

Spatial Dynamics of Cultural Diversity in The Netherlands

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In this paper we analyse the spatial dimension of changing ethnic diversity at the neighbourhood level. Drawing from recent work on income convergence, we characterise the evolution of population diversity in the Netherlands over space. Our analysis is structured over three dimensions, which allow us to find clear spatial pattern in how cultural diversity changes at the neighbourhood level. Globally, we use directional statistics to visualise techniques of exploratory data analysis, finding a clear trend towards “spatially integrated change”: a situation where the trajectory of ethnic change in a neighbourhood is closely related to that in adjacent neighbourhoods. When we zoom into the local level, a visualisation of recent measures of local concordance allow us to document a high degree of spatial heterogeneity in how the overall change is distributed over space. Finally, to further explore the nature and characteristics of neighbourhoods that experience the largest amount of change, we develop a spatial, multilevel model. Our results show that the largest cities, as well as those at the boundaries with Belgium and Germany, with the most diverse neighbourhoods, have large clusters of stable neighbourhood diversity over time, while concentrations of high dynamic areas are nearby these largest cities. The analysis shows that neighbourhood diversity spatially “spills over”, gradually expanding outside traditionally diverse areas.

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Introduction

Many Western countries have witnessed an increase in the ethnic diversity of their populations. However, this increase has been especially apparent in big cities. Density of economic activities offers opportunities for workers, and cities therefore attract immigrant workers. Once groups of immigrants are present in certain areas, this tends to attract more immigrants from the same background (Card 2001). Although many big cities have a diverse population, it is often that ethnic groups tend to sort themselves across different neighbourhoods resulting in clustering of people from the same ethnic group (Krysan and Farley 2002; Saiz and Wachter 2011; Bayer, Fang, and McMillan 2014; Bakens, Florax, and

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Mulder 2018). The cultural diversity of cities on the aggregate level is thus not always reflected at the neighbourhood level.

However, with an increasingly more diverse population, it is not a priori clear how population diversity will develop spatially. In the Netherlands, the average neighbourhood diversity increased 12% between 2004 and 2011, from 0.18 to 0.20.¹ The increase in the most diverse city, Amsterdam, was about 7% between 2004 and 2011, while the average increase in neighbourhood diversity per municipality ranged between -22% and 80% between 2004 and 2011. Figure 1 shows that those municipalities with the highest neighbourhood diversity in 2004 witnessed a lower growth in diversity than less diverse municipalities. So even if the biggest population diversity in 2011 is still observed in neighbourhoods of municipalities that were already very diverse in 2004, which are the largest cities in the country, it is not the large cities that have experienced the largest changes in diversity between 2004 and 2011.

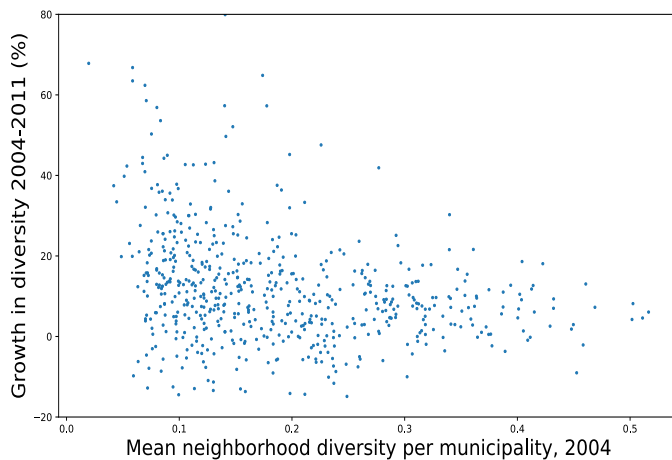


Figure 1: Growth in population diversity over Dutch municipalities

Given increasing shares of minority groups in Western populations, this paper is concerned with the question of whether there is a spatial pattern of increasing ethnic diversity, or a pattern of increasing segregation at the neighbourhood level. It may be that already diverse areas become even more diverse, or that less diverse places become more diverse. In addition, this paper focuses on whether space mediates the process of expansion of cultural diversity, thus leading into a situation where places close to diverse areas become more diverse sooner than places further away. Figure 1 signals that changes (defined as the growth) in diversity are not necessarily only visible in large cities, and diversity may slowly become a phenomenon also observed outside of large cities. This may be one of the reasons

¹ All the numbers in this paragraph are own calculations based on Statistics Netherlands, <http://statline.cbs.nl/Statweb/publication/?VW=T&DM=SLNL&PA=70751NED&D1=0&D2=1-4&D3=a&D4=8,15&HD=170607-1153&HDR=G2,G3&STB=G1,T>

why immigration and population diversity has become such an important topic in national policy debates throughout Western countries as not only urban societies are exposed to changes in the ethnic population composition. However, to study these changes in a more structural way and describe possible spatial patterns, this paper uses some of the most recent developments in spatial dynamics and proposes new visualization approaches to study the change in ethnic neighbourhood composition in the Netherlands in a period where the population is becoming more and more ethnically diverse.

