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Social mix and the city: Council housing and neighbourhood income inequality in Vienna

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Abstract
The Austrian capital of Vienna is widely acknowledged as one of the most livable cities, featuring a unique model of council housing that accounts for roughly 25% of all residential dwellings. This paper studies whether the broad provision of council housing is linked with a higher social mix in the neighbourhood. The analysis is based on administrative wage tax data at a small-scale raster grid of 500 $\times$ 500 meter with neighbourhood income inequality as an indicator for the social mix. While council housing is widely spread across the city, we find distinct spatial clusters of high and low income and inequality. Spatial econometric models show that council housing in Vienna is associated with lower income areas but slightly correlates with higher neighbourhood income inequality. These findings suggest that well-designed public housing policies may contribute to a higher social mix in a city.

Keywords
administrative data, council housing, neighbourhood income inequality, social mix, Vienna

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摘要

奥地利首都维也纳是公认的最宜居的城市之一，该城市拥有独特的公营住房模式，该类型的住宅约占所有住宅的 25%。本文主要研究广泛提供的公营住房是否与街区中较高的社会混合度有关。该分析基于 500*500m 的小规模栅格上的工资所得税行政数据，街区收入不平等是社会混合中的一个指标。虽然公营住房遍布整个城市，但我们发现高收入和低收入以及收入不平等呈现明显的空间集群。空间经济计量模型表明，维也纳的公营住房与低收入地区相关，但与街区收入不平等程度较高的地区略有关联。这些发现表明，精心设计的公共住房政策可能有助于改善城市的社会混合度。

关键词

行政数据、公营住房、街区收入不平等、社会混合、维也纳

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Introduction

Income inequality in recent decades has not only been characterised by regional divergences between urban and rural areas, but also by increasing disparities within urban centres (Musterd et al., 2016). High levels of inequality and spatial segregation in cities entail myriad social and economic perils such as higher crime rates (Metz and Burdina, 2018), decreased wellbeing (Ala-Mantila et al., 2018), eroding support of the welfare state (Bailey et al., 2013) and lower economic growth (Glaeser et al., 2009). Thus, improving the social mix has taken a prominent place in the policy agendas of city planners.

One of many policies to tackle social disparities is the provision of decent and affordable social housing (OECD, 2018). However, the role of such policies is disputed as public housing might have the counterproductive impact of increasing segregation when it is focused on low-income areas only (Machline et al., 2018). The Austrian capital of Vienna is a widely acclaimed role model for social housing due to its extensive and well-distributed provision of council housing. Vienna transformed from a socially divided city with high levels of segregation, abject poverty and poor housing conditions at the beginning of the 20th century (Kadi and Suitner, 2019) to one of the most livable cities today with a high standard of living and an unrivalled social housing sector. Even though there have been trends toward recommodification and deregulation in the housing sector since the 1980s, the city of Vienna is still one of the largest landlords in Europe a century after the public housing programme was initiated in 1919. Today, roughly 25% of all residential dwellings in Vienna are owned by the municipality.

This paper analyses the relationship between council housing, income levels and the social mix in Viennese neighbourhoods. We address the question of whether the unique housing model still meets its initial goal, that is to provide housing for low- and middle-income households and at the same time foster the social mix. We provide empirical evidence of small-scale income inequality and its relation to council housing by using cluster analysis and spatial econometric models with novel data from administrative wage tax records on a 500 × 500 m raster grid. The results show that while council housing is associated with lower income areas, it is linked to slightly higher neighbourhood income inequality, that is, more diverse neighbourhoods. From a policy perspective, these findings cautiously suggest that the broad provision of council housing in the Austrian capital is well targeted at low-income individuals but nevertheless associated with a higher social mix rather than residential segregation. This conforms with earlier findings on the larger spatial scale of administrative districts (Gutheil-Knopp-Kirchwald and Kadi, 2017). In this respect, the situation in Vienna differs substantially from many other urban centres, including European cities with a formerly strong social housing sector, where council housing is associated with income polarisation (Musterd, 2014; Skifter Andersen et al., 2016).

Social mix in neighbourhoods

Social mix often vaguely describes the diversity of a neighbourhood's residents in terms of ethnicity, income, education, or housing tenure. In this paper, we focus on the income component of the social mix and analyse the income variation in neighbourhoods, where high inequality indicates that higher-income and lower-income individuals live next door to each other (Glaeser et al., 2009; Walks and Maaranen, 2008). This approach has the advantage over conventional measures of segregation in that we do not limit the analysis to specific subgroups in society (Massey and Denton, 1988), but examine diversity in income as such.

The neighbourhood context may exert a considerable impact on individual opportunities, as a low social mix might impede interaction between members of different income groups and exacerbate social mobility. For instance, there is evidence that unemployed people living in neighbourhoods with high unemployment rates and hardly any social contact to economically better-situated neighbourhoods have the lowest chances of finding employment (Galster et al., 2008; Vandecasteele and Fasang, 2021). A low social mix within the neighbourhood also shapes political preferences and may decrease the support for redistribution policies (Bailey et al., 2013; Chen et al., 2012; Nieuwenhuis et al., 2019; Reardon and Bischoff, 2011). However, neighbourhood effects are not always clear-cut and some research points toward a selection effect rather than a causal effect on socio-economic outcomes (Hedman and Van Ham, 2012; Manley et al., 2012). Spatial disparities in urban areas, which predominantly run along the lines of social classes in Europe (see e.g. Arbaci, 2007; Bischoff and Reardon, 2014; Scarpa, 2015), have nonetheless gained the attention of city administrations. Redistributive measures, investments in public services and the provision of public goods are considered suitable policy instruments to enhance the social mix (Michelangeli and Peluso, 2016).

