Does Income Redistribution Prevent Residential Segregation?*

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Abstract: Living in low-income neighborhoods can have adverse effects. Public policies reducing income inequality might prevent residential segregation by income. However, previously documented associations between income inequality and residential segregation may not reflect residential sorting effects. We use rich full-population data for Sweden 1991–2014 and take advantage of how in-moving residents change the municipal income composition to rule out the influence of reverse causation and mechanical effects. We find that changing taxes and transfers has limited residential sorting effects on segregation. However, our results strongly suggest that raising the education levels of low-income residents is effective for fighting segregation.

Keywords: income inequality, residential segregation by income, neighborhood sorting, public redistribution

JEL classification: D31, H31, I32, J11, R23

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1. Introduction

Economists have mapped the rising income inequality in the industrialized world since World War II and attributed much of this trend to increasing top incomes (see the review by Atkinson et al., 2011).[1] A broad literature suggests that inequality has negative consequences on economic, health, and social outcomes at the individual level (see the review by Neckerman and Torche, 2007). Recently, there is growing attention on spatial inequality between regions within countries (Diamond, 2016; Gaubert et al., 2020). Income inequality between residents in different neighborhoods within cities, typically referred to as residential segregation by income, is another type of spatial inequality.[2]

Segregation could create some neighborhoods with a high share of low-income residents. Researchers have found empirical evidence showing that living or growing up in such neighborhoods have adverse effects, potentially because of less beneficial social networks (Katz et al., 2001; Kling et al., 2007; Ludwig et al., 2012; Chetty et al., 2016). Since segregation is likely harmful to residents with neighborhood effects serving as a mediating channel, understanding whether inequality leads to segregation is important. Segregation can be a crucial link between inequality and negative individual outcomes.[3]

While income inequality is a pre-requisite for residential segregation by income, there are only a handful of empirical studies of income inequality as a driver of residential segregation (Mayer, 2001; Wheeler and La Jeunesse, 2006; Watson, 2009; Reardon and Bischoff, 2011; Chen et al., 2012). These studies used decennial census data at the neighborhood level for cities, typically in the U.S., and they documented interesting correlations between changes in inequality and segregation. However, they provide few policy insights on whether and which types of public policies reducing inequality could prevent segregation due to residential sorting across neighborhoods.

We have access to geo-coded administrative data at the individual level covering the entire population in Sweden for each year during the period 1991–2014. During this period, Sweden experienced an unprecedented growth in income inequality concurrent with a welfare state deterioration. These trends are remarkable even in an international comparison.[4] We leverage the data and contribute to existing research by identifying how changing different determinants of income inequality affect residential sorting and segregation. We focus on the role of determinants related to public redistribution and socio-demographic composition. Our results provide new and detailed insights for policymakers who want to fight segregation, e.g.,

[1] Piketty et al. (2006), Piketty (2011, 2013), and Saez and Zucman (2016) have presented deeper analyses of potential causes of the rising inequality.

[2] Massey and Denton (1988), Jargowsky (1996), Massey and Fischer (2003), Ioannides (2004), Reardon and O'Sullivan (2004), and Wheeler and La Jeunesse (2008) have discussed how to measure segregation and identified trends over time in the U.S.

[3] Residential income segregation may also be a mechanism through which residential racial or ethnic segregation affects individual outcomes.

[4] For disposable incomes, our data show that inequality between residents within municipalities (standard deviation of the logarithm of income) increased by 69%, and residential segregation (neighborhood sorting index) increased by 44%. In terms the Gini coefficient, inequality increased from 0.250 to 0.334 between 1991 and 2014. Data from the World Bank reveal that among Nordic countries, Sweden went from being the most equal country in 2003 to become the most unequal in 2015. For the U.S., the Gini coefficient increased from 0.346 to 0.402 between 1979 and 1997, after which the trend has been flat.

regarding whether they should equalize abilities to consume or to earn income, and regarding the importance of poverty versus affluence reduction.

Neighborhoods typically differ regarding housing quality (e.g., living area and amenities) and access to public goods (e.g., schools and recreational facilities). Tiebout (1956) showed that if residents also have varying abilities and willingness to pay for housing quality and public goods, systematic neighborhood sorting patterns will emerge. Schelling (1969) proposed an alternative explanation to residential segregation: residents who are similar in different ways, e.g., with respect to income or education levels, could prefer to reside in the same neighborhoods. Unlike in Tiebout's theory, residential preferences (willingness to pay) can depend on the income level for reasons unrelated to the ability to pay. For instance, high-income residents typically have higher education levels and could for this reason value school quality more compared to others with the same ability to pay. They might also prefer to live and interact with similar-minded or care more about neighborhood of residence as a status marker.

Both Tiebout (1956) and Schelling (1969) predicted that residential preferences and choices vary with income levels. In this sense, income inequality or its determinants affect residential sorting and thereby segregation. From a policy perspective, it is crucial to understand which determinants that matter.[5] However, with existing segregation, the development of inequality and segregation over time may be associated in two ways unrelated to residential sorting. First, segregation may reinforce inequality leading to reverse causation because neighborhood effects could generate differential income growth in low- and high-income neighborhoods even when nobody makes a new residential choice. Moreover, consider urban planning policies affecting neighborhood characteristics (housing quality and public goods). In the models by Tiebout and Schelling, for a given income distribution, such neighborhood characteristics also affect residential choices. Once policies affect segregation, neighborhood effects could generate subsequent effects on inequality. Second, changing economic conditions have varying effects on different individuals and therefore affect neighborhoods differentially depending on their residential composition. For instance, new welfare benefits to low-income families mechanically reduce both inequality and segregation before anybody moves.

Unlike previous research, we rule out reverse causation and mechanical effects, enabling us to offer policy recommendations on how to reduce current inequality to prevent future segregation due to residential sorting across neighborhoods.[6] Our novel strategy takes advantage of the fact that new residents arriving from other municipalities are not part of existing segregation, but they affect the municipal income composition and inequality. We use the municipality-by year variation in this external inequality shock, and we identify subsequent segregation effects due to active residential choices of the in-movers' and the original population's responses after the inequality shock.[7]

Public redistribution through taxes and transfers is a determinant of disposable incomes reflecting abilities to consume and pay for housing, which are central for generating the type of segregation Tiebout (1956) mentioned. Previous literature focused on inequality and

[5] However, the "causal" effect of inequality on segregation holding all policy-relevant determinants of inequality (e.g., public redistribution) constant is less interesting for policymakers.
[6] It is beyond the scope of this paper to *estimate* the segregation effects of urban planning.
[7] Migration has previously been exploited as an exogenous shock to the population composition, e.g., for studying the effects of ethnic composition in a geographical area (e.g., Edin et al., 2003; Andersson et al., 2021)

segregation in terms of disposable incomes. However, disposable income is pre-tax income adjusted for taxes and transfers. To evaluate whether public redistribution can prevent segregation, one need to account for that pre-tax income and its determinants may have separate effects on segregation. Such determinants include individual characteristics such as age, education, and innate ability, but also structural factors affecting local labor market conditions, e.g., institutional, organizational, and technological factors.

Unlike previously used data, we observe pre-tax incomes in our rich data, allowing us to control for pre-tax income effects. We rely on remaining municipality-by-year variation in the distribution of disposable incomes due to changes in the tax and transfer system for identifying the influence of disposable income inequality on residential segregation.[8]

We find a positive correlation between changes in *disposable income* dispersion within municipalities (standard deviation of log income, Sd, measuring inequality) and the between-neighborhood share of this dispersion (the neighborhood sorting index, Nsi, measuring segregation). However, our main result is that once ruling out reverse causation and mechanical effects, the correlation disappears. Thus, unequal consumption abilities were not decisive for residential sorting in a way that can explain growing between-neighborhood income dispersion. Finding limited residential sorting effects of disposable income inequality represents discouraging news in terms of fighting overall segregation by using public redistribution. However, our results do show that increasing relative disposable incomes of high-income residents have led to a higher concentration of these individuals in certain neighborhoods. Therefore, there is scope for fighting such segregation with top income taxes.

Even with homogenous disposable incomes due to perfect public redistribution, residents might prefer neighborhoods with others who are similar to themselves, e.g., with respect to pre-tax incomes reflecting abilities to earn income (in the labor and capital markets). To prevent this type of segregation following from Schelling's (1969) theory, policymakers could target the determinants of pre-tax income inequality such as education levels.

We find that increasing *pre-tax income* dispersion within municipalities (Sd) over time can account for the entire surge in between-neighborhood income dispersion (Nsi) since the 1990s. Particularly, growing municipal shares of residents with low pre-tax incomes can explain most of the rising concentration of such individuals in certain neighborhoods. However, when controlling for municipal changes in the educational composition of residents, most of the influence of inequality change on segregation change due to residential sorting disappears.[9] Hence, increasing pre-tax incomes of low-income residents by raising their levels of education and thereby earning abilities is most likely effective for fighting segregation.

The next section describes our data and explores overall income inequality and residential segregation trends over time. Section 3 outlines our empirical strategy. Section 4 reports our estimates for overall inequality and segregation. Section 5 distinguishes effects of inequality on segregation along different parts of the income distribution. The final section concludes.

[8] In research in public finance, the tax and transfer system or its change is regularly assumed an exogenous determinant of an individual's disposable income (see, e.g., the critical review by Saez et al., 2012).

[9] In contrast, our estimates are insensitive to accounting for effects due to the country-of-birth composition in municipalities. A deeper study of residential ethnic segregation is beyond the scope of this paper.

2. Data and trends over time

2.1 Data and institutional background

We use annual data from the GEO-Sweden database for the years 1991–2014. These data cover the entire population of around 10 million inhabitants (in 2014) and contain income variables used by the tax authorities, including information on taxes and transfers. We link observations for each person over time using his or her social security number, and we link the observations to other administrative registers containing, for instance, demographic background variables. While Swedish social scientists have frequently used good microdata before,[10] a unique additional feature of GEO-Sweden is that it geographically links individuals to the real estate where they reside (via their registered addresses). Due to this feature, some researchers have used GEO-Sweden for studying neighborhood effects.[11] GEO-Sweden also allows us to pinpoint residential moving patterns.[12]

Sweden has three levels of government: central, county, and municipal levels. The institutional setting is streamlined across administrative units. The 290 municipalities are each organized around a central town or village. They are independent actors playing a key role in the Swedish society providing daycare, education, care of the elderly, and other welfare services. While we measure income inequality at the municipal level, we characterize residential segregation by income for a municipality as differences in income distributions across neighborhoods within the municipality. We let the 7,442 Swedish SAMS-areas (small areas for market statistics) represent our neighborhood units. Municipalities and SAMS-areas are the geographical levels at which the previous literature using Swedish data (e.g., Scarpa, 2016) operationalized income inequality and residential segregation.[13]

While previous segregation research on U.S. data (e.g., Reardon and Bishoff, 2011) frequently used families or households as income units, we use individuals as income units to avoid a number of complications. First, we do not need to address the fact that there are many unmarried cohabiting couples with or without children in Sweden. Second, we circumvent the issue of unstable and not fully comparable units over time due to the high and changing divorce rate. Third, we do not need to address the fact that families or households differ in number of members. When constructing measures of inequality and segregation, we use residents between the ages of 25 and 59 since these working-age individuals are the most interesting from a labor market perspective.

