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Mapping the evolution of hierarchical and regional tendencies in the world city network, 2000-2010

Abstract

This paper visualizes the evolution of the dominant hierarchical and regional patterns in the world city network, drawing upon an analytical framework integrating categorical correlation, hierarchical clustering, and alluvial diagrams. Our analysis confirms the continued interweaving of hierarchical and regional patterns in the world city network as measured by cities' similarities in the presence of globalized service firms, but equally highlights some of the key changes that have occurred between 2000 and 2010 such as the rise of the BRIC cities, Dubai's leading positions in the Arab Gulf, and the stratification of US cities.

Keywords: advanced producer servicing network, urban system, temporal evolution, alluvial diagram, hierarchical clustering

Highlights

- Visualizing changes in the world city network through alluvial diagrams.
- Highlighting (changes in) hierarchical and regional patterns in the world city network.
- The analytical framework can be adapted to study urban systems at other geographic scales.

1. Introduction

More than a decade ago, Hall (1999, p. 173) posited that the significance of face-to-face contact and the continuing significance of agglomeration imply that cities will continue to thrive. However, at the same time he suggested that we need a new urban theory of location of service industries in the context of increasing informationalization and globalization (see also Castells, 2001; Sassen, 2001). Hall's (1999) general ideas have been picked up in a wide variety of literatures, including the 'world city network' (WCN) research conducted in the context of Globalization and World Cities research network (GaWC, http://www.lboro.ac.uk/gawc). In WCN analysis, data on the office networks of producer services firms is used to estimate the shape and the geographies of emerging 'urban networks' at the global scale (Taylor, 2001; 2004; Taylor et al., 2013).

Diverse empirical researches into the geographies of the WCN have revealed that these can best be described as a variegated mix of hierarchical and regional tendencies. In the context of WCN, regions are defined based on network ``clusters'', which are groups of densely connected cities, so that connections within clusters are stronger than connections between clusters. Network-based regions are similar to *functional regions* in economic geography, where interactions are more intense within regional ``borders'' than across them (Anderson, 2012). These network-based regions often coincide with *formal* - geographical, institutional, or cultural - regions, i.e., cities from the same geographical or cultural region tend to reveal similar network connectivity patterns. For instance, based on a cluster analysis applied to a dataset specifying the location strategies of 100 globalized service firms in 234 cities across the world for the year 2000, Derudder et al. (2003) find that the cluster results can best be described through both tendencies. More specifically, the hierarchical tendencies are revealed through the co-presence of cities with similar levels of overall involvement in the networks of globalized services firms. As a corollary, all clusters can be ranked based on the relative importance of their member cities, ranging from a two-city cluster made up of New York and London to a cluster with cities only housing a small number of globalized service firms such as Teheran, Labuan and Yangon.

However, the results do not simply reflect a straightforward hierarchical arrangement: there is also a series of regional dimensions, demonstrated by the presence of different clusters with cities of comparable importance but with different regional affiliations. This is for instance shown by the presence of two clusters just beyond the New York-London dyad: one cluster made up of leading non-US cities (Frankfurt, Tokyo, Hong Kong, Paris and Singapore), and the other of leading US cities (San Francisco, Chicago and Los Angeles). Similarly, there are different clusters of *inter alia* secondary Commonwealth cities, secondary United States cities, and secondary German cities, and this in spite of the comparable overall importance of their member cities in the office networks of globalized services firms. Derudder et al. (2003, p. 880, emphasis in original) thus conclude that the "results show more than clusters in an abstract 'service space', they represent *urban arenas* in geographical space." Rather than presenting a mere hierarchical ranking of clusters, they thus opt to organize their description of the global urban system around a combination of 'hierarchical bands' in which clusters with different regional orientations can be discerned.

The Derudder et al. (2003) study obviously represents a specific empirical take by focusing on the location strategies of leading service firms for the year 2000, and by applying a fuzzy clustering algorithm for discerning patterns. However, it can be noted that this mixture of hierarchy and regionality constantly re-emerges in this literature, irrespective of the data source, the data analysis technique, and the time period. Wall and van der Knaap (2011) and Ducruet et al. (2011), for instance, use a host of network analysis techniques to examine the WCN around 2005 as created by multinational corporations and air passenger/maritime freight networks, respectively, and thereby come to similar conclusions.

The ongoing presence of hierarchical tendencies and regional patterns in the WCN obviously does not preclude significant *change*. For instance, the quasi-general 'rise' of cities in China and the Arab Gulf has been widely documented, as well as the hierarchical unevenness of these changes as individual cities such as Shanghai, Beijing and Dubai surpass their wider regional trends, thus assuming an importance in line with that of the likes of Tokyo and Chicago (Alderson et al., 2010; Mahutga et al., 2010; Derudder et al., 2010). The presence of such multilayered change in the WCN in the face of its ongoing hierarchical and regional complexity leads to the question how this change can be comprehensibly analyzed and represented (see Orozco-Pereira and Derudder, 2010).

To date, this challenge has not yet been taken up in this literature. As a consequence, longitudinal research into the WCN has generally been restricted to analyses of the shifting position of individual cities. However, this obviously falls analytically short of the detailed cross-sectional descriptions as detailed in the work of Derudder et al. (2003), Ducruet et al. (2011), and Wall and van der Knaap (2011). Against this backdrop, the purpose of this paper is to apply a visualization framework that allows for a *comprehensive* assessment of the multilayered evolutions in urban systems.

An exploratory visualization framework seems to usefully complement previous centrality-based studies (Rosvall and Bergstrom, 2010), as the visualization approach is able to, amongst other things, (1) synthesize information more compactly than tables; (2) reveal trends in data via visual aids, and most importantly, (3) explore unexpected trends and serve as hypothesis-generating tools. Indeed, visualization has long been identified as promising ways forward in the global urban network (Taylor, 2004), however -- probably due to the fact that empirical global urban network studies usually involve hundreds of cities and firms -- few empirical attempts have been made to realize the potential of visualization (however see Hennemann, 2013).

Our study employs a non-map based visualization framework to supplement conventional map-based methods (e.g., Liu et al. 2012) for the following reasons: Firstly, city networks in general and world city networks (WCNs) in particular represent a “meta-geography” (Beaverstock et al., 2000) in which relative positions of cities do not necessarily correspond to their absolute geographic locations, thus rendering maps – the conventional way of representing absolute geographic sites – less relevant for mapping WCN (Hennemann, 2013). Secondly, while maps remain the dominant way of visualizing spatial information, non-map based visualizations have been increasingly adopted to reveal dynamics of cities (see for example, Batty 2006; Angel 2012). These methods often focus on the hierarchical rather than the regional nature of urban systems. For example, Batty's (2006) *Nature* paper reveals the trajectories of individual cities within urban hierarchies (e.g., the rise and fall of Buffalo, NY) but focuses less on dynamics of groups of cities (e.g., the overall diverging trajectories of cities from the "Rust-Belt"). Thirdly, visualizing intercity networks by cities' absolute geographic positions (see for example, Liu et al. 2012) would usually produce cluttered networks due to strong geographical and network clustering (i.e., the regional tendencies discussed in this paper), make it difficult to represent long-term spatiotemporal changes (i.e., representing four-dimensional spatiotemporal information on a two-dimensional surface), and often need to be **supplemented** by other techniques (Rae 2009).

The framework used here rests on two key premises. First, we argue that longitudinal research needs to use partitioning methods that provide 'consistent' grouping results across the entire timespan. That is, results for the different time points should be comparable in the sense that changes reflect structural change in the system rather than data heterogeneity. Second, assessments of change should not simply focus on the shifting position of individual cities, but allow tracking the broader changes in the hierarchical and regional geographies of the system as a whole. In this paper, we propose to tackle this by **adopting** a framework that combines categorical correlation, hierarchical clustering, and alluvial diagrams to assess the temporal evolution of the WCN.

Our framework is applied to GaWC data garnered for 2000, 2004 and 2010. For each year, the data provide ordinal measures of the importance of cities in the networks of the world's most important producer services firms. The data are transformed so that consistent datasets of 139 cities and 92 firms are used for describing the geographies of the WCN. The three 139 x 92 ordinal matrices are used as the input to our measurement and visualization framework, and the results are thereupon to explore the potential of this approach by identifying a number of key changes in the geographies of the WCN.

The remainder of this paper is organised as follows. In the next section, we discuss previous approaches to revealing geographical patterns in the WCN, and use this to sketch the general framework for examining change in the WCN. This is followed by a specification of our analytical framework, and a description of our data. In the results section, we explore the possibilities offered by our framework by discussing some key changes in the geographies of the WCN. The paper is concluded with an overview of our main findings, a discussion of our framework's limitations, and an overview of avenues for further research.

2. Identifying 'clusters' in WCNs

The empirical starting point for WCN analysis is a city-by-firm matrix, which is basically a two-mode or bipartite network (Liu and Derudder, 2012). Unlike more conventional one-mode networks where nodes are connected directly (e.g., cities linked by airline flows), a two-mode network features relationships between two disjoint groups of nodes (e.g., cities and firms) whereby there is no direct linkage between nodes of the same group (i.e., between cities or between firms). Two-mode network datasets can be either binary or valued (e.g. when values reflect cities' importance in firm's locational strategies).