Among public goods, well-designed social housing ranks as a key tool to revitalise low-income communities and increase the social mix of neighbourhoods (Diamond and McQuade, 2019; Musterd et al., 2016). There is evidence that cities with an integrated rental system are less divided than cities with a dualist rental system, where social housing is exclusively reserved for the poor and largely different from private dwellings (Hatz et al., 2016; Kemeny, 1995). Social housing should thus be spatially distributed and accessible to a broad fraction of the population (Machline et al., 2018). However, recent trends of liberalisation and privatisation in many countries have partly reversed the positive effects of social housing by restricting its scope and limiting access to low-income households only. For instance, this has been observed in post-socialist countries (Lux and Sunega, 2014) as well as other European countries with a formerly large social housing sector (Musterd, 2014).

Policymakers have repeatedly used the framing of social mix as a pretext for gentrification, the dismantling of social housing and the displacement of low-income earners from city centres. As a result, policies under the heading of social mix have even contributed to polarisation and ghettoisation in some cases (Blanc, 2010; Bricocoli and Cucca, 2016; Capp et al., 2022; Lees, 2008; Shaw and Hagemans, 2015).

A brief history of council housing in Vienna

Vienna comprises about a fifth of the Austrian population and ranks among the fastest growing cities in the European Union. The city of roughly 1.9 million inhabitants has been ranked the most livable city in the world from 2009 to 2019 by the Mercer Quality of Living Survey. Vienna is among the European capitals with the lowest levels of inequality and it is characterised by a strong corporatist welfare regime with a high degree of income redistribution and a widely decommodified housing market (Hatz et al., 2016; Musterd et al., 2016). The capital is a city of renters with a homeownership rate as low as 20%. Today, roughly 220,000 dwellings or 25% of all residential dwellings in Vienna are owned by the municipality ('Gemeindebau'), making the city one of the largest real estate owners in Europe (Hatz, 2008). Taking another 15% or almost 150,000 dwellings owned by non-profit housing associations ('Gemeinnützige Bauvereinigungen') into account, the share of social housing rises to 40%.

The rapid expansion of social housing in Vienna began after World War I with the electoral victory of the Social Democratic Workers' Party in 1919. As the city became an autonomous province in 1922, it obtained the privilege to introduce local taxes that helped finance the political agenda later known as 'Red Vienna' (Kadi and Suitner, 2019; Novy, 2011). At the core was a progressive tax on private housing construction ('Wohnbausteuer') which financed the extensive public housing programme. During the period of Red Vienna, more than 60,000 municipal flats were built together with additional 10,000 flats constructed by non-profit housing associations. Social housing popped up across the city and was not limited to specific low-income neighbourhoods. The era of Red Vienna ended with the political rise of fascism in 1934, but the construction of social housing accelerated after World War II and its provision remained a key element of Viennese welfare policies (Friesenecker and Kazepov, 2021; Kadi, 2015).

In the 1980s and 1990s, the housing market was characterised by the liberalisation and deregulation of housing policies such as more flexible rent-setting rules, right-to-buy options and the introduction of temporary rental contracts (Kadi et al., 2021). However, in contrast to other cities, like Berlin, Vienna has not pursued a comprehensive privatisation of its municipal housing stock. Between 1980 and 2001 non-profit associations re-entered the arena of social housing and built 69% of all units while the city only contributed 31% (Kadi, 2015; Matznetter, 2002). The decision of city authorities to abstain from further construction of council housing in 2004 left the provision of new social housing in Vienna to non-profit associations for more than a decade up to the opening of a new municipal housing complex in 2019. During this period, property prices have surged enormously, inhibiting the construction of new social housing (Musil et al., 2022). Despite the city's temporary withdrawal as a housing developer, rent subsidies were retained and the construction of apartments remained subsidised by the city for instance with so-called 'Housing Initiatives' (Hatz et al., 2016). The shift from constructing municipal housing to subsidising social housing affected the inclusionary mechanisms as tenants in the non-profit housing sector typically have to pay down-payments while tenants in council housing do not (Friesenecker and Kazepov, 2021). The city currently plans to build roughly 4300 new municipal flats by 2025 which is probably too little to keep up the share of council housing in the housing stock (Kadi et al., 2021).

The access to council housing is regulated by a number of eligibility criteria. Applicants for a municipal flat must have registered their main residence in the city for at least two years and fulfil one of seven needs-based eligibility criteria. These include the overcrowding of the current habitation, single parenthood, the need for moving due to old age, illness or disability and moving out from parents for young adults under 30 years of age. Finally, there are income thresholds related to household size; however, these are very generous as the current income threshold for a single person is more than twice the average net income in Vienna. Two major modifications of the access restrictions were made in the 2000s with a substantial increase in income thresholds in 2010 and an extension of accredited citizenship among applicants to EU and EEA member states, Switzerland, and to recognised refugees in 2006.