We use two different income measures: disposable income and pre-tax income. Pre-tax income includes income from all recorded sources, with labor and capital income being the dominant components. Disposable income is pre-tax income minus taxes plus transfers.[14] Disposable income is indicative of consumption ability, and it is the definition of income previously used in segregation research. On the other hand, pre-tax income is indicative of earning abilities, and it is a definition of income often used in inequality research.

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[10] Edin and Fredriksson (2000) compiled an individual longitudinal data set (around 300,000 individuals) and sparked a wider use of Swedish administrative data in economic research.

[11] Examples of studies include those by Edin et al. (2003), Galster et al. (2008), and Hedman et al. (2015).

[12] Andersson and Turner (2014) used this feature to study moving chains in Stockholm.

[13] We use the municipal and SAMS borders in 2014. Few municipal borders changed during the sample period. SAMS-areas are used only for statistical purposes and border changes were more frequent.

[14] We adjust for all taxes and transfers except consumption taxes.

Public redistribution introduces a wedge between pre- and disposable incomes. This wedge is substantial since Sweden is among the most egalitarian societies in the world with total public spending accounting for around 50% and municipal public spending accounting for around 20% of the national GDP. Municipalities and counties have fiscal autonomy; among other things, they set their own local tax rates. The tax and transfer system as a whole has differential impacts on individuals depending not only on their pre-tax income but also on factors such as number of children and municipality of residence. The exact rules and policy changes during our sample period has been documented before in research in public finance.[15]

2.2 Overall inequality and segregation and their development over time

There are several ways of quantifying inequality from an income distribution. In Section 5, we will use multiple measures, each focusing on a limited part of the income distribution. However, it is also convenient to have a summarizing measure accounting for the entire income distribution. There are many candidates for such an overall measure, each with different pros and cons (Silber, 1999). Typically, overall measures correlate highly with each other. For our purposes, we want an overall inequality measure with an intuitive meaning that is also simple to relate to an overall measure of residential segregation. Our choice falls on the standard deviation of CPI-adjusted logarithm of income across individuals in the municipality (Sd_{mt} for municipality m in year t).[16] Using logarithms offers a better relative measure, and the standard deviation quantifies the dispersion of a distribution in a way that is easy to relate to the mean.

The municipal standard deviation (Sd_{mt}) has the advantage that it contains a between-neighborhood component ($BetweenSd_{mt}$) and a within-neighborhood component ($WithinSd_{mt}$) such that $Sd_{mt}^2 = BetweenSd_{mt}^2 + WithinSd_{mt}^2$. The between-neighborhood component reflects income disparities across neighborhoods, and it is a potential measure of overall municipal segregation. If there is no inequality ($Sd_{mt} = 0$), there cannot be any segregation ($BetweenSd_{mt} = 0$).

The previous empirical literature does not use $BetweenSd_{mt}$ as the main segregation measure. To understand why, consider the case where the income distribution is stretched out without affecting the relative income ranks of the residents in the distribution. In this case, both Sd_{mt} and $BetweenSd_{mt}$ increase if no residents spatially reallocate. When quantifying the residential sorting effects of inequality on segregation, one wants to eliminate the influence of this mechanical effect of Sd_{mt} on $BetweenSd_{mt}$.

The neighborhood sorting index (Nsi_{mt}) is the *share* of municipal income dispersion that is due to the between-neighborhood income dispersion:

$$Nsi_{mt} = \frac{BetweenSd_{mt}}{Sd_{mt}}. \qquad (1)$$

This index is free from the above-mentioned mechanical effect and assumes values between zero and one. Just like when it comes to inequality measures, there are several more or less correlated segregation measures, each with different advantages and disadvantages (Reardon

[15] For instance, Blomquist and Selin (2010) and Liang (2012) provided detailed descriptions for the period before year 2000, and Edmark et al. (2016) described major changes thereafter.

[16] We use the logarithm of income (2014 SEK) plus a constant of one as the logarithm of zero is not defined.

and O'Sullivan, 2004). In addition to Nsi_{mt}, we also use other segregation measures, each focusing on a different part of the income distribution, as we discuss in Section 5.

In Figure 1, we plot across-municipality yearly weighted means of our measures of overall municipal inequality (Sd_{mt}) in Panel A and segregation (Nsi_{mt}) in Panel B for disposable income (solid lines) and pre-tax income (dashed lines), respectively. We use municipal working-age population weights throughout the paper, as we think of residents as the fundamental units experiencing inequality with potential effects on their residential choice.[17]

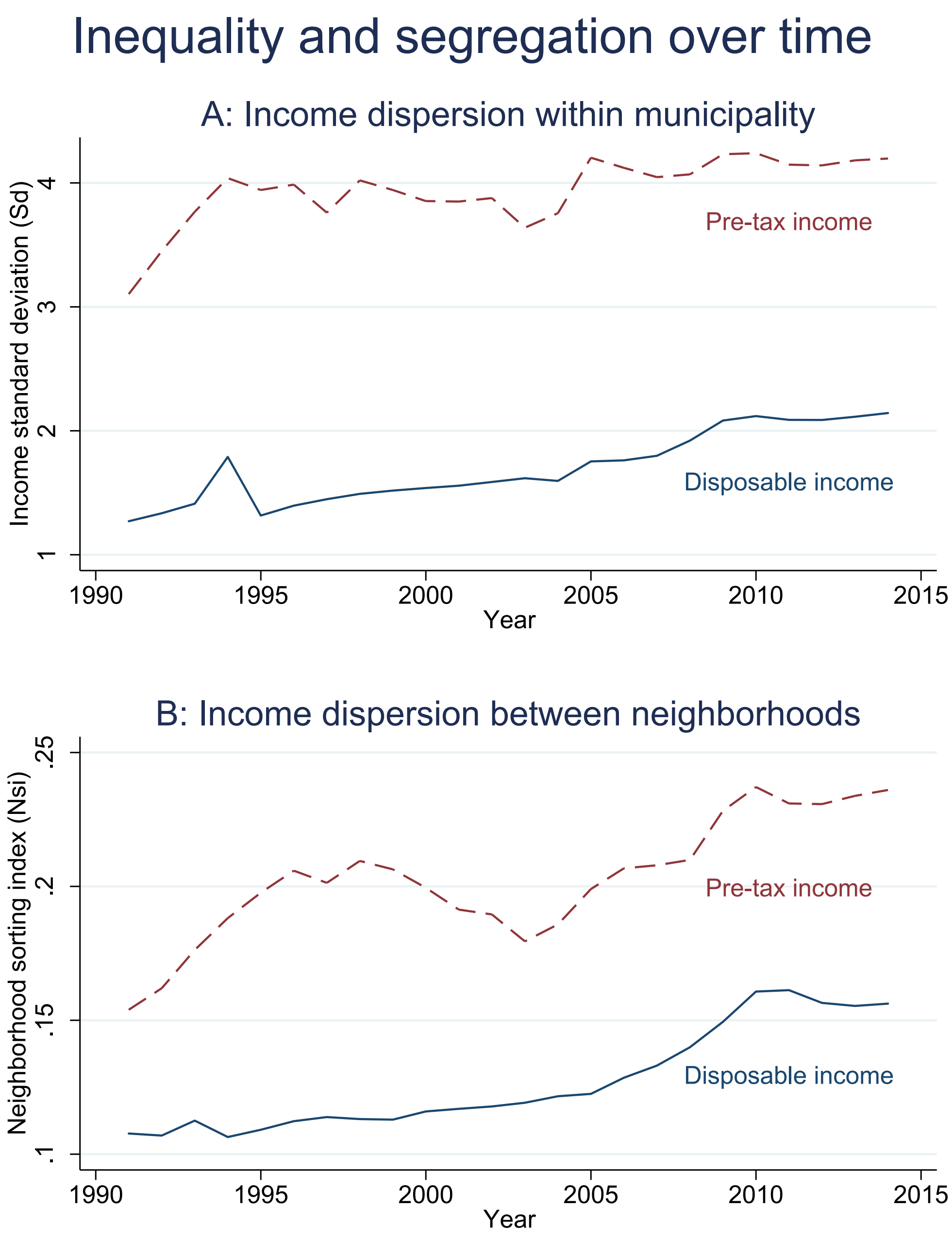

Figure 1. Overall municipal inequality and segregation, across-municipality yearly means

[17] The patterns and results in this paper are robust to giving each municipality the same weight.

Because of the large Swedish tax and transfer system, Sd_{mt} is much lower for disposable income than for pre-tax income. Figure 1 shows that disposable income mean Sd_{mt} increased by 69% (from 1.27 to 2.14) between 1991 and 2014, whereas the corresponding increase in terms of pre-tax income is 35% (from 3.10 to 4.20) and less consistent over time. This pattern reflects the downsizing of public redistribution experienced by Sweden during the sample period. For segregation, we see that mean Nsi_{mt} increased by 44% for disposable income (from 0.108 to 0.156) and by 53% for pre-tax income (from 0.154 to 0.236). With regard to both income measures, income inequality and residential segregation closely followed each other over time.

3. Empirical strategy

3.1 Starting from a first-difference design

In Figure A1 in Appendix A, we find a positive relationship between income inequality and residential segregation across our 290 municipalities. However, municipalities differ regarding a range of observable and unobservable factors correlated with municipal inequality and segregation, for instance, socio-demographic composition, labor market condition, and topography. Many of those factors (e.g., topography), the policymakers cannot affect. Since are interested in the effects of changing policy-relevant determinants of income inequality, we regard such factors as confounders.

Following previous research, we first address cross-sectional confounders by using a first-difference design exploiting within-municipality variation over time. If inequality affects segregation, ceteris paribus, municipalities facing inequality changes over time will also experience segregation changes. Comparing municipalities with different inequality changes, those facing greater inequality changes should also experience greater segregation changes. Confounders varying across municipalities but remaining constant within each municipality over time do not affect municipal changes in inequality and segregation. Hence, municipality-fixed effects have been differenced away.

In Figure A2 in Appendix A, we show scatter plots of municipal changes in overall segregation against inequality during the sample period 1991–2014. The plots reveal positive correlations between inequality and segregation changes across municipalities.

It is possible to construct municipal changes spanning shorter time intervals than the entire sample period; for instance, we can construct 23 one-year changes (1991–1992, 1992–1993, …, 2013–2014) for each municipality. We let $\Delta Sd_{mt} = Sd_{m,t+\Delta t} - Sd_{m,t}$ and $\Delta Nsi_{mt} = Nsi_{m,t+\Delta t} - Nsi_{m,t}$ denote changes in overall inequality and segregation for municipality m between base year t and end year $t + \Delta t$ where Δt is difference length.

To fully utilize our municipal panel, we pool changes with different base years when possible. Thus, each combination of municipality and base year forms an observation. However, changes from different base years are likely not fully comparable with each other (even for the same municipality). Underlying national factors changing over time but common to all municipalities at a certain point in time could generate differential segregation trends over time even absent inequality change. We address time-varying confounders correlated with both inequality and segregation changes using base-year dummies in the estimation.

