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Assessing daily urban systems : a heterogeneous commuting network approach

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Daily Urban Systems (DUSs) are not only an attractive concept for planning locations for jobs, housing, schools and retail, but also for managing services such as public transportation and health care. If we can match geographically demand and supply of goods and services, higher levels of spatial efficiency can be reached. Since 50 years most of the research delineating DUSs uses thresholds of commuting levels, thus identifying labor markets polarized towards central cities. Few research grasps the more recent complex interactions within metropolitan areas due to growth and decentralization of activities. In this paper, we use techniques of complex network theory, namely community detection, on nearly 4,500,000 Belgian commuting links to define DUSs. Secondly, we explore differences for DUSs by gender and by income group. The results confirm the usefulness of community detection techniques for delineating Daily Urban Systems. Commuting patterns of females and low and very low income commuters are geographically more restricted than those of male and high and very high income commuters.

Keywords

Daily urban system
DUS
Labor markets
Commuting
Gender
Income group
Community detection
Louvain method
Belgium

1. Introduction

The United Nations booklet on World's Cities in 2016 (United Nations 2016) starts with a discussion on how to best define the geographical limits of a city. Even though there is a lack of an effective and standard definition of the concept of a city, multiple boundary definitions are available. The 'city proper' definition includes the area within the administrative boundary and the 'urban agglomeration' concept refers to the built-up area (Patacchini et al. 2009; United Nations 2016). Both definitions are commonly used, especially with respect to international comparative studies, due to the availability of data worldwide. The administrative criterion is easy to use, however because of the rapid growth of urban areas it appears not to be suitable anymore (van der Laan and Schalke 2001; Vliegen 2005; Williams et al. 2010). A lot of work has been done during the last years on defining the urban agglomeration using earth observation techniques and comparable results on delineating the built-up area are now at use (European Commission 2016). A third concept of the city, the 'metropolitan area' includes the nearby areas according to their economic and social interconnectedness (Berry et al. 1969; United Nations 2016; Williams et al. 2010). The social and economic interactions can be calculated for example by commerce or commuting relations, but as no standardized data or methodology are available, it is worth to explore further this question of delineating 'metropolitan areas' (Guérois et al. 2016).

From the 1960s on, a growing body of research has been trying to delineate these Functional Urban Regions (FURs), called, 'City Regions', 'Stadtregionen', 'Stadsgewesten', 'Aires Urbaines Fonctionnelles' (Guérois et al. 2016; Van Der Haegen and Pattyn 1979; Vliegen 2005). Until recently, mostly commuting data towards central cities has been used to delineate labor markets by including municipalities trespassing a threshold. Also the definition of 'Standard Metropolitan Areas' in the US, already from the fifties on, uses commuting

thresholds to reflect frequent social and economic interactions which take place on a daily basis to delineate the ‘Daily Urban System’ (Bretagnolle et al. 2009).

This approach of Daily Urban Systems (DUSs) results in the delineation of a labor market polarized towards a central city. DUSs were originally introduced to assess the increasing (auto)mobility of labor-supply that chose to live outside the city, while labor demand remained in the urban core. Because of this, the local urban labor market became a synonym for DUS, as well as ‘Functional Urban Regions’ or ‘Standard Metropolitan Statistical Areas’ according to van der Laan (1998). Nowadays the urban sprawl results in spacious urban regions exceeding the distance of frequent social interactions. As a result new centers emerge (McMillen 2001;). It seems now more appropriate to use ‘functional urban region’ or ‘metropolitan region’ for the entire territory connected socially and economically with a central city, and to use ‘daily urban system’ for the regions delineated by daily commuting flows. As the largest metropolitan regions extend far beyond the distances for daily commuting, they must consist of several DUSs and show polycentricity. So far studies on polycentricity in Belgium displayed no clear features of a functionally polycentric mega-city-region, however some indications are found (Hanssens et al. 2014; Riguelle et al. 2007).

