Forecasting the World City Network

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1. Introduction

An immense literature has developed around measuring and describing urban systems through the lens of city networks (Neal, 2013). Analyses in this literature range from the formation of megaregions consisting of proximately located and densely interconnected cities (e.g. Kloosterman and Musterd, 2001; Harrison and Hoyler, 2015; Liu et al., 2016; Li and Phelps, 2017, 2018), to the intensification of world-regional transportation networks between major cities (e.g. Cheng et al., 2015; Dai et al., 2018), to the emergence of global corporate networks anchored in the world's leading metropolitan areas (e.g. Rozenblat, 2010; Martinus et al., 2015; Wei & Liao, 2013). Irrespective of the functional and scalar focus of the analysis, this research literature is important because cities' centralities in all sorts of networks are increasingly shown to have significant impact on their economic and functional development. Since Capello (2000) posited the idea of urban network externalities – broadly conceived as the impact of city 'networking' on city 'performance' – this impact has been identified across contexts. For example, Bel and Fageda (2008) find that centrality in air transport networks has a sizable influence on the location of headquarters of global corporations, while Meijers et al. (2016) show that even though size remains the most significant determinant for most types of economic functions in European cities, network connectivity further enhances the presence of such functions.

Taken together, this body of research has given us an increasingly robust understanding of how city networks *were* organized and enabled us to explore how urban economies *were* impacted by city networks (cf. Kourtit et al., 2017). However, we still lack a clear understanding of how urban economies *will be* impacted by network formation because the existing literature implicitly takes the shape of post hoc analyses of how networks evolved and how and why this mattered. Although clearly very relevant, this does not shed light on how city networks *will* be organized and how vibrant (or not) certain cities *will* be in the future. In this paper, we aim to help address this gap by examining the feasibility of forecasting city networks.

To this end, we will focus on the specific case of the world city network, defined in Taylor and Derudder (2015) as the aggregation of the myriad flows within the office networks of advanced producer services firms. Our forecasting analyses build on a model proposed by Neal, Derudder, and Taylor (2019) for predicting these firms' office locations. Specifically, we seek to answer two research questions. First, drawing on two decades of Globalization and World Cities (GaWC) data about firm office locations, we ask: *What is the correct temporal lag for a world city network forecast*? Second, we generate a forecast of the world city network based on firm office locations in 2018, using it to ask: *Which cities are likely to maintain, gain, or lose centrality in the world city network in the future*?

The remainder of the paper is organized in four sections. In the first section, we introduce the specific conception of the world city network adopted here, Taylor's (2001) interlocking world city network model, and briefly review the existing literature on the longitudinal and dynamic features of this network. In the second section, we describe our data on the locations of advanced producer services firms from 2000 – 2018 and the forecasting model we apply to make predictions about their future locations. Using these data and this model, in the third section we report the accuracy of our forecasts at different temporal lags, and identify the cities our most recent forecast suggests will gain or lose centrality in the world city network. Finally, we conclude with a discussion of the limitations of these forecasts, future directions for the further development of these techniques, and the implications of forecasting the world city network for both the broader scholarly literature and urban economic development efforts.

2. Background

2.1. The interlocking world city network model

We begin by outlining the basic parameters of the interlocking network model (INM) as applied in world city network (WCN) research. Although the INM can in principle be cast as a generic approach to the study of city networks (Taylor, Hoyler, & Verbruggen, 2010; Taylor, 2019), its application in WCN analysis as put forward in Taylor & Derudder (2015) has arguably been most prominent. In this case, globalized advanced producer services firms – firms providing knowledge-based (expert/profession/creative) services to other corporations to facilitate their business activities – are envisaged as producers of connections between the world's major cities.

In contrast to direct measures of inter-city connectivity such as the ones that can be gleaned from airline networks (e.g. Smith and Timberlake, 2001; Neal, 2014a; Zhang et al., 2019; Zheng et al., in press), the INM produces indirect measures. The INM's input data are location data – the (importance of the) presence of producer services firms across cities – that are mathematically transformed into a proxy indicator of inter-city connections (Derudder, 2020; Neal, 2020). In the literature, there are different mathematical transformations specifying how location data can be used to measure interactions between these locations, most of which have been developed by drawing on analogues developed in the social network analysis literature (Neal, 2014b, 2017). Here we adopt the INM projection function not only because it has been the most longstanding approach in WCN analysis, but also because of the clearly defined assumptions in the specification of inter-city connectivity based on producer services firms' location data.

In other words, the data used in the INM are derived from information on the location strategies of globalized producer services firms across world cities (Taylor, 2001). To facilitate combining and comparing different forms and types of locational information, it is standardized into a service value V_{ij} ranging from 0 to 5 and measuring the importance of the presence of firm *j* in city *i*. These values can be arrayed as a service value matrix **V**. Although this matrix can be directly analyzed using standard multivariate analyses (e.g. Taylor et al., 2013), the INM transforms it into an intercity network **N** that views the offices of a firm across cities as commercial assets that are important because of the *flows* of information, knowledge, instruction, ideas, innovations, personnel, etc. they generate between cities. The transformation of **V** into **N** is achieved via bipartite projection:

$$\mathbf{N} = \mathbf{V} \times \mathbf{V}' \tag{1}$$

where **V′** indicates the transpose of **V**. This transformation, which allows researchers to measure inter-city connections based on firms' location data, comes with a set of assumptions, the most basic ones being that (1) the shared presence of a firm in a pair of cities opens up the potential for inter-city interaction with (2) the level of potential interaction depending on the importance, size, and operational capabilities associated with the firm's presence in those cities. A city's overall connectivity in this network – termed 'global network connectivity' GNC – can then simply be calculated by summing the strength of each city's links:

$$\mathrm{GNC} = \mathbf{N} \times \mathbf{1} \tag{2}$$

where **1** is a column vector of ones. GNC measures are equivalent to what in social network analysis (SNA) would be called measures of weighted degree. They are hard to interpret on their own terms as they depend on the values in **V** (i.e. the number and size of firms and cities in the data). To facilitate comparison between analyses of different data, GNC measures are therefore commonly normalized as proportions of the GNC of the most central city to provide a common range from 1 (for the most central city) to 0.