Figure 1 shows the dispersion of council housing by construction period across Vienna's 23 districts. There are rather small units in the more central neighbourhoods, while larger complexes are found in the outer districts, mostly built in the post-war era. Roughly 55% of council housing blocks (representing 61% of flats) have been built in the period between 1945 and 1980, 28% (32%) before 1945 and 17% (7%) after 1980. The density of council housing is lower in the city centre as well as in the eastern outskirts of Vienna. However, in contrast to other European cities, public housing in Vienna has not been limited to working-class districts but is also present in better-off areas like the western outskirts (Hatz et al., 2016). The map also depicts some geographical reference points that are of interest for our analysis. There are two circular roads which mark the former location of the city walls and the outer line of fortifications. The former is called the *ring road* ('Ring'), a grand boulevard with prestigious buildings encircling the historical city centre, while the *beltway* ('Gürtel') is an important arterial road through the city dividing the bourgeois inner districts from the predominantly working-class outer residential areas.

Data

Our analysis is based on the Austrian wage tax statistics for 2017. We use a novel and unique data set providing average annual gross earnings and inequality measures on a 500 $\times$ 500 m raster grid for Vienna. It includes all employees and pensioners living in Vienna, except for apprentices and individuals earning less than 70% of the minimum earnings threshold for social security. The sample comprises 716,638 individuals living in 1221 raster cells. For reasons of data protection, raster cells with fewer than five taxpayers were masked, leaving 1122 cases to be analysed. An important feature of such small-scale raster data is that the cells are equally sized and objectively delineated, meaning that borders did not evolve historically or politically. Our data set contains average annual gross earnings, the Gini coefficient measuring inequality in gross earnings between 0 (perfect equality) and 1 (maximum inequality), and a set of labour market indicators for each raster cell.

Table 1 provides summary statistics for the variables in our analysis. The annual mean gross income ranges between € 13,200 in the poorest and € 323,500 in the richest raster cell. This spread is enormous; however, the maximum value is an outlier with the second highest value being less than half of that figure. It is the same raster cell where

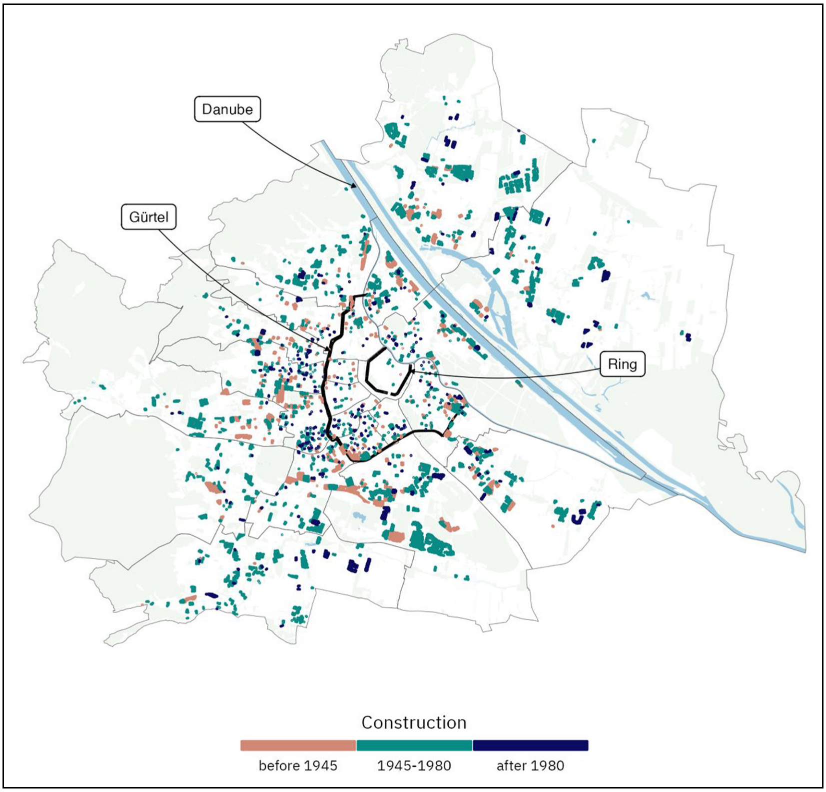

Figure 1. Location of council housing in Vienna.
Note: This figure shows the spread of council housing across Vienna. Two circular roads mark the boundaries of the first district (Ring) and the demarcation between the bourgeois inner and the predominantly working-class outer districts (Gürtel).

Table 1. Summary statistics for raster cells.

Variables	Mean	SD	Min	P25	Median	P75	Max
Mean income	44,127	15,890	13,211	34,511	42,004	49,571	323,477
Gini coefficient	0.39	0.07	0.2	0.34	0.38	0.43	0.84
Share part-time empl. persons	0.29	0.07	0	0.26	0.28	0.32	0.79
Share less than full-year empl. persons	0.16	0.07	0	0.11	0.16	0.2	0.53
Number of individuals	639	756	5	90	335	887	3373
Share migration background	0.31	0.11	0.05	0.24	0.29	0.37	0.7

the Gini coefficient (0.84) is also highest. The wage tax data include the shares of part-time employees and not full-year employed persons which may have a strong effect on income and inequality in a raster cell. The part-time share ranges from 0% to

79%, while the share of not full-year employed persons varies between 0% and 53%. The number of taxpayers in a raster is used as a proxy for population density, which is found to be positively associated with inequality in cities (Glaeser et al., 2009). Finally, the share of migrants is added to the analysis as ethnic segregation still plays an important role in some European cities (Panori et al., 2019) and to a lesser extent also in Vienna (Hatz et al., 2016). In this paper, migrants are defined as people born abroad or holding foreign citizenship. Unfortunately, information on migration status is only available on the sub-district level, where we obtain 2017 census data from the open-source data portal of the city of Vienna. Vienna consists of 250 sub-districts that represent the smallest administrative units of the city. We allocate each raster cell to one exclusive sub-district according to the central coordinate of the quadratic cell. On average, a sub-district comprises seven raster cells with a minimum of one and a maximum of 27 cells. Thereafter, we assign the value from the sub-district data to the associated raster cells.

