Journal of World Business xxx (2016) xxx–xxx

Contents lists available at ScienceDirect

Journal of World Business

journal homepage: www.elsevier.com/locate/jwb

Interactive visualization for research contextualization in international business

Andreas P.J. Schotter [a,*], Olha Buchel [b], Tatiana Vashchilko (Lukoianova) [c]

[a] Ivey Business School, Western University Canada, 1255 Western Road, London, ON N6G 0N1, Canada
[b] siTechnologygroup, Inc., 213 Bournemouth Drive, London, ON N5V 4S8, Canada
[c] University of Calgary, 2500 University Dr NW, Calgary, AB T2N 1N4, Canada

ARTICLE INFO

Article history:
Received 1 December 2015
Received in revised form 1 January 2017
Accepted 26 January 2017

Keywords:
Contextualization of research
Interactive visualization
Interdisciplinary research

ABSTRACT

We respond to calls for advances in the contextualization of international business (IB) research by introducing interactive visualization as a methodology for generating contextual insights during the exploratory phases of IB research projects. We suggest that applying interactive visualization early on improves contextualization by means of simultaneous dynamic representations of various phenomena and their respective properties and relationships, even for phenomena that have been widely researched before, like in the cases of international joint ventures and MNE foreign direct investment. The goal of this introduction is to make interactive visualization more accessible to IB scholars.

1. Introduction

Despite repeated calls for a more advanced treatment of context in international business (IB) (Buckley, 2002; Child, 2009; Teagarden et al., 1995), most extant IB research has deployed only static contextualization approaches and has been mainly based on categorical dimensions including country, nationality, and/or industry (Shenkar & Von Glinow, 1994). Oesterle and Wolf (2011) urged that because the scope of IB is expanding rapidly, new conceptual and methodological approaches are overdue in order to remain relevant. In this paper, we show how interactive visualization improves research contextualization and insight generation from spatial, temporal, and other relational data beyond those generated by existing approaches. Our contribution does not lie in the introduction of a novel methodology, but in making an emerging methodology developed in other domains more accessible to IB scholars.

Visualization in organization and management research, including IB, is only slowly gaining popularity (see Appendix I). Most extant visualization applications are post hoc illustrations of traditional statistical analyses. Recent technological advances, however, have encouraged some researchers in adjacent domains to take visualization beyond merely illustrating findings. For example, in strategy, DeSarbo and Grewal (2008) (see also DeSarbo, Grewal, Hwang, & Wang, 2008) deployed a new approach for dynamic visualizations of strategic groups. Similarly, Tarakci et al. (2014) introduced a new visualization approach for multidimensional, multilevel, and longitudinal analyses of strategic consensus amongst team members. Increasingly, interactive visualization is used in exploratory, discovery, spatial, and network analyses across various disciplines. However, a major challenge thus far has been the development of a 'common language' (Meyer, Höllerer, Jancsary, & van Leeuwen, 2013: 536) for applying visualization systematically. With this paper, we provide a starting point for resolving this issue.

Visualization in its most narrow sense is a static image, illustration, graphic, or any other visual representation (e.g., map or network chart). Scientific visualization goes far beyond static representations. Here, the term 'visualization' implies interactions as part of information processing, visual analytics, and geovisualization (Dykes & MacEachren, 2005; Keim et al., 2008; Robinson, 2010; Wise et al., 1995). "*Interactive visualizations are graphical models or visual representations from data that support direct user interaction for exploring and acquiring insight into useful information embedded in the underlying data*" (Ferreira de Oliveira & Levkowitz, 2003: 378). Wise et al. (1995) suggested that interactive visualizations support the discovery of otherwise difficult-to-identify contextual properties in data. Visualizations open up new opportunities for early-stage research contextualization in ways that have not been possible in the past (Thudt, Hinrichs, & Carpendale, 2012).

IB research, in general, is notably more phenomenon- rather than theory-driven. Regularly, the exploration of unusual patterns

* Corresponding author.
E-mail addresses: aschotter@ivey.ca (Andreas P.J. Schotter), obuchel@sitechnologygroup.com (O. Buchel), tatiana.vashchilko@haskayne.ucalgary.ca (T. Vashchilko (Lukoianova)).

http://dx.doi.org/10.1016/j.jwb.2017.01.006
1090-9516/

in international data leads to analyses of contextual connections. Some of the most important theoretical advances in IB have come from exploratory investigations of patterns in data (Cheng, Guo, & Skousen, 2011). Examples include Hymer's (1976, 1979) seminal work on the theory of the MNE, Bartlett and Ghoshal's (1989) transnational configuration, and Birkinshaw's (1997) work on MNE subsidiary initiatives. Even though these examples are powerful, most extant IB research defaults on static contextualization approaches and testing of existing management theories. We argue that the major reason for the apparent absence of interactive visualization from IB research is not its applicability. Instead, two major assumptions seem to prevail amongst IB scholars, including (a) most of the relevant visualization tools are already well established in the field (Bell & Davison, 2012; Meyer et al., 2013) and (b) visualization is only applicable for results illustration and not for exploratory contextualization.