This precise specification guides the actual data collection for research drawing on the INM: data are required on the (importance of the) presences of major producer services firms across major world cities. A number of these data gatherings have been carried under the umbrella of the Globalization and World Cities (GaWC) research network, and here we briefly describe the basic tenets of the latest exercise in data collection for 2018 (see figure 1, and Taylor and Derudder). The selection of firms is based on rankings of leading firms in different producer services sectors (i.e. financial services firms, management consultancy firms, advertising firms, law firms, and accountancy firms). Firms are selected based on sectorial rankings for each sector: 175 firms across 5 sectors in 2018. The selection of cities, in turn, is based on a number of overlapping criteria, including size, capital city function, and overall economic prominence: 707 cities in 2018. A putative global presence – no matter how uneven it is in practice – has become an integral part of the leading firms' public marketing and recruitment policies (e.g. Beaverstock et al., 2010). Hence among producer service firms, locational strategy is perforce quite transparent. The corporate websites of these firms therefore customarily showcase the geographical range of the services on offer. Advantage is taken of this geographical transparency for information gathering on the location strategies of the 175 firms across the 707 cities based on corporate websites. For each of the firms, two types of information are gathered to gauge their presence across cities. First, information about the size of a firm's presence in a city is obtained, ranging from the number of offices the firm has in a city for accountancy/financial services firms to the areas of expertise for law firms. Second, the extra-locational functions of a firm's office (e.g. headquarter functions) in a city are recorded. The end result is that for each of the firms, information is available to create a standardized service value V_{ij} in each of the cities. This standardization involves assigning ranging from 0 to 5 based on the above-mentioned information. The city housing a firm's headquarters is scored 5, a city with no office of that firm is scored 0. An 'ordinary' or 'typical' office of the firm results in a city scoring 2. With something missing (e.g. no partners in a law office), the score is reduced to 1. Particularly large offices are scored 3 and those with important extra-territorial functions scored 4. The end-result is a 175x707 matrix **V** that can be used as the input for the INM. Here, our main focus will be on the opportunities engendered by having different such snapshots of the WCN for the analysis of its dynamics from 2000 onwards. These data collections were conducted along similar lines at irregular intervals, the only change being the incremental scope of included cities and firms. Given that the same logic and the same sources of information are used, this generates a unique source of information for carrying out longitudinal research.

The relevance of this approach to data gathering and subsequent data standardization is of course largely dependent on the quality of the information available on corporate websites. But the key issue in terms of data quality is the subjectivity inherent in the process of the data creation: the resulting data do not have the key property of inter-subjectivity, in that two people using the same information may not always decide on the same boundaries for the service values. However, the data gathering approach has been designed to counter possible concerns arising from this lack of inter-subjectivity. First, the means of scoring has been designed to be as simple as possible, pivoting on '2 as normal' and with decision making restricted to a limited set of boundaries. Second, the exercise is carried out over a large number of firms so that particular differences will likely be ironed out in the aggregate analyses that the data are designed for. And third, for each firm there is metadata – with detailed information on boundaries – that is reviewed by a coordinator for consistency.

2.2. Dynamics in the world city network

In addition to the literature that takes an intensive, qualitative and case study-based approach to understanding world cities' changing stature (e.g. Abu-Lughod, 1999; Wu and Ma, 2006), there is also a literature that takes an extensive, quantitative and systematic approach to grasping this change. Much of the latter research on dynamics in the WCN is *descriptive*. For example, echoing the earlier work by Smith and Timberlake (2001) on shifting patterns in the global urban hierarchy as visible in cities' changing centralities in airline networks, Taylor and Aranya (2008), Derudder et al. (2010), and Liu et al. (2014) have provided detailed accounts of the evolving position of cities in INM specifications of the WCN. Drawing on standardized versions of data gatherings along the lines set out in the previous section, this research commonly reveals significant connectivity gains for a small set of cities such as Dubai, Shanghai, Beijing, and Moscow in the face of stability as visible in the continued dominance of New York and London (Wojcík, 2013).

The quantitative literature that tries to *explain* observed WCN dynamics is more fragmented, and draws on a range of different statistical and network-analytical tools to provide post-hoc interpretations of the major drivers of the observed changes. Pereira and Derudder (2010), for example, use connectivity change as the dependent variable in a linear regression model, and find that large cities with extensive airports and located in countries with extensive international trade registered the most significant connectivity gains between 2000 and 2004.

This analytical connection between WCN dynamics on the one hand and economic performance of host countries and airline connectivity on the other hand is confirmed in other analyses of the global urban system (e.g. Ma and Timberlake, 2013; Bel and Fageda, 2008), and has therefore unsurprisingly been adopted as the starting point in other explanatory research. For example, Liu et al. (2013) analyse the co-evolution of the WCN and global air passenger networks between 2000 and 2010/2011. Drawing on a stochastic actor-based modelling framework, they identify a combination of (1) exogenous effects, such as the impact of economic development and regionality; (2) endogenous micro-level effects producing macro-level patterns, such as preferential attachment processes; and (3) mutual interdependence in the growth of both networks. The same group of authors also experimented with exponential random graph modelling framework and suggest that observed WCN patterns emerge out of exogenous city characteristics (e.g., GDP and population) and endogenous local network structures (e.g., 'star' network structures; Liu et al., 2015).

These qualitative and quantitative literatures, as well as recent scholarship combining these approaches (e.g. Li & Phelps, 2019), enhances our understanding of how the WCN has evolved and some of the main driving forces behind this evolution. However, these post hoc analyses have not been explicitly used to prospectively predict (i.e. forecast) how the WCN will evolve. In the next section, we describe a forecasting model that allows making such predictions.

3. Methods

3.1. Standardizing firm location data across data gatherings

The data gatherings underlying our analysis are described in section 2.1, so here we focus on how these data gatherings were standardized so that comparisons and forecasts become possible.

The specific conception of the WCN we are concerned with is derived from the locations of offices of producer services firms, which is therefore the raw data from which we make forecasts and verify their accuracy. GaWC began collecting these data in 2000, when they compiled the sizes of offices of 100 advanced producer service firms in each of 315 cities around the world (Taylor, Catalano, & Walker, 2002). The data we use in this paper draws on this and subsequent data collections along similar lines at irregular intervals of 2 to 6 years, incrementally increasing the scope of included cities and firms. This has generated 6 cross-sectional datasets on firm location in the form of service value matrices. To facilitate these data's use for verifying the accuracy of forecasts, we focus only on those cities and firms that appear in at least two datasets. Additionally, although office sizes were originally recorded on a 0-5 scale, we found that that there were very few minor offices assigned a value of 1 and, in addition, it was often difficult to distinguish these from typical offices assigned a value of 2. Therefore, for all years we recoded these values on a simpler 0-4 scale where 4 represents the office designated as the firm's global headquarters, 3 represents an office designated as a regional headquarters, 2 represents an office that is larger than average but not designated as a regional headquarters, 1 represents all other offices, and 0 indicates that the firm does not maintain an office of any size.

3.2. Forecasting firm locations

To forecast firm locations we use a model developed by Neal, Derudder, and Taylor (2019), which is itself an adaptation of the stochastic degree sequence model (SDSM; Neal 2014, 2017; van Meeteren, Neal, & Derudder 2016). Details of the forecasting model are provided in these papers, so here we sketch the basic conceptual and computational steps (see figure 1).

While many different factors may influence whether a firm chooses to locate, remain, grow, or expand a location in a given city, this model adopts a stylized view in which these can be reduced to two categories: firm factors and location factors. Firm factors include any factors that influence when or the extent to which a firm will expand or contract its office network, such as its size, current growth rate, demand for its product, and its management's leadership style. Collectively, these firm factors give each firm some capacity to expand. Location factors include any factors that influence a city's ability to attract or retain firms, such as a strong labor pool, the offer of tax incentives, and accessibility via transport links. Collectively, these location factors give each city some capacity to attract firms. Under this highly stylized view, a firm's optimal office size in a given city is a joint function of the firm's capacity for expansion and the location's capacity for attraction. Accordingly, a firm with significant capacity to expand is expected to operate its largest offices in the cities with the most significant capacity to attract. Conversely, a firm with limited expansion capacity is expected to operate the smallest offices, or more likely no office at all, in cities with the least capacity to attract.