From an urban planning and policy perspective, it is interesting to analyse the spatial dependence between neighbourhoods in terms of their change in ethnic diversity. Understanding the spatial patterns underlying ethnic neighbourhood dynamics, segregation, and diversity sheds light on the possibilities for people- and place-based policies to counteract the negative effects of, for example, the clustering of poverty, or discrimination. Neighbourhoods that are geographically close may be more prone to increase their levels of diversity than neighbourhoods further away. This research provides evidence on the spatial dimension of the distribution of population diversity, in addition to other neighbourhood characteristics that are shown to play a role.

From the literature on neighbourhood formation and ethnic clustering, one of the most important explanations of the clustering of ethnic (minority) groups and immigrants is their socio-economic background (see, for example, Hårsman and Quigley 1995; Bayer, McMillan, and Rueben 2004; Glaeser, Kahn, and Rappaport 2008). Generally, ethnic minority groups have a lower socio-economic position than the native population, resulting in them being clustered in the neighbourhoods with the least expensive (social) houses that they can afford with a low income (Bayer, Fang, and McMillan 2014; Bakens, Florax, and Mulder 2018). Research also shows that these socio-economic characteristics cannot fully explain the patterns of ethnic clustering in cities and countries (Ioannides and Zabel 2008; Bayer, McMillan, and Rueben 2004; Hårsman and Quigley 1995), and that preferences for the own ethnic group play a role (Krysan and Farley 2002; Saiz and Wachter 2011; Bayer, Fang, and McMillan 2014).

Bakens, Florax, and Mulder (2018) show that neighbourhood relocations of ethnic groups in the cities of Amsterdam and the Hague in the Netherlands is as much positively impacted by the presence of the own ethnic group, as by socio-economic characteristics of neighbourhoods. Most people move over short distances however, which may signal the importance of social network ties (Bakens, Florax, and Mulder 2018). Given the spatial patterns of the change in ethnic diversity in neighbourhoods, from these observations it can be expected that there will be spill-over effects of ethnic diversity between adjoining neighbourhoods. Bakens, Florax, and Mulder (2018) also show that if ethnic homophily - "birds of a feather flock together" - exists at the neighbourhood level, it is not necessarily clear whether neighbourhoods become more or less diverse if there is one dominant ethnic group and many small ethnic minority group. If most people of a minority group cluster in a couple of neighbourhoods in a city but the group as a whole is relatively small, this clustering will not show at the aggregate neighbourhood level. Zwiers, Van Ham, and Manley (2017) find that the ethnic neighbourhood composition in the largest cities of the Netherlands tends to be rather stable over time, but that many neighbourhoods become more diverse, except for the high income neighbourhoods with predominantly natives.

Johnston, Poulsen, and Forrest (2015) seem to find broadly comparable results for ethnic neighbourhood change in London. They find that neighbourhoods become more diverse in general, especially the neighbourhoods that have very few Whites to start with. In many countries, there is also a suburbanisation trend for ethnic minority groups. This process can lead to more diverse suburban neighbourhoods, but also to segregated ones (Farrell 2016; Massey and Tannen 2016). Ultimately, it is a matter of “tolerance” (Card, Mas, and Rothstein 2008) and an empirical question whether there is more or less diversity at the neighbourhood level with an increasingly more diverse population and how the spatial patterns of diversity develop.

Our results show a clear spatial dimension to changes in neighbourhood diversity in the Netherlands between 2004 and 2011. The general pattern in the analysis shows how adjacent neighbourhoods tend to show very similar trajectories of ethnic population change. When we focus on specific clusters of neighbourhoods, we find that clusters of already very diverse neighbourhoods, especially in the largest cities and at the border in the South, have been statistically significantly more stable than expected based on a random distribution of neighbourhood diversity. The clusters that, statistically speaking, are significantly more dynamic than expected are predominantly outside of the largest cities, but in areas that already had some degree of population diversity. Only for some areas does our analysis point towards suburbanisation of diversity. Finally, we distinguish clusters of neighbourhoods that have been stable but are surrounded by highly dynamic ones and vice versa. The spatial patterns for these clusters have a very local dimension, but are generally close to areas that have been either significantly stable or dynamic over time.

The remainder of this paper is structured as follows. In the next section we discuss how spatial dynamics of neighbourhoods can be measured. Section 3 presents the data used for the analysis. Section 4 provides a detailed overview of the different spatial processes at the neighbourhood level between 2004 and 2011. Finally, section 5 concludes.

Measuring spatial dynamics

Our strategy to characterise the spatial dynamics of cultural diversity in the Netherlands is structured along three main dimensions. In the first one, we consider global trends and overall patterns; in the second one, we zoom in to further characterise these developments at a local level, exploring the heterogeneity in the dynamics of neighbourhoods, and connecting them to the overall patterns found; finally, we propose an explanatory model that allows us to further characterise local dynamics, extracting general trends. Given some of the methods are novel in their application to the study of cultural diversity, this section provides an introduction to their intuition and interpretation.