Letting In_{mt} and Seg_{mt} denote different possible inequality and segregation variables, respectively (only Sd_{mt} and Nsi_{mt} discussed so far), we start by estimating the following first-difference equation by least squares:

$$\Delta Seg_{mt} = \beta \Delta In_{mt} + \sigma_t + \varepsilon_{mt}. \quad (2)$$

The coefficient β is the main parameter of interest. Time-fixed effects are captured by σ_t (base-year dummies), and ε_{mt} represents idiosyncratic errors. Throughout the paper, we weight regressions by the municipal working-age population in the base year, and we cluster standard errors at the municipality level. This standard first-difference design exploits the combined municipality-by-year variation in inequality and segregation.

In Figure 2, we explore the dynamics over different time horizons by estimating Eq. (1) letting difference length vary between 1 and 23 years, and we report point estimates (dots) and 95% confidence intervals (bars).[18] The point estimates are all positive. While the point estimate for disposable income is negatively dependent on the difference length, confidence intervals are relatively wide when the difference length is long. The different point estimates do not statistically differ from each other.[19]

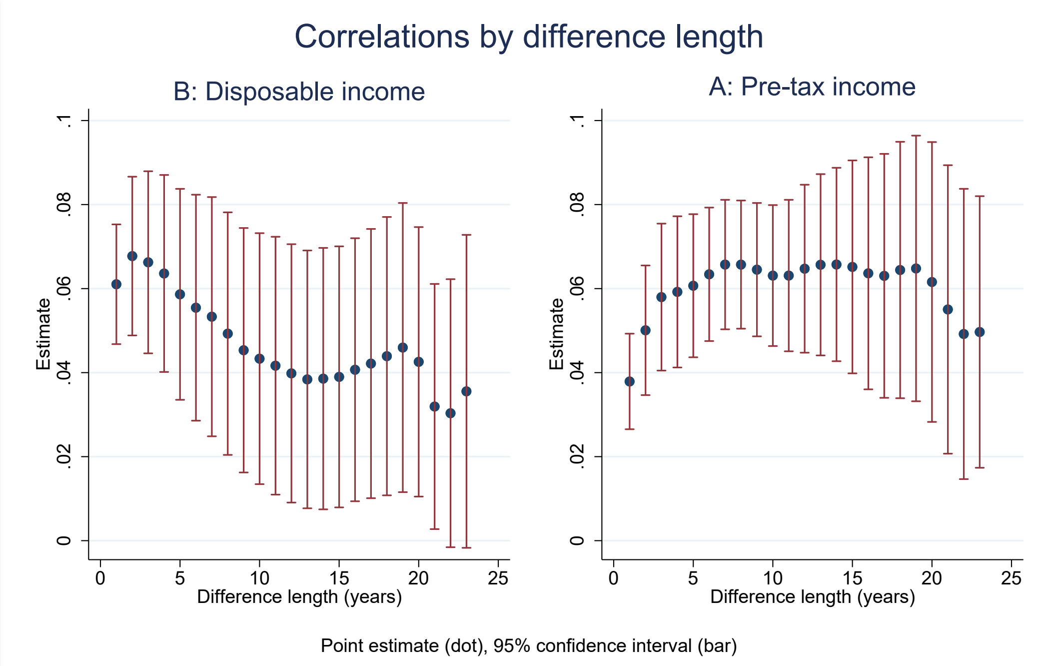

Figure 2. Regression estimates of Nsi_{mt} change on Sd_{mt} change by difference length

Notes: We report estimates from regressions of $Nsi_{m,t+\Delta t} - Nsi_{mt}$ on $Sd_{m,t+\Delta t} - Sd_{mt}$, $\Delta t = 1, \dots, 23$.

[18] The estimates are not directly comparable with each other as we lose observations when increasing difference length. However, the patterns remain when keeping the number of observations constant by only using observations with base years between 1991 and 2004 and varying the difference length from one to ten years.

[19] Reallocation frictions may cause residential sorting effects to vary with the time horizon. Moving involves fixed costs, and it takes time to update knowledge on neighborhood-level information. Thus, residents may not immediately respond to changing conditions, and longer-run residential sorting effects could therefore be larger. However, we cannot interpret the patterns in Figure 2 in support of (or against) this hypothesis, since the impact of reverse causation and mechanical effects likely also varies with the time horizon.

3.2 Accounting for confounding trends

Confounders could still drive correlations between municipal *changes* in inequality and segregation. For instance, inequality and segregation could have increased primarily in high-population municipalities due to agglomeration economies. We account for confounding heterogeneous segregation trends between municipalities by adding control variables to Eq. (2). We add covariates that we will describe in detail below consecutively, and the following equation describes our main regression specification:

$$\Delta Seg_{mt} = \beta \Delta In_{mt} + \gamma_1 \Delta \overline{In}_{mt} + \boldsymbol{\gamma}_2 \boldsymbol{z}_{mt} + \boldsymbol{\gamma}_3 \Delta \boldsymbol{Pop}_{mt} + \gamma_4 \Delta In_{mt}^{stay} + \sigma_t + \varepsilon_{mt}. \quad (3)$$

When facing an inequality change, it may take some time for residents to spatially reallocate. This justifies using a longer difference length. However, there is a political impatience in terms of quickly achieving effects, and for this reason, policymakers are also interested in shorter-run effects. Moreover, the number of first-differences increase as we decrease the difference length, which improves statistical precision. When we report regression estimates, we strike a balance between these concerns and focus on five-year changes.[20] In Tables A1 and A2 in Appendix B, we provide summary statistics for our estimation sample.[21]

We separately estimate Eq. (3) for inequality and segregation measures with respect to disposable income and pre-tax income, respectively. Hence, we run a separate regression where disposable income ΔNsi_{mt} and ΔSd_{mt} are the dependent and main independent variables of interest and similarly for pre-tax income ΔNsi_{mt} and ΔSd_{mt}. When estimating the influence of disposable income Sd_{mt}, we will account for the influence of pre-tax income Sd_{mt}, and vice versa. For this purpose, we include the covariate $\Delta \overline{In}_{mt}$, which is inequality change for the complementary income measure. Thus, when ΔIn_{mt} equals disposable income ΔSd_{mt}, $\Delta \overline{In}_{mt}$ equals pre-tax income ΔSd_{mt}, and vice versa.[22]

Previous literature focused on inequality and segregation in terms of disposable income which is pre-tax income adjusted for public redistribution. To evaluate the role of public distribution, one need to account for the correlation between disposable income and pre-tax income. Otherwise, the estimated relationship between disposable income inequality and segregation may just reflect the corresponding relationship for pre-tax income, which in turn may be driven by determinants of pre-tax incomes. Such determinants include individual characteristics such as age, education, and innate ability, but also structural factors affecting local labor market conditions. These factors may all have independent effects on residential preferences and segregation. Given that we control for changes in pre-tax income inequality, we have shut down the channel through which its determinants correlate with changes in disposable income inequality. Remaining variation derive entirely from the municipality-by-year variation in the distribution of disposable incomes due to changes in the tax and transfer system.

Changes in the tax and transfer system have different effects on residents across municipalities for two major reasons. First, residents have to pay local taxes consisting of

[20] Thus, $\Delta Var_{mt} = Var_{m,t+5} - Var_{mt}$ for different variables Var.

[21] Additional inequality and segregation variables will be discussed in Section 5.

[22] Our results are insensitive to controlling for additional parameters of the distribution of the complementary income measure, e.g., the poverty and affluence rate variables in Section 5.

county-specific and municipality-specific taxes, and these taxes have changed differentially across municipalities and over time. Second, taxes and transfers set by the central government have different effects on residents not only depending on pre-tax income but also depending on other individual characteristics, e.g., the number of children. Since the residential composition differ across municipalities (and over time), the same rules (or rule changes) do not affect the municipalities in the same way. Moreover, these rules interact with local taxes.[23] In research in public finance, the tax and transfer system or its change is regularly assumed to be an exogenous determinant of an individual's disposable income (see, e.g., the critical review by Saez et al., 2012). The differential impact of the tax and transfer system in Sweden has been documented and used many times before in this literature (e.g., Blomquist and Selin, 2010).

Whereas our identification of disposable income effects relies on only variation in public redistribution across municipalities and over time, pre-tax income effects may be driven by a host of factors determining the pre-tax income distribution. We control for several municipality-specific *base-year* covariates in the vector $\boldsymbol{z}_{mt}$. First, $\boldsymbol{z}_{mt}$ includes a number of socio-economic background variables related to education, country of birth, age, and population. The municipal-level covariates consist of share that did not graduate high school, share with university degree, share born in Europe outside Sweden, share born outside Europe, share of young residents (aged 24 or below), share of old residents (aged 60 or above), shares in six age groups (five-year intervals), and number of residents. Second, $\boldsymbol{z}_{mt}$ includes base-year segregation (Seg_{mt}) and inequality (In_{mt}), which account for mean-reversion patterns correlated with inequality change. Such patterns would exist in case, for instance, it takes some time for segregation to revert to a long-run equilibrium after having been high because of transitory factors.

The vector $\Delta\boldsymbol{Pop}_{mt}$ contains municipal population change and in-moving residents from other municipalities as shares of base-year population. These covariates control for general underlying urbanization and age-related processes.

We exercise caution in controlling for *changes* in socio-demographic variables other than those in $\Delta\boldsymbol{Pop}_{mt}$ since public policies designed to change inequality may achieve this by changing the municipal socio-demographic composition. In contrast, the base-year socio-economic composition (which we control for using $\boldsymbol{z}_{mt}$) is determined prior to inequality and segregation changes due to subsequent policy. In order to understand which type of changes in socio-demographic composition associated with inequality change that matters, we provide estimates controlling for changes in educational, country-of-birth, and age compositions. Thus, we can pin down the importance of these inequality determinants for fighting segregation.

3.3 Accounting for reverse causation and mechanical effects

Even with all covariates in Eq. (3) except ΔIn_{mt}^{stay}, a conditional correlation between inequality and segregation changes may not reflect residential sorting effects of inequality on segregation arising from how residential choices change as incomes change (Tiebout, 1956; Schelling, 1969). Existing residential segregation by income in the base-year due to past residential choices can lead to future changes in inequality and segregation for multiple reasons unrelated

[23] For instance, capital losses are deductible also toward local taxes.

to new residential choices.[24] First, neighborhood effects may reinforce income inequality generating reverse causation. Second, changes in economic conditions can have mechanical effects on inequality and segregation. Over (potentially long) time, as residents overcome reallocation frictions, the impact of reverse causation and mechanical effects diminishes, whereas the residential sorting effect of inequality on segregation strengthens.

In order to evaluate whether public policies reducing inequality can affect residential sorting and segregation, we rule out reverse causation and mechanical effects using a novel strategy. We exploit the fact that in-moving residents from other municipalities are not part of existing residential patterns in the destination municipality that may drive inequality and segregation changes. However, they do change the population income composition and thus inequality in the destination municipality. Any effects on segregation have to involve active residential choices including where the in-movers decide to reside. In-movers is a group we know have overcome reallocation frictions. They may also cause subsequent neighborhood reallocation of other residents in the destination municipality.