Firm and location capacities are unobserved, but current office locations provide an approximation. Specifically, the total number of each size office currently operated by a given firm gives an approximation of its capacity; high capacity firms will have many offices, including several regional headquarters offices (i.e. size = 3)[1], while low capacity firms will have fewer and less important offices (i.e. size = 1). Likewise, the total number of each size office currently located in a given city gives an approximation of its capacity; high capacity cities will be the location of many offices, including several global headquarters (i.e. size = 4). The model then involves fitting an ordinal logistic regression in which the size of a particular firm's office

[1] Firms generally have exactly one global headquarters (i.e. size = 4), so counting the number of a firm's size 4 offices is not informative for approximating its capacity.

in a particular city is predicted as a function of the firm's capacity, the city's capacity, and their interaction. From the fitted model, probabilities are derived that capture the likelihood of a particular firm operating each possible size office in a particular city *if the firm is seeking to optimize its office network given firm and location capacities*, which we assume all firms are. Finally, by comparing these probabilities to the firm's current office size in a city, a forecast can be made about whether the firm will maintain its current office because it is already optimal, expand its current office because a larger office would be more optimal, or contract its current office because a smaller office would be more optimal.

3.3. Evaluating forecasts temporal lags

Neal, Derudder, and Taylor (2019) found that forecasts of firm locations made using this model from 2010 firm locations were accurate in 86.1% of cases by 2016 (Cohen's $\kappa = 0.407$), that is with a 6 year temporal lag. Although 86% accuracy is already quite high, it is unknown whether 6 years is the appropriate temporal lag for this forecasting model; the model's forecasts may be more accurate over a shorter or longer time period. To investigate this, we use the data described above to both make and verify forecasts over different temporal lags (see Table 1). For example, forecasts based on firm locations in 2000 can be verified for accuracy by comparing them with observed firm locations in 2004 (4 year lag), in 2010 (10 year lag), in 2013 (13 year lag), in 2016 (16 year lag), and in 2018 (18 year lag). This table also highlights that different opportunities for forecast verification depend on the extent to which cities and firms appear in both years. For example, while forecasts based on firm locations in 2000 are made using all 315 cities and 100 firms in these data, only forecasts for 315 cities and 89 firms could be verified in 2004, and only those for 313 cities and 44 firms could be verified in 2018. In each case, we use Cohen's κ to measure the forecast's accuracy. This index ranges from 0 when the forecast is no more accurate than random guessing, to 1 when the forecast is perfectly accurate. We use κ rather than the raw percentage of accurate forecasts because the latter is inflated by the very large number of trivially accurate forecasts that if a firm is not located in a city now, it will not be located there in the future.

3.4. Forecasting the world city network

Forecasts generated using Neal, Derudder, and Taylor's (2019) model are not perfect, but involve some errors. By using forecasts that can be subsequently verified, we estimate the frequency of specific types of error. For example, we identify the frequency with which this model incorrectly forecasts that a firm will expand its location in a city when, in reality, the firm contracted its location in that city. When making a forecast, we can use these estimated error rates to construct not a single forecast, but a set of plausible forecasts that capture this uncertainty. In each forecast and for each type of error, we select a random set of firm location forecasts, and change them. For example, if we know that on average 10% of the time the model forecasts an expansion, a contraction actually occurs, then we select a random 10% of cases the model forecasts an expansion, and change this forecast to a contraction. This process yields a new forecast that reflects one way that the errors in the original forecast might be corrected.

To forecast the world city network, we first apply the Neal, Derudder, and Taylor (2019) model to the 2018 GaWC data to generate a preliminary forecast (**F**) of 122 firms' future office sizes in each of 532 cities. Second, we use the process outlined above to randomly select and correct potentially erroneous forecast firm office sizes, thereby creating an updated plausible forecast (**F***). Third, we apply the interlocking world city network model to **F***, deriving a forecast world city network (Taylor, 2001). Fourth, we measure each city's centrality using its normalized GNC. Fifth, we repeat these steps 10,000 times, thereby creating a distribution of forecast centralities for each city that reflect the uncertainty of the forecasting model. Finally, we compare a city's observed centrality in 2018 to this distribution to forecast whether it is expected to increase, decrease, or maintain its world city network centrality.

4. Results

4.1 Temporal lags and forecast accuracy

For each set of firm office location forecasts we made, table 1 shows its accuracy (expressed as Cohen's κ) over different temporal lags. For example, a forecast made in 2004 more accurately predicted the size and location of firms' offices in the long term, 12 (in 2016, κ = 0.360) and 14 (in 2018, κ = 0.356) years later, than in the short term, 6 (in 2010, κ = 0.309) or 9 (in 2013, κ = 0.313) years later.

Figure 2 plots the lag and accuracy values from table 1, and thus more clearly illustrates their relationship. As the solid black regression line and black regression equation show, there is no relationship between forecast accuracy and temporal lag when all forecast windows are considered. However, this masks a potential interaction with the presence of a systemic shock during the forecast window. The dashed red regression line and red regression equation show a strong relationship between forecast accuracy and temporal lag for forecast windows that do not include the global financial crisis in 2008, while those in blue show a similarly strong but different relationship for forecast windows that do include the global financial crisis in 2008. In both cases, the forecast is more accurate over longer temporal lags, however, forecast accuracy is on average lower and improves slower when the forecast window included a systemic economic shock such as the global financial crisis.

4.2 Centrality winners and losers

Table 2 reports the predicted and actual firm office size changes, pooled across all forecast windows shown in table 1 and figure 2. These values provide an estimate of the model's average error rate for specific forecasts. For example, although 38.5% of the model's forecasts of office contraction are accurate, 55.4% are errors because the office actually maintained its size, and 6.1% are errors because the office actually expanded. When generating a forecast of the 2018 world city network and world cities' centralities, we use these error rates to capture the degree of uncertainty in the forecast.

Figure 3 compares each city's observed centrality in 2018 to its average forecast centrality over all 10,000 forecasts. We find that the ranking of world cities by centrality is not likely to change significantly in the future (spearman $\rho = 0.997$). Cities located along the diagonal line are forecast to have unchanged centrality, while those above the line are forecast to have increased centrality and those below the line are forecast to have decreased centrality. This figure highlights that although most cities' centrality is not expected to change, there are a few cases where a change in centrality is expected. Figure 4 illustrates the centrality forecast for nine cities that are highlighted in red in figure 3. For each city, the plot shows the city's forecast centrality, which is presented as a distribution rather than a single value because the forecast involves some uncertainty. The black vertical line indicates the city's observed centrality in 2018.

The first row of figure 4 illustrates the cases of Tokyo, Frankfurt, and Seoul, which are forecast to become more central in the future. For example, in 2018 Tokyo was observed to have a world city network centrality near 0.5 (i.e. half the most central city's centrality). The majority of forecast scenarios indicate that Tokyo will be more central in the world city network in the future, with a centrality of around 0.55 being most likely, and centralities as high as 0.6 or 0.65 being plausible. The forecast scenarios suggest similar increases in centrality for both Frankfurt and Seoul.