Exploring the major tendencies in large two-mode networks such as WCN datasets often implies reducing the overall complexity to a coherent set of major patterns. In the empirical WCN literature, the identification of these tendencies is most commonly achieved by following one of three major directions: (1) applying a network community detection algorithm to a one-mode network projected from the original two-mode dataset; (2) performing a multivariate analysis on the two-mode dyads; or (3) adopting network partition algorithms for two-mode networks.

The first approach begins by projecting the two-mode city-by-firm network into a one-mode city-to-city network (e.g. Taylor, 2001; Alderson and Beckfield, 2004; Neal, 2008). The resulting networks can then be analysed through readily available community detection/network clustering algorithms for one-mode networks, such as blockmodelling

(Alderson and Beckfield, 2004) and graph-based clustering techniques such as clique analysis (Derudder and Taylor, 2005). However, recently it has been recognized that this approach is plagued by (1) the loss of information through the application of an assumption-rich projection function (Hennemann and Derudder, 2014); (2) the structural determinism of the one-mode network as imposed by the projection function (Neal, 2012); and (3) the tendency to create over-connected clusters, making it difficult to extract meaningful clusters (Derudder and Taylor, 2005: see, however, Neal 2013).

The second approach avoids these problems through direct and more traditional multivariate analysis of the two-mode dataset. For instance, clustering methods have been applied to identify groups of cities that host comparable combinations of firms (Derudder et al., 2003), while principal component analysis has been used to analyse the dominant locational strategies of firms after which cities associated with these strategies are identified (Taylor et al., 2013). Although these analyses go a long way in describing the main patterns in a cross-sectional datasets, this approach risks to be problematic in longitudinal analyses in that the number of clusters/principal components should remain 'appropriate' for each point in time. Put differently: using these techniques requires a tailored approach towards defining the number of meaningful clusters/components.

An additional problem is that most two-mode WCNs essentially represent ordinal measures, while traditional multivariate techniques assume that data are measured on a ratio scale (whereby the differences between neighbouring values are equal). For instance, GaWC data (see the data description for more details) essentially differentiate between office *types*: data values of 5, 3, and 1 respectively denote the global headquarters, a large office, and the presence of a local partner office of a service firm. The assumption that the 'measured' difference between a global headquarters and a large office is equal to the difference between a large office and a local partner office is unlikely in reality, and this calls for non-ratio approaches when differentiating cities based on the presence of such firms.

The third approach acknowledges the non-ratio nature of the two-mode city-by-firm matrices by building on analytics for categorical two-mode networks, such as generalized blockmodelling (Doreian et al., 2004). However, these methods are usually computationally prohibitive and only applicable to datasets of medium sizes. Therefore, although promising, the usage of this third approach is often limited by the fact that analysing urban systems through intercity corporate networks often involves hundreds of cities and firms.

In this paper, we propose to overcome the analytical issues sketched here by adopting a hierarchical clustering framework that allows treating the city-by-firm matrices as ordinal data. We thereby interpret the two-mode network as a dissimilarity matrix, and avoid pre-specifying the number of clusters as input. The resulting cluster structures for each dataset can then be organized so that exploring change is facilitated through recent advances in the visualization of cluster change affiliations.

3. Methods and data

The analytical framework proposed here involves three main steps: (1) for each time period, measuring how cities are (dis)similar in terms of their collections of firms by producing a city-to-city dissimilarity matrix based on the city-by-firm matrix; (2) for each time period, applying a hierarchical clustering to group cities that host similar combinations of firms; and (3) using alluvial diagrams to highlight the evolution of clusters over time. The remainder of this section describes these steps in more detail, followed by a discussion of our data.

3.1. Dissimilarity between cities' portfolio of firms

The first step focuses on measuring how (dis)similar any pair of cities is in terms of its number, collection, and type of offices. To this end, we use Gower's general dissimilarity coefficient (Gower and Legendre, 1986), which is one of the conventional methods for measuring proximity in categorical datasets. By treating the city-by-firm matrix as an *ordinal* multivariate dataset, we employ Gower's general dissimilarity coefficient to capture the correlation between the collections of firms in two cities as follows

$$\mathrm{D}_{ij} = \frac{\sum D_{ijk}}{N}$$

$$\mathrm{D}_{ijk} = \frac{|X_{ik} - X_{jk}|}{R_k}$$

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Where D_{ij} denotes the dissimilarity between city i and j's collections of firms; D_{ijk} represents the contribution provided by firm k; X_{ik} and X_{jk} represent the service values (or the standardized 'importance') of firm k in cities i and j, respectively; K is the total number of firms; and R_k is the range of service values for firm k. For example, the advertising company Hakuhodo has a headquarters in Tokyo (a service value of 5), a normal office in Hong Kong (a service value of 2), and no presence in Jakarta (a service value of 0), then the dissimilarity between Tokyo and Hong Kong in terms of this particular firm is calculated as (5-2)/(5-0) = 0.6 Without information about firms' characteristics, we hereby assume all firms are contributing equally in the dissimilarity measurement. The resulting coefficients for all pairs of cities range from 0 (i.e. the same collection of firm offices in two cities) to 1 (i.e. two cities hosting completely different sets of offices of firms).

3.2. Identification of clusters

The next step is the application of a hierarchical clustering on the dissimilarity matrix. Hierarchical clustering has the advantage that it is in principle open-ended, as it does not require pre-determined parameters such as the number of clusters. *Complete-linkage* clustering or maximum distance clustering is adopted, so that the distance between clusters is measured as the furthest distance between a pair of nodes, that one node is from one of the clusters, and one from the other cluster. An alternative hierarchical clustering method is the *single linkage* method, where the distance between two clusters is computed as the minimized distance between a pair of nodes, with one from each cluster. We adopt complete-linkage clustering as it avoids the *chain phenomenon* in single-linkage clustering, where two clusters, even though many of their nodes are “dissimilar”, are forced together due to a single pair of “close” nodes. The hierarchical clustering process is visualized through a tree-like dendrogram (Ahn et al., 2010), whereby in each consecutive step (groups of) cities are merged based on their level of similarity. The ‘height’ at which the merger occurs reflects the dissimilarity between cities/groups of cities.

In hierarchical cluster analysis, the number of clusters used for further analysis is determined by defining a threshold of (dis)similarity. A conventional method is to use a predefined threshold, but this produces less-than-ideal results in complicated and nested dendrograms. More importantly here, however, is that an arbitrary and constant threshold may be problematic when the subsequent goal is to make longitudinal comparisons as the strength of (dis)similarity patterns may shift over time.

Therefore, we employ a dynamic method that explicitly allows for different thresholds for different parts of the dendrogram (Langfelder et al., 2008): instead of using constant thresholds, this dynamic method considers both the shape of dendrogram and dyadic (dis)similarity to identify nested clusters. Although different parameter settings obviously affect the final clusters, we emphasize that the advantage here is that - once a set of shape parameters are chosen - the intra-cluster variances and inter-cluster differences can be held constant for different dendrograms, thus providing the basis for a consistent longitudinal comparison. This may imply that different numbers of clusters are produced for the different datasets, but these different numbers correspond to similar levels of variability in the dataset and are thus in reality comparable than a constant number of clusters.

Tables 1-2 present an example of the practical implications of this approach. Table 1 show a sample two-mode dataset detailing the (importance of the) presence of five firms in five cities for 3 different points in time (2000, 2004, and 2010 as in the actual data); and Table 2 presents the results of the clustering. Figure 1 and Table 2 show that in 2000 the major distinction is between Tokyo and Hong Kong on the one hand and Beijing, Jakarta and Bangkok on the other hand. Over time, however, Beijing’s mix of firms changes in a way that

– when a similar threshold for overall heterogeneity is used - makes the city distinct from both Jakarta/Bangkok and Tokyo/Hong Kong in 2004, and distinct from Jakarta/Bangkok but similar to Tokyo/Hong Kong in 2010.

[Tables, 1 and 2 about here]

3.3. Mapping temporal evolution of clusters with alluvial diagrams

The third and final step is to represent change in the clustering results. We employ alluvial diagrams to summarize and highlight the evolution in the major tendencies in the WCN (Rosvall and Bergstrom, 2010). Our usage of alluvial diagrams is illustrated in Figure 1 based on the sample dataset in Table 1 and its clustering in Table 2.

[Figure 1 about here]

In an alluvial diagram, individual blocks represent clusters, whereby for each year blocks are ranked hierarchically (i.e., clusters are plotted from top to bottom based on the average number of firms per member city). The blocks are named after the common denominator of clusters members, while the width of a streamline is proportional to the number of cities with the corresponding membership change. Horizontal streamlines connect preceding and succeeding clusters, thus allowing tracing how memberships of (groups of) cities evolve over time. In addition, the trend for individual cities can be highlighted for enhanced interpretation. For example, in Figure 1 the streamline for Beijing is highlighted, clearly showing its rise in the WCN over time as it memberships change as summarized in Table 2.