Global spatial dynamics are considered through LISA rose diagrams, an approach that combines the intuition and accessibility of visualisation with the power of formal inference provided by statistics. Rooted in the economic convergence literature, Rey, Murray, and Anselin (2011) extend the exploratory space-time toolbox by proposing a new approach based on circular data (Brunsdon 2017) and directional statistics (Rohde and Corcoran 2015). Their suggestion includes a spatially explicit way to visualize dynamics and to detect

spatially integrated change, or change that occurs in a spatially correlated fashion (i.e. similar location, similar evolution). At the core of this method is a comparison of subsequent Moran Scatter Plots (Anselin, Syabri, and Kho 2006), a particular case of a scatter plot that displays a given variable (e.g. cultural diversity) against its spatial lag (i.e. the average value of that variable in the surrounding locations). A Moran plot is created for each point in time, and the dots representing the same observation are connected, building true space-time trajectories. These trajectories are standardised to have the same origin, and they are summarised visually in a circular histogram. Because moves in this context can be interpreted in terms of the spatial dynamics of an observation and its neighbourhood, the plot of all the directional vectors is a spatial summary of the global distributional dynamics in the system. In that regard, all the vectors in the upper right (lower left) quadrant imply movements in which both the observation itself and its neighbours are growing (shrinking) in relative terms to the overall distribution; alternatively, vectors in the upper left (lower right) quadrant represent changes in which the observation shrinks (grows) but the surrounding ones tend to grow (shrink). It is important to note that the focus here is on the directionality of the moves, not on their magnitude; circular histograms take account of *how many* moves are in each quadrant, but not on *how long* they are. Once the diagram is built, (S. Rey, Murray, and Anselin 2011) also provide a mechanism to compute empirical inference. This is implemented through simulation of distributions of spatially random moves, and then comparison with the observed ones. This approach allows to determine how likely it is the pattern we see in the data could have come from a purely random process.

To complement the global analysis discussed above, we disaggregate indices by small area. Thus, we complement the assessment of overall summaries with insight into the degree of heterogeneity in contributing to the general pattern. The starting point is Kendall's τ , a global indicator of rank concordance by (Kendall 1948). In the context of spatial dynamics, τ can be expressed as:

$$\tau(y_t, y_{t+1}) = \frac{c - d}{n(n - 1)/2} \quad (1)$$

where y_t and y_{t+1} represent a given variable at periods t and $t + 1$, c is the total number of concordant pairs of observations (i.e. those which have not swapped positions in the ranking) and d captures discordant (i.e. those which have swapped). The statistic is bounded $-1 \leq \tau(y_t, y_{t+1}) \leq 1$. A value of $\tau = 1$ represents perfect concordance between both periods, implying the ranking has remained untouched, while $\tau = -1$ implies every observation has changed ranks. Recently, (S. J. Rey 2016) proposed a local version of τ :

$$\tau_i = \frac{c_r - d_r}{(n - 1)} \quad (2)$$

where c_r corresponds with the number of concordances in the transition between the two periods considered, concerning i and the rest of the sample. Similarly to its global

counterpart, τ_i considers the rank correlation between the relative position of i in t and that in $t + 1$. If i has not moved its relative position, $\tau_i = 1$; conversely, if i has changed its rank relative to every single other observation in the sample, then $\tau_i = -1$. Additionally, the connection between τ_i and τ is direct, as (S. J. Rey 2016) shows the latter can be expressed as the average of the former ($\tau = \frac{1}{n} \sum_i^N \tau_i$). In this sense, τ_i can be understood as i 's contribution to the overall measure of concordance.

Once the global and local nature of spatial dynamics have been characterised, we conclude by providing an explanation of the latter that relies on insights from the former. In particular, we propose a linear, spatial, multilevel model to explore the main factors behind areas that exhibit large degree of dynamism:

$$\tau_{i[m]} = \alpha + \alpha_m + \beta_1 X_i + \beta_2 W X_i + \beta_3 X_m + \epsilon_i \quad (3)$$

where τ_{im} corresponds to the local τ measure from Eq. (2) for neighbourhood i in municipality m ; α (α_m) is a global (municipality specific random) intercept; X_i is a set of explanatory variables at the neighbourhood level; W is a spatial weights matrix defining geographic neighbours for every observation, making $W X_i$ effectively the spatial lag of the neighbourhood variables; X_m is a set of covariates at the municipality level; and ϵ is an individual, well-behaved error term. In this analysis, we consistently use a row-standardised W in which the five nearest observations are selected as neighbours. This is commonly known in the literature as k -nearest neighbours with $k = 5$ and it is widely used in spatial analysis. In this context, two main reasons make it an especially appropriate choice: on the one hand, this rule eliminates the differences in the number of neighbours that might appear due to polygons of very diverse sizes (e.g. urban neighbourhood versus areas in the countryside); on the other, it alleviates the problem of missing values introduced by the interpolation performed over time to unify different boundaries. We fit the model using restricted maximum likelihood (REML), as implemented in `lme4` (Bates et al. 2014) and `statsmodels` (Seabold and Perktold 2010).