We implement our strategy accounting reverse causation and mechanical effects by controlling for the part of ΔIn_{mt} that is due to "staying" residents who did *not* move in from other municipalities between the base and end years. In Eq. (3), we include the following synthetic inequality covariate:

$$\Delta In_{mt}^{stay} = In_{m,t+5}^{stay} - In_{mt}. \tag{4}$$

All residents used for calculating $In_{m,t+5}$ except those who moved in between t and $t+5$ are used to calculate $In_{m,t+5}^{stay}$.[25]

With the synthetic inequality covariate in Eq. (4), only variation in inequality change caused by the income distribution of in-movers will identify β in Eq. (3). To see this, note that $\beta\Delta In_{mt} + \gamma_4\Delta In_{mt}^{stay} = \beta(\Delta In_{mt} - \Delta In_{mt}^{stay}) + (\gamma_4 + \beta)\Delta In_{mt}^{stay}$. Identification of β relies on variation in $\Delta In_{mt} - \Delta In_{mt}^{stay}$. The variables ΔIn_{mt} and ΔIn_{mt}^{stay} assume different values only when in-movers have a different income distribution than stayers ($In_{m,t+5} \neq In_{m,t+5}^{stay}$), and varying income distributions of in-movers provide the identifying variation.[26]

The last row in Table A2 in Appendix shows that 14.5% of the municipal population in $t+5$ consist of residents that moved in after t. Hence, there is scope for in-movers to cause a substantial external shock to the population income composition in the destination municipality. We rely on the municipality-by-year variation in this shock. To investigate the amount of variation in this shock, in Table 1 we report means and standard deviations for our overall

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[24] To some degree, controlling for base-year segregation in $\boldsymbol{z}_{mt}$ accounts for this issue. However, the functional form of this dependence is likely complicated and unlikely linear in one specific measure of base-year segregation.

[25] Our definition of "stayers" used for calculating $In_{m,t+5}^{stay}$ does not only include "actual stayers" used for calculating both $In_{m,t}$ and $In_{m,t+5}$ for two reasons. First, in-moving residents from other *countries* are not dropped when calculating $In_{m,t+5}^{stay}$. Second, staying residents who were aged 24 or less at t and 25 or more at $t+5$ enter the working-age sample used for constructing both $In_{m,t+5}$ and $In_{m,t+5}^{stay}$ (but not $In_{m,t}$).

[26] To account for reverse causation and mechanical effects, it is sufficient that in-movers are not part of existing segregation. It matters less which factors determine the income distribution of in-movers. Nevertheless, since we include base-year covariates in $\boldsymbol{z}_{mt}$ and population change and migration streams in $\Delta\boldsymbol{Pop}_{mt}$ in Eq. (3), we account for the dependence between the income distribution of in-movers and general urbanization processes, such as selective migration to more populous municipalities.

inequality variable ΔSd_{mt} and its two additive components $\left(\Delta Sd_{mt}^{t} - \Delta Sd_{mt}^{stay}\right)$ and ΔSd_{mt}^{stay}. The standard deviations are smaller for $\left(\Delta Sd_{mt} - \Delta Sd_{mt}^{stay}\right)$ than for ΔSd_{mt}^{stay} but only by a factor of two to three (0.097 vs. 0.219 in column 2, and 0.097 vs. 0.311 in column 4). Hence, there is substantial variation in inequality changes due to in-movers.[27]

Table 1. Variation in five-year inequality changes due to stayers and in-movers

	(1)	(2)	(3)	(4)
	Disposable income		Pre-tax income	
	Mean	Standard dev.	Mean	Standard dev.
ΔSd_{mt} (total)	0.173	0.207	0.129	0.311
ΔSd_{mt}^{stay} (stayers)	0.195	0.219	0.125	0.311
$\Delta Sd_{mt} - \Delta Sd_{mt}^{stay}$ (movers)	0.003	0.097	0.003	0.097

4. Main results

4.1 Estimates for overall inequality and segregation

Starting with overall inequality and segregation, in Table 2 we analyze the relationship between Sd_{mt} (standard deviation of log income) and Nsi_{mt} (neighborhood sorting index). Specifically, following Eq. (3), we report estimates of β from first-difference regressions of five-year changes in segregation (ΔSd_{mt}) on inequality (ΔNsi_{mt}) for disposable income (Panel A) and pre-tax income (Panel B). In column (1), we include only year dummies as covariates. In column (2), we also control for the complementary measure of inequality change ($\Delta \overline{Sd}_{mt}$, constructed using pre-tax income in Panel A and disposable income in Panel B). In column (3), we add base-year covariates ($\boldsymbol{z}_{mt}$) and controls for population change ($\Delta \boldsymbol{Pop}_{mt}$). In the second rows of estimates in each panel, we rule out reverse causation and mechanical effects by including the stayer control (ΔSd_{mt}^{stay}). Identification of the residential sorting effect of inequality on segregation then fully relies on how in-moving residents from other municipalities change inequality in the destination municipality.

In Panel A of Table 2, we find point estimates of the slope coefficient that are positive (0.0551 to 0.0586) and statistically significant at the one percent level when omitting the stayer control. While disposable incomes are highly correlated with pre-tax incomes, controlling for changes in pre-tax income inequality in column (2) does not affect the point estimate or standard error much. In doing so, identification of disposable inequality effects also fully relies on municipality-by-year variation due to changes to the tax and transfer system.

[27] Ultimately, regression results will reveal whether there is an issue with statistical power or not.

Table 2. The influence of overall inequality (Sd) on segregation (Nsi)

Dependent variable: ΔNsi	(1)	(2)	(3)
Independent variable: ΔSd	A: Disposable income estimates		
No stayer control (ΔSd^{stay})	0.0586**	0.0555**	0.0551**
	(0.0128)	(0.0130)	(0.0127)
With stayer control (ΔSd^{stay})	-0.0367	-0.0463*	-0.0396
	(0.0197)	(0.0200)	(0.0218)
	B: Pre-tax income estimates		
No stayer control (ΔSd^{stay})	0.0607**	0.0692**	0.0688**
	(0.00869)	(0.0103)	(0.00866)
With stayer control (ΔSd^{stay})	0.0563**	0.0627**	0.0991**
	(0.0179)	(0.0183)	(0.0191)
Base-year dummies	Yes	Yes	Yes
Inequality complement ($\Delta\overline{Sd}$)	No	Yes	Yes
Base-year covariates ($\boldsymbol{z}$)	No	No	Yes
Population changes ($\Delta\boldsymbol{Pop}$)	No	No	Yes

Notes: There are 5,510 observations of five-year changes (290 municipalities and 19 base years). Base-year covariates ($\boldsymbol{z}_{mt}$) include share that did not graduate high school, share with university degree, share born in Europe outside Sweden, share born outside Europe, share of young residents (aged 24 or below), share of old residents (aged 60 or above), shares in six age groups (five-year intervals), population, and base-year segregation (Nsi_{mt}) and inequality (Sd_{mt}). Population changes ($\Delta\boldsymbol{Pop}_{mt}$) include population change and in-moving residents from other municipalities as shares of base-year population. We weight regressions by the working-age population in the base year, and we report standard errors clustered at the municipality level in parentheses. * p<0.05, ** p<0.01.

Once accounting for reverse causation and mechanical effects using the stayer control in Panel A, the point estimate decreases and become statistically insignificant in columns (1) and (3). Thus, the positive relationship between changes in inequality and segregation without the stayer control might exist because segregation leads to inequality through neighborhood effects. Alternatively, tax- and transfer system changes mechanically affected residents in low- and high-income neighborhoods differently. Such changes could strengthen both existing segregation and inequality patterns leading to a positive relationship without the stayer control.[28]

Our results show that changes in disposable income inequality due to in-moving residents did *not* lead to in residential sorting across neighborhoods in a way that had a greater impact on residential segregation. With the stayer control, in columns (2) and (3), identification relies on the differential municipality-by-year impact of the tax and transfer system on the in-moving residents' disposable incomes. Thus, we can conclude that public redistribution changing the municipal income dispersion did not result in active residential choices such that the between-neighborhood share of municipal income dispersion was affected. In column (3), the estimated residential sorting effect of disposable income inequality due to public redistribution is -0.03696. Although standard errors are a bit larger with the stayer control than without, from the 95% confidence interval (-0.0396$\pm$1.96*0.0218), we can rule out greater positive effects above 0.003.

[28] The existence of a positive correlation due to reverse causation and mechanical effects, but not due to residential sorting, is consistent with how the disposable income correlation changes in Figure 2 as the difference length increases. As the time horizon becomes longer, the impact of reverse causation and mechanical effects diminishes, and the point estimate should decrease if there are no residential sorting effects, which is what we saw.

In Panel B of Table 2, the pre-tax income point estimates are all positive and statistically significant at the one percent level. We obtain a point estimate of 0.0991 when we include all covariates (column 3), including the stayer control. This estimate shows that inequality changes that were generated by population income composition changes due to in-moving residents resulted in subsequent residential sorting across neighborhood. As municipal income dispersion increases, between-neighborhood income dispersion will make up a larger *share* of the municipal income dispersion. This means that the between-neighborhood dispersion will proportionally increase more than the municipal income dispersion. In the next subsection, we will attempt to sort out the importance of some determinants of pre-tax incomes for segregation.

We can relate the point estimates to the summary statistics in Table A1 in Appendix B (where mean $\Delta Sd_{mt} = 0.129$ and mean $\Delta Nsi_{mt} = 0.012$ for pre-tax incomes). The estimate of 0.0991 translates into a (sample) mean five-year effect of 0.013 (=0.0991*0.129), which is almost exactly the mean five-year segregation change. Hence, mean inequality growth can account for the *entire* mean segregation rise over time during the sample period. This result also means that if inequality hypothetically had not increased (stayed constant at its level in 1991), segregation would not have changed.[29]

Our results so far indicate that the scope for public redistribution to affect residential sorting across neighborhoods and thereby segregation seems limited. Instead, policymakers who want to prevent segregation due to residential sorting by reducing inequality could focus on equalizing pre-tax incomes rather than disposable incomes. Since unequal pre-tax incomes matter conditional on disposable income inequality, unequal earning capacities matter even if consumption capacities are equalized via public redistribution. Progressive taxes and welfare transfers (e.g., housing allowance) only affect consumption capacities (at least in the short run) and such policies do not affect pre-tax incomes. Changing the pre-tax income distribution might be hard and take time. Policymakers could attempt to equalize "skills" that matter on the labor market.[30] In the next subsection, analyze the role of socio-demographic determinants of pre-tax incomes.

4.2 The role of the municipal socio-demographic composition

Since pre-tax incomes correlate with socio-demographic characteristics, policymakers could influence income inequality by changing the population composition along socio-demographic dimensions. In Table 3, we explore how some aspects of this composition play a role by controlling for changes in educational, country-of-birth, and age compositions. These variables are five-year changes of the base-year covariates. We start from the full regression specification in Eq. (3) with all basic covariates (column 1) and then add either municipal share changes in education groups (column 2), country-of-birth groups (column 3), or age groups (column 4). In column (5), we include all basic and additional covariates.