Finally, the council housing variable is based on a map of all municipal residential blocks and their number of flats provided by the city of Vienna. We allocate each building to a raster cell and obtain an indicator variable for the presence of council housing which is true for roughly 44% of all raster cells in Vienna. For robustness analysis (see Robustness checks and limitations section), we construct two alternative measures for council housing density at the raster and at the sub-district level ('Zählbezirk').

Methodology

We assess the relationship of income and inequality to council housing and a set of other socio-economic variables in multivariate regression models on the raster level. The underlying data, however, gives some indication for spatial autocorrelation that might render ordinary least squares (OLS) estimates inefficient or biased. Figure 2 shows the distinct spatial patterns of income and inequality in Vienna. With respect to income (upper left panel), the city centre as well as the western outskirts belong to the more affluent parts of the city while the beltway area shows low average incomes. This social and cultural divide between the centre and the rest of the city has historical origins in Vienna (Musterd et al., 2016). The spatial patterns of the Gini coefficient (upper right panel) are similar to income; however, we do not find a distinct cluster of low values in the beltway area. High levels of inequality are clustered in the city centre and the western outskirts, while low levels of inequality are mainly found in the eastern part of Vienna.

We ran several tests for spatial dependence to detect autocorrelation in income and the inequality measure. In our case, these are based on a spatial weight matrix that is a row-standardised queen contiguity matrix, such that raster cells are defined as neighbours when they share a common border or vertex. An informative indicator for spatial autocorrelation is the local G-statistics (Ord and Getis, 1995) that does not only detect the presence of clusters but also the distance of those clusters from the average. The G-statistics reports a z-score and denotes

$$G_i = \frac{\sum_j w_{ij} y_j - W_i \bar{y}}{s\{[(n-1)S_{1i} - W_i^2]/(n-2)\}^{1/2}}$$

with W_i being the sum of spatial weights w_{ij} between neighbours i and j; S_{1i} is the sum of the squared weights; $\bar{y}$, s^2 and n are the sample mean, variance and number of observations for the variable of interest y. High positive values indicate clusters of high income or inequality and negative values similar clusters of low income or inequality.

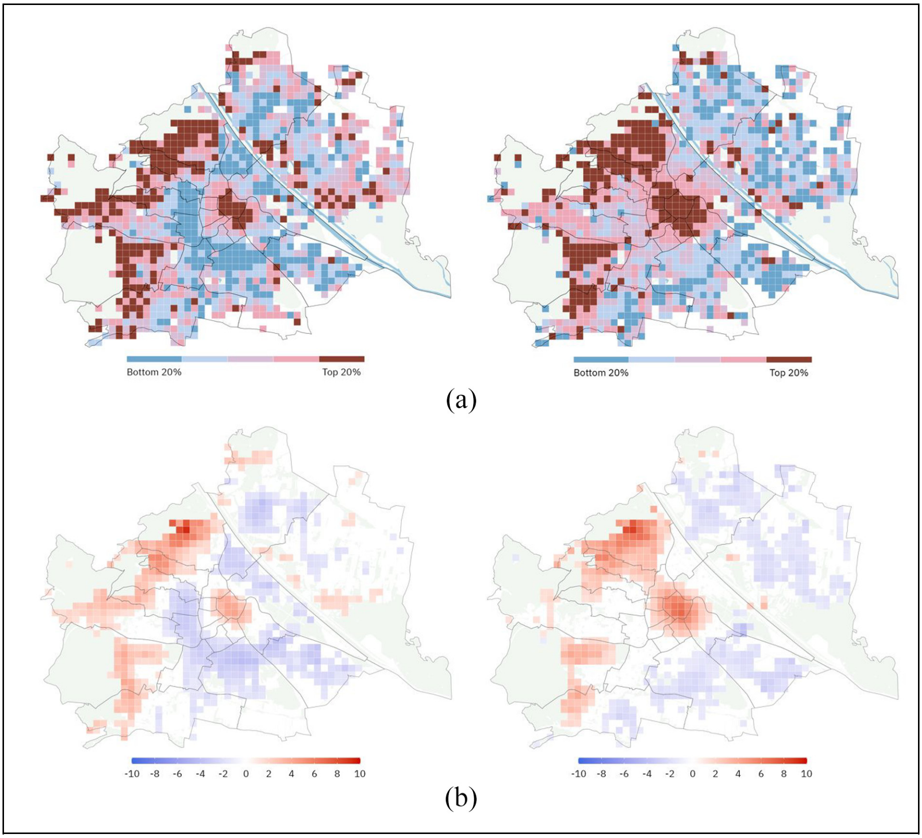

Figure 2. Mapping of income and the Gini coefficient.
(a) Quintiles
(b) G-statistics.
Note: The upper panels of this figure depict quintiles of mean income (left) and the Gini coefficient (right) for 500×500 m raster cells in Vienna. The lower panels show the local G-statistics (significant at the 5% level) where high positive values indicate clusters of high values and negative values similar clusters of low values. There are distinct clusters of high income and inequality in the city centre and in the western outskirts. For income, there is a striking cluster of low values in the outer districts along the Gürtel road.

