Associating street-network centrality with spontaneous and planned subcentres

Abstract

Scientific studies have long demonstrated how economic activities regularly distribute themselves within a city in response to geographical centrality. Following the growth in interest in network geography in understanding urban dynamics, rather than measuring centrality (accessibility) by *a priori* knowledge of central business district (CBD) locations, in this paper we measure the centrality of each link in a city's street-network, modelled as a topological graph. We use this to understand clustering behaviour of firms by industrial classification in the city of Ankara, Turkey. Our underlying hypothesis rests on the assumption that the geometry and topology of an urban grid contains accessibility information about the distribution of agglomeration economies and diseconomies, and that different types of enterprises are sensitive to this distribution in various ways. Among other things, the results of the study allow us to predict the evolution of what we call candidate centres (locations that could, by virtue of their connectivity footprint, become subcentres), actual subcentres and CBD functions in response to changes in a city's street-network. Decoding how commercial cluster locations interact with the detailed pattern of street-network based centralities will be helpful for urban planning policy, in particular for commercial zoning decisions such as expanding CBDs and identifying locations for new subcentres that have an acceptable chance of success.

Keywords: Centrality; Street-Network; Accessibility; City Centers; Ankara

1- Introduction

Long before VonThunen and Alonso set Ricardo's residual value theory of land into an explicitly spatial context, speculators and landowners were no doubt using their own varied heuristics to guess the best sites to invest in for new urban landuses. All would have taken some account of distance, or more abstractly, accessibility. In this paper, we adopt an *intra*-urban network model to index the links comprising a city's street-network, for centrality. We then examine the association between link-based centrality and spontaneous centres measured by the clustering of newly registered commercial units in Ankara, Turkey. Our hypothesis is that a set of *potential* urban centres can be defined geometrically through measuring spatial network centrality and that some of these 'candidate centres' emerge to become real centres through the spontaneous locational choices of new firms.

We test whether the connectivity information captured in a network's topology can be used as a surrogate indicator for the potential commercial viability of different sub-sets of the network and find that it can be. By showing that the spatial distribution of spontaneous economic activity clustering follows its own logic, we demonstrate that network analysis can be used to test the viability of policy-defined planned commercial zones. Street-network centrality should be accounted for before locating growth and consolidation plans. Specialised software for measuring network-based relationships in cities supplement generic GIS network platforms and include Space Syntax (Hillier, 1999), Urban Network Analysis (UNA) (Sevtsuk and Mekonnen, 2012) and sDNA (Cooper et al., 2019). Methodological developments from wider network science have found their way into urban studies, such as the early application of network-based centrality measures to urban design (Hillier and Hanson, 1984), network Kernel Density Estimation (Han et al., 2019), and network evolution models (Masucci et al., 2014).

We use various terms to describe central places in the study, which for clarity are defined here. *Urban centre* is used to refer to the area of the city close to the city's geometrical centre with highest centrality and accessibility; thus attracting most trips in a day compared to other centres. *Subcentres* are closer to residential areas and refer to sites where mostly convenience, and daily goods and services are provided. A *commercial centre* is a general concept used to cover both urban and subcentre formations. As the city of Ankara is expanding on its fringe, more commercial centres emerge in the existing network, which we refer to as *emergent centres*. *Planned centres* are located in the government supplied zoning plans, whereas *spontaneous centres* are not. *Candidate centres*, as explained, are network locations with connectivity attributes that make them potentially suitable for commercial centre formation, be it planned or spontaneous. *Clusters* are empirically observed commercial centres comprising statistically-significant co-locations of new commercial registrations.

We constructed a set of parsimonious models that regress street-network link-based cluster descriptors on link-based centrality using sDNA+, a plug-in for ArcGIS (Cooper et al., 2019; Chiaradia et al., 2019), with controls for housing density, other choice dimensions and land price. Measuring the clustering tendencies of different kinds of economic units in urban space has been a major challenge in assessing agglomeration patterns, scale and intensity of facilities, and there is a need to diversify the methodology to accurately measure spatial concentration or dispersion of economic units in an area (Garracho-Rangel et al., 2013; Law, 2017; Scoppa and Pepponis, 2015). Our study follows and extends other recent applications of network urban geometry, reviewed in the following sections, to gain deeper understanding and predictive power in modelling the clustering of urban functions.

An interesting feature of the new urban network analytics, is that a network geography with the street segment as the smallest unit of analysis, is more amenable to analyzing urban design interventions. 20th century quantitative urban social science tended to be based on vector and raster geographical data models (even in traffic studies, which relied on demand zones), and its analysis was of little use to urban planners working via urban and environmental design. Network analytical studies of urban economy, environment, policy, planning and geography opens up a powerful connection between urban science and design, since urban performance in these spheres can be explicitly associated with the multi-scalar design of cities from streets to neighbourhoods to quarters and whole cities and city regions.

The paper comprises seven sections. Section 2 reviews the literature on urban centre formation and centrality. Section 3 summarises our network-theoretic model of centrality and economic clustering. Section 4 describes the study of economic clustering and centrality in Ankara, capital of Turkey. Section 5 explains our methodology. Section 6 presents empirical results and section 7 concludes.

