1), 63–81 (2011)

Kleiber, C., Kotz, S.: Statistical Size Distributions in Economics and Actuarial Sciences. John Wiley and Sons, New York (2003)

König, J., Schluter, C.: How Informative are Imputations for Top-coded Earnings? AMSE and DIW Working Paper (2022)

König, J. , Schluter, C., Schröder, C.: Who are The Rich? New Data, Methods, and Estimates for Germany. AMSE and DIW Working Paper (2022)

McDonald, J.B., Xu, Y.J.: A Generalization of the Beta Distribution with Applications. J. Econ. **66**, 133–52 (1995)

Nanos, P., Schluter, C.: Search Across Local Labour Markets. AMSE/Sheffield Working paper (2020)

Popp, M.:. Warum klaffen die Löhne in der Stadt stärker auseinander als auf dem Land? IAB-Forum (2019). https://www.iab-forum.de/warum-klaffen-die-loehne-in-der-stadt-staerker-auseinander-als-auf-dem-land/, 01/12/2022

Reardon, S.F., Matthews, S.A., O'Sullivan, D., Lee, B.A., Firebaugh, G., Farrell, C.R., Bischoff, K.: The Geographic Scale of Metropolitan Racial Segregation. Demography. **45**(3), 489–514 (2008)

Schluter, C., Trede, M.: Local versus Global Assessment of Mobility. Int. Econ. Rev. **44**(4), 1313–1336 (2003)

Schluter, C., Wilemme, G.: A Dynamic Empirical Model of Frictional Spatial Job Search. *SSRN Working Paper 4517222.* (2023). https://ssrn.com/abstract=4517222