[29] This does not mean that inequality change is the only determinant of segregation change. Explanatory power is not 100% (R-squared is not equal one).

[30] Moreover, municipalities could try to change the skill distribution via migration; in other words, they could make themselves more attractive for mid-skill residents and less attractive for low- and high-skill residents. However, at least regarding internal migration within a country, this is typically a zero-sum game among the municipalities and the effects cannot be scaled up to the national level.

Table 3. Effects of inequality (Sd) on segregation (Nsi) accounting for socio-economic changes

Dependent variable: ΔNsi	(1)	(2)	(3)	(4)	(5)
Independent variable: ΔSd	A: Disposable income estimates				
No stayer control (ΔSd^{stay})	0.0551**	0.0544**	0.0532**	0.0554**	0.0535**
	(0.0127)	(0.0126)	(0.0117)	(0.0114)	(0.0106)
With stayer control (ΔSd^{stay})	-0.0396	-0.0429	-0.0433	-0.0347	-0.0426
	(0.0218)	(0.0240)	(0.0221)	(0.0253)	(0.0255)
	B: Pre-tax income estimates				
No stayer control (ΔSd^{stay})	0.0688**	0.0683**	0.0526**	0.0606**	0.0535**
	(0.00866)	(0.00753)	(0.00922)	(0.00719)	(0.00621)
With stayer control (ΔSd^{stay})	0.0991**	0.0320	0.0931**	0.0793**	0.0295
	(0.0191)	(0.0175)	(0.0202)	(0.0186)	(0.0171)
Education changes	No	Yes	No	No	Yes
Country-of-birth changes	No	No	Yes	No	Yes
Age changes	No	No	No	Yes	Yes

Notes: There are 5,510 observations of five-year changes (290 municipalities and 19 base years). All regressions include base-year dummies, the inequality complement ($\Delta\overline{Sd}_{mt}$), base-year covariates ($\boldsymbol{z}_{mt}$), and population changes ($\Delta\boldsymbol{Pop}_{mt}$). See the notes of Table 2 for more details. Education changes include changes in share that did not graduate high school and share with university degree. Country-of-birth changes include changes in share born in Europe outside Sweden and share born outside Europe. Age changes include changes in share of young residents (aged 24 or below), share of old residents (aged 60 or above), and shares in six age groups (five-year intervals). We weight regressions by the working-age population in the base year, and we report standard errors clustered at the municipality level in parentheses. * p<0.05, ** p<0.01.

Panel A of Table 3 shows that the additional covariates do not affect the disposable income estimates much. Moreover, in Panel B, the correlation between changes in pre-tax income inequality and segregation without the stayer control remain stable to the inclusion of additional covariates.

When including the stayer control in Panel B to rule out reverse causation and mechanical effects, the pre-tax income point estimate of 0.0991 (column 1) becomes sensitive to controlling for changes in the educational composition in column (2). It decreases to 0.0320 (by 68%) and is no longer statistically significant. Hence, once controlling for how in-movers, providing the identifying variation, change the educational composition, much of the subsequent residential sorting effects across neighborhoods disappears. Therefore, the educational composition is the main driver of the influence of pre-tax income inequality on segregation due to residential sorting. This finding strongly suggests that policies equalizing educational levels, and thereby skill levels, are effective in terms of fighting segregation. However, controlling for changes in the country-of-birth composition in column (3) have small effects on the point estimate (which moves from 0.0991 to 0.0931). Hence, the relationship we find is not driven by residential sorting patterns of foreign-born residents.

In addition to being relevant to policy, our results are useful for understanding residential sorting mechanisms. We *cannot* establish that unequal disposable incomes indicating unequal abilities to pay for housing quality and public goods (Tiebout, 1956) led to residential sorting in the form of between-neighborhood dispersion in disposable incomes. On the other hand, unequal pre-tax incomes reflecting unequal earning abilities led to residential sorting and segregation. This pattern could be rationalized by people being attracted to neighborhoods with others similar to themselves in terms of skill levels or factors determining skill levels. (Schelling, 1969). In particular, we find that the education level drove such residential sorting.

Higher educated individuals with higher income levels might value certain types of housing forms (e.g., single-family vs multifamily residential buildings) or public goods (e.g., better schools) more compared to others with similar consumption abilities. Moreover, they might prefer to live and interact with similar-minded or care more about neighborhood of residence as a status marker.

5. The tails of the income distribution

5.1 Inequality and segregation along the tails of the income distribution

Different measures of income inequality and residential segregation do not weight different parts of the income distribution in the same way.[31] Our detailed data allow us to operationalize inequality and segregation along any quantile of the income distribution in a more precise manner than the overall measures discussed so far. In Figure 3, we show kernel density fits of the national income distributions in 1991 and 2014. To adjust for growth enabling comparability over time, we display the x-axis in terms of relative income as proportion of the median income for each year.[32] The most striking change over time is that the share of residents with income levels around the median in the middle of the income distribution has decreased.

For each distribution in Figure 3, we mark *year-specific* first- and ninth-decile cutoffs with vertical lines. We also mark the mean of (midpoint between) the two year-specific first- and ninth-decile cutoffs, respectively, on the x-axis. Each of these proportions is a fixed constant across the two years and represents a *normalized* across-year national decile cutoff.[33]

Each of the income distributions in Figure 3 has a peak around one and a lower and an upper tail. Starting with the upper tails, we see that the year-specific top-decile (9th decile) cutoffs have increased, implying that high-income residents have become relatively richer. In this sense, the upper tails have become *longer* (outstretched horizontally). Moreover, above the normalized top-decile cutoff, the densities have increased, meaning that there is a larger number of rich residents in 2014 than in 1991. In this sense, the upper tails have become *thicker* (uplifted vertically).[34] Moving to the first-decile cutoffs, we can similarly conclude that low-income residents have become poorer (longer tails) and more numerous (thicker tails). We can construct simple and intuitive inequality measures along different decile cutoffs.

Each municipality has its own income distribution that varies over time. To measure the thickness of the tails of the *municipal* income distribution, we construct municipal poverty (affluence) rates varying across years. We first express each individual's income relative to the year-specific *municipal* median, and the poverty (affluence) rates are defined as the municipal shares of residents with relative incomes below (above) normalized across-year *national* decile

[31] For instance, the standard deviation of income gives top incomes higher weight compared to the standard deviation of the logarithm of income.
[32] Hence, median income assumes a value of one on the x-axis.
[33] Such decile cutoffs almost correspond to decile cutoffs of the income distribution for the pooled sample of individuals from the two years.
[34] For continuous distributions, tail thickness and length typically correlate, but not perfectly. The tails could primarily become longer without getting thicker, and vice versa.

cutoffs.[35] These normalized national cutoffs (illustrated in Figure 3) enable meaningful comparisons of poverty and affluence rates across municipalities and years. For the lower tail, we construct $Share_{mt}^{d}$ for deciles $d = 1,2,3,4$ as shares of poor residents with relative income *below* the 1st to 4th normalized national decile cutoffs. Similarly, for the upper tail, we construct $Share_{mt}^{d}$ for $d = 6,7,8,9$ as shares of rich residents *above* the 6th to 9th normalized national decile cutoffs.

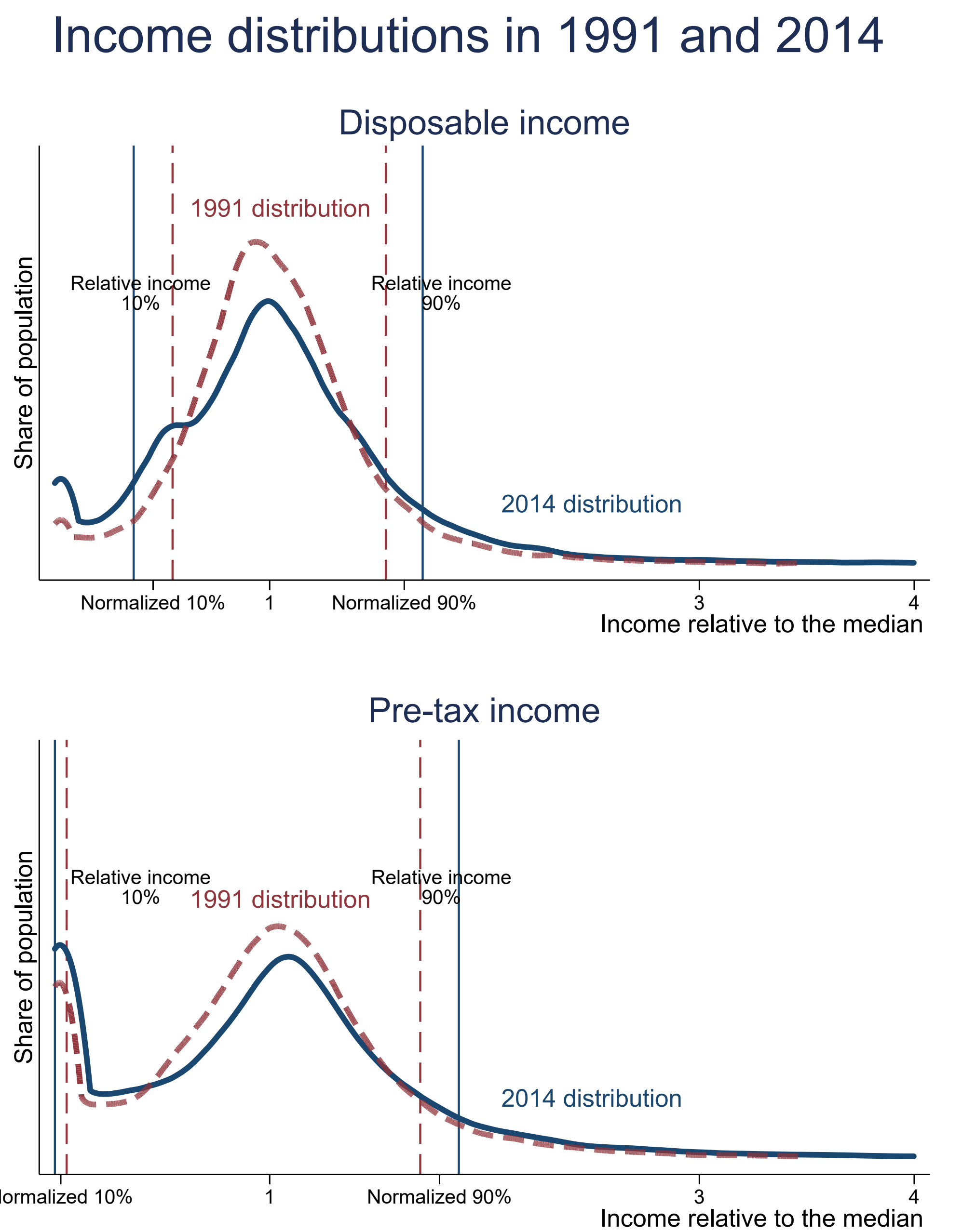

Figure 3. Kernel fits of the national income distributions in 1991 and 2014

[35] Let $Income_t^d$ be income at the national decile d in year t and let T denote the number of years. Then, $Proportion^d = [\sum_t (Income_t^d / Income_t^5)]/T$ for $d = 1,2,3,4,6,7,8,9$ are the normalized national decile cutoffs. For municipality m in year t with median income $Income_{mt}^5$, $Share_{mt}^d$ is the share of the population with an income divided by $Income_{mt}^5$ that is less (more) than $Proportion^d$ where $d = 1,2,3,4$ ($d = 6,7,8,9$).