2- Urban subcentre formation and centrality

Urban centres of varying sizes and functional rank tend to emerge naturally in any settlement beyond the scale of a single-centre village. Central Place Theory (CPT) modelled a market of perfectly substitutable clusters of services, where consumers travel to the nearest centre of each rank, with spacing and number of centres being determined by market size, range, threshold and a spatial demand curve (Christaller, 1933; Lösch, 1940). Models from the geography tradition tend to be naïve about market structure and economic behaviour but seek ever more sophisticated ways of representing the friction of distance. Because of this focus, these approaches tend to be more explicit about "push" dynamics in clustering models and abstract from "pull" effects. Earlier "push-dynamics" in urban economic models that spatialised Ricardo's residual value theory of land in the tradition of VonThunen and Alonso (1964), endogenise distance decay while abstracting agglomeration dynamics (Fujita and Thisse, 2013). These contrast with Krugman's approach to general equilibrium models of urban clustering, which yield a model of urban agglomeration as a function of the endogenous behaviour of firms seeking economies of scale (Fujita and Krugman, 2004).

The dominance of cost in such models is understandable. To gain meaningful insights into how economic activities cluster to shape cities requires a robust but simple model of *interaction* (Rosenthal and Strange, 2004; Puga, 2010; Burger and Meijers, 2012). A city is a system of interacting co-located individuals and a useful model needs an abstraction of geography because the shape of a city and its transport infrastructure, define the cost-surface over which people interact. The more accurately the cost-surface is modelled, the more realistic and useful the analysis is. This quest has a long and continuing history (Hansen, 1959; Giuliano, 2004; Chiaradia et al., 2013; Geurs and vanWee, 2004; Bertolini et al., 2005; Ewing and Cervero, 2010). Our approach is to index each link in a city's road grid by topological measures that capture various kinds of interaction potential, for example, as explained later, the expected through-movement from surrounding catchments of varying network radii. The result is a set of friction-cost surfaces based on access of a location to all other locations within certain travel distances. This approach moves from continuous space (Arbia, 2001) or discretised zonal network space (Hansen, 1959) to a street-network link-based centrality index as a model of intra-urban transaction costs.

Network methods of modelling urban friction present obvious advantages for studying the distribution of urban activities. Studies have examined relationships between topological street-network configuration and pedestrian behavior, an underlying determinant of urban landuse (Hillier and Hanson, 1984; Porta et al., 2009). More generally, landuse patterns have been related to urban morphological configuration using links (Zhang et al., 2015), buildings, parcels, blocks (Sevtsuk, 2014), street density and connectivity (Agryzkov et al., 2014; He et al., 2019; Liu et al., 2020).

Our study empirically examines the association between the centrality attributes of a city's street-network and the fine-grained spatial sorting of different economic activities, in particular, commercial activities. Previous studies including Liu et al. (2020) showed how leisure activities in Beijing, agglomerate in space and are distributed on a network according to various centrality measures. One finding was that leisure activities in the Chinese city tend to be used by pedestrians more than in Western countries and that agglomerations are therefore likely to cluster in parts of the city's network that have strong local centrality (network centrality indicators measured within a walking distance network radius). He et al. (2019) looked at the same question in Wuhan, and differentiated the network centrality preferences of leisure activities by type, such as chess and card houses, karaoke bars, parks and theatres, identifying potential growth points for each type. Han et al. (2019) studied how retail categories tend to locate in different parts of the road grid of Zhengzhou, a city in central China. Sevtsuk (2014) did the same for the Cambridge, MA in the USA. Zhang and Zhuang (2019) also examined retail clustering preference on a network (in Shanghai), but considered different networks as well as different retail types. They found that while hourly pedestrian flow in malls built at metro stations are significantly associated with the centrality of the station on the metro network, patterns of retail and leisure clustering are jointly determined by metro centrality and pedestrian network centrality in the metro neighbourhood. Multi-scale network connectivity jointly determines intra-urban central place formation, a finding by Chiaradia et al. (2013) in London. Xiao et al. (2017) examined the patterns of landuse outcomes in the primary and secondary land markets of Wuhan, China. They compared these with designated zones in the city's master plan and found a tendency for public uses to be located on small sites and in the periphery of the urban network; a planning outcome consistent with profit-maximizing behaviour of local governments but not necessarily with social optimisation.

Our empirical study of Ankara has similarities to these studies. We calibrate the network centrality preferences for an urban landuse (commercial); differentiate those preferences for different classes of commercial use; and compare planned and spontaneous locations of commercial zoning on the basis of network centrality. At the same time, our approach provides an alternative method for identifying subcentres and understanding their respective importance, size and size-distribution, contrasted with non-network approaches, such as rank-size-based methods, gini coefficient analysis, and standard deviation analysis (Liu and Wang, 2016).

Focusing on a cost-side model of urban friction to explain and predict intra-urban clustering might seem like a backward theoretical step, given the effort over the last 50 years to make geographical models more economically realistic with respect to the formation of agglomerations and economies of scale. The simplifying approach is not without precedent, however. VonThunen's model has an abiding appeal as a powerful abstraction for understanding how diverse economic activities arrange themselves around a central market, based on costs alone. The "pull-factors" in the model are totally abstracted from. Similarly, Coase's theory of the firm (Coase, 1937; Loasby, 2015) is a powerful abstraction that explains the size and size distributions of firms using a cost-based analysis– it was one of two essays that gave Coase his Nobel Prize in economics in 1991. Like VonThunen and Alonso's transaction cost models of the city, the transaction costs model of the firm is an example of an effort-minimisation theory, which has created a powerful class of explanatory models across sciences and humanities (Zipf, 1949; Webster and Lai, 2003). In spite of many useful developments in "pull-side" models of the firm that focus on economies of scale, a simple explanation based on the avoidance of transaction costs became one of the most powerful theories of industrial order in the 20th century. We feel justified, therefore, in exploring a novel approach to mapping implicit intra-urban transaction costs, to revisit a primarily cost-side model of subcentre formation.