There are several variables that could be behind the dynamism of a neighbourhood. We consider the area and initial population of a given neighbourhood, effectively measuring density and whether initial levels are associated with more change in diversity. The rationale is to test whether areas beginning the period with higher density of population tend to see more change. Density is a proxy for several elements of the built-environment, as well as for the type of neighbourhood within a given city or town (e.g. central, peripheral, suburban) so the association of these variables will give us an idea of the intra-city distribution of diversity dynamics. Given the focus on diversity, we also include initial presence of immigrant population in the neighbourhood. This is implemented through the percentage of the population considered as Western and non-Western immigrants, which are also the components used in the calculation of the diversity index described below. Whether previous immigrant presence has any effect on the subsequent amount of change in an area is very relevant to understand the process and channels through which cultural diversity evolves. Finally, we include the average house price in the neighbourhood as a proxy for income and socio-economic status of the residence population. Capturing the

income level of the area will further characterise the types of neighbourhoods where most of change has taken place. In addition to each neighbourhood's characteristics, we include information about their surroundings. This idea is captured by the average neighbouring values for the same variables. Including an explicit measure for geographic context is particularly relevant as it will help us understand to what extent space place a role as mediator for change in diversity. Finally, we are also interested to find out to what extent the nature and characteristics of the environment operate at coarser scales than the neighbourhood. Specifically, we consider whether the overall level at the municipality is relevant. One could think that whether a neighbourhood experiences changes in diversity over a period of time depends not only of its own characteristics or of those in the surrounding area, but also of the overall levels in the municipality where it is located. To further explore this concept, we include municipality percentage of Western and non-Western immigrants, the average house value, and an ordinal value provided by CBS that expresses the degree of "urbanity", where 1 is very strong urban, and 5 is non-urban.

Data

All the data employed in this study is obtained from Statistics Netherlands (CBS Netherlands). The original dataset contains total population as well as the proportions of Western and non-Western immigrants. In this context, a person is considered an immigrant if at least one of his/her parents was born outside the Netherlands. "Western" immigrants include those from Europe, North America, Japan, Indonesia² and Oceania. "Non-Western" refers to other places of origin. Additional socio-demographic variables used also come from CBS. Our unit of analysis is the neighbourhood (*buurt*). "Neighbourhoods" are the smallest unit at which immigrant population are available to the public and estimates exist for several continuous years, making them very attractive for the purposes of this study. We use a panel that includes the Dutch neighbourhoods over the years from 2004 to 2011, both included. Although neighbourhoods are very stable over time, they are not immutable, resulting in inconsistencies over time. To overcome this problem, we use areal interpolation. This technique consists in selecting the geography associated with one year and adjusting the data of the rest of the sample in a way that they conform to it. Our procedure reassigns the data to the geography of reference (target) based on the amount of area shared by the polygons in the original geography (source) and the target.

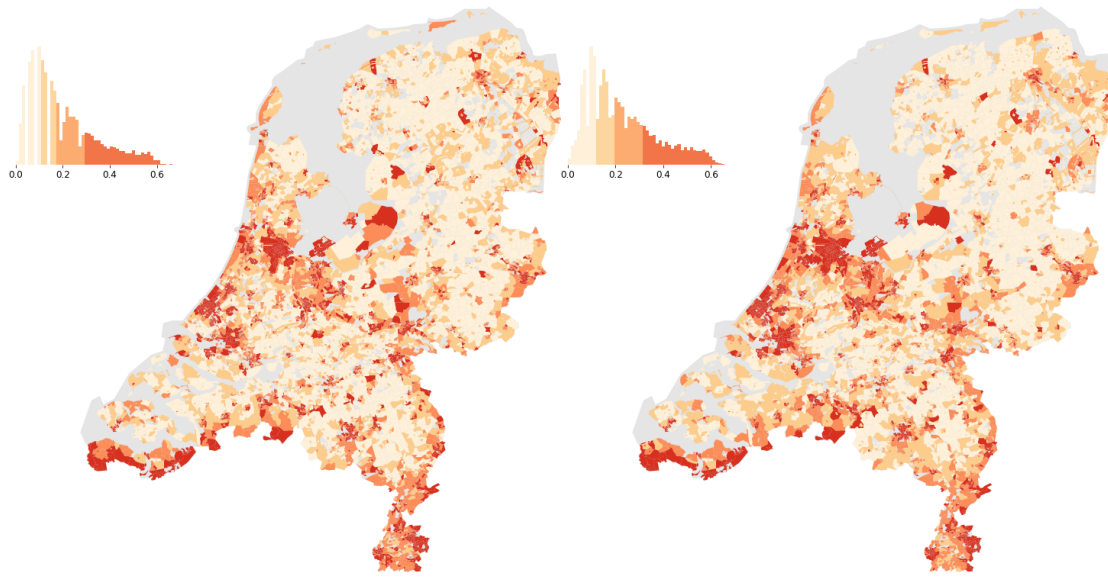
With data on immigrants in hand, we next need to adopt a definition of cultural diversity that allows us to measure it properly and study its spatial dynamics. We consider a similar framework as in (Ottaviano and Peri 2006) and use the so called *index of fractionalization*, popularized by (Mauro 1995) and widely used in the political economics literature. The intuition behind this measure is to estimate the probability that two individuals living in