The second row of figure 4 illustrates the cases of London, Phoenix, and Johannesburg, which are forecast to have no change in the centrality in the future. For example, in 2018 London was observed to have a centrality of 1 (i.e. it was the most central city). Nearly all of the forecast scenarios indicate that London will continue to be the most central city in the world city network in the future; there is virtually no uncertainty here. The forecast is more uncertain for Phoenix and Johannesburg, with forecast scenarios including cases where these cities either increase or decrease their centrality slightly. However, the most probable forecast in both cases indicates no change in centrality.

The third row of figure 4 illustrates the cases of Athens, Vienna, and Buenos Aires, which are forecast to become less central in the future. For example, in 2018 Athens was observed to have a centrality of only about 0.28, while most forecast scenarios indicate this value will be even lower in the future, perhaps declining to one-quarter or less relative to London. While Vienna and Buenos Aires are both forecast to remain more central than Athens, the forecast scenarios suggest they will experience similar centrality losses.

5. Discussion

5.1 Summary and interpretation

In this paper, we have adopted Neal, Derudder, and Taylor's (2019) firm location forecasting model to make forecasts about the future of the world city network, aiming to answer two research questions. First, we ask w*hat is the correct temporal lag for a world city network forecast*? Applying this model to make forecasts of firm location, then verifying the forecasts over different temporal lags, we find that longer lags yield more accurate forecasts about firms' locations in cities. This is likely due to firms' slowness to make changes in their office sizes and locations. A forecast may indicate that a firm will expand its presence in city, but inertial forces mean that it takes time for the firm's executives to realize the need for such an expansion, and for the firm to actually initiate the expansion. This corroborates Markusen's (1996) observation that cities are 'sticky places in slippery space', and explains why forecast accuracy improves with longer temporal lags, as this provides more opportunity for firms' planned location changes to occur and appear in the data. Although longer temporal lags improve forecast accuracy, these improvements are mitigated when an economic shock occurs during the lag period (see figure 2). Economic shocks such as the global financial crisis disrupt firms' planned location changes, either by slowing them further or by changing the economic landscape in ways that make such changes no longer advantageous. Because major economic shocks are both infrequent and inevitable, these findings suggest a complex relationship between forecast lag and accuracy: rapid marginal increases in forecast accuracy over the short term (steep red line in figure 2), followed by a sharp drop in forecast accuracy when a shock occurs (difference in red and blue lines), followed by modest marginal increases in forecast accuracy over the long term (shallow blue line). Therefore, there is likely no single "correct" temporal lag for Neal, Derudder, and

Taylor's (2019) forecasting model, but instead we anticipate its accuracy will oscillate as economic shocks disrupt firms' typical location strategies.

Second, we ask *which cities are likely to maintain, gain, or lose centrality in the world city network in the future*? Using Neal, Derudder, and Taylor's (2019) model to make a forecast about future firm locations based on their locations in 2018, then using these forecasted locations to derive a world city network, we find that the most cities will exhibit little change in their centrality in the world city network (see figure 3), but that some cities will experience notable gains or losses in their centrality (see figure 4). Because this model is designed to be predictive rather than explanatory, it provides little information about why certain cities are forecast to gain or lose centrality. Potential explanations are therefore necessarily speculative, and show the need to complement this approach with some of the insights from the retrospective perspectives discussed above; however, the subtle oscillation of cities around the diagonal in figure 3 suggests one possibility: that change in centrality is organized into four urban regimes.

The first regime, composed of cities with 2018 centralities greater than 0.8 (i.e. London and New York), are the *entrenched center* of the global economy. These cities cannot experience further gains in centrality because they are already are the center. The second regime, composed of cities with 2018 centralities between about 0.4 and 0.8 (e.g. Tokyo, Frankfurt, and Seoul, but also Hong Kong, Beijing, Singapore, Sydney, etc.), are *Matthew cities*: they are beneficiaries of the Matthew effect whereby the rich get richer because they are already highly central, and from these initial structural advantages have opportunities to further enhance their centrality in the future.

The third regime, composed of cities with 2018 centralities between about 0.2 and 0.4 (e.g. Buenos Aires, Vienna, and Athens, but also Budapest, Cairo, Tel Aviv, Copenhagen, etc.), are *overshadowed cities*. These cities play a more limited role in the global economy, in many cases because they are overshadowed by other more central cities in their regions, which limit their opportunities to acquire more central positions in the network. For example, many US cities are also in this group (e.g. Cleveland, Denver, Minneapolis, Philadelphia, Seattle), owing perhaps to their peripheral role in the US economy, which is dominated by New York in the first regime, and by Los Angeles and Chicago in the second regime. This is consistent with how these cities relate to major globalization processes described by Derudder and Taylor (2020): conspicuous by their absence from the two prime globalization subnets (Intensive and Extensive), they form part of a local US-based subnet where New York is conspicuous by its absence. Finally, the fourth regime, composed of cities with 2018 centralities between 0 and 0.2 (e.g. Bissau, Hyderabad, and Lucknow), are in the *emerging periphery*. These cities play virtually no role in the global economy currently, not because they have been overshadowed, but because they are only recently emerging as economic centers in the developing world. As emerging centers in their respective regions, they have significant potential for increasing their role in the global economy.

5.2. Limitations and future directions

These findings must be interpreted in light of some important limitations, which relate to the forecasting errors identified in table 2. We have used these errors to generate forecasts with uncertainty, and thus to present distributions of cities' forecast centrality rather than a single definitive forecast. However, identifying the source of these errors and developing refined forecasting models with reduced error will allow forecasts to be made with less uncertainty, and thus for the distributions of forecast centrality to be narrower and more precise. Two limitations of the current model point to two potential sources of error.

First, although this model can forecast changes in the sizes of offices operated by firms that remain intact, it cannot forecast structural changes in the firms themselves. For example, it cannot forecast when two firms will merge (e.g. Banco Itaú and Unibanco merged in 2008 to become Itaú Unibanco), when a firm will cease operations (e.g. Coudert Brothers dissolved in 2006), or when a new firm will emerge (e.g. Herbert Smith Freehills formed in 2010). Our analyses implicitly omit these types of changes by focusing on firms that appear both in the data from which the forecast is made, and the data with which the forecast's accuracy is evaluated. Following a similar approach to our incorporation of forecast uncertainty based on estimations of error frequency, a refined version of this forecasting model might also aim to capture the uncertainty surrounding which firms will remain intact or merge with other firms.

Second, this model cannot forecast system-wide phenomena. This is a potentially significant limitation because, as we have demonstrated, the accuracy of the model's forecasts depends on whether a system-wide economic shock such as the global financial crisis of 2008 occurred. The loss in accuracy during periods that included such a shock are modest and mitigated by applying the forecast over a longer temporal lag, but this model may nonetheless be viewed as forecasting firm behavior during "ordinary" periods. In this analysis, we have investigated the impact of major shocks, however other system-wide phenomena may also warrant attention in refined versions of this model. For example, general tendencies toward global economic expansion or contraction, which can occur gradually and without major shock events, may also be responsible for forecasting errors. Future version of this model may explore whether firms are likely to expand (contract) their office sizes beyond what is forecast to be optimal during such periods of system-wide expansion (contraction).