Recent developments in network-based urban accessibility modelling have converged from several research agenda, including network science, transport planning, GIS and urban design. Measuring accessibility at the scale of individual network link (section of road between junctions) and using a variety of systemic connectivity measures computed at multiple scales, leads to better understanding of the role of connectivity in locational choice (Liu et al., 2020). In this kind of network-analytic landuse study, centrality is typically assessed through indexing each link's connectivity using *betweenness*, *straightness* or *closeness* metrics, measured relative to the rest of the network (Lin et al., 2018; Scoppa and Peponis, 2015; Porta et al., 2009; Araldi and Fusco, 2019; Sevtsuk, 2014); through ranking links or nodes as a relative map of several specific forms of accessibility (Agryzkov et al., 2014); or through summing over administrative zones (see Liu et al., 2020 for traffic analysis zones). The methods applied in such studies have, as noted above, been used to explain, for example, land use indicators such as commercial frontage density (Scoppa and Peponis, 2015); number of commercial activities (Lin et al., 2018; Porta et al., 2009; Agryzkov et al., 2014); level of retail clustering (Sevtsuk, 2014); spatial distribution of leisure activities (He et al., 2019). Various modelling strategies have been adopted, such as Bayesian clustering to assess the difference between centre and periphery (Araldi and Fusco, 2019); kernel density estimation to produce sector-specific access probabilities (Lin et al., 2018; Porta et al., 2012; Han et al., 2019); multi-scale network connectivity graphs to associate green space and housing sub-market formation (Xiao et al., 2016a,b); and spatial autoregression (Sevtsuk, 2014; Ozuduru, 2013). The atomic geography of such studies makes them more capable than earlier genres of accessibility modelling of rating urban sites for activity potential. They become, therefore, more useful for evaluating planning and urban design proposals and assessing impacts of precise network changes, such as new links (Agryzkov et al., 2014).

3- A network model of subcentre formation

Transportation networks are assemblies of fundamental urban units that have typically emerged over centuries, and show global universal statistical properties (Masucci et al., 2014). Evolved, self-organizing transportation networks tend to be distinct from planned versions, though the latter may try to emulate the former. The network in a strongly planned city bears a relationship with the planned landuse pattern, which reflects planners' doctrines and heuristics as well as designers' visions and politicians' ambitions. In an evolved city, the relationship between urban network configuration and pattern of economic activities reveals information about how accessibility benefits and separation-costs together create activity clusters (Xiao et al., 2017).

The concept of *centrality* has always been a part of urban theory. The law of minimum effort (Lösch, 1940) framed under CPT and neo-classical urban economics, suggests that people travel to the closest goods and services deterred by the friction of distance, time, money, or more generally, by 'inconvenience'. In the context of cities, however, the principle of least effort does not generate a regular hexagonal grid of central places. In reality, no centre is an exact substitute for any other centre. Therefore, there is neither a uniform nor a random distribution of commerce across a city's network. Centres and subcentres nevertheless form with discernible order. Since every subcentre is a mix of substitutable and non-substitutable services and every location confers a unique set of connections to all other locations, this pattern may be described as a monopolisticly competitive set of clusters. Intra-urban clusters are uniquely determined by these differentiated pull dynamics, moderated through network friction (Scott, 1988; Porter, 1990; Krugman, 1991; Webster, 2010).

While specific pull-effects are always moderated by spatial friction, it is not necessarily true that friction centrality is always moderated by specific pull-effects (Webster, 2010). Centrality in an urban network can be described with or without taking explicit account of the distribution of demand for travel. Strong general patterns of accessibility persist, inspite of differing specific demands for centrality across sectors and the city. Friction-based centrality described by network metrics alone, can be thought of as measuring *accessibility supply* (Webster, 2010). This approach has been adopted by studies of urban design (Chiaradia et al., 2013); commercial frontage density (Scoppa and Peponis, 2015); leisure activity clustering (He et al., 2019); retail fabric assessment (Araldi and Fusco, 2019); intensity of landuses (Porta et al., 2009); locations of retail stores (Lin et al., 2018; Agryzkov et al., 2014); spatial epidemiology (Sarkar et al., 2018; 2014); risk modelling (Quinn, 2013); and hedonic property market studies with network-based market geography (Xiao et al., 2016a; Xiao et al., 2017).

Commonly in transport-landuse studies, network centrality is analysed, however, as an explicit function of supply *and* demand (Xie and Levinson, 2007; Burger and Meijers, 2012; Burger et al., 2011), using population, gross domestic product, number of daily trips to a location, employment opportunities and so on, to calculate a link's demand-weighted centrality. Centrality is thus conventionally defined in a weighted network, with the *cost of friction* set against some measures of demand or attraction. This approach should, in principle, be superior to a pure network friction model in capturing the distribution of "gravity" (push-pull, choice-friction effects) in the spatial economy that causes place and land-value diversification, and gives rise to multi-scale distribution of centres in a city (Chiaradia et al., 2013). But the studies cited, demonstrate that a network model that is *un*weighted for demand can still powerfully predict a city's system of intra-urban central places.