The increase of mobility and the related growth of commuting results in far more complex interactions. The question arises if the polarization towards the central city is still dominant or if new ‘Daily Urban Systems’ arise. New methodologies from complex network theory applied on detailed (‘big’) data allow us to develop a new delineation approach. Like Burger et al. (2014), we include individual heterogeneity including extra attributes like gender and income level. This allows us to also address the question whether DUSs differ according to gender and education. Section 2 gives a literature overview of the efforts made to delineate Daily Urban Systems. We present the used data on commuting and the methodology for partitioning in Section 3. Section 4 presents the results of the complete dataset and the results for gender groups and different income classes. In Section 5 these results are discussed and conclusions are drawn.

2. Delineation of Daily Urban Systems efforts

The delineation of functional urban regions reached a level of international standardization as a result of extensive comparative research. The OECD (2013) summarizes the first step as ‘identification of core municipalities through gridded population data’. This is followed by respectively ‘connecting non-contiguous cores

belonging to the same functional urban area' and 'the identification of urban hinterlands'. Doing so, predefined thresholds of commuting flows (mostly between 15 and 20%) towards these centers were applied in order to delineate the FUR. Besides, a minimum population size is often used as criterion, which varies greatly: from around 50,000 to several hundreds of thousands (Farmer and Fotheringham 2005; Guérois et al. 2016; OECD 2013; Pumain et al. 1992; van der Laan 1998; van der Laan and Schalke 2001; Vliegen 2005; Williams et al. 2010). The growing availability of commuting data through the different national censuses provided comparative data. For a long time this approach was considered mainstream and broadly accepted. These socio-economic geographical analyses were massively incorporated in European, economic and spatial planning policies (Antikainen and Vartiainen 2005; Farmer and Fotheringham 2005; Williams et al. 2010).

Also in Belgium one finds in the last decennia a series of research applying this method of delineating labor markets that reflect the Daily Urban Systems (Fig. 1) (Lockhart and Vandermotten 2009; Van Der Haegen and Pattyn 1979; Van Hecke et al. 2007; Vandekerckhove et al. 2014; Vanderbiesen and Jacobs 2012; Wasseige et al. 2001). Local labor markets, used in Wasseige et al. (2001), Lockhart and Vandermotten (2009), Vanderbiesen and Jacobs (2012), are areas in which most inhabitants find work and employers recruit most of their employees. Wasseige et al. (2001) used a hierarchical classification method to group municipalities together using the highest flux from each municipality to another. Lockhart and Vandermotten (2009) first defined 21 'labor centers' based on the amount of employees and density of employees. Other municipalities were then assigned to one of these 'labor centers' based on the largest outgoing flux to one of these centers. Van Der Haegen and Pattyn (1979), Vanderbiesen and Jacobs (2012) and Van Hecke et al. (2007) used the largest outgoing commute flow to assign a municipality to a predefined city (using population size), a threshold of 15% of the total commute flow from a municipality was used. Vandekerckhove et al. (2014) delineated DUSs by predefining urban regions using criteria such as services and accessibility. The DUSs were further detected based on public transport links, allowing for overlapping daily urban systems. Because of the growth of metropolitan areas paired with the decentralization of activities and more complex spatial interactions, two problems arise when using this kind of methodology (Kloosterman and Musterd 2001; McMillen 2001; van der Laan and Schalke 2001). First, within and between the traditional urban areas new labor markets may emerge, which makes it difficult to predefine central places. Second, due to complex spatial interactions, it is rarely possible to identify one (or even two) major polarization(s).

Fig. 1

Functional urban regions (Van Hecke et al. 2007)

New methodologies from complex network theory can help us to overcome these problems (Ducruet and Beauguitte 2014). Patuelli et al. (2007) demonstrate how the analysis of German commuting flows benefits from advanced network theory and network analysis. We explore how partitioning or community detection algorithms can help to gain further insight in commuting patterns. The predefinition of neither central places nor thresholds is needed, the communities are rendered bottom-up from detailed network data. De Montis et al. (2009) elaborate in their chapter on ‘Complex Networks Analysis of Commuting’ on how recently urban, regional and environmental sciences gained new insights from tools provided by network science. They develop a new research agenda and conclude that community