A final future direction involves continuing to verify the accuracy of our forecasts from 2000 – 2016 over increasingly longer temporal lags, and to verify the accuracy of the new 2018 forecast we present here. The forecast illustrated by figures 3 and 4 represents the one of the first *prospective* predictions about the evolution of the world city network and cities' position in it. If this form of prospective prediction can be performed accurately, it may have significant implications for the scholarly study of the global economy, as well as for city leaders seeking to enhance or protect their city's position in the global economy.

5.3. Conclusions and implications

Our findings point to several conclusions about the dynamics of the world city network, which have both academic and practical implications. The accuracy achieved by this simple forecasting model, over long temporal lags and during periods of significant systemic shock, suggest that firms behave in relatively simple and predictable ways when crafting their global branch office strategy. Firms' location decisions on the global stage are often framed as complex and highly strategic, with business leaders having to account for such nuances as international political trends or personal whims of influential boards of directors. However, our findings suggest that decisions might actually be driven by two straightforward questions: *how many offices can this firm handle* and *how many offices can that city handle*? Thus, we may need to rethink conventional understandings of the complexity of firm behavior on the global stage, or perhaps recognize that the complexity of the global economy means location decisions are made with significantly bounded rationality (Radner, 1996; Sterman et al., 2007).

We also observe a remarkable level of stability in the spatial distribution of advanced producer services, and therefore of the world city network. At the level of specific firms and cities, table 2 shows that this forecasting model is most likely to forecast that a firm will maintain its current office size in a given city, and similarly this is the most likely observed outcome for all temporal lags. Accordingly, this model's forecasts of firms maintaining their current office sizes are accurate in 92.7% of all verifiable cases. At the level of cities as nodes in a global network, figure 3 shows that the relative centrality of cities – their rank ordering as centers of the global economy – is forecast to change little from 2018 onward. These findings of stability might seem at odds with the growing literature on world city network dynamics (e.g. Taylor & Aranya, 2008; Derudder et al., 2010; Pereira & Derudder, 2010), however they are consistent with the long-term stability of GaWC city rankings, particularly at the top of the hierarchy. They suggest that future research on world city dynamics may require a more targeted approach focused on portions of the system where meaningful change is taking place.

This forecasting model may offer one way to identify such places, and thus may serve as a tool providing world city researchers an "early warning" about cities where change is likely and thus which warrant careful attention. For example, much research on world cities focuses on places such as London and New York, but our forecasts suggest that as nodes in a world city network, these places are relatively static and thus perhaps not especially interesting cases (Wojcík, 2013). In contrast, world city research is less often focused on second- or lower-tier cities such as Frankfurt or Athens. However, to the extent that the world city network is dynamic, our forecasts suggest this is where the biggest changes are likely to occur. Specifically, Frankfurt is poised to significantly increase its centrality in the network of advanced producer service provision, while Athens' is expected to become even more peripheral despite its capital city status. Because these forecasts have a long temporal lag (see figure 2), world city researchers have an opportunity to document and understand these changes before they begin and as they unfold, while city planners likewise have an opportunity to take steps to avert potential losses to centrality and economic vibrancy through concerted development policies (c.f. Liu et al., 2019). In addition to identifying cities where change is likely, it can also identify sets of cities where re-orderings of the global urban hierarchy are possible. Figure 5 shows the centrality forecast for the three "winner" cities in figure 4, but by overlaying the forecast distributions, clearly identifies the probability for one of these cities to surpass the others in a global urban hierarchy. For example, although most forecasts suggest Seoul (in blue) will be less central than Frankfurt (in red) in the future, some forecast scenarios (the overlap, in purple) suggest that Seoul will become more central than Frankfurt.

In this paper, we have focused on a very specific conception of the global urban system, that of a world city network in which cities are interlocked by producer services firms. However, although this approach was initially developed – and again invoked here – to understand a particular process both functionally (servicing large corporations) and temporally (contemporary globalization with its facility for instantaneous communication worldwide), the model can be also interpreted in a broader, generic manner (Taylor, Hoyler, & Verbruggen, 2010; Taylor, 2019). This is because cities are, and have always been, commercially connected by economic agents operating to create trading and financial links: cities are always collectively 'interlocked' in their operation as commercial centers, and our approach and findings can therefore be interpreted as particular examples of both long-standing historical and broader functional practices of inter-city relations. There are of course many other city network makers, producing what Krätke (2014) calls 'multiple globalizations of cities', while Burger et al. (2014) refer to this diversity as the inherent ‘multiplexity’ of city networks. Extending our understanding of the dynamics of the global urban system requires us to take this diversity seriously, which implies that our findings need to be considered alongside those produced by other, often very different actors that will see different cities on’ and ‘off’ the map depending on the process studied. However, these other city network makers often forge linkages between pairs cities in ways similar to the firms we examine here, namely, by maintaining some form of presence and engagement in both places. Thus, although we have applied the INM and forecasting model here to firms, and thus have adopted a specific conceptual and empirical scope, these models can in principle be used to capture and explore the dynamics in a diversity of city networks.

References

Abu-Lughod, J. (1999). New York, Chicago, Los Angeles: America's Global Cities. Minnesota: U of Minnesota Press.

Beaverstock, J., Faulconbridge, J. & Hall, S. (2010. Professionalization, legitimization and the creation of executive search markets in Europe. *Journal of Economic Geography*, 10, 825-843

Bel, G. & Fageda, X (2008). Getting There Fast: Globalization, Intercontinental Flights and Location of Headquarters. *Journal of Economic Geography, 8*, 471-495.

Burger, M. J., Van Der Knaap, B. & Wall, R. S. (2014). Polycentricity and the multiplexity of urban networks. *European Planning Studies, 22*, 816-840.

Capello, R. (2000). The City Network Paradigm: Measuring Urban Network Externalities. *Urban Studies, 37*, 1925-1945.

Cheng, Y., Loo, B. & Vickerman, R. (2015). High-speed rail networks, economic integration and regional specialisation in China and Europe. *Travel Behaviour and Society*, *2*, 1-14.

Dai. L. Derudder, B. & Liu, X. (2018). The evolving structure of the Southeast Asian air transport network through the lens of complex networks, 1979–2012. *Journal of Transport Geography, 68,* 67-77.

Derudder, B. (2020). Bipartite network projections of multi-locational corporations: Realising the potential. *Geographical Analysis*.

Derudder, B. & Taylor, P. J. (2020). Three globalizations shaping the twenty first century: understanding the new world geography through its cities. *Annals of the American Association of Geographers*.

Derudder, B., Taylor, P., Ni, P., de Vos, A., Hoyler, M., Hanssens, H., Bassens, D., Huang, J., Witlox, F., Shen, W., & Yang, X. (2010). Pathways of change: Shifting connectivities in the world city network, 2000-2008. *Urban Studies, 47*, 1861-1877.