As shown in the bottom panels of Figure 2, the local G-statistics finds clusters of high values of income and inequality in the city centre as well as in the south-western and north-western outskirts. In contrast, clusters of low levels of income and inequality are much weaker. Notably, we do not find distinct spatial patterns of inequality in the beltway area. Alternative tests for spatial dependence, like local Moran's I and Geary's C, mirror the results from the local G-statistics and are available upon request.

To assess whether there is spatial dependence in an OLS specification with income and inequality as dependent variables, we employ robust Lagrange multiplier (LM) tests (Anselin et al., 1996). These diagnostic tests are based on the OLS residuals and indicate whether there is spatial error autocorrelation in the presence of a spatially lagged dependent variable (LM lag test), or spatial lag dependence in the presence of spatial error autocorrelation (LM error test). If the test signals missing spatially lagged dependent variables, we estimate spatial autoregressive models (SAR) that include the spatial lag of the dependent variable in the set of explanatory variables. The spatial lag is obtained by weighting the values of neighbouring raster cells with respect to the spatial weight matrix. If the autocorrelated spatial lag of a dependent variable is excluded from the model, omitted variable bias might impair the results (LeSage and Pace, 2010). If there is spatial dependence in the residuals, the estimation of a spatial error model (SEM) increases the efficiency of estimators. Neglecting this dependence results in biased standard errors and hence decreases the efficiency of an OLS estimator. However, the costs of ignoring a spatial error structure, especially with a large sample size, are lower than the costs of ignoring a spatial lag structure (LeSage and Pace, 2010).

The spatial regression model nesting both a spatial autoregressive model (SAR) and a spatial error model (SEM) can be written as:

$$y_i = \rho W_{ij} y_j + X_{ij}\beta + u_i$$

$$u_i = \lambda W_{ij} u_i + \epsilon_i$$

where y_i is the dependent variable, X_{ij} the matrix of explanatory variables, ρ the spatial lag parameter, W_{ij} the $n \times n$ spatial weight matrix, u_i the spatially correlated error term and λ the spatial error parameter with $\epsilon \sim N(0, \sigma^2)$. Both ρ and λ indicate the extent of spatial dependence. When evaluating a SAR model, λ is set to 0 and in the case of an SEM model, ρ is set to 0. The (robust) Lagrange multiplier tests suggest a SAR specification for the Gini coefficient and a SEM specification for income.

Results

As first descriptive evidence, Figure 3 illustrates the dispersion of mean income and the Gini coefficient for raster cells with and without council housing. There are 488 raster cells with and 634 cells without council housing. The spreading of both income and inequality is larger across neighbourhoods without council housing. While the figure shows that the mean income in neighbourhoods with council housing is considerably lower, the Gini coefficient is similar between rasters with and without council housing.

Next, we study the relationship between income, inequality and council housing in a multivariate analysis on the raster level. Since six raster cells are islands without any adjacent cells, we have to exclude them from our analysis. On average, these cells only comprise 10 individuals with a mean gross income slightly higher than the total sample mean (€ 49,700 vs € 44,100). Table 2 shows the results of the OLS and spatial regression models.

The Lagrange multiplier test favours a spatial error specification for income. The parameter capturing spatial error dependence λ indicates positive spatial dependence in the residuals, which likely originates from the omission of non-observed variables. Optimally, we would have spatial data on educational attainment, occupation and industrial sectors to explain the spatial clusters of income, but these variables are not available to us on the raster level. As expected, a higher share of part-time workers, not full year employed persons and residents with a migration background are negatively related to income. When controlling for these factors, the presence of council housing in a raster cell shows a negative correlation with average income. The negative association might indicate that decision makers accurately targeted low-income areas