detection on commuter networks is very promising. Nelson and Rae (2016) proved the usefulness of such an approach by identifying megaregions in the US using a computational partitioning algorithm on a data set of more than 4 million commuter flows. In Belgium, Blondel et al. (2010) delineated ‘telephone bassins’ by the ‘Louvain method’ (Fig. 2). These ‘telephone basins’ can be interpreted as a proxy for Daily Urban Systems, because the telephone data may reflect the daily interactions between home, work, school, family, friends and so on. Although the resulting communities cover the entire territory, as a drawback they can include loosely linked municipalities which do not really belong to a DUS. Until now few studies demonstrate some first interest in a network analysis of commuting flows in Belgium. Van Nuffel and Saey (2005) assess the urban system in Flanders by using analytical tools such as the degree of polarization and the degree of nodality and openness, they search for polynuclear and multi-nodal structures both between and within city regions. However, they also started from a priori identified central cities. Van Meeteren et al. (2016) built on this approach when using the connectivity field method in Belgium. However, they still apply the traditional approach with predefined central places.

Fig. 2

Phone basins based on cell phones billing addresses (Blondel et al. 2010) (1) regional city, (2) major city, (3) provincial border

Parallel with the exercise in the US by Nelson and Rae (2016), we apply a partitioning algorithm on commuting data in Belgium. We apply the method on the same social security data set used by Van Meeteren et al. (2016). Using an algorithm of partitioning opens new possibilities: As this analysis constructs communities bottom up, no job/city centers are predefined, moreover it is also possible to identify overlapping communities. In fact this methodology implies no spatial contiguity. Only after mapping the communities, one can identify the cities/job locations around which communities appear. Decomposing the commuting network into local labor markets using a network approach helps to uncover sub-units. In particular two questions arise: Are the resulting communities spatially contiguous? Can we compare them with the traditionally identified DUSs or do we discover a new spatial reality?

Despite the long lasting research on DUSs, until now little attention has been paid to differences in local labor markets for commuter characteristics like gender and income. We agree with Burger et al. (2014) who state that individual level heterogeneity needs to be taken into account, and there is a need to differentiate analyses according to subgroups, as individual level heterogeneity may also lead to very different patterns of relationships in metropolitan areas. It is widely known that commuting distances of women are shorter than men's commuting distances (Vandersmissen et al. 2011) and consequently that women spent less time commuting (Gimenez-Nadal and Molina 2016; Roberts et al. 2009). Although a slowly converging trend for men's and women's distances is noticed, the average trip of female commuters to work differs still significantly from the average male commuter (Crane 2007). Previous research on commuting behavior of low-income commuters focuses especially on the commuting burden of this group. Many researchers found that low-income commuters often face greater time costs to access their job (Helling 2002; Powell 2002; Zhao 2015), meanwhile longer distances commuting is often associated with higher incomes and career opportunities for the individual (So et al. 2001; Van Ommeren et al. 2000). However, no study was found that specifically focuses on the differences in DUS of high and low income commuters. The second objective of this paper is therefore to assess differences in local labor markets considering commuters' gender and income, and thus constructing adapted Daily Urban Systems for different gender and income groups. Can we identify smaller DUSs for female and low income groups? Do male and higher income groups have larger DUSs?

3. Data and Methodology

The study area of this paper is restricted to Belgium. For readers unfamiliar with the Belgian geography, we add in Fig. 3 a map with the language border between the Flanders Region (northern Dutch speaking area) and Walloon Region (southern French speaking area), the administrative Brussels Region (bilingual, mainly French speaking), provincial borders and the location of the general accepted 17 main cities defined by Van Hecke (2007). The Belgian characteristics for commuter traffic are the outcome of historical housing policies, land use planning and mobility policies. Due to a process of suburbanization from the end of the nineteenth century (with the introduction of cheap public transport) and an extensive sprawl after the second world war (by accommodating car use), thousands of employees moved to an expanding urbanized area while still having their job in the agglomeration (Verhetsel and Vanelander 2010). Employees increasingly choose to live outside the city, while labor demand remained in the central areas

(Riguelle et al. 2007; Van Nuffel and Saey 2005). This resulted in a problematic/severe spatial mismatch between the home location and the work location, which consequently lead to an increase in commuter traffic (Verhetsel et al. 2007).