A network graph of a city's transport grid, indexed by various connectivity metrics measured at various spatial scales (accessibility to the whole city network, to the network within walking distance of the indexed link etc.), will identify multiple sets of links, each with similar connectivity characteristics. We call these *candidate centres*. They represent sub-sets of locations with similar potential to become commercial centres of different sizes and mix. Viewed another way, consider it a probabilistic Christallerian map with monopolistic competition; probabilistic in the sense that these are points on the network at which Christallerian centres could emerge. Not all *will* emerge, but they could have, or may in the future. First-come locations are first-served, since there is limited demand. As a city densifies, other candidate centres may become emergent centres.

The empirical literature reports various methods for defining functional centres and subcentres (Giuliano and Small, 1999; Anderson and Bogart, 2001). Urban mobility indices (Zhong et al., 2014; Burger et al., 2011), structure of employment and population density (Burger et al., 2011), network accessibility and employment centers (Giuliano et al., 2012) and more recently graph-theoretic approaches (Bertazzon and Zaninotto, 1996; Porta et al., 2012; Liu et al., 2020) and street-network indices (Sevtsuk, 2014; He et al., 2019) have been used as proxies for defining centres. Several studies have used street layout density around a city centre to specify functional subcentres (Strano et al., 2012; Rui et al., 2013). Chiaradia et al. (2013) identify centres as regions of the urban grid where centrality measured at multiple spatial scales coincides. We adopt a version of this approach. The idea of *candidate centres* means that there are likely to be many alternative locations in a city where CBDs and other commercial centres will or could work, subject to a policy of investment. For example, in Istanbul, there is some evidence that CBD functions, such as finance and real estate service companies show a tendency to cluster in the non-core districts, suggesting that alternative CBD policy zones might have been at least as good as or better than actual zones (Berkoz and Eyuboglu, 2007). In the following sections, we identify and compare realised and and non-realised candidate centres in Ankara.

4- Ankara's development characteristics

Ankara, with a population of 5,503,985 and an urban area of 25,632 km^2, once had a highly monocentric urban structure that has transformed to a polycentric urban structure through controlled decentralization policies in the 1990s. This followed two main transportation corridors in the city's west and southwest, which have developed significantly in the last two decades. The city's southwest is populated by industrial uses and west by university campuses and government offices associated with capital city functions. In 2007, the latest master plan was approved through to 2023, which included new commercial cores in the form of proposed subcenters, attempting to shift the urban core along these development corridors. However, there has been a mismatch between policy-driven planned development and development governed by incremental partial plans. A study of Ankara's southwestern corridor (Balta and Eke, 2011) showed that the size of the area experiencing piecemeal development on the periphery was significantly more than initially planned under the first plan of Cayyolu, the 'Cayyolu Mass Housing Master Plan' (1225.7 hectars developed compared to 415 hectares planned). Consequently, Ankara's street-network has densified due to the significant, fast-paced expansion of the city's urban area through planned and spontaneous decentralization. We investigate the association between the distribution of such densified network centrality and the locations of spontaneous commercial clustering, the distribution of candidate centres, and the relationship between these and the designated commercial centres in government plans.

5- Method and data

We use three data sources: (i) Ankara's 2023 Master Plan, dated 2007 (AGM, 2007); (ii) Chamber of Commerce (CoC) data, dated 2013, covering all commercial units registered at Ankara's CoC since 1990 (the date when such registrations began), which totals 178,101 enterprises; and (iii) the existing street-network of the metropolitan area in 2013 obtained from a private company (not extracted from the Master Plan). We selected the 2013 network in order to correspond to the firm-registration data. Onto this network, we superimpose both our empirically discovered clusters, processed from the CoC registrations data, and the subcentres identified from the city's master plans. This allowed us to identify the street-network connectivity patterns associated with emergent clusters and to compare spontaneous market-driven subcentre formation with planned subcentre formation. Our method of analysis has six steps.

First, we mapped centre locations by neighbourhoods from the published master plan, which are of five types: CBD, CBD Extension, Subcentres, Industry Centres, Non-Commercial Districts. We take these planned economic zones for 2023 to be the *government's supply of central places*. Second, using the 2013 CoC data, we geo-locate commercial registrations to network links, giving us a spatial database of the location of newly registered companies over about quarter of a century. Third, we applied a clustering algorithm to identify link-based clusters and plotted the locations of commercial enterprise clusters onto the network. We did this for three classes of commercial activities. According to the European Community's two-digit NACE industry codes[1], the majority of commercial units in Ankara are composed of 'retail trade, except motor vehicles and motorcycles (NACE47)' (21.0%, 37,386 units); 'wholesale trade, except motor vehicles and motorcycles (NACE46)' (13.6%, 24,225 units); and 'construction of buildings (NACE41)' (11.7%, 20,868 units). Fourth, we indexed each link in Ankara's 2013 street-network by various measures of centrality/connectivity (elaborated below). We identified 334 commercial clusters of new registrations formed over the past quarter. Fifth, we overlayed empirically discovered cluster locations, onto designated commercial centres identified from the city's master plans. Sixth, we measured the association between clustering of the commercial firm registrations in our three categories of activity and centrality on the street-network by fitting regression models to obtain revealed demand for network centrality. This analytical strategy reveals the associations between clustering and centrality, how demand for centrality is distributed across the city's accessibility surface, and how market-led spontaneous cluster locations may differ from the planned 'supply' zones, in other words, designated centres.