3.4. Data

The data used here to operationalize the model as described above are derived from our previous research in the context of GaWC. Following Sassen (2001), the GaWC model is operationalized through an assessment of the urban geographies of producer services firms' globalized office networks. The data required for this exercise are readily available on producer services firms' websites where they promote their 'global' status as a means of both impressing clients in a competitive services market and recruiting graduates in a competitive jobs market. However, this source, plus supplementary information as available, produces different levels and types of information for every firm. Thus the data have to be converted using a simple ordinal coding system to enable cross-firm comparison for analysis. In practice, a 6-point scale ranging from 0 to 5 is used. Thus, 0 indicates a city where firm has no presence, 5 is firm headquarter city. Codes 1 to 4 are then allocated as follows: a typical office of a firm scores a city 2, there must be something deficient to lower the score to 1, and something extra for it to rise above 2. For the latter, an especially large office scores 3, an office with extra-city jurisdictions (e.g. regional HQ) scores 4. To improve the robustness of data, the assignment of ``service values'' was conducted and cross-examined by three independent teams (Taylor et al. 2013) at the Chinese Academy of Social Sciences (China), Ghent University (Belgium), and Loughborough University (UK).

In the data gatherings, all major cities across the settled world were included, while firms were chosen based on their importance in corporate rankings of key producer services sectors (accountancy, financial services, management consultancy, law, advertising). The original GaWC datasets thus summarize the geographic distribution of 100 firms in 315 cities for 2000, 92 firms in 315 cities for 2004, and 175 firms in 526 cities for 2010. However, for consistency and robustness purposes, in our analysis these datasets are transformed by (1) selecting 92 firms for each data gathering; (2) focusing on 139 cities that host at least 15 firms in all three years; and (3) enforcing a consistent sectorial composition of firms for all datasets (i.e., in each dataset, we single out the leading 17 accounting firms, 13 advertising agencies, 19 banks and financial firms, 10 insurance firms, 16 law firms, and 17 managerial consultancy firms). As a result, the datasets used as the actual input in our analytical framework are three 139x92 matrices, with each row showing a city’s service mix as an ordinal string of values ranging from 0 to 5.

The GaWC data describe the relative importance of individual branches within intra-firm networks, and do not capture: (1) measurable amounts of work performed in individual offices, such as billable hours, processed documents, telephone calls, and emails; (2) the (usually back-office) jobs outsourced to third-party companies, as the GaWC dataset focuses on intra-firm networks and the core-business of producer servicing; and (3) off-shore financial centres, which often contain no physical presence, but virtual registrations of producer services firms. In other words, the current study focuses on the ``revealed'' geographies of office networks.

4. Results

To obtain results, the analytical framework described in the previous section was applied to our data through an implementation in the statistical software package R. Meanwhile, the "alluvial generator" available at http://www.mapequation.org/ was used to produce the diagrams. Moreover, we have implemented codes to produce input files for the "alluvial generator", which offers a wide range of online interactive functions, such as selection, move, highlight, and search of individual cities.

Network patterns in the world city network consist of three major tendencies: Firstly, there is a hierarchical tendency that cities with similar levels of network connectivity (similar ``portfolio'' of firms in the intercity corporate network) tend to form network clusters. Secondly, there is a regional tendency that cities with geographical, institutional, or cultural proximity tend to form network clusters. Thirdly, hierarchical and regional tendencies tend to interact and change over time. In the hierarchical cluster analysis, a pragmatic choice was made regarding the set of shape parameters, generating clustering results that cover a broad diversity in both hierarchical and regional patterns[1]. A total of 17, 15, and 18 clusters were thus obtained for 2000, 2004, and 2010, respectively (Table 3). For each year, the clusters were reordered to reflect the hierarchical tendencies in the results (i.e. clusters are ranked based on the average number of firms in each of the member cities[2]). Clusters were labelled based on an interpretation of the dominant trait of the member cities, with a particular focus on hierarchical and regional patterns. The regionality is labelled by simply referring to what seems to the overriding regional geography of the cluster (e.g.

[1] We use the cutTreeDynamic R function, and the parameters are set to cutHeight = 0.5, deepSplit = 3, minClusterSize = 2 (for more details about parameters, see Langfelder et al., 2008)

[2] Clusters can also be ranked on other city-attributes (e.g., GDP, population; Yang and Liu, 2005) and network properties (betweenness and closeness network centralities; Everett and Borgatti, 1999), while ranking cities based on number of firms (headquarters) is widely used and theoretically justified (see Godfrey and Zhou 1999).

‘Scandinavian cities’ or ‘Gulf of Tonkin cities’)[3]. The hierarchical tendencies, in turn, are described by distinguishing between ‘global cities’ for clusters dominated by top 20-ish cities, followed by the identification of ‘primary’, ‘secondary’, and if needed ‘tertiary’ cities for different regions (e.g. ‘US global cities’, ‘primary US cities’, and ‘secondary US cities’). No hierarchical designation is used if there is no significant presence of other cities from that region in other clusters (e.g. ‘Scandinavian cities’). The ``peripheral'' cities refer to a group of cities with very few connections in the advanced producer servicing network. We should note that these cities are ``peripheral'' in relative terms, as their (absolute) average number of producer firms increases from 22.79 in 2000 to 27.32 in 2010. Finally, each cluster analysis features a ‘miscellaneous’ cluster consisting of medium-ranked cities without clear hierarchical/regional affiliation.

Figure 2 shows the alluvial diagram summarizing the changes in the WCN between 2000 and 2010. The alluvial diagram immediately shows that in addition to stability at the top (the continued dominance of New York and London) and the bottom (a sizable group of peripheral cities), there have been substantial shifts in between: some cities or groups of cities switch clusters, while clusters emerge and dissolve over time. To facilitate the discussion of the empirical details of these changes, the diagram is replicated in further figures, each time highlighting different notable sets of cities, i.e. cities in Brazil/Russia/India/China (BRIC), the Gulf region, the Former Eastern Bloc, and the United States.

[Table 3 about here]

[Figure 2 about here]

BRIC. While BRIC cities are overall gaining in importance in the WCN (Wilson and Purushothaman, 2006), the alluvial diagram reveals different patterns at the national level (Figure 2). In the case of Chinese cities, Shanghai and Beijing emerge from a cluster of

[3] Obviously, these regional dimensions are far from neat. For example, in the 2000 data, Sydney is clustered together with US global cities, while Rotterdam is grouped with Commonwealth cities. In addition, we do not further prune the large group of peripheral cities, as that would generate a large number of small clusters and blur the interpretation of overall tendencies.

primary Asia-Pacific cities in 2000 to join Hong Kong as part of a cluster of global cities after NY-LON in 2010. This finding confirms Lai's (2012) reading of the emerging 'peer' interdependence between these three cities, consisting of a complex mix of competition and collaboration, in connecting China to the global economy via the WCN. The 'China stream' in the lower half of the diagram represents the trajectory of Guangzhou (Figure 3), which is also becoming more important over time, and leaves the group of peripheral cities to become part of a new regional cluster featuring cities around the Gulf of Tonkin.

Largely similar patterns of variegated growth can be found in India. In this case the two primary cities (Mumbai and New Delhi) join a cluster of major regional-global cities in 2010 from a much-lower ranked cluster of Asian cities in 2000, whereas other secondary Indian cities rise from the periphery and form a regional cluster of their own (Bangalore, Calcutta, and Chennai).

Leading cities from Russia (Moscow) and Brazil (Sao Paulo) also gain in prominence as they move from regional clusters of Former Eastern Bloc (Moscow) and Latin American cities (Sao Paulo) in 2000 to a cluster of major global cities in 2010.

Arab Gulf. In addition to the overall rise of BRIC cities, our analysis also highlights the rise of Arab Gulf cities (Figure 3). Within this region, Dubai has been the most remarkable example of the changing insertion of cities in the office networks of globalized service firms. In 2000 and 2004, respectively, it was still part of medium-ranked clusters dominated by Asian cities, but by 2010 its dominant resemblance is with well-established world cities such as Brussels and Madrid and with other emerging world cities such as Moscow and Sao Paulo (see above). Other Gulf cities also gain further prominence, but thereby exhibit a sizable coherence in their overall mix of firms, as these cities (Manama, Abu Dhabi and Riyadh) form a cluster of Arab Gulf cities housing similar levels of globalized firms as major cities in Eastern Europe and Scandinavia. In spite of the general 'rise' of major Arab Gulf cities in the WCN, Dubai clearly dominates other cities. This reflects Dubai's elites objective of building an 'instant world city', a node on transnational flows of capital, people and knowledge, through rhetoric (city marketing), form (architecture), and function ((air)ports) (Acuto, 2010; Bassens et al., 2010).

[Figure 3 about here]

Former Eastern Bloc cities. Collectively, cities from the Former Eastern Bloc (FEB, Fratesi, 2012) provide us with good examples for showing the breadth of information captured in our analytical framework. Figure 4 shows the extreme variegation amongst cities in FEB. In 2000, a number of key FEB cities already boasted moderate levels of involvement in the networks of globalized service firms, which can be thought of as key vectors of globalized capitalism that had started entering the region (Meyer and Pind, 1999). The situation was relatively clear-cut, with the major distinction between a cluster featuring the leading cities of the largest and economically most important countries (Moscow, Budapest, Warsaw, and Prague) and other FEB cities being part of the cluster of peripheral cities. In addition, there were some cities whose service mix resembled mostly that of secondary German cities (Bratislava, Dresden, and Leipzig).