Harrison, J. & Hoyler, M. (2015). Megaregions: Globalization's New Urban Form? Cheltenham, UK and Northampton, MA, USA: Edward Elgar.

Kloosterman R. & Musterd, S. (2001). The polycentric urban region: Towards a research agenda. *Urban Studies, 38*, 623-633.

Kourtit, K., Suzuki, S. & Nijkamp, P. (2017). Tracing high-sustainability performers among world cities - design and application of a multi-temporal data envelopment analysis. *Habitat International*, *68*, 43-54.

Krätke, S. (2014). How manufacturing industries connect cities across the world: extending research on 'multiple globalizations'. *Global Networks*, *14*, 121-147.

Li, Y. & Phelps, N. A. (2017). Knowledge polycentricity and the evolving Yangtze River Delta megalopolis. *Regional Studies, 51*, 1035-1047.

Li, Y. & Phelps, N. A. (2018). Articulating China's science and technology: Knowledge collaboration networks within and beyond the Yangtze River Delta megalopolis in China. *Chinese Geographical Science, 28*, 247-260.

Li, Y. & Phelps, N. A. (2019). Megalopolitan glocalization: the evolving relational economic geography of intercity knowledge linkages within and beyond China's Yangtze River Delta region, 2004-2014. *Urban Geography, 9*, 1310-1334.

Liu, X., Derudder, B., & García, C. G. (2013). Exploring the co-evolution of the geographies of air transport aviation and corporate networks. *Journal of Transport Geography, 30*, 26-36.

Liu, X., Derudder, B., Witlox, F. & Hoyler, M. (2014). Cities as networks within networks of cities: The evolution of the city/firm-duality in the world city network, 2000-2010. *Tijdschrift voor Economische en Sociale Geografie, 105*, 465-482.

Liu, X, Derudder, B. & Liu, Y. (2015). Regional geographies of intercity corporate networks: The use of exponential random graph models to assess regional network-formation. *Papers in Regional Science, 94*, 110-126.

Liu, X., Derudder, B. & Wu, K. (2016). Measuring polycentric urban development in China: An intercity transportation network perspective. *Regional Studies, 50,* 1302-1315.

Liu, Z., Wang, S., and Wang, F. (2019). Isolated or integrated? Planning and management of urban renewal for historic areas of Old Beijing city, based on the association network system. *Habitat International, 93*, 102049.

Ma, X. & Timberlake, M. (2013). World city typologies and national city system deterritorialisation: USA, China and Japan. *Urban Studies, 50*, 255-275.

Martinus, K., Sigler, T., Searle, G. & Tonts, M. (2015). Strategic globalizing centers and sub-network geometries: A social network analysis of multi-scalar energy networks. *Geoforum, 64*, 78-89.

Meijers, E. J., Burger, M. J. & Hoogerbrugge, M. M. (2016). Borrowing size in networks of cities: City size, network connectivity and metropolitan functions in Europe. *Papers in Regional Science, 95,* 181-198.

Neal, Z. P. (2013). *The Connected City: How Networks are Shaping the Modern Metropolis*. New York: Routledge.

Neal, Z. P. (2014a). The devil is in the details: Differences in air traffic networks by scale, species, and season. *Social Networks, 38*, 63-73.

Neal, Z. P. (2014b). The backbone of bipartite projections: Inferring relationships from co-authorship, co-sponsorship, co-attendance and other co-behaviors. *Social Networks, 39*, 84–97.

Neal, Z. P. (2017). Well connected compared to what? Rethinking frames of reference in world city network research." *Environment and Planning A, 49*, 2859–77.

Neal, Z. P., Derudder, B., & Taylor. P. J. (2019). Should I stay or should I go: Predicting advanced producer service firm expansion and contraction. *International Regional Science Review, 42,* 207-229.

Neal,. Z. P. (2020). Fallacies in world city network measurement. *Geographical Analysis*.

Pereira, R. A. O. & Derudder, B. (2010). Determinants of dynamics in the world city network, 2000-2004. *Urban Studies, 47*, 1949-1967.

Radner, R. (1996). Bounded rationality, indeterminacy, and the theory of the firm. *The Economic Journal, 106*, 1360-1373.

Rozenblat, C. (2010). Opening the black box of agglomeration economies for measuring cities' competitiveness through international firm networks. *Urban Studies, 47*, 2841-2865.

Smith, D.A. & Timberlake, M.F. (2001). World city networks and hierarchies, 1977-1997: an empirical analysis of global air travel links. *American Behavioral Scientist, 44*, 1656-1678.

Sterman, J. D., Henderson, R., Beinhocker, E. D., and Newman, L. I. (2007). Getting big too fast: Strategic dynamics with increasing returns and bounded rationality. *Management Science, 53*, 683-696.

Taylor, P. J. (2001). Specification of the world city network. *Geographical Analysis, 33*, 181-194.

Taylor, P. J. & Aranya, R. (2008). A global 'urban roller coaster'? Connectivity changes in the world city network. *Regional Studies, 42*, 1-16.

Taylor, P. J., Hoyler, M., & Verbruggen, R. (2010). External urban relational process: introducing central flow theory to complement central place theory. *Urban Studies, 47*, 2803-2818.

Taylor, P.J., Derudder, B., Hoyler, M. & Ni, P. (2013). New regional geographies of the world as practised by leading advanced producer service firms in 2010. *Transactions of the Institute of British Geographers, 38*, 497-511.

Taylor, P. J., & Derudder, B. (2015). *World city network: A global urban analysis*. New York: Routledge.

Taylor, P. J. (2019). City generics: external urban relations in ancient-Mesopotamian and modern-global city networks. *Urban Geography, 40*, 1210-1230.

Taylor, P. J., Catalano, G., & Walker, D. R. F. (2002). Measurement of the world city network. *Urban Studies, 39*, 2367-2376.

van Meeteren, M., Neal, Z. P., & Derudder, B. (2016). Disentangling agglomeration and network externalities: A conceptual typology. *Papers in Regional Science, 95*, 61–80.

Wei, Y.H. & Liao, F. (2013). The embeddedness of transnational corporations in Chinese cities: Strategic coupling in global production networks? *Habitat International*, *40*, 82-90.

Wójcik, D. (2013). The dark side of NY–LON: Financial centres and the global financial crisis. *Urban Studies, 50*, 2736-2752.

Wu, F. & Ma, L. (2006). Transforming China's globalizing cities. *Habitat International*, *30*, 191-198.

Zhang, L., Hongru, D., Yannan, Z., De Maeyer, P., Dessein, B., and Zhang, X. (2019). Drawing topological properties from a multi-layered network: The case of an air transport network in “the Belt and Road” region. *Habitat International, 93*, 102044.

Zheng, S., Duan, L., and Sun, W. (In press). Global air network and cross-border venture capital mobility. *Habitat International*.