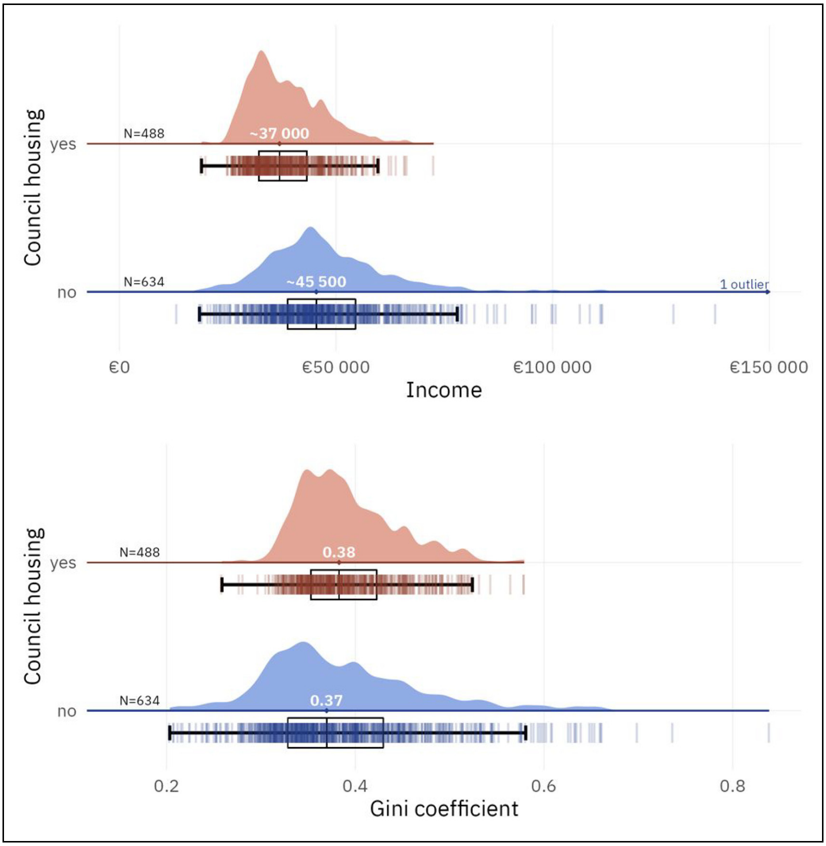

Figure 3. Dispersion of income and the Gini coefficient by council housing.
Note: This figure shows the dispersion of mean income and the Gini coefficient across raster cells with and without the presence of council housing. The box plots depict the 25th, 50th and 75th percentile of distribution.

for the construction of council housing in the past, or that individuals with lower incomes have moved to areas where council housing is provided. The latter could also be the result of gentrification dynamics where tenants are forced to move into these neighbourhoods as other housing market segments have experienced enormous price increases and tenement conversions (Molina et al., 2020; Musil et al., 2022). However, the negative coefficient is rather small, which can be explained by the dispersion of council housing throughout the city and even in better-off neighbourhoods. Council housing is present in almost half of all raster cells and tests for spatial autocorrelation show only small and weak clusters that are spread across the city. Additionally, the principle of council housing not being reserved for the poorest but accessible to broad parts of the population might explain the weak relationship.

Turning to the Gini coefficient, the favoured model is the SAR specification. The spatial autocorrelation parameter ρ shows statistically significant spatial dependence which might indicate that higher (lower) income inequality reaches beyond

Table 2. Regression outputs.

	Income		Gini coefficient	
	OLS	SEM	OLS	SAR
Income			0.25*** (0.01)	0.21*** (0.01)
Direct effect				*0.21**** *(0.000)*
Indirect effect				*0.05**** *(0.000)*
Council housing	−0.04* (0.02)	−0.08*** (0.01)	0.02*** (0.00)	0.01*** (0.00)
Direct effect				*0.01**** *(0.00)*
Indirect effect				*0.00**** *(0.000)*
Population density	−0.00* (0.00)	−0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)
Part-time employed	0.05 (0.11)	−0.53*** (0.08)	0.39*** (0.02)	0.34*** (0.02)
Less than full-year employed	−1.90*** (0.12)	−1.57*** (0.08)	0.50*** (0.02)	0.45*** (0.02)
Migration background	−0.32*** (0.09)	−0.32*** (0.08)	0.05** (0.01)	0.04* (0.01)
Intercept	11.07*** (0.04)	11.19*** (0.04)	−2.46*** (0.06)	−2.15*** (0.07)
λ		0.76*** (0.02)		
ρ				0.21*** (0.03)
Adj. R^2	0.37		0.72	
Num. obs.	1116	1116	1116	1116
Log Likelihood	69.59	396.42	2053.94	2082.92
AIC	−125.17	−776.84	−4091.89	−4147.85
LR test: statistic		653.67		57.96
LR test: *p*-value		0.00		0.00

***$p < 0.001$. **$p < 0.01$. *$p < 0.05$.
AIC, Akaike information criterion; LR, likelihood-ratio; Num. obs., number of observations; OLS, ordinary least squares; SAR, spatial autoregressive model; SEM, spatial error model.

raster cells to a larger neighbourhood area. As the coefficients of the SAR model cannot be interpreted straightforwardly due to feedback effects, we show direct and indirect effects for our main variables of interest, income and council housing. The decomposition of direct and indirect effects for the remaining control variables are available upon request.

Looking at the relationship between income and inequality, we find a positive nexus that is particularly driven by the direct effects. The higher the average income in a neighbourhood, the higher the inequality. These results for Vienna conform to the general pattern that is found for Austria as a whole (Moser and Schnetzer, 2017). Higher shares of part-time employed persons, less than full-year employed individuals and persons with migration background are associated with more diverse neighbourhoods in terms of income.

We find a weak but positive relationship between the Gini coefficient and the presence of council housing. These results cautiously suggest that neighbourhoods with the provision of council housing are less homogeneous in terms of income than other areas in the city and feature a stronger social mix. There is thus evidence that council housing is not associated with polarisation or ghettoisation in Vienna but, if anything, correlates with a higher social mix in the neighbourhood.