Fig. 3

Administrative map of Belgium

AQ2

The dataset used for this study is derived from social security data (Van Meeteren et al. 2016). It contains home and work addresses of approximately 4,500,000 Belgian commuters, including commuters' gender and income (incomes are defined by quartiles, whereby the first quartile refers to very low income and the fourth represents very high incomes). Detailed information of the dataset is listed in Table

1. All analyses in this research were executed taken the entire dataset into consideration, thus also commuting flows within municipalities. However, the cross-border commuting with Luxemburg, the Netherlands and France are not taken into account, even though previous research has shown that a group of 67,700 foreigners comes to work in Belgium and 83,800 Belgians are commuting to a workplace abroad (Vanderbiesen and Jacobs 2012).

Table 1

Details of commuting dataset

	Total	4,426,474
Gender	Males	2,402,869
	Females	2,023,605
Income (quartiles)	Very low	895,158
	Low	958,749
	High	912,207
	Very high	777,892

Exploratory analyses of the dataset were conducted to search for differences in the commuting behavior along a gender dimension and income classes. Average commuting distances are a good indicator for the commuting patterns of these groups. Calculations of average commuting distances were done using the network analyst in ArcGIS 10.3®. Average commuting distances are based on a real road network and were calculated between the centroids of municipalities.

The delineation of the DUSs has been done using the Louvain method. For the delineation of the labor markets a 589×589 origin/destination matrix was constructed, representing the commuting links between the 589 Belgian municipalities, the nodes of the network. The partitioning was exerted using the Louvain method (Blondel et al. 2008). We chose the Louvain method as it has been frequently applied to Belgian data (telephone data, commuting data, migration data, logistics networks) and the methodological pitfalls are well known (Adam et al. 2017; Beckers et al. 2017; Thomas et al. 2017). This community detection algorithm evaluates the gain in modularity that would take place by including a certain node in one of the communities. Modularity is a measure which allows to check the ‘goodness’ of the partitioning process. It measures the fraction of links inside communities as compared to the expected fraction in a randomized network

with similar characteristics, i.e. with the same total number of links and nodes. Positive values indicate higher than expected fractions. The modularity typically ranges between 0.3 and 0.7 (Newman 2006; Newman and Girvan 2004). Finally, the node is placed in the community for which the gain in modularity is maximized. A first important note concerning the applied algorithm is that the resulting communities depend on the input order of the nodes. To correct for this issue, the algorithm was repeated a 1000 times with randomized ordering of the input data. Then a matrix was created where each line represented a municipality and each column the number of times it was added to a community. Finally, maps were produced representing the different communities. As we abstained from fixed boundaries where every municipality is assigned to only one community, we hatched municipalities in cases where the maximum community membership has been less than 70%. One could say that these hesitate for membership of a community. A second remark is that the choice for the standard Newman-Girvan modularity strongly biases the effect of space, facilitating the formation of spatially contiguous communities (Expert et al. 2011). Nonetheless, running the same algorithm for male and female commuters separately as well as for the highest and lowest income groups allows the identification of the influence of these non-spatial forces.

The community detection algorithm fails to provide information on the centrality of different nodes in the communities. Beckers et al. (2018) therefore propose to calculate two parameters, the within-module degree z and the participation coefficient P , to identify the role of each node in the overall network (Guimerà and Amaral 2005). The within-module degree z_i estimates the connectedness of node i with other nodes in its community s_i and is calculated by:

$$z_i = \frac{k_i - \bar{k}_{s_i}}{\sigma_{k_{s_i}}}$$

with k_i the number of links between node i and the other nodes in its community. A strong embeddedness is reflected in a high z value. The participation coefficient P_i indicates the participation of node i in the remaining network. The indicator [is defined as](#) I corrected the next formula