Figure 1. Analytic plan

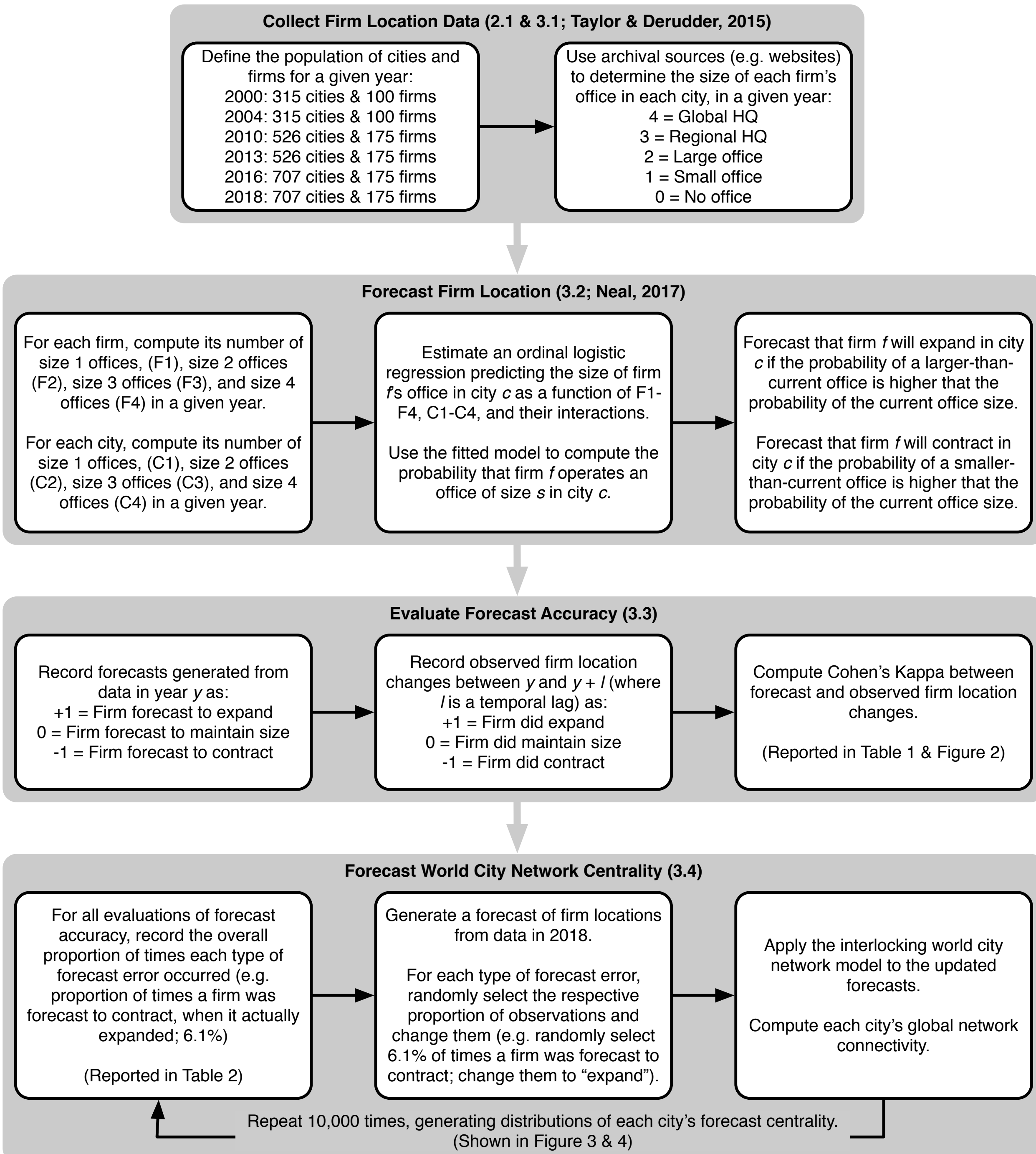

Table 1. Verifications of forecast accuracy

Forecast derived from…	Forecast verified against…	2000	2004	2010	2013	2016	2018
	2000	——	C = 315 F = 89 L = 4 κ = 0.377	C = 307 F = 47 L = 10 κ = 0.316	C = 307 F = 45 L = 13 κ = 0.311	C = 313 F = 46 L = 16 κ = 0.365	C = 313 F = 44 L = 18 κ = 0.347
	2004		——	C = 307 F = 47 L = 6 κ = 0.309	C = 307 F = 41 L = 9 κ = 0.313	C = 313 F = 42 L = 12 κ = 0.360	C = 313 F = 41 L = 14 κ = 0.356
	2010			——	C = 525 F = 106 L = 3 κ = 0.329	C = 526 F = 106 L = 6 κ = 0.417	C = 526 F = 98 L = 8 κ = 0.429
	2013				——	C = 525 F = 128 L = 3 κ = 0.421	C = 525 F = 112 L = 5 κ = 0.418
	2016					——	C = 532 F = 119 L = 2 κ = 0.323
	2018						——

C = Number of cities, F = Number of firms, L = Lag in years, κ = Cohen's Kappa

Figure 2. Forecast accuracy by temporal lag

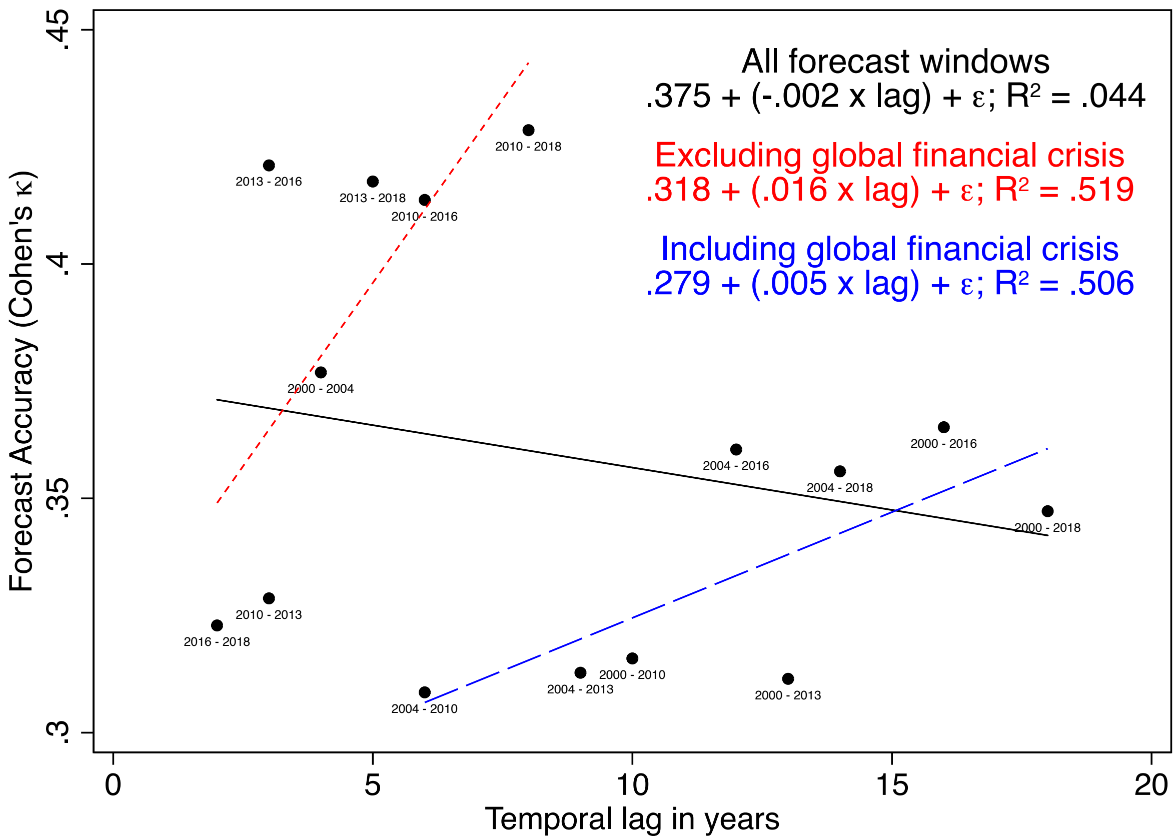

Table 2. Predicted and actual firm location changes (pooled)