A decade of change, in our analysis captured by major service firms entering and sometimes leaving FEB cities between 2000 and 2010, has resulted in a distinctive situation. Moscow has joined a cluster of major global cities (Brade and Rudolph, 2004), while a more inclusive set of primary FEB cities has emerged, suggesting that globalized service firms have continued opening offices in FEB, albeit now mainly in leading cities of countries that were no yet on the maps of these firms in 2000. Thus along Warsaw and Prague, in 2010 we now see also the likes of Kiev and Bucharest in the cluster of primary FEB cities. The resulting cluster does feature a smaller average number of firms/city than in 2000, but this above all the stagnation of former primary FEB cities (Budepest, Prague, and Warsaw's number of firms remain roughly the same between 2000 and 2010). In addition, a number of secondary/tertiary FEB cities also leave the large cluster of peripheral cities to join a miscellaneous group of cities (Dresden and Leipzig) and form a distinctive cluster (Sofia and Zagreb). Above all, however, the main pattern shown in Figure 4 is that despite myriad change and continuing hierarchical differentiation within FEB cities (i.e. Warsaw/Prague versus Bucharest/Kiev versus Sofia/Zagreb), there is enough correspondence amongst service mixes to continuously cluster cities from this erstwhile geopolitical region together:

from the vantage point of globalized service firms, FEB cities continue to resemble each other, and this despite far-reaching changes.

[Figure 4 about here]

United States cities. In contrast to the major fluctuations in the BRIC, the Arab Gulf and the FEB, cities in the US have remained stratified along similar lines with few if any change between 2000 and 2010 (Figure 5), although US clusters have become slightly less important over the past decade. In 2000 and 2010, there are four ‘bands’ of US cities: New York in its own cluster with London, a cluster of US global cities (Chicago, Los Angeles, and San Francisco, see Abu-Lughod, 1999 and Neal 2011), a cluster of primary US cities (e.g., Washington, D.C., Atlanta, Dallas), and a cluster of secondary US cities (e.g. Phoenix, Cleveland, Detroit). This corroborates the findings of Taylor and Lang (2005), in which it is argued that the USA appears to be operating as a distinctive market for producer services within the wider world market. Taylor and Lang (2005, 11) give two reasons for this: a ‘shadow effect' caused by many non-US service firms only locating in New York, and a ‘comfort effect' caused by many US service firms not wanting to leave their large ‘home market' for riskier foreign investments so that we see clusters of US cities in Figure 6. In 2004, however, the clusters of primary and secondary cities are not as clear-cut as non-US cities join in, resulting in lower average rankings for both clusters. The 2004 set of results is thus still largely consistent with the overall picture painted for the overall changes in 2000-2010, but it does also flag some of the limitations of our approach, which we will address in the next and final section.

[Figure 5 about here]

Latin American cities. Cities of larger states – both in size and in the size of their economy – (e.g., Mexico, Argentina, Brazil, Columbia, and Chile) are locate in the upper half of Figure 6, whereas capitals of smaller Latin American countries (e.g., Salvador, Ecuador, Costa Rica; Coe et al. 2007 p. 202) are clustered in the bottom half of the diagram. One notable change is the rapid fall of Caracas in the world city network, which coincides with the renationalisation of oil companies and other foreign investments in Venezuela after 2007 (McNew 2008).

[Figure 6 about here]

5. Conclusions and avenues for further research

In this paper, we combined categorical correlation, hierarchical clustering, and alluvial diagram to reveal the temporal evolution of the dominant hierarchical and regional patterns in the WCN. Our analysis confirms the continued interweaving of hierarchical and regional patterns in the WCN as measured by cities' similarities in the presence of globalized service firms, but equally highlights some of the key changes that have occurred between 2000 and 2010.

Hierarchical clustering is an exploratory data analysis technique, and alluvial diagrams are merely convenient visual aids. As such, our analysis suffers from some of the typical ails of exploratory research. First, hierarchical clustering produces 'crisp' results, making it difficult to identify cities that are 'close' to multiple clusters. The results for the US, for instance, are hampered by the fact that lower-ranked US cities equally show some resemblance with Commonwealth cities so that minor changes may result in a result that looks distinctively different (see the 2004 results). Future research may therefore look at more nuanced ways of defining group allegiance, with fuzzy clustering algorithms as obvious candidates (Hwang and Thill, 2009). Second, although we have tried to alleviate the well-known problems associated with comparing clustering results through using a dynamic method that considers both the shape of dendrogram and dyadic (dis)similarity to identify nested clusters, the results remain influenced by preselected thresholds. Therefore, natural objective functions seem to be another promising way forward to determine optimal levels at which the clustering tree is cut (Ahn et al., 2010). Third, in order to enhance visual clarity, we have purposely inserted vertical spacing between blocks, producing different total heights of columns for each year and causing shifts in blocks' absolute vertical positions. For example, New York and London stay atop for all three years, however their absolute vertical positions are lower for 2004, due to fewer clusters and consequently less vertical spacing for that year. However, the vertical spacing has been minimized and the formative interpretations are focused on major changes and merge/split of clusters.

Finally, we suggest that the data underlying our analysis represents a specific take on 'the global urban system': we have focused on the myriad patterns emerging from an analysis of office networks of globalized producer service firms. Following Hall (1999), Castells (2001) and Sassen (2001), this is justified by the importance of this economic sector in economic globalization through these firms' strategic uses of cities. Thus we can interpret our results more widely as changes in the basics structure of the contemporary world economy, but economic globalization is of course much more complex than this single context (Coe et al., 2004; Brown et al., 2010). Future analyses could therefore replicate the computational framework advanced here to analyze change from different conceptual and empirical vantage points (e.g. Fragkias and Seto, 2009).

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Table 1 Multi-year pedagogic datasets on APS firms' location strategies.

2000							2004							2010					
	EY	HA	MF	JD	BN			EY	HA	MF	JD	BN			EY	HA	MF	JD	BN
BK	0	3	4	0	0		BK	2	3	2	0	0		BK	2	4	2	0	0
BJ	0	2	3	0	2		BJ	2	3	0	2	2		BJ	3	3	3	3	2
HK	0	2	4	2	2		HK	3	3	3	3	2		HK	3	2	4	3	2
JK	0	2	3	0	0		JK	2	2	2	0	0		JK	3	1	3	0	0
TK	2	2	5	2	2		TK	3	5	5	4	2		TK	3	5	5	3	2

Codes for cities: BK = Bangkok; BJ = Beijing; HK = Hong Kong; JK = Jakarta; TK = Tokyo. Codes for firms: EY = Ernst and Young (accounting); HA = Hakuhodo (advertising); MF = Mizuho Financial (banking/finance); JD = Jones Day (law); BN = Bain (managerial consultancy). Codes for service values: 5 = global headquarters; 4 = regional headquarters; 3 = major offices; 2 = normal offices; 1 = minor offices; 0 = no office.

Table 2. Hierarchical clustering of the pedagogic dataset.

Cluster no.	2000	2004	2010
1	Hong Kong, Tokyo	Hong Kong, Tokyo	Beijing, Hong Kong, Tokyo
2	Bangkok, Beijing, Jakarta	Beijing	Bangkok, Jakarta
3		Bangkok, Jakarta	

Table 3 Rank of clusters

	2000				2004				2010			
rank	cluster	cities	firms	exemplar	cluster	cities	firms	exemplar	cluster	cities	firms	exemplar
1	NY-LON	2	90.00	New York, London	NY-LON	2	91.00	New York, London	NY-LON	2	88.50	New York, London
2	Pacific Asian global cities	3	83.33	Hong Kong, Singapore, Tokyo	Global cities	9	76.56	Hong Kong, Tokyo, Paris	Global cities I	6	81.33	Hong Kong, Tokyo, Paris
3	European global cities	7	68.29	Paris, Brussel, Frankfurt	Mainland China's global cities	3	72.00	Beijing, Shanghai	Global cities II	7	70.71	Brussel, Dubai, Sao Paulo
4	US global cities	5	65.60	Chicago, Los Angels, San Francisco	US global cities	3	62.33	Chicago, Los Angels, San Francisco	US global cities	3	68.67	Chicago, Los Angels, San Francisco
5	Primary Pacific Asian cities	6	56.17	Beijing, Shanghai, Seoul	Primary Latin American cities	5	60.40	Mexico City, Buenos Aires, Sao Paulo	Major regional global cities	14	57.36	Seoul, New Delhi, Sydney
6	Primary former Eastern Bloc cities	5	52.40	Moscow, Warsaw, Prague	Primary former Eastern Bloc cities	5	56.80	Moscow, Warsaw, Prague	Primary German cities	3	52.33	Dusseldorf, Hamburg, Munich
7	Primary Latin American cities	8	50.38	Mexico City, Buenos Aires, Sao Paulo	Primary German cities	5	56.80	Dusseldorf, Hamburg, Munich	Miscellaneous	9	51.33	Instanbul, Mexico City, Lisbon
8	Miscellaneous	6	45.00	Dallas, Rome, Melbourne	Primary Pacific Asian cities	6	53.50	Seoul, Bangkok, Jakarta	Primary US cities	7	51.29	Boston, Houston, Washington
9	Scandinavian cities	5	44.80	Copenhagen, Helsinki, Oslo	Miscellaneous	12	46.08	Athens, Bogota, Dubai	Primary former Eastern Bloc cities	9	45.44	Bucharest, Kiev, Warsaw
10	Primary German cities	4	44.50	Dusseldorf, Hamburg, Munich	Primary Indian cities	2	46.00	New Delhi, Mumbai	Arab Gulf cities	3	41.67	Abu Dhabi, Manama, Riyadh
11	Primary Asian	8	44.13	New Delhi, Instanbul, Dubai	Scandinavian & secondary South European cities	6	41.00	Copenhagen, Helsinki, Oslo	Scandinavian cities	5	40.60	Copenhagen, Helsinki, Oslo
12	Commonwealth cities	12	28.08	Adelaide, Montreal, Wellington	Primary US & Commonwealth cities	12	37.00	Adelaide, Boston, Montreal	Gulf of Tonkin cities	3	38.33	Guangzhou, Hanoi, Ho Chi Minh
13	Primary & secondary US cities	16	27.38	Boston, Cleveland, Houston	Secondary US & secondary European cities	24	25.25	Cleveland, Detroit, Glasgow	Canadian cities	3	34.00	Calgary, Montreal, Vancouver
14	Secondary German cities	6	25.33	Cologne, Dresden, Leipizig	Secondary German cities	6	23.17	Cologne, Dresden, Leipizig	Secondary Indian cities	3	34.00	Bangalore, Calcutta, Chennai
15	Secondary Pacific Asian cities	3	25.00	Guangzhou, Ho Chi Minh, Osaka	Peripheral cities	39	24.13	Beirut, Lagos, San Salvador	Secondary former Eastern Bloc cities	2	29.50	Sofia, Zagreb
16	Secondary European cities	9	22.56	Geneva, Glasgow, Lyon					Secondary US cities	12	29.08	Cleveland, Detroit, St. Louis
17	Peripheral cities	34	22.79	Beirut, Lagos, San Salvador					Secondary Commonwealth & Tertiary European	20	26.60	Adelaide, Glasgow, Rotterdam
18									Peripheral cities	28	27.32	Beirut, Lagos, San Salvador