Several factors might help to interpret the positive relationship between council housing and the social mix in Vienna. First, there is weak residential mobility due to specific legal arrangements such as the right to pass on municipal flats to near relatives under certain conditions. While an income threshold limits access to council housing, residents may keep their flats even if their income later rises beyond that limit. Second, the city abstains from typical surcharges (e.g. location premium), down-payments and fixed-term rental contracts for council housing and thus rents are less dynamic than in the private market. This means that rent is still affordable even in areas that gentrify. Third, the provision of housing benefits to income-poor households has slowed down processes of replacement and gentrification in more attractive areas. Fourth, unlike in many other European cities, it has been a political strategy to provide council housing in better-off areas also, not only in working-class districts. Fifth, despite tendencies of recommodification of the housing market since the 1980s, the city's housing policy has remained fairly resilient toward these developments. All these factors might have contributed to the social mix in neighbourhoods with council housing (Hatz et al., 2016; Kadi, 2015).

Robustness checks and limitations

We conduct a series of sensitivity analyses to check the robustness of our results for income in Appendix Table A1 and inequality in Appendix Table A2. First, we re-estimate the models using a different neighbourhood definition, that is, spatial weight matrix. The second order queen contiguity matrix includes all neighbours of neighbouring raster cells and shows only marginal quantitative and no qualitative differences compared to the main specification (column 1). We find similar results for alternative neighbourhood definitions like a rook contiguity matrix, where neighbours are adjacent rasters with a common border only (results are available upon request). Thus, our findings are robust regarding the choice of spatial weight matrix.

We assess whether the results change with alternative measures of council housing in a next step and replace the dummy variable with two measures for council housing density on the raster and the sub-district level. First, we calculate the ratio of flats to the number of taxpayers observed in a raster cell (column 2). Second, we make use of the share of municipal flats in total flats from the 2011 census which is only available on the sub-district ('Zählbezirk') level (column 3). The negative association between council housing and average income remains stable in both robustness checks. However, the relationship with income inequality becomes statistically insignificant for the sub-district variable. We detect neither an increase nor a decrease in the social mix with these alternative housing variables. These findings do not change qualitatively when using social housing density (including non-profit housing associations) rather than council housing density; however, the negative association with income is even larger (column 4).

As described above, the private housing market experienced recommodification and deregulation in the 1980s and the city's housing policy changed from the provision of council housing to the reliance on non-profit housing associations (Kadi, 2015). We thus distinguish between building periods of council housing before and after 1980 and check for differences in the neighbourhood context (columns 5 and 6). Roughly 83% of municipal buildings in our data set were built before 1980. In contrast to council housing built after 1980, these older buildings are associated with lower average income and a slightly higher social mix according to the Gini coefficient. Finally, we exclude outliers in the dependent variables, that is, values that are 1.5 times the interquartile range beyond the third quartile, from our analysis (column 7). Again, this robustness check does not alter the results significantly.

Finally, we reran all regressions with two alternative measures for neighbourhood inequality, that is, the mean/median ratio and the P80/P20 ratio, as dependent variables. The results largely mirror the findings for the Gini coefficient and are available upon request. Based on the various sensitivity analyses, we conclude that our findings on the relationship between council housing and income inequality are robust and largely unaffected by the definition of neighbourhood, the choice of social housing and inequality variables and the exclusion of outliers.

Nevertheless, we face some limitations in our analysis. As the spatial scale might play an important role, it would be beneficial to test different sizes of raster cells. We only have data on a 500×500 m raster as smaller raster sizes would reduce the sample substantially due to the obligation of data confidentiality. However, an even more fine-grained analysis of single neighbourhoods could provide additional insights that are masked by the global approach used here. For instance, a recent study by Molina et al. (2020) examines social status in Vienna on a very small scale with reference to specific raster cells and finds islands of low social status and poverty in some neighbourhoods. Another caveat of our study is that we cannot assess whether inequality at the raster level is driven by inter- or intra-household inequality. High income inequality could either arise from high- and low-income families living next door to each other or high- and low-income individuals living in the same household. Finally, our data do not offer any information on vertical segregation, that is, social stratification by floor of residence in apartment buildings. We thus measure social mix by income only in horizontal but not in vertical dimensions of urban space.

Discussion and conclusion

This paper explores small-scale spatial patterns of social mix in terms of income and its relation to the availability of council housing in Viennese neighbourhoods. Vienna serves as an interesting example with its long welfare state tradition and its extensive provision of council housing that makes the city one of the largest real estate owners in Europe.

A multivariate spatial regression approach suggests that council housing is linked to lower average incomes and slightly higher within-neighbourhood inequality. We interpret these results cautiously as a positive association between council housing and the social mix. While council housing is more present in low-income raster cells, these neighbourhoods are on average somewhat more diverse than other areas. This finding differs from the pattern of many other cities, where social housing is associated with stronger polarisation (Skifter Andersen et al., 2016). The difference might be explained by the high number and dispersion of council houses throughout Vienna, even in more affluent areas.

Another important aspect is that traditionally, council housing has not been restricted to low-income applicants but has been accessible to broad parts of the population. Marginalisation and residualisation trends do exist but are much weaker than in other cities, including those with a historically similar social housing tradition like Stockholm and Amsterdam (Andersson and Turner, 2014; Musterd, 2014). In addition, Vienna has refrained from anchoring purchase options and similar mechanisms of privatisation in council housing, which has further reduced the social mix in other cities (e.g. Bricocoli and Cucca, 2016; Shaw and Hagemans, 2015). This leads to the conclusion that with the large spreading of council housing, Vienna has provided affordable dwellings for low- and medium-income households without causing ghettoisation in the past. Our results show that social housing policies can be designed in such a way that they are associated with a high social mix in the neighbourhood rather than residualisation.