Elaborating this method, link-based enterprise clusters were identified in the following way. Each CoC data point was assigned to the mid-point coordinate of its street. A Hot Spot Analysis clustering algorithm, Getis-Ord's G_i[2] in ArcGIS, identified statistically significant clusters in any of the three major enterprise sectors. Getis-Ord's G_i^* was selected as the most appropriate for our datasets, which inherently covers variable clustering bound to geography, and jointly evaluates the spatial dependency and the frequency of the attribute values within the framework of the conceptualized spatial relations. Therefore, commercial

[1]Nomenclature statistique des activités économiques dans la communauté européenne (http://ec.europa.eu/eurostat/documents/3859598/5902521/KS-RA-07-015-EN.PDF(access date:26.04.2018)).
[2] http://desktop.arcgis.com/en/arcmap/10.3/tools/spatial-statistics-toolbox/hot-spot-analysis.htm(access date:25.10.2017).

clusters were identified according to their level of spatial agglomeration. Positive values indicate clusters with high number of enterprises, statistically significant at the 0.10 level (Ord and Getis, 1995). Standardized Getis-Ord statistics, G_i^*, were derived for each link containing any of the three classes of commercial activity registrations, with the threshold distance for the clustering algorithm set to 100 kilometres so that our clusters are defined with respect to enterprise distribution across the entire city (Cubukcu, 2011). Using Equations (1-3) below, we identified cluster locations[3].

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j}\, x_j - \overline{X \sum_{j=1}^{n} w_{i,j}}}{S\sqrt{\frac{\left[n \sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w, i, j\right)^2\right]}{n-1}}} \tag{1}$$

For all *j*, x_j is the attribute value for feature *j*; $w_{i,j}$ is the asymmetric zero/one spatial weights matrix between feature *i* and *j*; n equals to the number of features, and $\overline{X}$ is the attribute sample mean:

$$\overline{X} = \frac{\sum_{j=1}^{n} x_j}{n} \tag{2}$$

S is the attribute sample variance, formulated as:

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - \left(\overline{X}\right)^2} \tag{3}$$

The resultant score, G_i^*, tests the presence of clusters with significant number of enterprises on each contiguous link. The size and locations of these clusters indicate the spatial distribution of revealed preference for centrality across Ankara's street-network. Comparing this to the locations of planned centres, we consider this as a demand-side revelation of *de facto* spontaneous candidate centre locations.

[3]http://resources.esri.com/help/9.3/arcgisengine/java/gp_toolref/spatial_statistics_tools/how_hot_spot_analysis_colon_getis_ord_gi_star_spatial_statistics_works.htm(access date:09.03.2018).

These are sub-sets of candidate centre locations that have emerged under market forces (illustrated as black dots in Figure 1).

Network centrality was assessed in relation to the topological network characteristics, *closeness* and *betweenness* indices[4], measured as network statistics using sDNA+ (Cooper et al., 2019) and at several spatial scales by measuring network characteristics within specified radii (Cooper, 2015). The equations for these measures are (Cooper et al., 2019).

$$MAD = \frac{\sum_{y \in R_z} d_M(x,y) W(y) P(y)}{\sum_{y \in R_z} W(y) P(y)}$$

(4)

where

- The angular distance along a geodesic defined by **M**, between an origin link **x**; a destination link **y** is denoted $\mathbf{d_M(x,y)}$
- The proportion of any link **y** within the radius is denoted **P(y)**
- Network weight of a line **y** is denoted **W(y)**. By default, **W(y)=1**

BtA is given by[5]:

$$Betweenness centrality(x) = \sum_{y \in N} \sum_{z \in R_y} W(y) W(z) P(z) OD(y,z,x)$$

(5)

where

- The set of links in the global spatial system is denoted **N**

[4] http://www.cardiff.ac.uk/sdna/wp-content/downloads/documentation/manual/sDNA_manual_v3_4_5/analysis-friendly.html#closeness(access date:03.09.2018).
[5]https://sdna.cardiff.ac.uk/sdna/wp-content/downloads/documentation/manual/sDNA_manual_v4_0_2/analysis-spec.html#betweenness

- W(y) and W(z) are the network weights of the geodesic end points y and z.
- Geodesic endpoints are y and z, not x where the betweenness is measured. OD(y,z,x) reflect the end links of geodesics which are traversed half as often on average, as journeys begin and end in the link centre on average. The contributions of 1/3 represent origin self-betweenness.

$$OD(y,z,x) = \begin{cases} 1, if\ x\ is\ on\ the\ first\ geodesic\ found\ from\ y\ to\ z \\ 1/2\,, if\ x = y \neq z \\ 1/2\,, if\ x = z \neq y \\ 1/3\,, if\ x = y = z \\ 0, otherwise \end{cases} \tag{6}$$

The measures for each spatial scale were taken as surrogates for accessibility in respect to different transportation modes. In our study, angular distance is used to measure network friction. It is the best denotation of multi-scale centrality for capturing vehicular traffic movement impedance, given its demonstrated link to route-choice preference and the geometry of speed theories (Wang et al., 2006). Empirical evidence shows that angular distances are related to cognition and pedestrian route-choice (Cooper and Chiaradia, 2015; Hillier and Iida, 2005; Shatu et al., 2019).

sDNA+ indices inherently account for spatial weights[6]. For example, the closeness index, Mean Angular Distance (MAD), is the inverse of closeness and measures the directness of navigating to all other possible destinations in the specified radius from each link, and its computation accounts for the weight of the network links based on geometric distance. *Closeness* centrality classifies links based on their proximity to other links. If the index is large, the network can be classified as more inaccessible (less direct). *Betweenness-Angular* (BtA) index classifies streets based on the number of shortest paths (most direct) between origin-destination pairs of all other links, passing through a link. This number reveals the degree and intensity of traffic flow/congestion potential on a link and measures the frequency with which each link falls on the shortest angular path between each pair of other links within the network contained in the specified radius (Cooper et al., 2019).