$$P_i = 1 - \sum_{s=1}^{N_M} \left(\frac{k_{is}}{k_i} \right)^2$$

with k_{is} representing the number of links of node i to other nodes in its community. The higher P , the more links the node has with nodes outside its own community. Guimèra and Amaral (2005) propose seven categories, defining the role of the node in the network based on the two parameters (Table 42). First, (ultra-)peripheral nodes form the network's periphery with limited links to other nodes. Non-hub connectors and kinless nodes have similar limited connectivity within the own community, but are better connected overall in comparison to the first two categories. The occurrence of these categories points to weaker community membership. Provincial hubs boast the combination of few external but many internal connections, indicating the local importance of the node. Connector hubs have a similar high internal connection, tying communities together, but have in addition a global importance. Finally, kinless hubs are almost equally connected to the whole network and thus do not enforce local communities (Table 2).

Table 2

Parameters of node connectivity in a network (Guimerà and Amaral 2005)

Node role	Within-module degree z	Participation coefficient P
Ultra-peripheral nodes	<2.5	<0.05
Peripheral nodes	<2.5	$0.05 < P < 0.62$
Non-hub connector nodes	<2.5	$0.62 < P < 0.8$
Non-hub kinless nodes	<2.5	>0.8
Provincial hubs	>2.5	<0.3
Connector hubs	>2.5	$0.3 < P < 0.75$
Kinless hubs	>2.5	>0.75

AQ3

The normalized mutual information metric (NMI) (Fred and Jain 2003) is used to quantify the similarity among the range of partitions and is calculated as:

$$NMI = \frac{-2 \sum_i \sum_j x_{ij} \log\left(\frac{Nx_{ij}}{x_i \cdot x_j}\right)}{\sum_i x_i \cdot \log\left(\frac{x_i}{N}\right) + \sum_j x_j \cdot \log\left(\frac{x_j}{N}\right)}$$

with x representing a matrix where each row represents a community in one partition and each column a community in another partition. x_{ij} is then the number of nodes classified in community i by the first partition and in community j by the second. N is the total number of nodes and $x_{i.}$ and $x_{.j}$ row and column sums respectively. A NMI of 1 indicates two identical partitions, a NMI of 0 indicates that two partitions are totally different.

The emergence of big data in geographical scholarship on transport and advances in the analysis of complex networks in other disciplines can be considered as a mixed blessing by bringing back old concerns with regard to ‘social physics’ (Schwanen 2016). ‘Social physics’ is what Miller (2017) has called the application of models and techniques developed for physical processes to social phenomena. It often denies the fundamental importance of context, situation and place (Schwanen 2016). Therefore we start every analysis with a map describing the used basic data, representing the main relations in the data through a simple GIS approach, as such making the link between traditional and network analysis.

4. Results

4.1. Average Commuting Distances

Average commuting distances are listed in Table 3. The average distance of all Belgian commuters is 20.4 km. The difference in average commuting distance between male and female commuters is 4.3 km. This means that the commuting distance of men is 20% longer than for female. The average commuting distances of the four different income groups vary widely. Very low income commuters travel on average 15.3 km from home to work, while the highest income class has an average of 23.1 km, a difference of almost 50%. These outcomes indicate different commuting patterns for different socio-economic groups.

Table 3

Average commuting distances

Dataset	Average commuting distance (km)
All commuters	20.4
Female commuters	18.1
Male commuters	22.4
Very low income quartile	15.3

Dataset	Average commuting distance (km)
Low income quartile	16.8
High income quartile	18.8
Very high income quartile	23.1

4.2. Community Detection in the Complete Commuting Dataset

Figure 4 maps the commuting links between Belgian municipalities where at least 51 commuters are present. When comparing to Fig. 1 with the FUR delineated around 17 regional and large cities, we trace these cities as nodes in the network. In addition, some new nodes appear and some of the 17 cities are highly interconnected. This suggests that new centers are emerging and that next to polarization more complex spatial interaction patterns appear. Therefore community detection can reveal more detailed insights.