Yet, the Vienna housing model is not unchallenged. Despite its resilient tradition dating back a hundred years, the regulatory framework of the housing market has changed in recent decades (Kadi, 2015). The weakening of corporatism led to the deregulation of the private rental market at the federal level and subsequently to tendencies of recommodification. Several measures introduced since the 1980s, like limited-term rental contracts and the deregulation of private rental housing built before 1945, have affected the housing market substantially and rent levels have been rising rapidly.

Given these recent developments in the housing market, we draw some policy conclusions that are in line with the recommendations by the OECD (2018). Well-developed public infrastructure, like schools, parks and public transport, might improve the social mix as individuals with different socio-economic backgrounds living next door are enabled to interact. Many council housing complexes in Vienna come with social, cultural and recreational infrastructure, like kindergarten, schools, theatres, shops, parks, etc, which are important spaces for encounters and interaction in the neighbourhood. Such everyday encounters in public spaces may enhance social cohesion (Peters, 2010; Piekut and Valentine, 2017) and shape preferences for social policy (Bailey et al., 2013).

In light of rapid population growth and the steep rise in private rents, the city has decided to put the construction of council housing back on the agenda; however, the plan to build 4300 new municipal flats by 2025 is hardly enough to keep the council housing share stable (Kadi et al., 2021). In addition, Vienna introduced a new land use category for social housing in 2019. Whether these measures will contribute to a higher social mix in the city is an interesting research question for future research.

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Appendix

Table A1. SEM robustness checks for income.

	Queen^2 matrix	Housing density	Housing sub-dist.	Social housing	Old building	New building	W/O outliers
Council housing	−0.08 ***						−0.07 ***
	(0.01)						(0.01)
Population density	−0.00 **	−0.00 ***	−0.00 ***	−0.00 ***	−0.00 *	−0.00 ***	−0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Part-time employed	−0.48 ***	−0.50 ***	−0.54 ***	−0.54 ***	−0.53 ***	−0.53 ***	−0.54 ***
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.07)
Less than full-year employed	−1.82 ***	−1.57 ***	−1.67 ***	−1.68 ***	−1.57 ***	−1.67 ***	−1.47 ***
	(0.09)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.07)
Migration background	−0.40 ***	−0.37 ***	−0.30 ***	−0.31 ***	−0.33 ***	−0.34 ***	−0.32 ***
	(0.08)	(0.08)	(0.09)	(0.08)	(0.08)	(0.09)	(0.07)
Housing density		−0.07 ***					
		(0.01)					
Housing sub-district			−0.12 ***				
			(0.03)				
Social housing				−0.19 ***			
				(0.03)			
Dwelling pre-1980					−0.08 ***		
					(0.01)		
Dwelling post-1980						−0.01	
						(0.01)	
Intercept	11.26 ***	11.19 ***	11.22 ***	11.27 ***	11.19 ***	11.20 ***	11.15 ***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)
λ	0.80 ***	0.74 ***	0.73 ***	0.71 ***	0.76 ***	0.75 ***	0.76 ***
	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)
Num. obs.	1111	1116	1116	1116	1116	1116	1076
Log Likelihood	324.97	399.58	384.83	395.73	395.17	377.26	541.69
AIC	−633.94	−783.16	−753.66	−775.46	−774.34	−738.53	−1067.39

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.
AIC, Akaike information criterion; Num. obs., number of observations.

Table A2. SAR robustness checks for the Gini coefficient.

	$Queen^2$ matrix	Housing density	Housing sub-dist.	Social housing	Old building	New building	W/O outliers
Income	0.22 ***	0.21 ***	0.21 ***	0.21 ***	0.21 ***	0.21 ***	0.20 ***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Council housing	0.02 ***						0.02 ***
	(0.00)						(0.00)
Population density	−0.00	0.00	0.00	0.00	−0.00	0.00	−0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Part-time employed	0.35 ***	0.34 ***	0.34 ***	0.34 ***	0.34 ***	0.34 ***	0.28 ***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Less than full-year employed	0.46 ***	0.45 ***	0.46 ***	0.45 ***	0.45 ***	0.46 ***	0.44 ***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Migration background	0.03 *	0.04 *	0.03 *	0.03 *	0.03 *	0.03 *	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Housing density		0.00					
		(0.00)					
Housing sub-district			0.00				
			(0.01)				
Social housing				−0.01			
				(0.01)			
Dwelling pre-1980					0.01 ***		
					(0.00)		
Dwelling post-1980						0.00	
						(0.00)	
Intercept	−2.24 ***	−2.12 ***	−2.10 ***	−2.07 ***	−2.14 ***	−2.09 ***	−1.97 ***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
ρ	0.19 ***	0.23 ***	0.23 ***	0.23 ***	0.21 ***	0.23 ***	0.23 ***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Num. obs.	1111	1116	1116	1116	1116	1116	1083
Log Likelihood	2067.00	2071.91	2070.62	2071.05	2082.90	2070.79	2123.92
AIC	−4116.01	−4125.83	−4123.25	−4124.10	−4147.79	−4123.59	−4229.85

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.

AIC, Akaike information criterion; Num. obs., number of observations.