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[6]https://www.cardiff.ac.uk/sdna/wp-content/downloads/documentation/manual/sDNA_manual_v3_4_7/analysis-spec.html#radius-description-measures

Choice of radii to measure network centrality indicators was made on the basis of travel behaviour. The analysis of pedestrian behavior in Ankara (UAP, 2014) shows that the duration of a commuting trip on foot is on average 18 minutes. In general, a person can walk about 75 metres/minute,[7] corresponding to a walking distance of 1,350 metres in 18 minutes. According to the Ankara Transportation Master Plan (UAP, 2014), the average duration of home-based work round-trips by car is 34.35 minutes. Major road and central road traffic speeds are known to differ markedly[8] but detailed information is not available in Ankara. Instead, we used WEGO[9] sampled traffic speed in Ankara and assumed that private cars travel at an average speed of 25 km/hour on a mix of major and local roads (accounting for distance friction in settled areas, such as traffic lights and congestion), and 12 km/hour in central areas, the average 34.35 minute journey covering between 14 km and 7 km or less. We assume a minimum of 5 km journey length. We therefore chose a 1,000-metre radius to measure centrality for walking trips, identifying locations/links that have high value for pedestrian-oriented landuses, and a 5,000-metre radius to measure centrality for driving, identifying locations/links that have high value for activities reliant on car-born traffic. These radii follow assumptions about walking and vehicular access and mobility characteristics, and are commonly used in urban network centrality studies (Cooper, 2019). The characteristics of a location in respect of its relation to the entire complex urban network within the measuring radius are captured in these metrics.

Line connectivity (LConn), the number of other line ends to which a link in the network is connected, also referred to as *degree centrality*[10], describes the overall connectivity characteristics of the street-network link. It establishes the relationship between network geometry and cluster locations, and shows the strength of connection at junctions in the network. Lines in a network refer to each individual link and all links consist of a line joining a junction; and are deemed to be connected if they have coincident endpoints.[11] For example, a line between two T-junctions will have LConn of 4.

[7] http://www.echocredits.org/downloads/2051055/With%2Bmy%2Bwalk.pdf(access date:03.05.2017)
[8] http://content.tfl.gov.uk/tlrn-performance-report-q1-2017-18.pdf(access date:11.10.2018)
[9] https://wego.here.com/traffic/turkey/ankara?map=39.92109,32.85393,11,traffic&x=ep(access date:11.10.2018)
[10] https://www.cardiff.ac.uk/sdna/wp-content/downloads/documentation/manual/sDNA_manual_v3_0_alpha0/analysis-spec.html(access date:20.09.2018)
[11] https://www.cardiff.ac.uk/sdna/wp-content/downloads/documentation/manual/sDNA_manual_v3_0_alpha1/analysis-friendly.html#links-and-network-radius(access date: 19.09.2018)

We regressed the number of commercial enterprises in clusters per link length, a proxy for revealed demand for centrality normalized by link length, against centrality metrics for links. To identify independent influence of network centrality, as two demand-side controls, we added land price (LP) and total number of housing units per link length (THU) to the model. These are surrogate controls for proximity to workforce, other locational benefits and land cost. We note the possibility of endogeneity in a model that regresses cluster size on line connectivity when the cluster identification algorithm clusters contiguous links.[12] However, we do not think that this should be problematic since (a) the clustering algorithm will cluster neighbouring links with sufficient commercial registration regardless of topology; (b) topological connectivity can vary independently of link density; and (c) although it is true that for a given number of commercial registrations, more links will become part of a cluster because the denser and shorter the links are, the regression models use number of registrations per link not number of links. To be sure, however, we tested for endogeneity by analyzing the box-plot distribution of cluster size and centrality variables, such as link length and density. The findings showed acceptable independence. We also regressed cluster size on the centrality variables. The explanatory power of these models is significantly low (as low as %0.8), suggesting that the endogeneity problem is negligible.

We tested for multicollinearity using variance inflation factor and found that all independent variables are sufficiently independent. The models comprise indicators of street-network characteristics, centrality, landuse and development, line connectivity, closeness, betweenness, total number of housing units per link length and land prices of each link. Log transformation was used when the distribution of variables was highly skewed.

Logarithm of Total Housing Units (LogTHU) is used as a proxy for population density (labour supply) and as a demographic indicator of demand. Logarithm of Land Price (LogLP) is included because while land price is affected by demand from commercial activities and will be higher in cluster links; relative low prices for a

[12]Thanks to an anonymous referee for pointing this out.

given centrality might be an attractor. Land price is, therefore, both a measure of demand for the underlying locational attractions independent of general accessibility, and a proxy for money value.

6- Findings

a. Clusters and centrality patterns

When we compared planned centre zones with revealed demand by superimposing clustered enterprise registrations on the planned centre zone map of Ankara, we found that 103 (30.8%) of the emergent cluster locations are *not* located in planned zones. We have not explicitly specified spatial boundaries of the naturally occurring urban centres of clustered firm registrations. This means that when we comment on differences between planned and emerging centres, we are comparing policy areas delineated as polygons with clusters formed by network links. We do not go as far as drawing up alternative policy zones that better match naturally occurring clusters, although that could be done.