To measure the length of the tails of the municipal income distribution, we construct relative income measures $Ratio_{mt}^{d}$ as municipal income of poor (rich) residents at different municipal income decile cutoffs for $d = 1,2,3,4,6,7,8,9$ divided by the municipal median income. As the lower tail of the income distribution becomes longer, $Ratio_{mt}^{d}$ for $d = 1,2,3,4$ *decreases*. Thus, these variables measure the "inverse" of lower-tail length. The opposite applies to the upper tail; as the tail becomes longer, $Ratio_{mt}^{d}$ for $d = 6,7,8,9$ increases, and these variables measure upper-tail length.

With regard to binary groups, such as poor and non-poor (or rich and non-rich), the dissimilarity index (Di_{mt}) is the established measure for the spatial concentration of similar-typed residents in certain subunits within an area. Let $Group_{nt}$ denote the number of poor, and let $\overline{Group}_{nt}$ denote the number of non-poor residents in neighborhood n in year t. Then, $Group_{mt} = \sum_n Group_{nt}$ and $\overline{Group}_{mt} = \sum_n \overline{Group}_{nt}$ are the numbers of poor and non-poor residents in municipality m in year t, respectively. Now:

$$Di_{mt} = 0.5 \sum\nolimits_n \left| \frac{Group_{nt}}{Group_{mt}} - \frac{\overline{Group}_{nt}}{\overline{Group}_{mt}} \right|. \tag{2}$$

In case the neighborhoods have the same mix of residents from the two groups, $Di_{mt} = 0$. Maximum neighborhood sorting occurs when all residents from one group are concentrated in the same neighborhoods and the remaining residents concentrated in the other neighborhoods, and in this case, $Di_{mt} = 1$. Typically, a higher concentration of residents means a lower within-neighborhood mix of residents from the two groups.

In constructing $Share_{mt}^{d}$ above, we used eight normalized national decile cutoffs. We can define poor and non-poor (or rich and non-rich) along each of the income cutoffs, and we construct dissimilarity indexes $DiShare_{mt}^{d}$ with respect to each of these income cutoffs. Similarly, for each inequality measure $Ratio_{mt}^{d}$, we construct a corresponding segregation measure $DiRatio_{mt}^{d}$.

In Figures A3 and A4 in Appendix C, we plot across-municipality yearly means of $Share_{mt}^{d}$, $DiShare_{mt}^{d}$, $Ratio_{mt}^{d}$, and $DiRatio_{mt}^{d}$ for $d = 2,8$ in terms of pre-tax income and disposable income, respectively. The figures show that along the bottom and top quintiles, inequality due to poverty and affluence both in terms of shares with extreme incomes and incomes relative to the median have increased quite consistently. At the same time, corresponding segregation with respect to poverty and affluence developed similarly, reflecting growing neighborhood concentrations of low- and high-income residents in different neighborhoods. The trends we describe are the clearest when it comes to disposable income.

5.2 Distinguishing poverty and affluence effects on segregation

We now analyze the role of different parts of the municipal income distribution with regard to the relationship between inequality and segregation. In Table 4, we report estimates from regressions (Eq. 3) of changes in neighborhood dissimilarity indexes along normalized national decile cutoffs ($\Delta DiShare_{mt}^{d}$) on changes in share of residents by corresponding cutoffs ($\Delta Share_{mt}^{d}$).

Our point estimates for disposable income are typically much smaller than for pre-tax income. Once including the stayer control to rule out reverse causation and mechanical effects in columns (2) and (4), most of the point estimates become statistically insignificant. However, we find positive point estimates for pre-tax income that are statistically significant for decile cutoffs below the median ($d < 5$). This means that raising pre-tax poverty rates increases neighborhood poverty dissimilarity.

In Figure 4, we translate the estimates in columns (2) and (4) of Table 4 into estimates of how much inequality change can account for the growing segregation over time. We calculate (sample) mean five-year effects (with the help of Table A1 in Appendix B) of $Share^{d}_{mt}$ on $DiShare^{d}_{mt}$ and then divide this by mean $\Delta DiShare^{d}_{mt}$ to obtain the share of mean $\Delta DiShare^{d}_{mt}$ that the estimates are able to explain. We plot these translated point estimates with dots and 95% confidence intervals with bars (y-axis) for each decile cutoff (along x-axis).

Panel B of Figure 4 shows that our estimated impacts of poverty rates for pre-tax income can account for 41–90% of the rise in poverty dissimilarity between neighborhoods when using the first to third decile cutoffs. To prevent neighborhood concentration of low-income residents, policymakers might decrease pre-tax income poverty by raising the skill level of residents with low pre-tax income. Potentially effective policies include labor market programs targeting working-age people with weak ties to the labor market. In the long run, we believe that improving school attainments and cognitive abilities of the children exhibiting the weakest results should be a top priority.

Having investigated the importance of inequality due to tail thickness for segregation, we now move on to the importance of tail length. In Table 5, we report estimates from regressions (Eq. 3) of changes in neighborhood dissimilarity indexes along municipal income decile cutoffs ($\Delta DiRatio^{d}_{mt}$) on changes in municipal ratios of decile incomes over the median income ($\Delta Ratio^{d}_{mt}$).

When including the stayer control in column (2), we find positive point estimates for disposable income that are statistically significant for decile cutoffs above the median. Hence, raising relative disposable incomes of high-income residents leads to higher neighborhood affluence dissimilarity. For pre-tax income in column (4), we mostly find negative pre-tax point estimates that are statistically significant for decile cutoffs below the median. This means that raising relative pre-tax incomes of low-income residents decreases poverty dissimilarity between neighborhoods.

In Figure 5, we translate the estimates in columns (2) and (4) of Table 5 into estimates of how much inequality change can account for the growing segregation over time as in Figure 4. While we could not establish any impacts of affluence rates in Figure 4, Panel A of Figure 5 reveals sizable estimated residential sorting effects of relative disposable incomes able to account for much of the change in neighborhood affluence dissimilarity over time. Growing relative top-decile incomes have led to 76% of the surge in top-decile dissimilarity between neighborhoods. To fight neighborhood concentration of high-income residents, policymakers could decrease their disposable incomes by, for instance, increasing top labor income taxes or by raising capital income taxes. In terms of residential sorting mechanisms, the results indicate that the richest residents who can afford better housing had an inclination to choose exclusive neighborhoods with a large share of other rich residents.

Table 4. Poverty/affluence rate ($Share^d$) effects on neighborhood dissimilarity ($DiShare^d$)

		(1)	(2)	(3)	(4)
Dependent variable	Independent variable	Disposable income estimates		Pre-tax income estimates	
		No ΔSd^{stay}	With ΔSd^{stay}	No ΔSd^{stay}	With ΔSd^{stay}
$\Delta DiShare^1$	$\Delta Share^1$	0.239	0.507	0.414**	1.379**
		(0.287)	(0.332)	(0.102)	(0.494)
$\Delta DiShare^2$	$\Delta Share^2$	0.140	0.361	0.176*	0.829*
		(0.137)	(0.209)	(0.0743)	(0.354)
$\Delta DiShare^3$	$\Delta Share^3$	-0.0231	0.202	0.228**	0.920**
		(0.116)	(0.153)	(0.0800)	(0.286)
$\Delta DiShare^4$	$\Delta Share^4$	-0.0932	0.102	0.232	0.853**
		(0.113)	(0.161)	(0.128)	(0.278)
$\Delta DiShare^6$	$\Delta Share^6$	-0.147	-0.214	0.0798	-0.269
		(0.107)	(0.228)	(0.0740)	(0.237)
$\Delta DiShare^7$	$\Delta Share^7$	-0.0790	-0.120	-0.102*	-0.335
		(0.0799)	(0.209)	(0.0506)	(0.234)
$\Delta DiShare^8$	$\Delta Share^8$	-0.0394	0.0320	-0.243**	-0.356
		(0.0638)	(0.195)	(0.0735)	(0.263)
$\Delta DiShare^9$	$\Delta Share^9$	-0.208*	0.164	-0.289**	-0.0551
		(0.0949)	(0.223)	(0.106)	(0.360)

Notes: There are 5,510 observations of five-year changes (290 municipalities and 19 base years). All regressions include base-year dummies, the inequality complement ($\Delta\overline{Share}^d_{mt}$), base-year covariates ($\boldsymbol{z}_{mt}$), and population changes ($\Delta \boldsymbol{Pop}_{mt}$). See the notes of Table 2 for more details. We weight regressions by the municipal working-age population in the base year, and we report standard errors clustered at the municipality level in parentheses. * p<0.05, ** p<0.01.

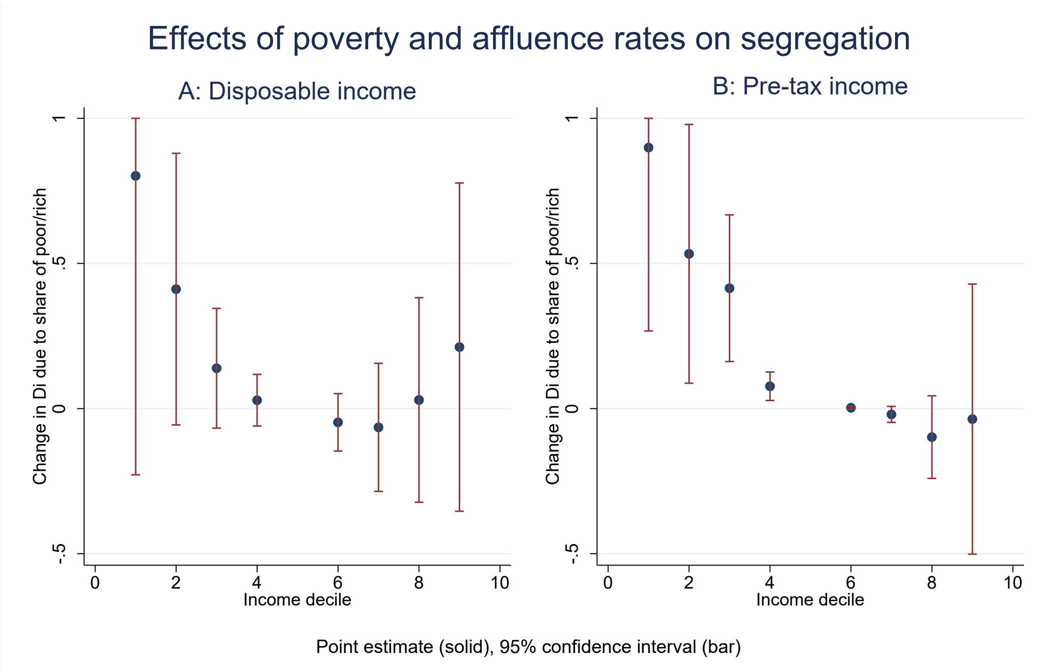

Figure 4. Dissimilarity changes accounted for by poverty/affluence rate changes (decile-wise)

Notes: We calculate the proportion of dissimilarity index change over time that can be accounted for using point estimates from regressions of $\Delta DiShare^d_{mt}$ on $\Delta Share^d_{mt}$ (from columns 2 and 4 in Table 4). The point estimates are multiplied by mean $\Delta Share^d_{mt}$ and divided by mean $\Delta DiShare^d_{mt}$ (from Table A1 in the Appendix) for each decile $d = 1,2,3,4,6,7,8,9$. Similarly, we construct confidence intervals from the standard error estimates in Table 4. The y-axis has been cut at the value of one.