Figure 1. An alluvial diagram of the pedagogic dataset (read stream represents Beijing).

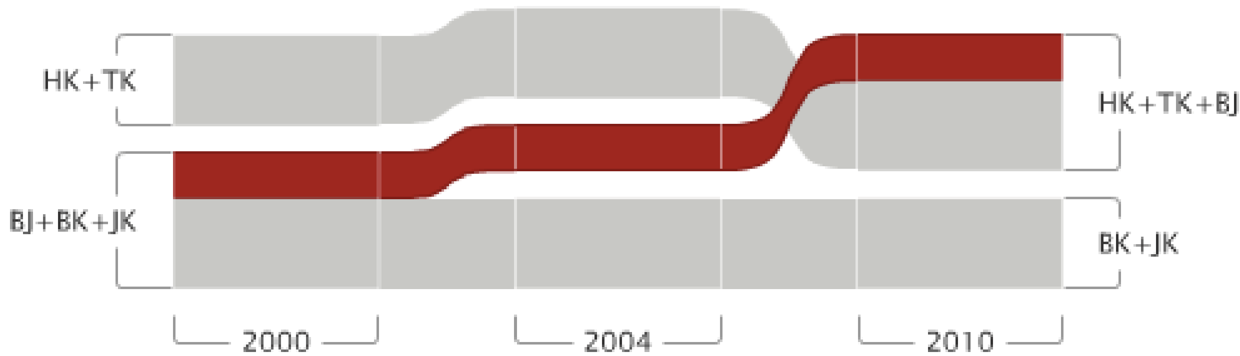
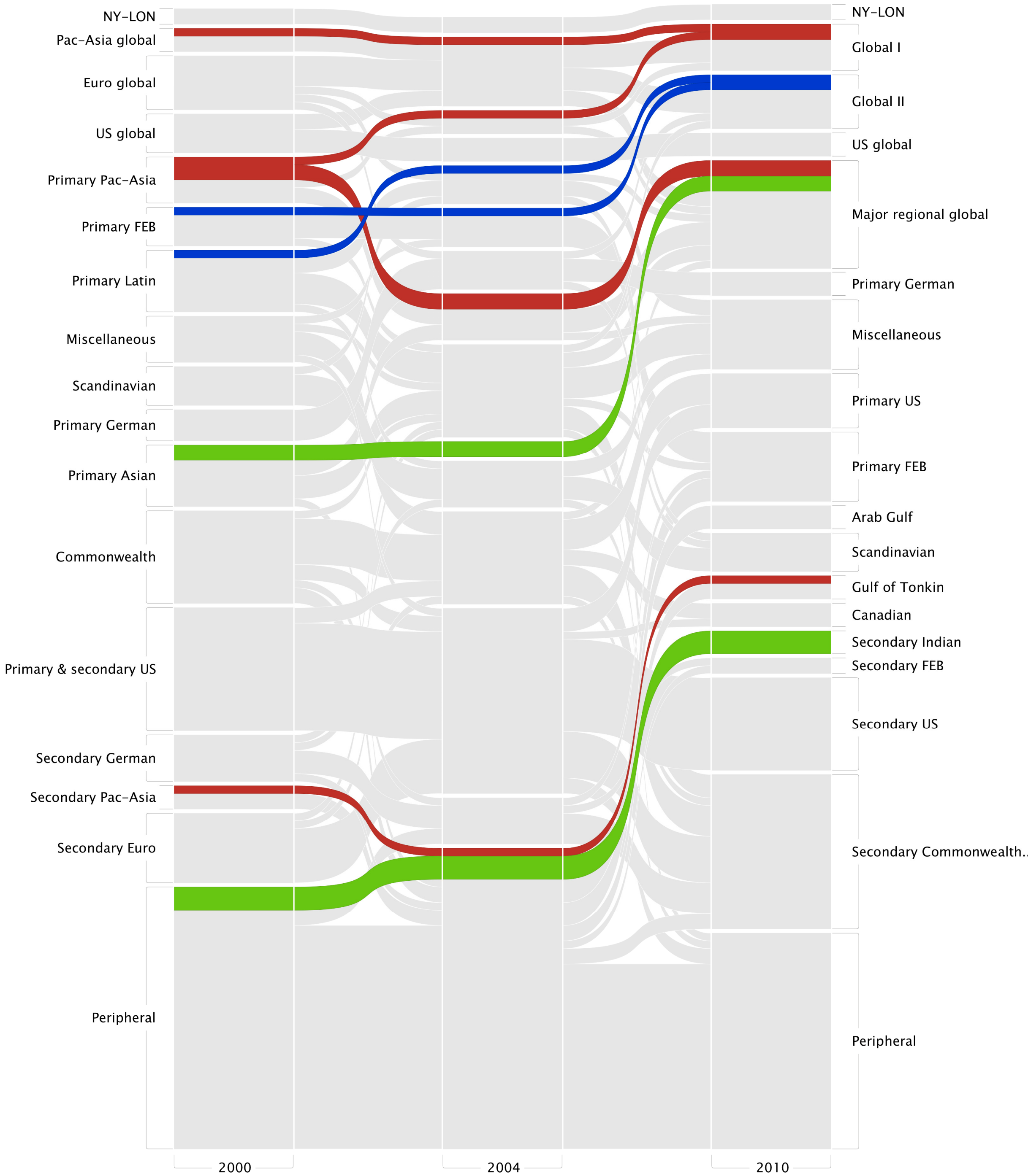
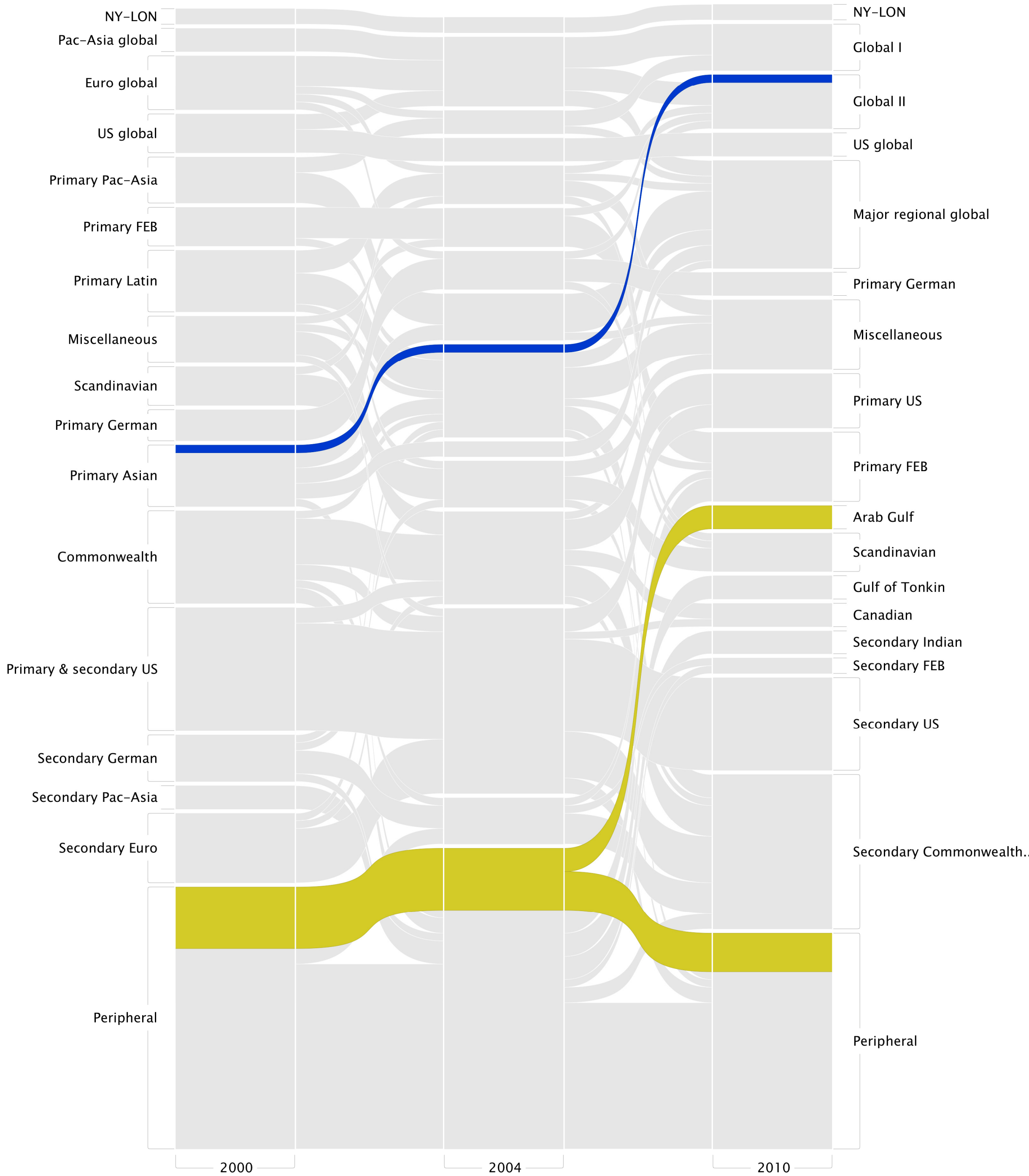