Fig. 4

Commuting flows between Belgian municipalities (absolute number)

Figure 5 shows the communities emerging from the Louvain method. The map contains 13 communities and has a modularity of 0.68, thus a higher than expected density of commuting flows. The amount of municipalities in a community ranges from 12 to 99. Around Brussels we observe the community with the highest amount of internal commuters (665,260), though the area of the Brussels community is relatively limited. This indicates a high density of commuters. The communities in the southern part of the country (Wallonia) are much larger in area compared to the northern communities (Flanders). There are 42 municipalities belonging to multiple communities (hatched on the map), The latter do not have clear linkages to one community, rather, in many cases the hatching happens at the limits of communities reflecting fuzzy borders. Striking is that the communities around Antwerpen and Sint-Niklaas are completely hatched. A possible explanation is that in 39% of the iterations they appear as one community. Sint-Niklaas appears as an independent

community in 47% of the iterations. In the remaining 14% of the iterations they merge within the Gent community. This reflects that the area around Sint-Niklaas is still independent from Antwerpen, however that the integration in the Antwerpen community is of considerable size. Integration into the Gent community happens to a far lesser extent.

Fig. 5

Communities of all Belgium commuting flows (hatched municipalities are those where the participation is <70%)

Applying different membership thresholds results in a robustness check of the communities' delineation. Moreover it allows to evaluate polycentricity, as commuting flows will be much more scattered because of the presence of many intervening opportunities in a polycentric metropolitan area. On the maps this

would be reflected by more dashed central areas like Antwerpen and Sint-Niklaas in Fig. 5. To detect more traces of polycentricity, the threshold was increased to 80%. Figure 6 maps the result for this 80% threshold, showing that hardly any new polycentricity is revealed, except in the regions of West-Vlaanderen, Namur and Mons. Lowering the threshold to 60% memberships results in two clearly separated communities for Antwerpen and Sint-Niklaas, which confirms the weakness of polycentricity even in this region (Fig. 7).

Fig. 6

Communities of all Belgium commuting flows (80% threshold)

Fig. 7

Communities of all Belgium commuting flows (60% threshold)

The 13 resulting communities can be interpreted as 13 Daily Urban Systems. Compared to the result of Van Hecke et al. (2007) who identified 17 Functional Urban Regions around 17 predefined major and regional cities (Fig. 1), the major differences are as follows: the integration of Bruges and Oostende in one DUS, Mechelen absorbed within the Antwerpen DUS, Mons hesitating between being independent or integrated in the Charleroi DUS, and Verviers integrated in the large Liège DUS. The language border appears prominently, except in the south of Brussels where this DUS extends to the south. The job attraction to Brussels Capital Region (BCR) transgresses the language border. Further, delimitations of the DUSs overlap more than expected with provincial borders, former administrative limits, that nevertheless have little practical implications today. This is quite contrary to the idea we raised in the beginning, namely that economic interactions is not affected by these kind of administrative borders. The results are similar to Adam et

al. (2017) who compare results for community detection in commuting and migration data.

Blondel et al. (2010) also use the Louvain method to delineate communities (Fig. 2), thus it is interesting to compare the results across the studies. At first sight, the DUSs resulting from the present research look quite similar to those delineated by means of telephone data by Blondel et al. (2010). A key difference is that the telephone data reveal a community between Gent and Brussels (Aalst), Namur is separated from Luxembourg, and Mons and Verviers appear as independent phone basins. As a result the map of the phone basins shows a pattern in between the map of urban regions by Van Hecke et al. (2007) and the DUSs delineated with the commuting data. The reason for this is the nature of the data used. Telephone calls by an individual vary in space, they are not bounded to a specific location in contrast to the job location. Telephone data represent all locations of activity, also the not-at-work time of people. Commuting data, in contrast, reflect the quite stable relation between home and job addresses. As a consequence one could conclude that the range for commuting is larger than for other dimensions of daily life. These differences are important as they reflect that work-related urban systems differ from not-work related urban systems, this was also revealed by Adam et al. (2017).