Table 5. Relative income ($Ratio^d$) effects on neighborhood dissimilarity ($DiRatio^d$)

		(1)	(2)	(3)	(4)
Dependent variable	Independent variable	Disposable income estimates		Pre-tax income estimates	
		No ΔSd^{stay}	With ΔSd^{stay}	No ΔSd^{stay}	With ΔSd^{stay}
$\Delta DiRatio^1$	$\Delta Ratio^1$	-0.0639	-0.0575	0.465**	0.373*
		(0.0628)	(0.0865)	(0.0951)	(0.151)
$\Delta DiRatio^2$	$\Delta Ratio^2$	0.0797	-0.158	-0.129**	-0.147**
		(0.150)	(0.123)	(0.0162)	(0.0467)
$\Delta DiRatio^3$	$\Delta Ratio^3$	0.196	-0.0822	-0.167**	-0.536**
		(0.177)	(0.166)	(0.0220)	(0.0964)
$\Delta DiRatio^4$	$\Delta Ratio^4$	0.306	-0.447	-0.153**	-0.942**
		(0.208)	(0.313)	(0.0439)	(0.212)
$\Delta DiRatio^6$	$\Delta Ratio^6$	-0.133	0.310	0.0131	0.423
		(0.118)	(0.179)	(0.0414)	(0.288)
$\Delta DiRatio^7$	$\Delta Ratio^7$	-0.0182	0.492**	-0.000802	0.215
		(0.0728)	(0.165)	(0.0280)	(0.182)
$\Delta DiRatio^8$	$\Delta Ratio^8$	0.0986**	0.445**	0.0236	0.148
		(0.0297)	(0.115)	(0.0215)	(0.127)
$\Delta DiRatio^9$	$\Delta Ratio^9$	0.0462*	0.228**	0.0282	0.101
		(0.0197)	(0.0667)	(0.0151)	(0.0617)

Notes: There are 5,510 observations of five-year changes (290 municipalities and 19 base years). All regressions include base-year dummies, the inequality complement ($\Delta\overline{Share}_{mt}^{d}$), base-year covariates ($\boldsymbol{z}_{mt}$), and population changes ($\Delta \boldsymbol{Pop}_{mt}$). See the notes of Table 2 for more details. We weight regressions by the municipal working-age population in the base year, and we report standard errors clustered at the municipality level in parentheses. * p<0.05, ** p<0.01.

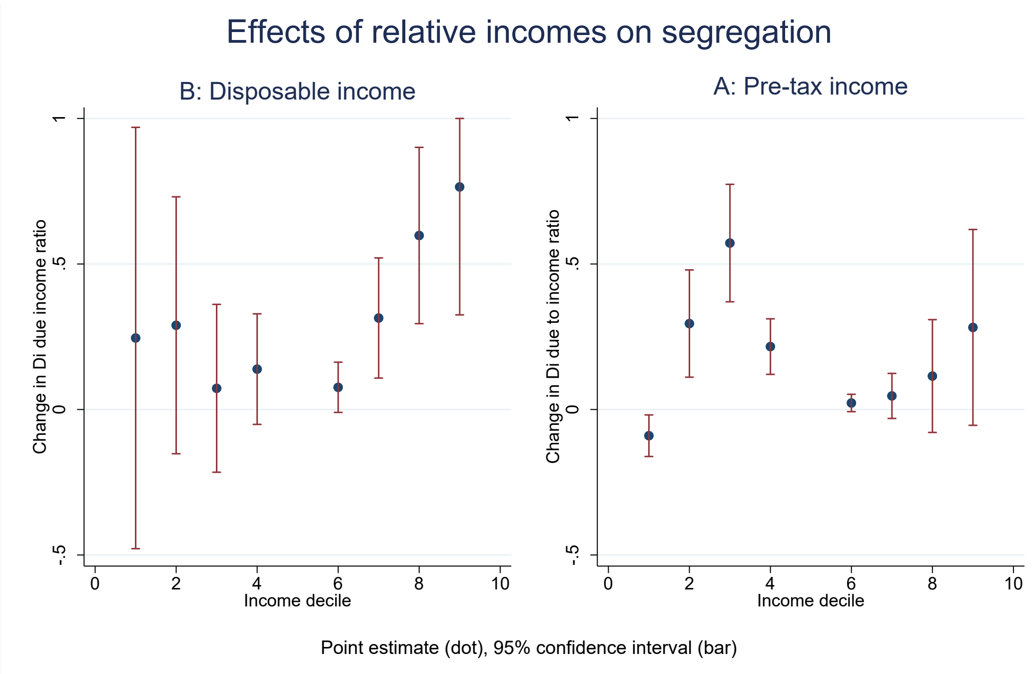

Figure 5. Dissimilarity changes accounted for by relative income changes (decile-wise)

Notes: We calculate the proportion of dissimilarity index change over time that can be accounted for using point estimates from regressions of $\Delta DiRatio_{mt}^{d}$ on $\Delta Ratio_{mt}^{d}$ (from columns 2 and 4 in Table 5). The point estimates are multiplied by mean $\Delta Ratio_{mt}^{d}$ and divided by mean $\Delta DiRatio_{mt}^{d}$ (from Table A1 in the Appendix) for each decile $d = 1,2,3,4,6,7,8,9$. Similarly, we construct confidence intervals from the standard error estimates in Table 5. The y-axis has been cut at the value of one.

6. Conclusion

Previous research documented correlations between changes in income inequality and residential segregation by income across neighborhoods. However, few policy conclusions could be drawn regarding whether and which types of public policies could prevent segregation due to residential sorting. Using richer full-population data for Sweden 1991–2014, we have analyzed how changing policy-relevant determinants of income inequality affects residential sorting and segregation in Swedish municipalities. We took advantage of how in-moving residents change the municipal income distribution and inequality to rule out reverse causation and mechanical effects. Moreover, we relied on changes in the tax and transfer system to estimate effects of public redistribution.

Our main result is that reducing disposable income inequality (standard deviation of the logarithm of income) using taxes and transfers has limited residential sorting effects on segregation (neighborhood sorting index). However, increasing relative incomes of high-income residents have led to a higher concentration (dissimilarity index) of such individuals in certain neighborhoods.

We also found that increasing pre-tax income inequality can account for the entire dramatic segregation surge since the 1990s, mainly because growing shares of low-income residents can explain rising concentration of such residents in certain neighborhoods. The educational composition is a main driver of the influence of pre-tax income inequality on segregation due to residential sorting.

In terms of policy recommendations, our results strongly suggest that raising the education levels of low-income residents is effective for fighting segregation. There is also scope for fighting segregation of high-income residents with top income taxes.

Appendix

Appendix A. Correlation figures

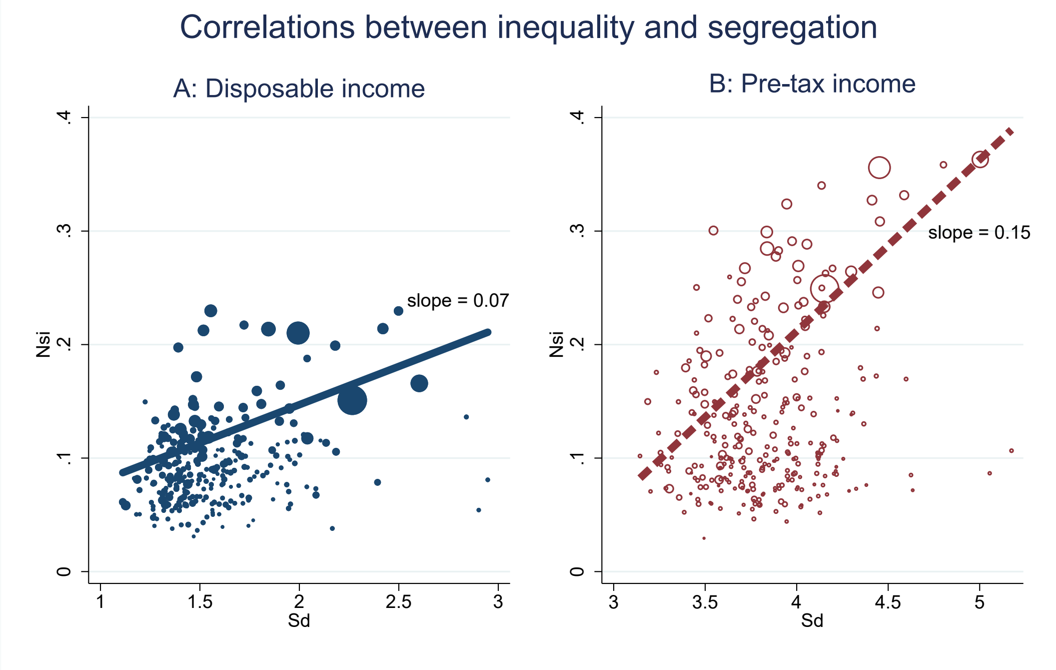

Figure A1. Inequality and segregation by municipality, municipal means 1991–2014

Notes: Each dot represents one municipality and the dots are population-weighted. We report estimated slope coefficients from regressions of across-year municipal mean Nsi_{mt} on Sd_{mt}.