² This is according to the Statistics Netherlands official definition. As Indonesia is a former colony of the Netherlands, the cultural distance between Indonesia and the Netherlands is considered to be much smaller than other, comparable, countries and immigrants from Indonesia are therefore considered Western.

the same neighbourhood belong to different cultural groups, when selected at random. The basic equation describing it is as follows:

$$div_r = 1 - \sum_{i=1}^M (CoB_i^r)^2 \quad (4)$$

where div_r is the diversity index in area r , M is the total number of different cultural origins and CoB_i^r is the share of the population with cultural origin i in area r . The index is bounded between 0 and $(1 - 1/M)$ and accounts for two aspects of cultural diversity: the *richness*, or how many different groups there are; and the *evenness*, or how the population is distributed across those groups. In an extreme case where everyone in a neighbourhood belonged to the same group, the probability of picking up two different groups at random is non-existent and, accordingly, $div = 0$. As a neighbourhood includes more variety (M increases) and the distribution across them stays even or proportionate, the probability of randomly selecting two different persons increases and so does the index.



(a) Year 2004

(b) Year 2011

Figure 2: τ_i

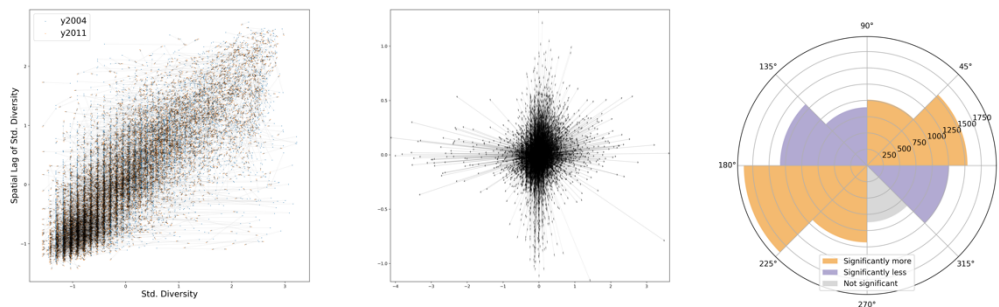
We implement this measure using the three different cultural groups described above: natives, Western immigrants and non-Western immigrants. It is possible to obtain a more detailed racial breakdown but this would have severe consequences in terms of missing observations since, for confidentiality reasons, CBS only reports data above a certain threshold of population. This situation reflects a more general trade-off between racial and spatial resolution. Because we are particularly interested in processes that operate at a small scale, we decide to put more weight on the spatial than the racial aspect of the data and decide for this strategy.

The geography of the final dataset can be seen in Figure 2, where choropleths based on 12 quantiles are displayed for the values of the diversity index in 2004 (a) and 2011 (b). The maximum diversity (0.667 and 0.656, respectively) is close to the theoretical *ceiling* of 0.667 (calculated as $1 - 1/M$), but it is interesting to note it decreases over time. The mean is larger than the median, implying over concentration of observations with lower values, a feature that can also be seen in the histograms of Figure 2. In both cases, the values increase over time, suggesting an overall trend by which cultural diversity has grown from 2004 to 2011.

The spatial dynamics of Dutch neighbourhoods

Global dynamics

In this section we explore whether, over the period considered in this study, the overall increase in cultural diversity of Dutch neighbourhoods displays spatial structure. In particular, we are interested in whether it responds to a marked spatially integrated process by which the evolution in one area is closely tied to that of its neighbours. To accomplish this task, we base our argument on a visual device with inferential support: the LISA rose diagrams (S. Rey, Murray, and Anselin 2011). Throughout the analysis, diversity indices are standardized (z-values) by year. As we have seen, the overall distribution shifted rightwards from 2004 to 2011; standardizing on a yearly basis subtracts this trend from the data and maintains only variation within each year's distribution. Using this way, for example, it is possible to account for *lagging* observations that, even if in absolute terms increase from one year to the next, loose diversity relatively speaking.



(a) Moves 2004-2011 (b) Standardised Moves (c) Rose Diagram

Figure 3: LISA Rose Diagrams, 2004-11

Figure 3 displays a visual summary of the dynamics of cultural diversity. It is composed of three panels relating to the changes occurred in the distribution of cultural diversity in Dutch neighbourhoods. Panel (a) comprises two overlaid Moran Scatter Plots, charts relating the value of the diversity index in a given location with that in its surroundings: one for 2004 (blue) and one for 2011 (orange). Furthermore, dots relating to the same neighbourhood have been connected through an arrow that expresses in a visual way the nature of the dynamics in that particular area. These arrows can be seen as vectors whose