The characteristics of the nodes in the network are mapped in Fig. 8, using a combination of the within-module degree z and the participation coefficient P proposed by Guimèra and Amaral (2005). Many nodes are identified as ‘peripheral’, which means these nodes are loosely linked with some other nodes in their community as well as with nodes in other communities. Between all these municipalities relatively few commuting flows exist. Though we do not observe any ‘ultra peripheral’ nodes, this means that there always exist some commuting flows towards other communities. The ‘non hub connectors’ are found at the limits of communities, where, due to the proximity towards neighbouring communities, relatively more commuting flows are present. The connector hubs coincide with most of the regional and major cities identified by Van Hecke et al. (2007), except for Genk, which only appears as a ‘provincial’ hub, Mechelen, which appears solely as a ‘non hub connector’ and Oostende and Verviers which even show up as ‘peripheral nodes’. In addition, some small cities in the Kortrijk community appear as connector hubs (Roeselare and Waregem) and provincial hubs (Ieper), witnessing polycentricity [in this community](#). here the paragraph must end. The figures 9 and 10 belong to the text in the next section.

So please delete this refernce to the figures here. ~~.... (Figs. 9 and 10).~~

Figure 8

z and P values for communities of all Belgium commuting flows

Fig. 9 Fig 9 and Fig 10 belong to the next section 4.3

ideally It would be far better to put fig 9 with basic data on female commute flows next to or right above fig 11

and fig 10 next or above fig 12

Commuting flows of females

Fig. 10 see comment figure 9
Commuting flows of males

AQ4

4.3. Community Detection Results by Gender

Maps of the commuting communities along gender [are shown in](#) better: Figs. 9 to 12. Figs. 11 and 12. The map of male commuting flows contains 11 communities, while female commuting flows generate 13 communities. Despite the different number of communities, the NMI of 0.914 between both partitions indicates a very strong correlation between the delineations. Differences in male and female DUSs are mainly found in Flanders. The province of West-Vlaanderen is not divided in two parts for male commuters, and around Sint-Niklaas a separate female DUS emerges. This indicates that male commuters have longer commuter links in these areas than female workers. This suggests that male employees search in a larger region for a job compared to their female counterparts. Modularity of the female communities (0.7) is slightly higher than that of male communities (0.64), which means that the former maintain stronger linkages. This is illustrated by the differences in the share of male and female commuters commuting within the

resulting DUS. This concerns 72.2% of all female commuters, which means that only 27.8% of the female commuters cross the community boundaries. In contrast, more than 38% of the male commuters travel across the borders of the delineated DUS. This indicates that male commuters cross borders of the DUS more easily and, given the spatial contiguity of the DUS, confirms their more extensive commuting range compared to female commuters. This is in line with the findings for female employees in the prior literature (Crane 2007; Vandersmissen et al. 2011). Women still tend to look for jobs closer to home in order to combine their professional life with family life, resulting in less extensive DUSs (Thévenon 2013). (~~Figs. 13 and 14~~).

Fig. 11

Communities of female commuters

Fig. 12

Communities of male commuters

Fig. 13 Fig 13 and fig 14 belong to nthe next section 4.4.
It would be far better to put fig 13 next to or right above fig 15

and figure 14 together with figure 16

Commuting flows of lowest income group

Fig. 14 see comment with fig 13

Commuting flows of highest income group

AQ5

4.4. Community Detection Results by Income Class

The results of community detection for the different income classes [are mapped in](#) better: Figs 13 to 16. Figs. 15 and 16. Far more communities (14) emerge from commuting flows of lower income commuters compared to higher income commuters (9), which results in a lower NMI of 0.741 between the two partitions. Both maps contain significantly more municipalities belonging to multiple communities compared to the maps taking into account a gender dimension. This is due to a larger degree of scattering of the commuting links, resulting in different community assignments during the 1000 iterations. It results in less clear delineations of the DUSs by income group, compared to the DUSs by gender. Modularity of the very low income commuters is 0.71, while that of very high income commuters is 0.56. The low income communities are thus more compact

and tied together around a higher number of provincial hubs. Another striking feature is that the extension of the community around Brussels increases with the income class. Finally, the map representing communities of the lowest income group shows some isolated cases of non-contiguity in the region around Leuven. This is an exceptional observation as throughout the study we see that geography matters.