When comparing cluster locations on the network with link centrality, we found that larger clusters tend to locate at sites with higher closeness (MAD1000), and this coincides with historical parts of Ankara where angularity of street segments is higher. They also tend to locate at sites with lower MAD5000, where car accessibility is higher. This reveals that spontaneous subcentres tend to geometrically locate towards the periphery of Ankara, and following Scoppa and Peponis (2015) and He et al. (2019), shows how urban arterials act as the new urban cores.

We analysed three commercial sectors. The construction sector clusters of Ankara tend to locate close to the CBD (51.4% of construction sector clusters), CBD Extension (20.6%), and non-central zones (19.8%), in particular on the southern parts where wealthier households live. This is partially explained by a local demand factor, namely that construction sector businesses have diversified into luxurious retail businesses such as high-end accessories and high-quality restaurants. The retail sector clusters are spread around the city close to residential areas (37.2% are located in the CBD; 34.0% are in non-commercial districts) The wholesale sector clusters are in the CBD, in industrial centres on the northern parts, and in the CBD extension in the southern parts of the city. Due to the spatial needs of manufacturing, these units are mostly in planned centre zones and are less likely to be in non-central zones (only 11.4%).

Closeness indices at 1000-metres (Figure 1(a)) and 5000-metres (Figure 1(b)) identify parts of the network with high level of inaccesibility (red) through to most accessible (blue). We observe that clusters tend to locate around links with smaller MAD (closeness-index) values at walking (MAD1000). The average MAD1000 value of Ankara's street-network in the CBD is higher than the average MAD1000 value for cluster sites. At driving distance, average MAD5000 values in planned centre zones are smaller than average MAD5000 values for cluster sites, indicating that centrality levels of functional centres along with level of clustering vary by location (Zhong et al., 2014) and new functional centres tend to move to the urban fringe.

<Insert> Figure 1. Closeness centrality index (MAD) measured at two radii: (a) 1000-metre, (b) 5000-metre; Betweenness centrality index (BtA) measured at two radii: (c) 1000-metre, (d) 5000-metre and cluster locations (illustrated as black dots)

Figure 1(c) shows that sites with high betweenness levels at walking distance are found in the central commercial districts. Clusters tend to locate on links with higher betweenness at walking distance; with the average BtA1000 value of the overall street-network being less than cluster sites, complying with the idea that clusters tend to locate at more walkable sites (Porta et al., 2009; Scoppa and Pepponis, 2015). The only exception is the BtA1000 value for cluster sites in subcentres, which is lower than for subcentres in general. This is because Ankara's subcentres, which are relatively new in the city, are car-dependent centers following the development of shopping centres (Ozuduru et al., 2014) and this in turn relates to a higher rate of car use in Ankara.

Figure 1(d) shows that major highways and main streets have higher BtA5000, and cover a diverse set of landuses, with a tendency to attract commercial clusters. In central neighborhoods, BtA5000 values are about three times higher than the overall BtA5000 values of the street-network in Ankara (the average BtA5000 value is 490,574 for the street-network and 1,454,161 for the street segments in cluster locations). Comparing higher values of BtA5000, reveals that clusters tend to locate at sites where through traffic is higher. Walking and driving distance centrality indicators are significantly divergent in explaining the qualifications of the urban structure, such as the street-network's association with green space and housing sub-market formation (Xiao et al., 2016a,b).

b. Regressing clustering on centrality

Model 1 (Table 1) shows that there is a significant relationship between line connectivity (LConn), some of the centrality indices and the total number of enterprises in clusters per link length. Walking-distance closeness, proxied by the Mean Angular Distance at 1000 metres variable (MAD1000) is not significantly related to number of enterprises per unit link length. This suggests that choice of destinations at a walking scale does not, in general, correlate with cluster density. However, betweenness, measured by the logarithm of angular betweenness variables (LogBtA) at walking scale *is* significantly associated with cluster size with elasticities ranging from 0.175 to 0.555. This shows that enterprise clustering in Ankara is sensitive to '*through* movement' but not '*to* movement' at a walking scale. This is an interesting finding, suggesting that commercial enterprises cluster at network locations that minimise search costs of customers (proxied by *betweenness* centrality) rather than those that minimise input or supplier search costs (proxied by *closeness* centrality). Similar findings have been specified for retail establishments (Sevtsuk, 2014; Lin et al., 2018; Porta et al., 2009) and leisure activities (He et al., 2019).

At driving distance, closeness and betweenness indices both have negative significant relationships to cluster size. The negative association suggests that commercial clusters tend to avoid streets that are well connected within a 5000-metre driving range in Ankara. The likely explanation is the avoidance of heavily trafficked and polluted streets.

<Insert> Table 1. Regression Model Results

Controlling for total housing units per unit length (THU) and land price (LP), gives us the unit change in commercial demand for a network link (log of enterprise density) per unit change in centrality. For example, log density of commercial clustering demand falls by 0.068 units as the log of LConn rises by one unit; increases by 0.212 units as the log of walking distance betweenness (LogBtA1000) rises by one unit; and falls by 0.136 units as the log of driving distance betwenness (LogBtA5000) rises by one unit.

Models 2, 3 and 4 (Table 1) repeat these results by different sectors and although the explanatory power decreases, the significance and elasticities do not change much. It is observed that LConn has a negative relationship with the dependent variable for construction and retail sector clusters, but the relationship is insignificant for wholesale trade clusters. Vehicular closeness, measured by the Mean Angular Distance at 5000 metres variable (MAD5000) has significant negative relationship only for retail sector clusters, demonstrating the reliance of other sectors on vehicle access. The insignificance of THU and LP for the wholesale sector shows that these firms tend to locate at sites independent of population and related land price variation.