directionality has clear implications for the kind of dynamics they represent, and thus warrant study. However, since there are almost 10,000 dots per year, and thus almost 10,000 arrows, it is hard to distinguish any overall pattern by considering this plot. Panel (b) takes the first step into abstracting the previous one to make it more comprehensible. It only contains the directional vectors, which have now been standardised to begin at the same origin. This plot thus simplifies the previous one and allows the reader to focus on the directionality of the moves, regardless of their actual values or position in the overall distribution. However, the graph suffers from a similar overload problem: because there are too many arrows, it is hard to tell any overall pattern on the direction of the vectors beyond the few outliers that manage to stand out from the core group of moves. A potential solution to this problem is that proposed in (S. Rey, Murray, and Anselin 2011): a rose diagram. This graphical device, presented in panel (c), is essentially a traditional histogram in which the horizontal axis has been “bent” over a circle, turning the usual bars into triangles (or “pie slices”) that represent the number of vectors in each angle spectrum. This approach simplifies visual load, and provides an intuitive summary of a large number of vectors into a small number of pie slices. We consider eight, with each of them representing a different class of dynamics. Those in the upper right and lower left quadrants contain spatially integrated moves: cases where the direction of change for an area is similar to that in its surroundings. Conversely, the upper left and lower right parts of the diagram contain spatially dissonant moves: instances where an area is changing in the opposite direction of that of its geographical neighbours. Furthermore, each quadrant is disaggregated into two sub-triangles which capture the extent to which the move is larger in an area itself or in its surroundings. It is possible to see that most of the moves in the diversity dataset presented in the figure fall within the first category of spatially integrated dynamics. In more detail, the largest categories include those where the change of a given area is larger than that of its neighbours.

Panel (c) contains a second layer of information encoded in the color assigned to each of the pie slices. These relate to the empirical significance of the size of the triangle (ie. the number of moves in that angle range). This measure is obtained by comparing the observed distribution of moves in panels (a) and (b) with those of 999 simulated sets of vectors constructed by randomly reassigning the neighbours to each observation and then obtaining the directional vector. There are three potential situations when considering inference on a rose diagram: a pie slice can contain significantly more vectors than expected from a spatially random distribution; it can contain significantly less; or an amount that is safely compatible with what would be expected under a spatially random process. Figure 3 (c) contains these three cases, structured in a way that gives rise to a clear overall pattern. Quadrants representing spatially integrated dynamics contain significantly more than expected; while (most of) those behind dissonant dynamics contain significantly less cases; only one triangle contains what would be expected under a random spatial distribution. This result is an outcome compatible with a case of outward diffusion: change seems to spread from foci into their surrounding areas, but with a lesser intensity. In other words, this is suggestive that neighbourhoods that increase or decrease their level of diversity have an effect on their surrounding areas by which they also change (either in the same direction, as for moves in the upper-right/lower-left quadrants; or in the opposite one, as in the upper-left/lower-right ones), but with a smoothed amplitude.

Local dynamics

So far, we have considered spatial dynamics at a global level, documenting the presence of strong spatial effects that imply that, *overall*, increases in ethnic diversity in a location tend to go hand-in-hand with similar trajectories in neighbouring locations. We now turn to local measures that disaggregate the global trend and identify specific areas of the Netherlands where such dynamic processes have taken place more intensely. The analysis relies on new techniques proposed by (S. J. Rey 2016), which decompose some of traditional global indices of mobility.

Given that τ_i is a local measure, a value is produced for every single area in the dataset. An efficient way to display the statistic is thus through a choropleth. Panel (a) in Figure 4 shows the spatial distribution of τ_i calculated using the 2004 for the entire period of analysis using an equal interval classification; the map is complemented by a histogram and the value of the global measure of concordance (τ). Values for τ are close to one, pointing towards an overall pattern of stability – correlation between ranks across periods is generally high. The use of equal intervals is motivated by the fact the large majority of areas display high levels of concordance, as shown in the histograms. In this context, equal spacing helps highlight outliers with extraordinary rank mobility. It is apparent most areas do not move ranks much across periods, as shown by their high values (dark purple), but clear hotspots of high mobility (green and yellow) exist.