Figure 2. Rise of the BRIC cities



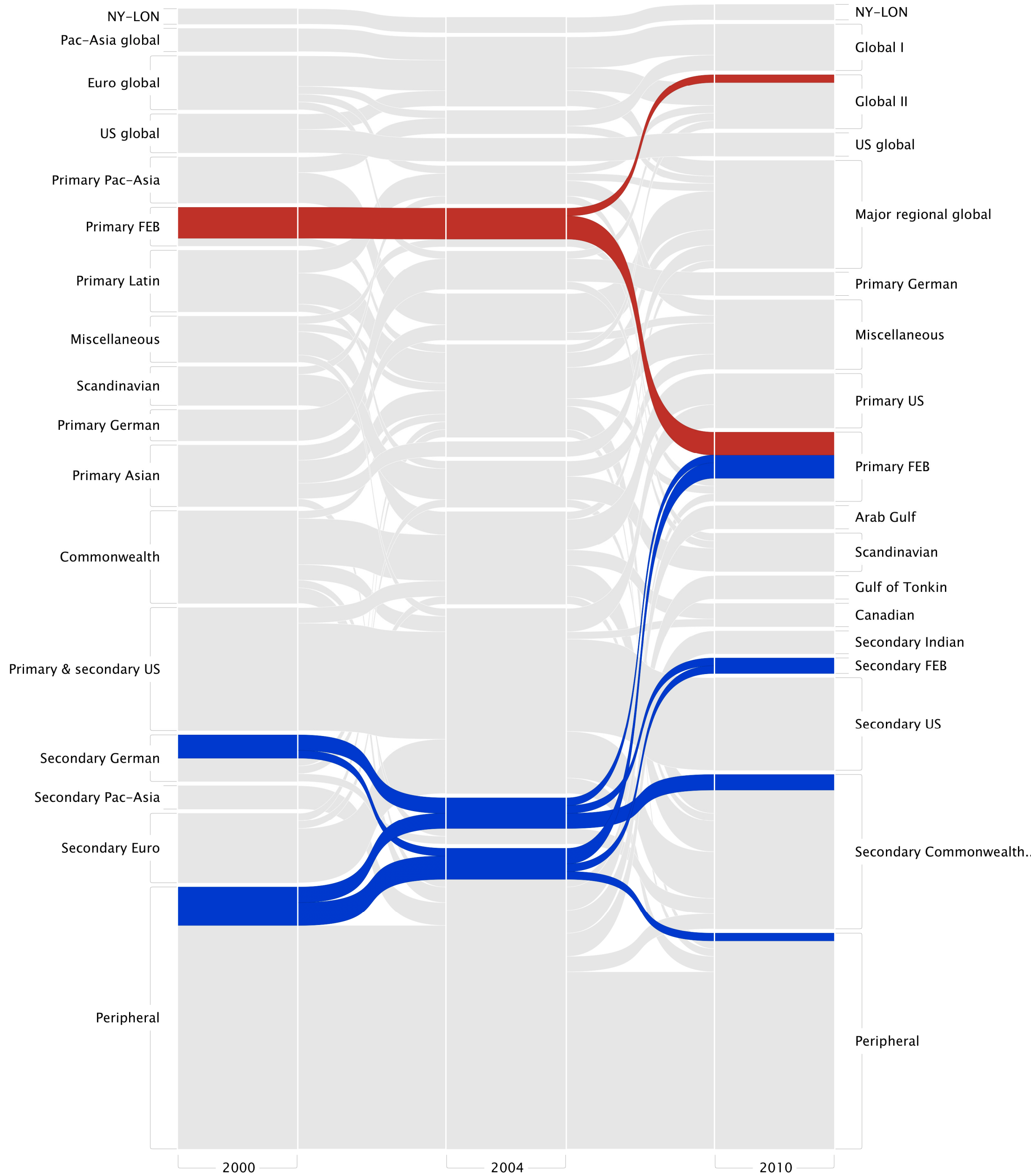
Red streamlines represent Chinese cities (Shanghai, Beijing, Guangzhou, Hong Kong and Taipei), green for Indian cities (Mumbai, New Delhi, Calcutta, Chennai, and Bangalore), and blue for leading Russian and Brazilian cities (Moscow and Sao Paulo)

Figure 3. Dubai's leading position among the Arab Gulf cities



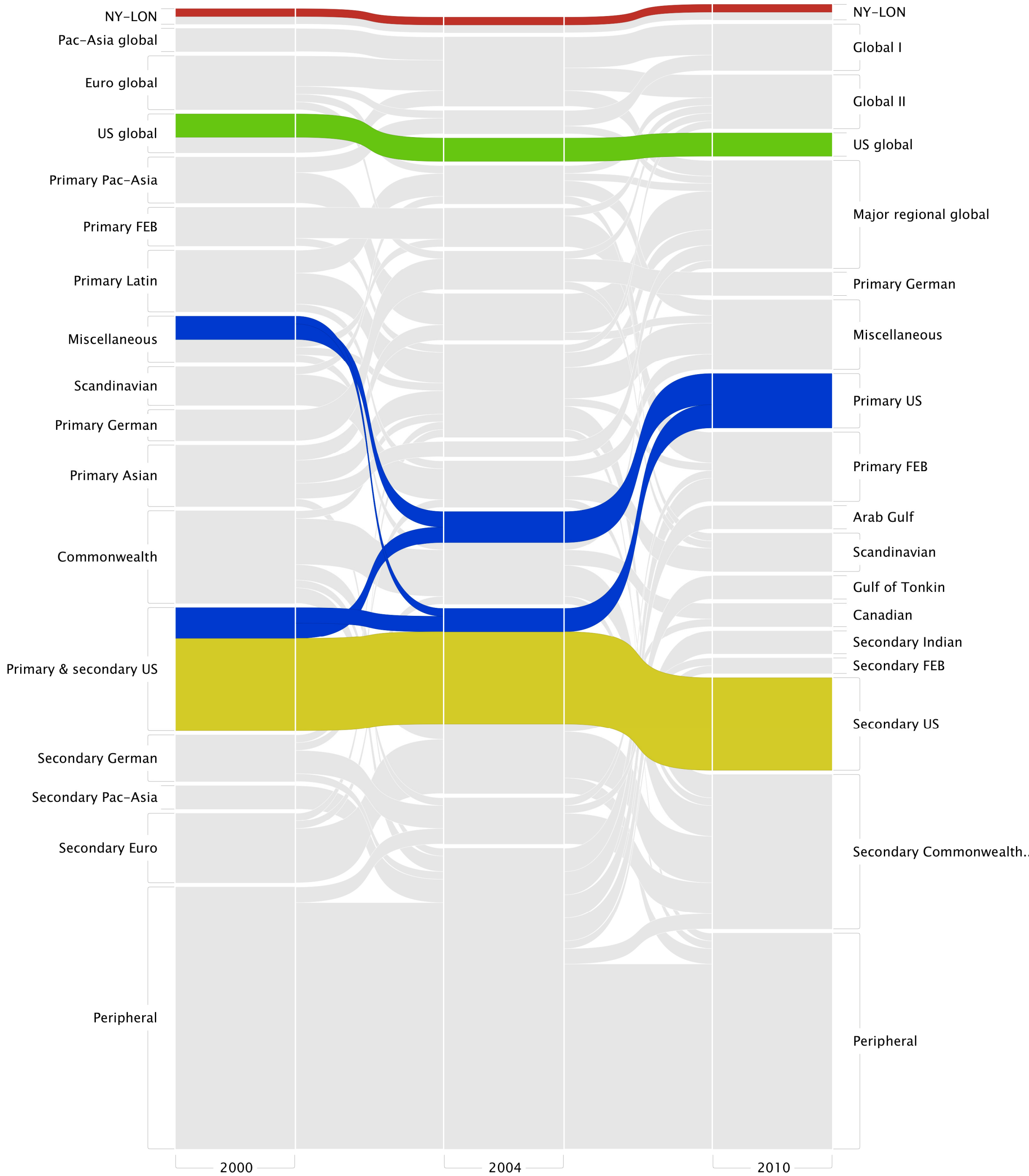
Blue streamline represents Dubai, and yellow for other Arab Gulf cities