We suggest that a different, visualization-supported, interactive contextualization approach that is positioned at the beginning of a research project will help to overcome current theory development gridlocks caused by an overreliance on static contextualization (Knigge & Cope, 2006). Interactive visualization also lends itself as a contextualization tool for grounded theory building, although visualization is not theory and does not replace theorizing, as pointed out by Sutton and Staw (1995).

We contribute to IB research in three ways. First, we show that incorporating interactive visualization during the early stages of emerging phenomena exploration permits systematic rather than random contextualization by identifying masked or weak patterns in complex data. Such an approach also helps to avoid losing contextual power because it avoids limiting empirical analyses to predetermined, more manageable contextual settings. Second, we make *interactive* visualization more accessible to scholars unfamiliar with these tools. Third, Beugelsdijk, McCann, and Mudambi (2010) and Beugelsdijk and Mudambi (2013), in two interdisciplinary special issues, encouraged connecting economic geography and IB research both methodologically and theoretically, because of their substantial contextual overlap. We therefore also provide a tool for building bridges between different research disciplines by improving communication and sense making within interdisciplinary research teams (Gilbert, Reiner, & Nakhleh, 2007).

In the remainder of this paper, we introduce a series of interactive visualization tools which we regard as most relevant for IB research contextualization. Because it is practically impossible to provide an exhaustive introduction of all visualization tools available or to go into deep technical detail in describing each of the tools within the journal's space constraints, we developed an interactive online IB toolbox with links to plug-in visualization packages for the statistical software R and to other software resources (https:// www. ivey. uwo.ca/ internationalbusiness/ research/ibvisualizationtoolbox/). The IB toolbox allows researchers to begin experimenting with some of the most applicable visualization tools available. In this paper, we will first briefly introduce the key conceptual foundations of interactive visualizations, including representations, visual interactions,[1] and community detection. We will then illustrate how interactive visualization advances early-stage contextualization in IB research by highlighting examples of some tools using international joint venture (IJV) and foreign direct investment (FDI) data (Toyo Keizai, 2014). We chose the IJV and FDI contexts because they are amongst the most widely researched phenomena in IB.

2. Conceptual foundations

2.1. Contextualization

Contextualizing based on interactive visualizations requires reconsideration of some IB research paradigms. When using interactive visualizations, both the theory development process and the generation of insights through exploratory analyses need to be taken into account in an iterative way. Cheng et al. (2011) referred to this process as theory conception and articulation. It allows for a better development of key concepts, including formal meanings of phenomena, constructs, and relationships, which subsequently facilitates a deeper understanding of context (Morrow & Brown, 1994).

Interactive visualization supports exploratory IB research for identifying, locating, distinguishing, categorizing, clustering, distributing, ranking, associating, and correlating variables (Wehrend & Lewis, 1990). However, first-order insights are not the final step in the interactive visualization process (Chernoff, 1973; Pickett & Grinstein, 1988; Yi, Kang, Stasko, & Jacko, 2008) and are often insufficient to fully understand the research context at hand. For this reason, information visualization scholars suggest using visual reasoning based on visual task analysis (Kohlhammer, Keim, Pohl, Santucci, & Andrienko, 2011; Turkay, Jeanquartier, Holzinger, & Hauser, 2014). Visual reasoning is defined as "*the process of distinguishing between ideas in order to create new relations and insights based on collected evidence*" (Meyer et al., 2013: 229), whereas evidence is derived from distributed sources, data, analysis, or prior knowledge. In this paper build on the relatively new visual forms of meaning construction (Meyer et al., 2013).

When using visualization for contextualization, both the theory development objective of a research project and the specifics of computer-based visualization have to be taken into account, where "*computer-based visualization tools have two principally new properties: interactivity and dynamics.*" (Andrienko, Andrienko, & Gatalsky, 2003: 511). In our view, the most promising application of interactive visualization in IB is the exploration of phenomenological linkages with weak or complex signals across three main manipulation dimensions, including (a) space, (b) time, and (c) other, non-spatial characteristics (see Fig. 1). Examples of other contexts can include various cultural characteristics, institutional characteristics, or political environment characteristics (e.g. variations in political systems or the magnitude of political violence).