These results show the usefulness of measuring network centrality in *ex-post* and *ex-anti* evaluations for urban planning policy. The analysis also yields specific insights, for example, finding that areas with higher walkable betweenness and closeness values tend to have larger commercial activity clusters (confirming and generalising Agryzkov et al., 2014; Lin et al., 2018).

6. Conclusions

The study systematically investigated associations between specific measures of urban road grid geometry and multi-sector enterprise clustering across an entire city. Its novelty is that it does this for new commercial enterprise registrations; it conducts the analysis over almost a quarter of a century; it analyses a city that, during the study period, has been through a strong period of market-led development, providing something of a natural experiment in comparing spontaneous versus planned commercial clustering. It is also the first such study in a Turkish city.

We interpret the commercial clusters of new commercial firm registrations as revealed demand for centrality. We also take these to be and a subset of the population of candidate centres – locations on the network where such clusters could possibly have emerged. Our analyses show that patterns of network topology are correlated with emergent centre location and suggest the following model of central place development:

A. Commercial centres emerge spontaneously across a city's network.
B. The locations are not random and can be partly explained (58.8%) by network centrality, controlling for land price and housing density.
C. Further, particular attributes of network centrality help explain specific location patterns for different sub-sectors.
D. Locations with those attributes but without emergent clusters are, from a centrality supply-side, candidate centres that may have emerged and could still emerge with additional densification and demand.

We have framed the study in terms of spatial economy, and the supply and demand of central places. For this reason, we started with early twentieth century CPT. Much better data, analytic algorithms and computational power mean that such matters, first modelled a century ago, can now be investigated in greater detail. As an update to the simplistic but conceptually powerful spatial demand curves of earlier central place models, we can now measure the elasticity of demand for network accessibility, measured at the smallest network scale possible, the street-network link. The elasticity of Ankara's commercial cluster density with respect to betweenness at walking distance, for example, is 0.212 and with respect to betweenness at driving distance is -0.136.

Our analysis also allowed us to compare planned supply of central places with those that have emerged spontaneously. Ankara is a perfect laboratory for such comparison because of the recent strong shift in government policy, which gave greater freedom to developers in shaping the city, transforming from monocentric to polycentric urban form over a quarter of a century. We have quantified the divergence from the planned zonal strategy and shown why it has happened: because the planned zones are not always located in strongly connected candidate centres and, conversely, some planned non-commercial zones have the right configuration of connectivity to attract commercial clusters. These findings are nuanced farther by conducting the analysis across three commercial sectors and two spatial scales of centrality measurement. This goes beyond earlier studies and points out how planning policy -in Turkey and elsewhere- should dwell on, and can account for, landuse development and street-network topology. We also evidence, more generally, that landuse development follows centrality characteristics of a city's street-network.

Our results have practical implications for policy-makers and planners. For example, investing in commercial centre infrastructure in zones on the urban fringe in Ankara's far southern neighbourhoods might be as productive as doing so in the currently planned centres on the southwestern corridor. Our findings suggest that all municipal master planning seeking to locate landuse activity zones, should first conduct a systematic analysis of the demand for centrality by different activities.

We have shown in empirical multi-scale network and multi-sectoral detail what VonThunen showed schematically: different economic activities have differentiated demand for centrality, governed by their particular spatial friction preference. Activity zoning aimed at rationalising urban infrastructure investment, regulating land supply and optimising negative and positive externalities, will be more successful if it confines itself to selecting zones from candidate centres appropriate to specific uses. Designating specific use zones on the basis of general (and unmeasured) notions of accessibility, distance or available land, may lead a redundant plan and wasted public investment.

The locational shift of urban centres in Ankara towards the urban fringe reminds us of the normative principles of Lösch's (1940) and Krugman's model, where transportation corridors play a significant role in 'fixing' Central Place geometry. By using topological centrality measures, we endogenise Lösch's graphical slight-of-hand (revolving overlaid meshes of central place systems to produce linear clusters of settlements suitable for transport corridor investment in a neat multi-scale hexagonal geometry). We have shown that our metrics can measure the effects of linearities, corridors and the demand for central spaces and that network analysis can deal with geometric complexity and can explain clustering, landuse development and spatial distribution of activities in the real world.

Limitations of the study include the use of new commercial registrations data to measure clustering rather than the full stock of commercial activities at a location. If preferred locations are full up or highly congested, then the revealed preference for locations that we have measured might include second best choices. We note, however, that our regression models control for land value and population density, which are both measures of locational congestion; and that the government's planned non-CBD central zones are not full up (AGM, 2018). The comparison of the network at a single time period with commercial registrations accumulated over time (1990-2013) is another limitation. However, we note that the 2013 network model used is also cumulative, containing all possible road links available for clustering during the 1990-2013 period. What we will not have captured is the changing centrality of different parts of the network as it has grown over time (for a study of the expansion of road and metro networks see Zhang et al., 2015). Future studies could use time-series of network data, which we did not have access to. We also acknowledge the possibility of endogeneity between the clustering of economic activities and centrality attributes such as link density. We tested for this and found that endogeneity is unlikely to be high enough to affect the robustness of the models and is less significant for 5000-metre analysis than for 1000-metre analysis.

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