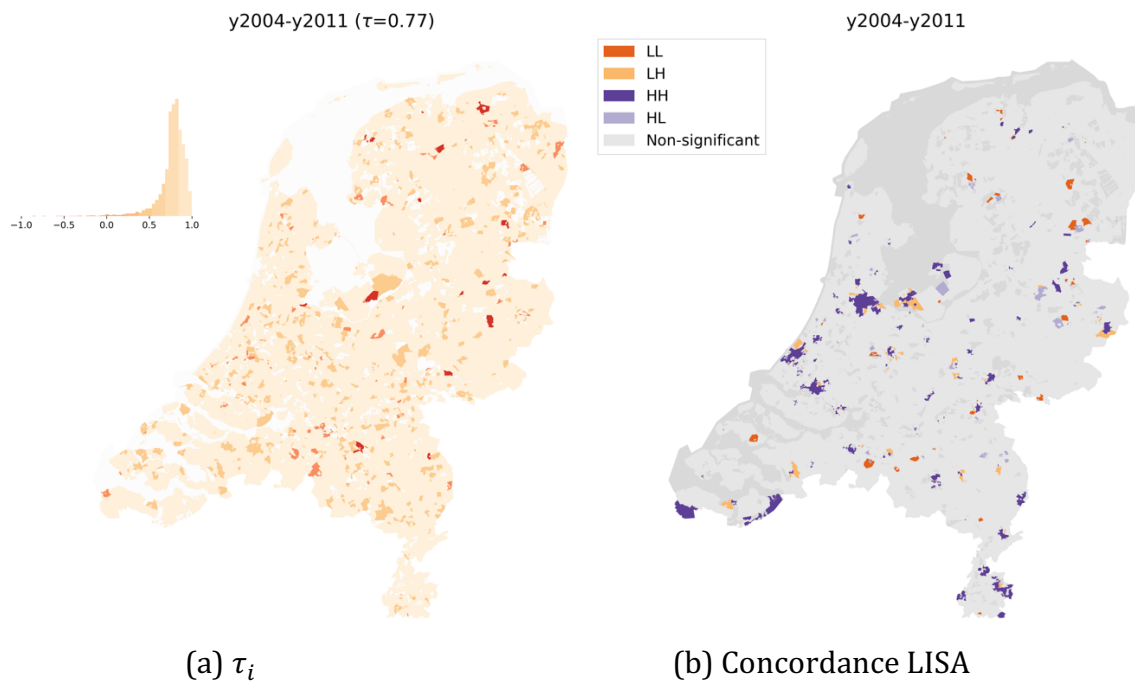


Figure 4: Local Diversity Index

Although τ_i provides a solution to spatially disaggregate inter-period mobility, it is not an explicitly spatial indicator as it does not account for the dynamics of neighbouring areas. An extension proposed by (S. J. Rey 2016) consists on applying local indicators of spatial association (LISA, L. Anselin 1995) to the raw τ_i measures to identify regions with unusual

concentration of (dis/)similar values, giving rise to the “concordance LISA”. This step brings geographical context into the otherwise purely temporal analysis. The result can be found in panel (b) of Figure 4. Similar to the previous panel, this map displays the geography of change in ethnic diversity; unlike that map however, the concordance LISA summarizes the color gradient into spatial clusters of varying degree of dynamism. Dark blue (HH) represents clusters with unusually high stability across periods, while dark red (LL) encodes regions associated with a concentration of very dynamic areas. At the same time, light colors capture cases of spatial outliers: either stable areas neighbouring highly dynamic ones (HL, light blue), or vice versa (LH, light red). The map shows that significantly stable clusters of neighbourhood diversity are predominantly found within the largest cities and at the Southern borders where neighbourhoods were already rather diverse in 2004. Clusters with unusually high dynamics are outside large cities, but in areas where there already was some level of diversity at the beginning of the period.

The maps in Figure 4 uncover substantial spatial heterogeneity in the degree of dynamism across the sample. Both the local measures τ_i as well as the LISA extension allow us to obtain a better understanding of the geography of changes in ethnic diversity. This section further advances insights obtained through the use of directional plots and spatially conditioned Markov matrices, and makes explicit the fact that, far from homogeneous across space, these overall dynamics are unequally spread across space.

Factors behind dynamics

So far, this paper has provided convincing evidence of the existence of an overall spatial pattern in the dynamics of diversity, as well as of its spatial character and imbalances. However, it sheds little light as to what are the characteristics behind the most dynamic areas or at what geographical scale they operate. This final part attempts to fill such gap.

		Coef.	S.E.
	Intercept	0.796	0.011
Buurt	Population	0.021	0.004
	Area (ha.)	-0.008	0.002
	% Non-Western	0.001	0.003
	% Western	0.017	0.004
	Mean House Value ($\times\text{€}1,000$)	-0.038	0.002
Neighboring Buurten	Population	-0.030	0.005
	Area (ha.)	-0.000	0.002
	% Non-Western	0.004	0.003
	% Western	0.020	0.005
	Mean House Value ($\times\text{€}1,000$)	0.003	0.003
Municipality	% Non-Western	0.013	0.005
	% Western	0.013	0.003
	Degree of Urbanity	-0.009	0.003
	Mean House Value ($\times\text{€}1,000$)	0.020	0.003



NOTE: Estimates larger in size than twice the standard error in bold. Municipalities with a random effect significantly at the 95% level above (below) the national average in red (blue).

Table 1: Explanatory Model

Table 1 presents the results from the regression specified in Eq. (3). Both population and area are significant at the buurt level and at the immediate neighbourhood. In the former case, the effect is consistent with a clear positive relationship between population density (i.e. more population in a smaller area) and dynamism, as expressed by the dependent variable τ_i . In the case of immediate neighbours, this effect is less clear as both variables present a negative association with τ_i (albeit only that of population density is significant). We interpret this as a case of spatial competition: areas with a higher population density induce more change, but if the neighbouring areas are also densely populated, this tempers the change. We find a link between the average housing value in the initial period and the subsequent amount of dynamism both at the neighbourhood level and at the municipality level, but not in the surrounding areas. More interestingly, the signs at these two scales are opposite: while areas with lower housing costs seem to preclude higher levels of change, it is cities with overall higher housing values that have more dynamic areas. These contradicting results point towards two different effects that are often observed in growing cities: while at the local level, the more affordable areas (those with relatively cheap housing) tend to grow more in diversity; at the city level it are the more economically successful, hence more expensive, cities that contribute most to the overall change in diversity. So it are the least expensive neighbourhoods in large expensive cities that change most. The municipality's degree of urbanity is also relevant, displaying a negative association. Given the coding in the variable we use (1 strongly urban; 5 non-urban), we interpret this as an urban bias in the distribution of diversity dynamics: it is in more urban areas that diversity has changed most during the period of analysis. It may be that the "second- or third-tier" cities in the country are getting more diverse, following the path of the first-tier, largest, and already very diverse cities in the country.