Figure 4. The trajectories of Former Eastern Bloc (FEB) cities



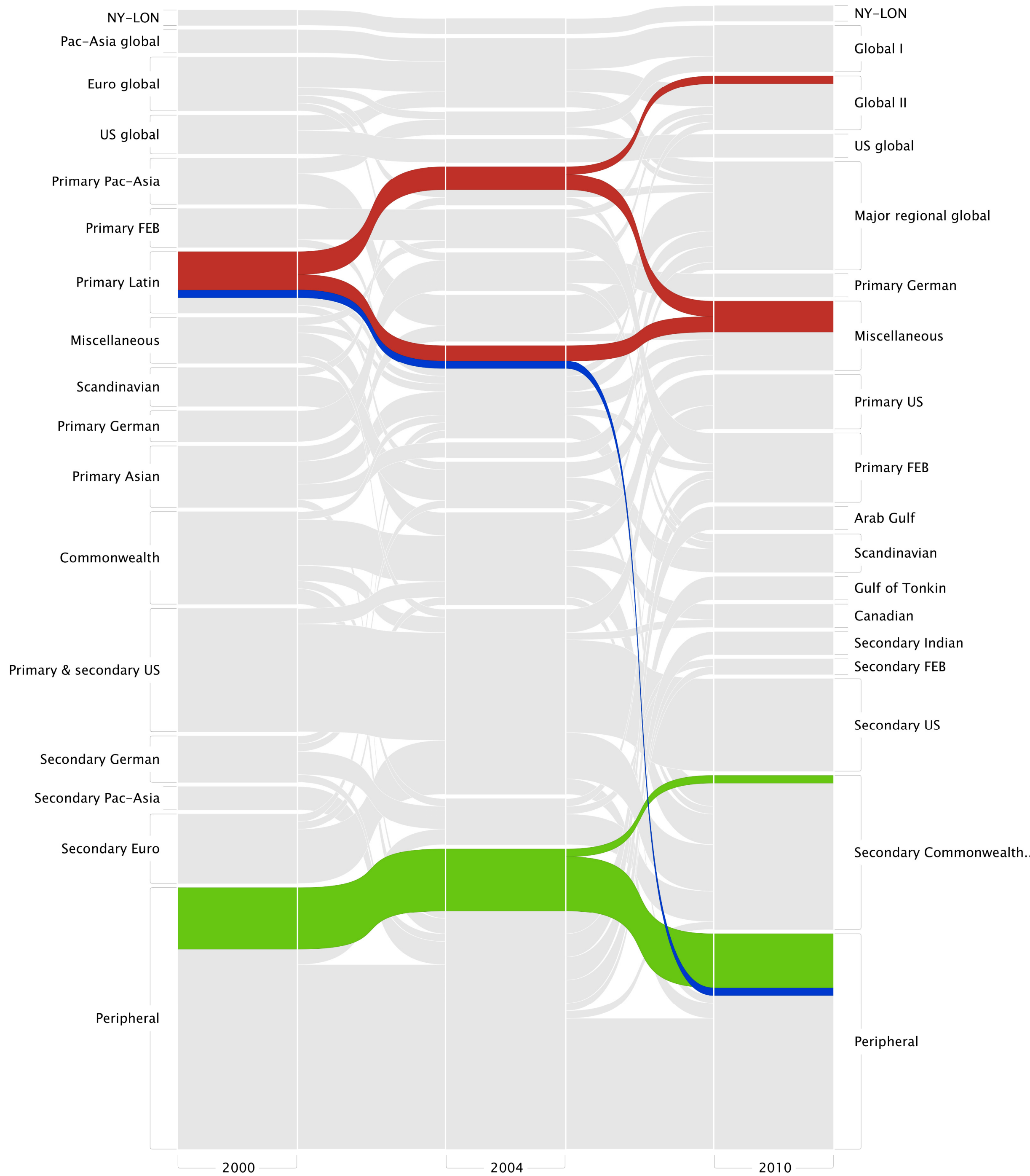
Red streamlines represent primary cities in former Eastern European communist countries (Moscow, Prague, Warsaw, and Budapest), and blue for secondary cities in the region (e.g., Bratislava, Bucharest, Kiev, Sofia, and Zagreb)

Figure 5. Stratification of the US cities



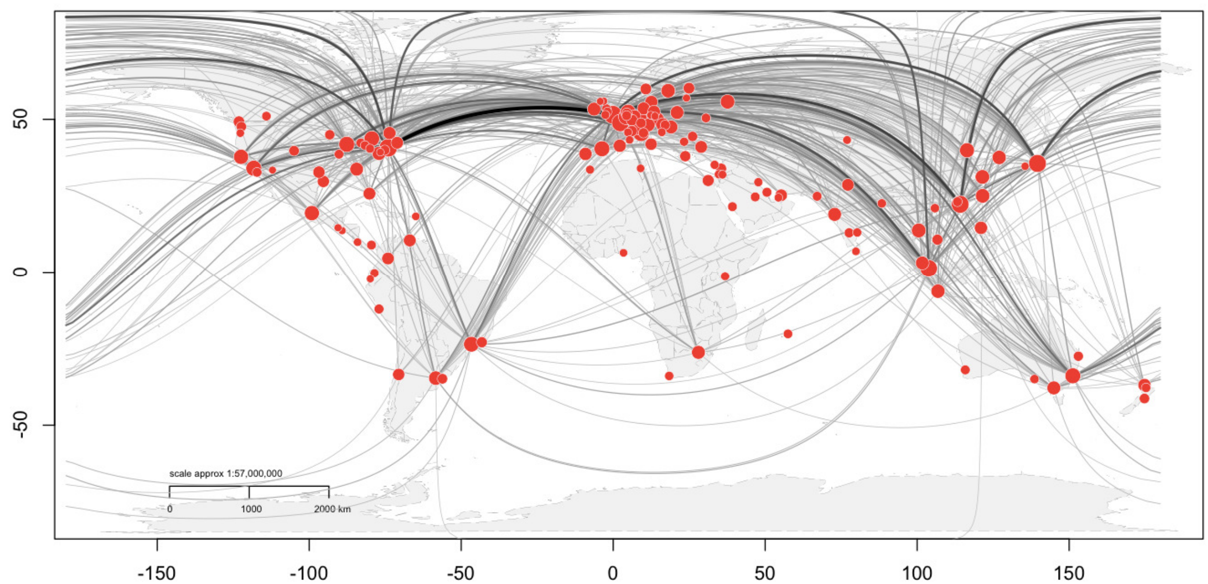
Red streamline represents New York, green for US global cities (Chicago, Los Angels, San Francisco), blue for primary US cities (Atlanta, Boston, Dallas, Houston, Miami, Philadelphia, and Washington), and yellow for other secondary US cities.

Figure 6. Latin American cities. Red streamline represents primary Latin American cities (e.g., Mexico City, Sao Paolo, and Buenos Aires), blue for Caracas (Venezuela), and green for secondary Latin American cities (e.g., Panama City, Quito, and San Salvador)

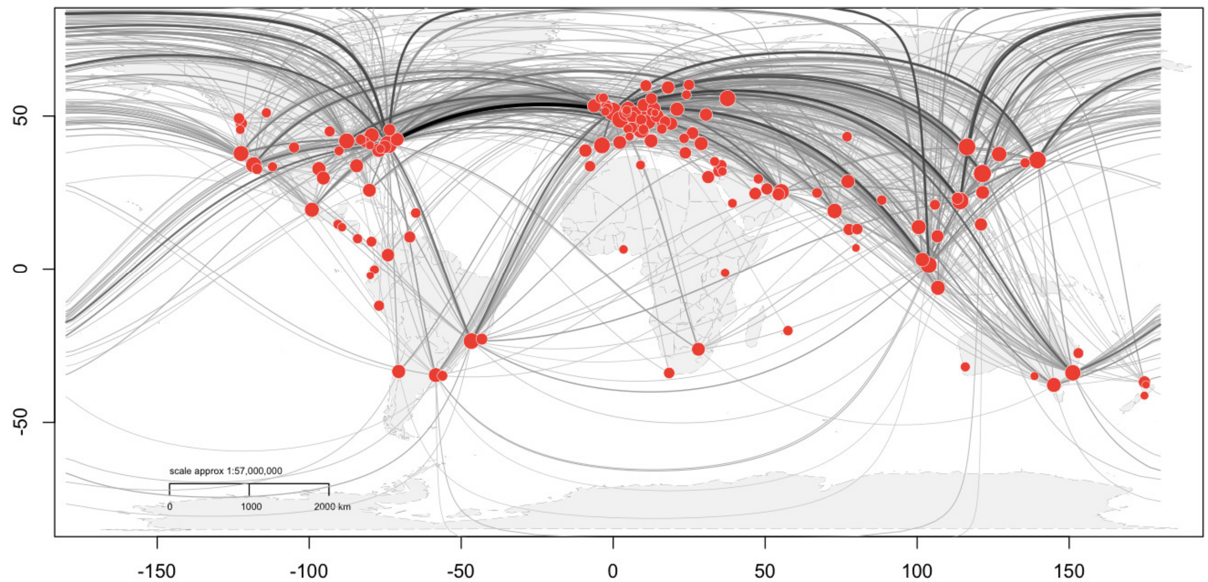


Appendix 1: Conventional map-based visualization of intercity networks. Each circle represents a city, and circle size corresponds to the number of firms in individual cities. Connections between cities are estimated using the Interlocking World City Network Model (Taylor 2001). Link width and colour (darkness) are proportional to the strength of estimated economic connections. A visual inspection of figure panels (1) and (2) would reveal some dynamics in the intercity networks, such as the rise of Shanghai and Beijing (enlarged circles and more connections); (2) The rise of Dubai (an enlarged circle with stronger connections to European cities); (3) the dominance of New York-London. Although correctly revealing the spatial distribution of connections, this conventional map-based visualization of networks is *inter alia* cluttered due to strong geographical and network clustering and less effective in revealing the ranks of individual cities as well as transnational city clusters (see figure panel (3)) in the global urban hierarchy. Therefore, we apply alluvial diagram and hierarchical clustering to supplement conventional intercity network maps and provide an alternative visualization of intercity corporate networks.