Fig. 15

Communities of lowest income group

Fig. 16

Communities of highest income group

Lower income groups commute in more and thus smaller DUSs than higher income groups. This is in line with the average commuting distances: lower income commuters travel shorter distances than higher income commuters. This results from the higher availability of jobs in nearby municipalities for lower income groups, while higher income groups rather find suitable jobs in larger cities that are on average located further away. This causes a high amount of commuting flows directed to a few larger cities. Furthermore, high income commuters get more attracted to the Brussels region while low income commuters travel more locally. This creates also extra communities in the periphery of the Brussels region for lower income groups. This confirms previous findings that people are not willing to invest a lot of time and costs while commuting to a low paid job (Helling 2002; Powell 2002; Zhao 2015). This results in lower income commuters having smaller average commuting distances and eventually smaller DUSs compared to higher income commuters.

5. Conclusion

The goal of the current study was to delineate Daily Urban Systems based on commuting flows of Belgian commuters with special attention on the commuter's gender and income. In the past decades, this has been done by first selecting cities that are important employment centers (offering a minimal absolute number of employment in the city), followed by identifying the municipalities that provide the employees for these jobs (surpassing a minimal threshold of commuters going into the city). The resulting 'labor basins' surrounding these cities were recognized as DUSs. As metropolitan areas are extending, one can expect that new employment centers are emerging. Moreover, due to the growing mobility opportunities more crisscross commuting fluxes are possible. Therefore, in this study, we propose a network approach building up DUSs from the partitioning of commuting fluxes between municipalities. In contrast to earlier studies, no locational data is used as input. Instead, the partitioning is performed on an a-spatial network. It is striking that by mapping the resulting communities a contiguous system of DUSs appeared. This shows that distance and geography still matter in a networked society. In line with Nelson and Rae (2016), we however want to emphasize that we must be careful not to assume that an absolute and final structure of regional divisions can be determined by the results. Adam et al. (2017) demonstrate this with different choices of the partitioning algorithm. We here compared different membership thresholds to check the robustness of the communities.

With the Louvain Method, Belgium is optimally partitioned into 13 'job basins' which is less than the 17 defined by Van Hecke et al. (2007). The traditional urban hierarchy with the five major cities (Brussels, Antwerpen, Liège, Gent and Charleroi) emerging clearly from the network analysis, and also the regional cities Kortrijk, Sint-Niklaas, Turnhout, Leuven, Tournai and Namur, remain the centers of polarized metropolitan areas. But the partitioning method identifies networked spatial patterns integrating Bruges and Oostende in one DUS, and including Mechelen in the Brussels DUS, Verviers in the Liège DUS and Mons meandering between the Charleroi DUS and constituting an independent DUS. Yet like Hanssens et al. (2014) and Riguelle et al. (2007) few traces of polycentricity were detected. Former research by Blondel et al. (2010) and Adam et al. (2017) provides similar network analysis results on migration and telephone data also resulting in smaller spatial interaction areas. As commuting is reflecting economic daily interactions whereby telephone and migration rather reflect social daily interactions, we can conclude that for economic purposes people are prepared to

travel longer distances in a larger area. Comparison of results by gender shows that male commuters cross the community boundaries more than female ones. This finding is in line with the fact that the average commuting distance of male commuters is 20% higher than of their female counterparts. Female commuters are geographically more restricted in their commuting patterns compared to male commuters. The same conclusion can be drawn with respect to income classes. Results show that low income class commuters have smaller DUSs than high income commuters.

For further research, we suggest to take into account time series. Nowadays the needed data can be bought on a yearly basis. More research is also needed in order to get a more detailed insight into hierarchies within DUSs. This can be done e.g. by calculating damping values as proposed in Grauwin et al. (2017) and previously applied on logistics linkages by Beckers et al. (2017). Additionally, we are in the process of applying the same network approach on other data, like shopping trips and school selection, in order to obtain a more multi-dimensional image of the DUSs. It would be interesting to use the proposed methods with other data and in other regions.

For policy issues there is no doubt that multiple approaches, traditional and new, are needed in studies looking for matching spatial demand and supply of services. The proposed network analysis enriches the picture and scientifically supports prospective policy plans.

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