		Actual			
		Contract	Maintain	Expand	TOTAL
Predicted	Contract	22992 A = 0.385	33103 E = 0.554	3641 E = 0.061	59736
	Maintain	4611 E = 0.011	380398 A = 0.927	25178 E = 0.061	410187
	Expand	5027 E = 0.213	11616 E = 0.493	6920 A = 0.294	23563
	TOTAL	32630	425117	35739	493486

Cohen's κ = 0.382
A = Proportion of predictions that were accurate
E = Proportion of predictions that were erroneous

Figure 3. World city centralities forecast from 2018

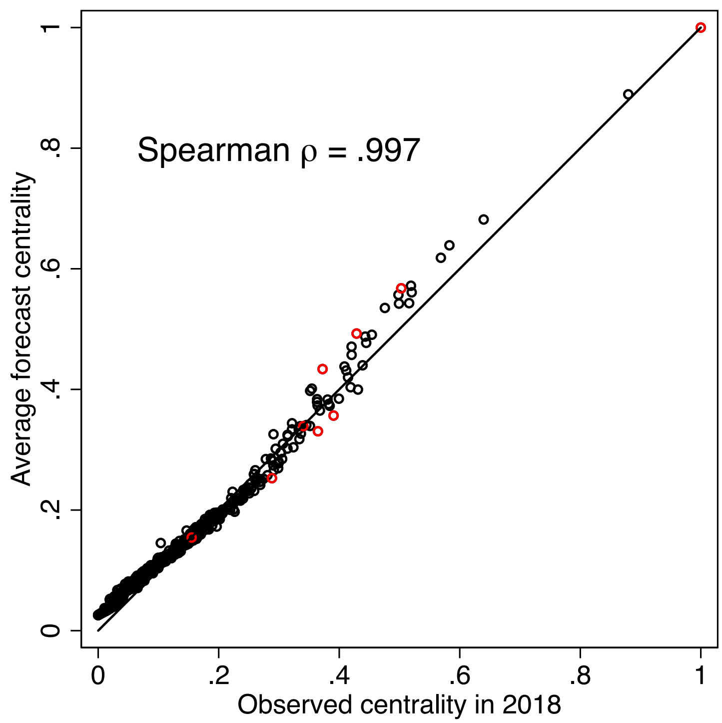

Figure 4. Forecasts of world city centrality winners and losers

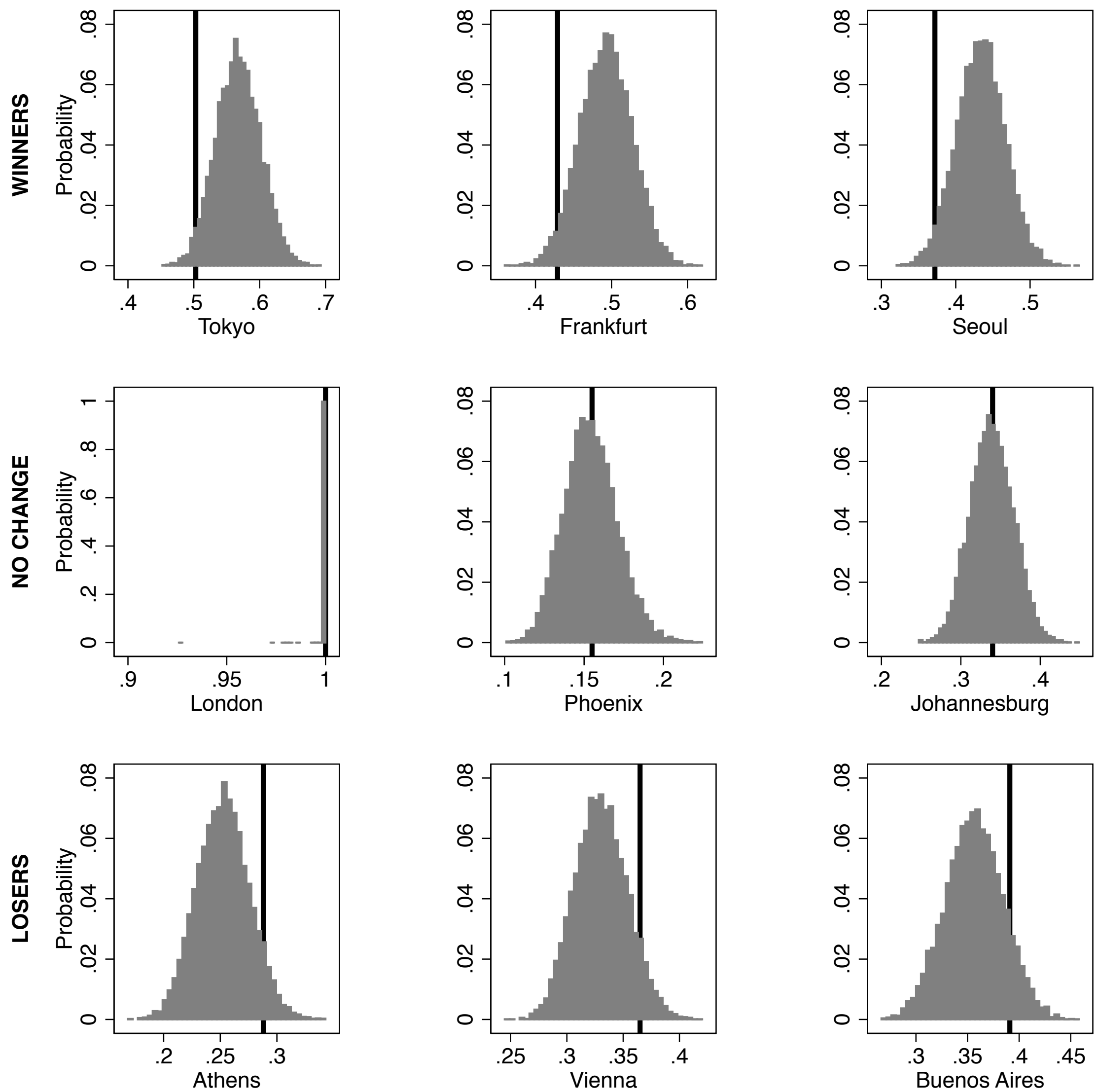

Figure 5. Forecasting changes in world city rank