The index of diversity we use is partly influenced by the proportion and type of the immigrant population. Hence, it is sensible to expect that the shares of different ethnic groups will also have an effect on the subsequent amount of change in the level of diversity. We find interesting results in this respect along the three dimensions considered. Both at the neighbourhood level and in its immediate surroundings, we only find a significant association for the proportion of Western immigrants already present in the area, but not for that of non-Western immigrants. Perhaps more interestingly, the coefficient is larger for the effect of surrounding areas than for the percentage of immigrants in a given neighbourhood. We interpret this as additional evidence for the presence of a clear spatial pattern in the dynamics of diversity: the initial pre-conditions of a given neighbourhood are important for change, but those of its neighbours are more important to explain how much the neighbourhood will change over the subsequent period. Our hypothesis in this context is that spill-over processes, such as those characterised at the global level, are at work and translate into areas neighbouring others with a high presence of immigrants will face more change.

Zooming out, we find the initial proportions of both Western and non-Western immigrants have a positive significant effect on τ_i . In this case, the point effect of the non-Western population is slightly higher than that of Western population. This result can be interpreted as the friendliness of a city to welcome immigrants (which can be related to the

mechanisms of spatial clustering of immigrants, such as economic opportunities and the presence of earlier cohorts of immigrants, described in the introduction), which influences positively the amount of change in all of its neighbourhoods.

Finally, the multilevel nature of our model allows to explore variation in the degree of dynamism across municipalities, once we have controlled for the effect of all the covariates included. This is possible thanks to the random effects, α_j , estimated around the overall intercept, α , which are also provided with a measure of uncertainty.³ The map displayed on the right panel of Table 1 presents in red (blue) the municipalities whose effect is statistically significant at the 5% level, being above (below) the global intercept. The first feature to point out is that there is only a handful of municipalities for which there is enough information in the data to extract significant differences. Furthermore, and although it is not entirely clear-cut, there is an emerging pattern in the location of both those above and below average: areas with low dynamism tend to be in the upper part of the urban hierarchy (e.g. Amsterdam, The Hague), while those with higher amount of change in diversity tend to be “second cities” either close to larger ones (e.g. Amersfoort close to the Randstad) or in the North. We interpret these results as evidence that with a growing diversity of the population, population diversity is not only a phenomenon observed in the largest cities in a country, but is a phenomenon that is gradually spreading throughout the country. The change is not big enough in our observed period to conclude that other parts of the country will start to look a lot like cities like Amsterdam, Rotterdam, or the Hague, as these cities are still by far the most diverse cities in the country. But other, smaller cities, have witnessed much more significant changes during the past years.

Conclusion

In this paper, we repurpose recent tools to study the spatial dynamics of economic growth to propose their use within the ethnic diversity literature. Using both visual and numeric, as well as global and local novel approaches, we show there is a clear spatial pattern in the evolution of ethnic diversity across Dutch neighbourhoods. In that sense, adjacent neighbourhoods tend to display similar patterns of change. Our analysis suggests that population composition in neighbourhoods tends to be rather stable over time, especially neighbourhoods that are at the right tail end of the population diversity distribution, i.e., the most diverse. This phenomenon clusters in the largest cities, which are found to be, statistically speaking, significantly more stable than what would be expected from pure chance. Most dynamic clusters are outside these largest cities in what we call “second- or third-tier” cities. We also look into areas that deviate from the overall pattern, and display stable patterns while adjacent neighbourhoods change significantly, and vice versa. We find these types of areas close to others with dynamic and stable neighbourhood clusters, both in the largest cities and close to these cities. In that sense, there are locations where we find suburbanisation of diversity. However, generally these patterns are very local and need

³ A more detailed explanation of random effects in the context of multilevel models is beyond the scope of this paper. The interested reader is referred to (Gelman and Hill 2006).

more specific, in depth, local analysis to describe in detail. For that reason, we develop a spatial, multilevel, regression model to characterise areas experiencing most change. We find these dynamics are related to the initial density, house price and migrant composition of the neighborhood, as well as to the initial levels of population and western migrants in the surroundings. Overall proportions of migrant population, as well as housing price and degree of urbanity of the municipality where a neighborhood is located are also found to be associated with higher dynamism.

We have shown that this type of explicitly space-time analysis can be used to describe ethnic neighbourhood change. Future research could extend our initial analysis on why certain areas are more dynamic than others. As neighbourhood change is generally a slow progress, future research should also look into neighbourhood dynamics over multiple decades to describe neighbourhood change over a longer time span. A final avenue for research is to expand the analysis beyond the Netherlands, considering different countries, for example, where spatial planning is less pronounced. In addition, using different spatial scales of analysis, i.e., street blocks, neighbourhoods, or high aggregated spatial units, may give more insights into the spatial patterns of demographic change.

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