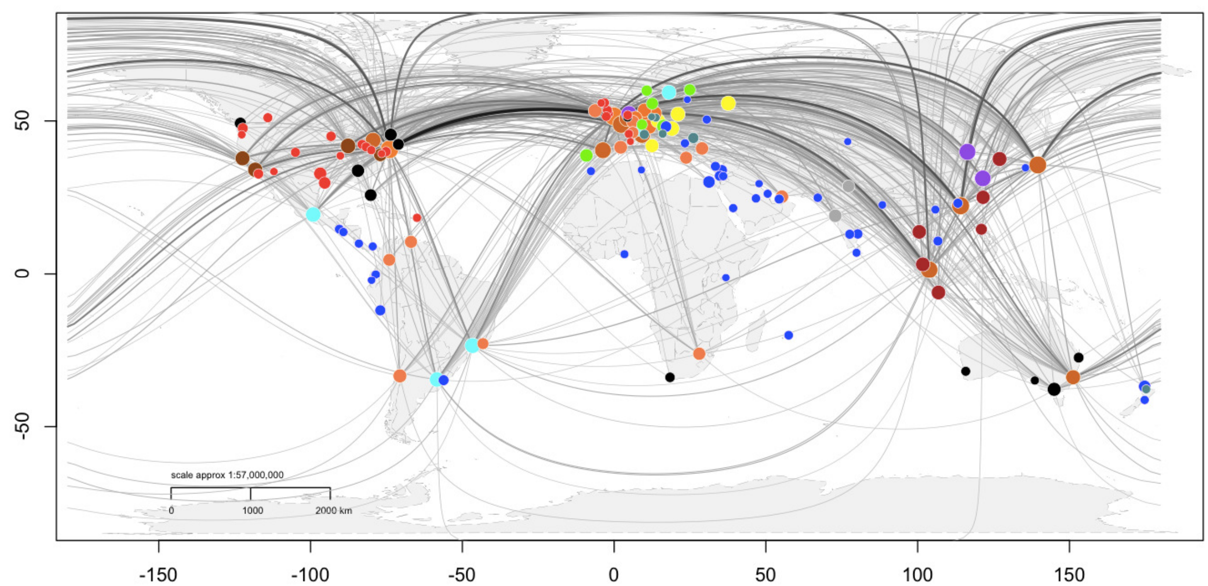
(1) The intercity corporate network 2000



(2) The intercity corporate network 2010



(3) Clustering of the intercity corporate network in 2004 (cities are labelled with different colours according to their cluster membership in Table 3.



Appendix 2
List of cities and firms

List of cities			
Abu Dhabi	Cleveland	Lima	Prague
Adelaide	Cologne	Lisbon	Quito
Almaty	Colombo	London	Riga
Amman	Copenhagen	Los Angeles	Rio De Janeiro
Amsterdam	Dusseldorf	Luxembourg	Riyadh
Antwerp	Dallas	Lyon	Rome
Athens	Denver	Madrid	Rotterdam
Atlanta	Detroit	Manama	San Diego
Auckland	Dresden	Manchester	San Francisco
Baltimore	Dubai	Manila	San Jose (Costa Rica)
Bangalore	Dublin	Marseille	San Salvador
Bangkok	Edinburgh	Melbourne	Santiago
Barcelona	Frankfurt	Mexico City	Sao Paulo
Beijing	Geneva	Miami	Seattle
Beirut	Glasgow	Milan	Seoul
Berlin	Guangzhou	Minneapolis	Shanghai
Birmingham (UK)	Guatemala City	Montevideo	Singapore
Bogota	Guayaquil	Montreal	Sofia
Boston	Hamburg	Moscow	St Louis
Bratislava	Hamilton	Mumbai	Stockholm
Brisbane	Hanoi	Munich	Stuttgart
Bristol	Helsinki	Nairobi	Sydney
Brussels	Ho Chi Minh City	New Delhi	Taipei
Bucharest	Hong Kong	New York	Tel Aviv
Budapest	Houston	Nicosia	Tokyo
Buenos Aires	Istanbul	Osaka	Toronto
Cairo	Jakarta	Oslo	Tunis
Calcutta	Jeddah	Panama City	Vancouver
Calgary	Johannesburg	Paris	Vienna
Cape Town	Karachi	Perth	Warsaw
Caracas	Kiev	Philadelphia	Washington
Casablanca	Kuala Lumpur	Phoenix	Wellington
Charlotte	Kuwait	Pittsburgh	Zagreb
Chennai	Lagos	Port Louis	Zurich
Chicago	Leipzig	Portland	

List of firms		
Sector	2000	2010
Accounting	AGN	Baker Tilly
	BDO	BDO
	Ernst & Young	Crowe Horwath
	Fiducial	Deloitte Touche
	Grant Thornton	Ernst & Young
	HLB	Geneva Group
	Horwath	Grant Thornton
	IGAF	HLB

	KPMG	KPMG
	Moore Stephens	Kreston
	Moores Rowland	Leading Edge Alliance
	MSI	Moore Stephens
	Nexia	Nexia
	PKF	PKF
	PricewaterhouseCoopers	Praxity
	RSM	PricewaterhouseCoopers
	Summit & Baker	RSM
Advertising	Asatsu DK	BBDO
	BBDO	DDB
	CMG	Dentsu
	Draft Worldwide	Draft FCB
	Euro RSCG	Euro RSCG
	FCB	Hakuhodo
	Hakuhodo	JWT
	Impiric	Kantar
	JWT	McCann Erickson
	McCann Erickson	OgilvyOne
	O&M	Publicis
	Saatchi & Saatchi	TBWA
	TMP	Y & R
Banking and finance	ABN Amro	Banco Santander
	Barclays	Bank of America
	BHV	Bank of China
	BLG	BBVA-Banco Bilbao Vizcaya
	BNP Paribas	BNP Paribas
	BTM	CCB-China Construction
	Citibank	Commonwealth
	Commerzbank	Crédit Agricole
	CSFB	Deutsche
	Deutsche	Generali
	Dresdner	Goldman Sachs
	Fuji	HSBC
	HSBC	ICBC
	ING	Intesa Sanpaolo
	Rabobank	JPMorgan Chase
	Sanwa	Mitsubishi UFJ
	Sumitomo	Sumitomo Mitsui
	UBS	UniCredit
	West LB	Wells Fargo
Insurance	Allianz	ACE
	CGNU	Aflac
	Chubb	AXA Group
	Fortis	Chubb
	Liberty	MetLife
	Lloyds	Munich Re
	Prudential	Société Générale Group
	Royal & Sun	Tokio Marine Holdings
	Skandia	Travelers Cos
	Winterthur	Zurich Financial Services
Law	Allen & Overy	Allen & Overy
	Baker & McKenzie	Baker & McKenzie
	Cameron McKenna	Clifford Chance
	Clifford Chance	DLA Piper
	Coudert	FBD
	Dorsey & Whitney	Greenberg Traurig
	FBD	Jones Day

	Jones Day	Kirkland & Ellis
	Latham & Watkins	Latham & Watkins
	Linklaters	Linklaters
	Lovells	Mayer Brown
	Morgan Lewis	Morgan, Lewis & Bockius
	Morrison & Foerster	Sidley & Austin
	Sidley & Austin	Skadden, Arps, Slate, Meagher & Flom
	Skadden	Weil, Gotshal & Manges
	White & Case	White & Case
Consulting	A.T. Kearney	A.T. Kearney
	Andersen Consulting	Accenture
	Bain	Alix Partners
	Booze A&M	Alvarez & Marsal
	Boston	Bain
	Compass	Booz
	CSC	Boston
	Deloitte	FTI Consulting
	Gemini	IBM
	Hewitt	L.E.K. Consulting
	IBM	McKinsey
	Logica	Mercer
	McKinsey	Monitor
	Mercer	NERA Economic Consulting
	Sema	Oliver Wyman
	Towers Perrin	Parthenon
	Watson Wyatt	Towers Watson