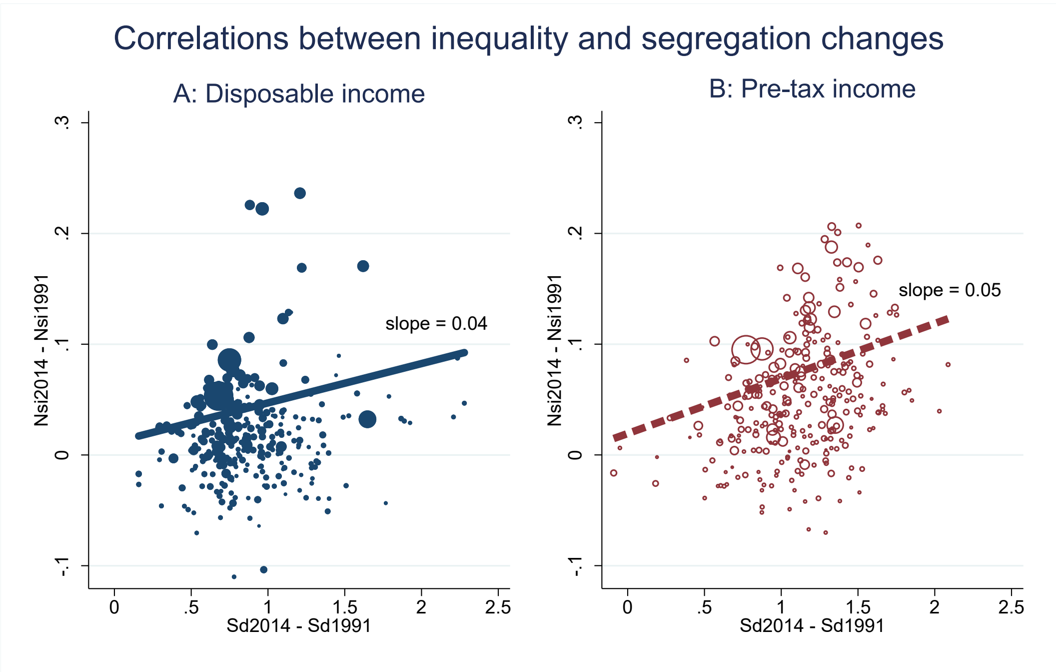

Figure A2. Inequality and segregation changes 1991–2014 by municipality

Notes: Each dot represents one municipality and the dots are population-weighted. We report estimated slope coefficients from regressions of $Nsi_{m,2014} - Nsi_{m,1991}$ on $Sd_{m,2014} - Sd_{m,1991}$.

Appendix B. Summary statistics

Table A1. Municipal population-weighted means of inequality and segregation variables

	(1)	(2)	(3)	(4)	(5)	(6)
	Disposable income			Pre-tax income		
Variable	Base-year	Change	ΔIn^{stay}	Base-year	Change	ΔIn^{stay}
	A: Inequality measures					
Sd	1.593	0.173	0.195	3.882	0.129	0.125
$Share^1$	0.092	0.016	0.015	0.117	0.007	0.007
$Share^2$	0.183	0.019	0.015	0.197	0.006	0.002
$Share^3$	0.290	0.012	0.007	0.296	0.004	-0.003
$Share^4$	0.396	0.005	-0.001	0.399	0.001	-0.006
$Share^6$	0.396	0.003	0.007	0.401	0.000	0.004
$Share^7$	0.291	0.007	0.009	0.300	0.001	0.003
$Share^8$	0.187	0.009	0.011	0.198	0.003	0.004
$Share^9$	0.089	0.007	0.008	0.095	0.004	0.005
$Ratio^1$	0.516	-0.044	-0.044	0.013	-0.005	-0.004
$Ratio^2$	0.699	-0.032	-0.029	0.287	-0.021	-0.006
$Ratio^3$	0.816	-0.016	-0.013	0.613	-0.011	0.001
$Ratio^4$	0.912	-0.005	-0.004	0.841	-0.003	0.002
$Ratio^6$	1.093	0.004	0.003	1.132	0.001	-0.002
$Ratio^7$	1.200	0.009	0.007	1.273	0.003	-0.001
$Ratio^8$	1.337	0.016	0.014	1.459	0.009	0.005
$Ratio^9$	1.582	0.030	0.027	1.802	0.025	0.024
	B: Segregation measures					
Nsi	0.119	0.012		0.195	0.012	
$DiShare^1$	0.160	0.010		0.201	0.010	
$DiShare^2$	0.149	0.017		0.172	0.009	
$DiShare^3$	0.143	0.018		0.149	0.010	
$DiShare^4$	0.142	0.017		0.134	0.011	
$DiShare^6$	0.154	0.014		0.138	0.011	
$DiShare^7$	0.167	0.012		0.149	0.011	
$DiShare^8$	0.187	0.010		0.170	0.010	
$DiShare^9$	0.225	0.006		0.211	0.007	
$DiRatio^1$	0.154	0.010		0.236	0.021	
$DiRatio^2$	0.145	0.017		0.172	0.011	
$DiRatio^3$	0.141	0.018		0.148	0.010	
$DiRatio^4$	0.141	0.017		0.135	0.011	
$DiRatio^6$	0.154	0.015		0.138	0.012	
$DiRatio^7$	0.167	0.013		0.150	0.012	
$DiRatio^8$	0.186	0.012		0.170	0.011	
$DiRatio^9$	0.218	0.009		0.208	0.009	

Notes: We report means for base-year level variables in columns (1) and (4), for five-year changes in columns (2) and (5), and for the stayer covariate version of the variables when applicable in columns (3) and (6).

Table A2. Municipal population-weighted means of socio-demographic variables

	(1)	(2)
	Base-year	Change
Education: no high school degree	0.104	-0.020
Education: high school degree	0.763	-0.004
Education: university degree	0.133	0.024
Born: Sweden	0.883	-0.014
Born: Europe outside Sweden	0.069	0.002
Born: outside Europe	0.048	0.011
Age < 25	0.318	-0.004
Age > 59	0.213	0.009
Age: 25–29	0.067	-0.003
Age: 30–34	0.070	-0.002
Age: 35–39	0.069	-0.001
Age: 40–44	0.069	-0.001
Age: 45–49	0.069	-0.002
Age: 50–54	0.066	0.001
Age: 55–59	0.060	0.003
Population (change as share of base-year population)	143,411	0.037
In-moving residents (share of base-year population)		0.145

Appendix C. Inequality and segregation due to poverty and affluence over time

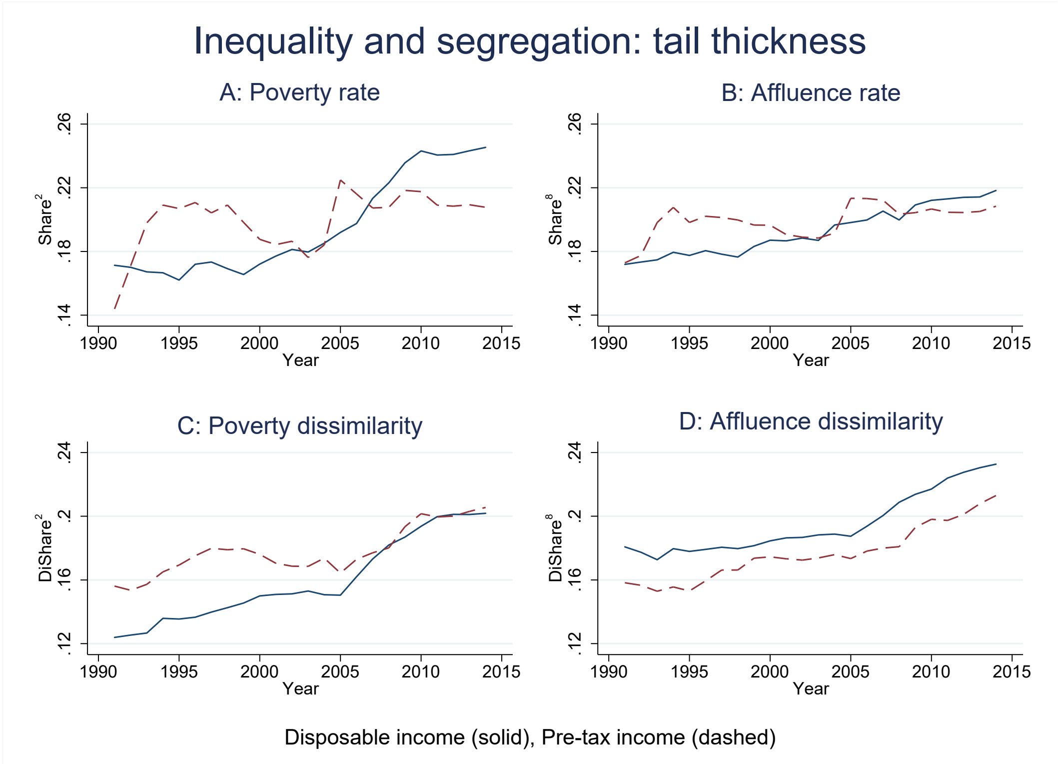

Figure A3. Poverty/affluence rate/dissimilarity, across-municipality yearly means

Notes: The municipal poverty (affluence) rate is the municipal share of residents with less (more) income than the 2nd (8th) normalized national decile cutoffs. Dissimilarity indexes are defined with respect to corresponding cutoffs.

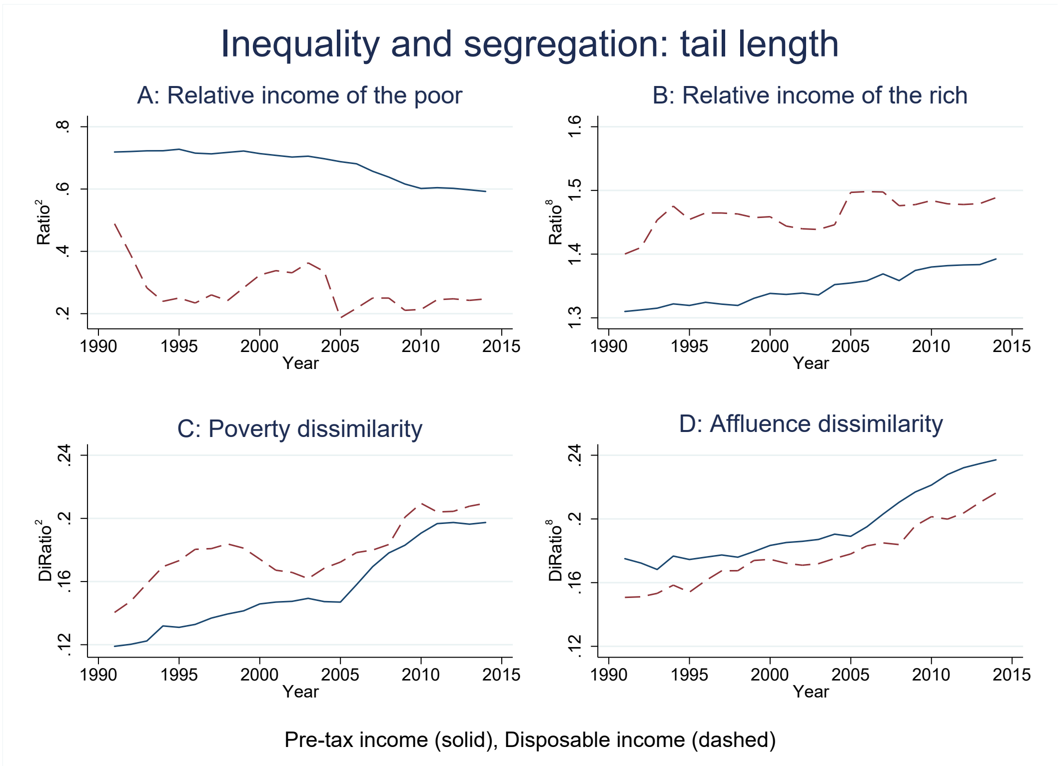

Figure A4. Relative income and dissimilarity index, across-municipality yearly means

Notes: The municipal relative income of poor (rich) residents is the municipal 2nd (8th) decile cutoff divided by the municipal median income. Dissimilarity indexes are defined with respect to corresponding cutoffs.

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