Fig. 1 illustrates how interactive visualizations can support the simultaneous examination of all these contexts across different levels of analysis and multiple dimensions, features that are limited in descriptive statistics techniques. By 'zooming in' on a visualized set of IB phenomena on a geographic map, we can explore a close-up view of those objects at a location or regional

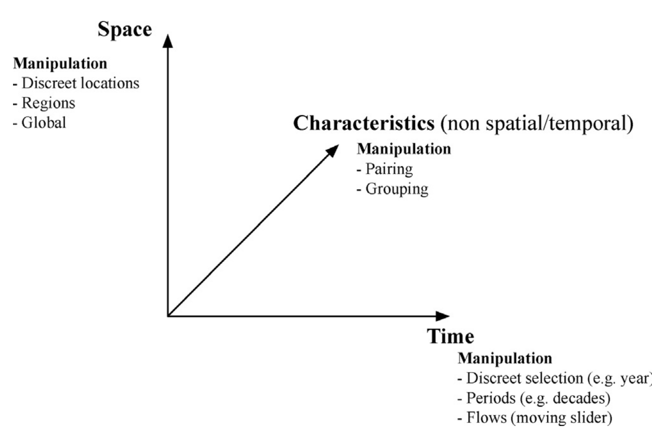

Fig. 1. Conceptual framework for interactive visualization in IB research.

[1] Note that the term 'interaction' is used in the relational sense, with the assumption that interacting variables may influence one another. The direction of the relationship still needs to be developed from both the context and the theoretical arguments that form the underpinnings of hypotheses development.

levels of analysis. By zooming out, we can investigate more of a geographic map moving from specific location to regional and to global levels of analysis. Such manipulations of a spatial context that can be built-in into an interactive visualization system allow for comparing IB phenomena across different "spatial" context levels of analysis dynamically. Furthermore, spatial context can be combined with other contexts to simultaneously explore additional characteristics and dimensions of many IB phenomena. Combined with spatial context, the temporal context's manipulations in interactive visualization systems include but are not limited to selecting a particular year or a specific time period to compare and better understand the dynamics of IB phenomenon across not only space, but also time. The power of interactive visualization does not stop there, as current advances in visualization and computing allow incorporating extra contexts to examine a particular IB phenomenon. For example, we developed an interactive visualization system for the exploration of the formation of IJVs, in the spatial and temporal and political contexts (e.g. political violence) simultaneously (see Fig. 8).

2.2. Visual representations

Knowledge can take many forms of representation including linguistic, algebraic, diagrammatic, and visual, amongst others (Markman, 2013; Peterson, 1996). In interactive visualizations, representations are based on mathematical models which convert data into visual forms and through this process make salient data properties distinctive by assigning visual variables (e.g. color, shape, size, position, orientation, and the two planar dimensions) to the smallest components of a representation (e.g., icons, symbols, lines, nodes, polygons, etc.).

Research in cognitive psychology suggests that dynamic transitions from one representation to another may result in knowledge discoveries (Peterson, 1996), in richer insights, in an improved understanding of the research context, and subsequently in better contextual framing of the phenomena under investigation (Bodner & Domin, 2000). In interactive visualizations, researchers experience thousands of such transitions as representations change dynamically with each move of a slider or click on a checkbox presented on the screen as part of a particular interactive visualization tool.

Effective representations depend on data properties which can be encoded as raw values or modified through additional treatment. Encodings include ratios, change rates, averages, or more complicated computations, depending on a user's individual research objective. Applying multiple encodings to the same data for visual representation purposes may lead to the discovery of additional patterns in the data (Yi et al., 2008) that might be overlooked when relying solely on traditional statistical analyses. For example, in network representations varying node sizes may add representation power by indicating centrality characteristics of a specific network node. In addition, different colors can be used for encoding the belonging of a node to certain networks or certain interconnected sub-groups within a network. Some representations require special data properties. Maps require geocoded data (i.e., data with coordinates). For time maps, data has to be arranged in a form of discrete timeframes. In network representations, objects[2] should have one or multiple links to other objects but not necessarily in a hierarchical form (Shneiderman, 1996). In hierarchies or tree structure representations, each object has to have at least one link to a higher-order and/or lower-order object.

Visual representations are useful when they allow users to generate new insights (Card, Mackinlay, & Shneiderman, 1999; Spence, 2014). Saraiya, North, and Duca (2005: 443) noted that "*arriving at an insight often sparks the critical breakthrough that leads to discovery: suddenly seeing something that previously passed unnoticed or seeing something familiar in a new light*." *Representations* should be chosen so they fit contextual mental models that can be equally well understood by all users across different research domains and practices (Liu & Stasko, 2010).

Each representation form has its pros and cons. For instance, cartograms (Roth, 2012), which distort geographic maps to accentuate the magnitude of, for example, a specific country characteristic, are more suitable for communicating information about densities. The reason is that cartograms utilize location characteristic variables other than geographic space to calculate the size of map areas. Ghemawat uses cartograms to magnify the importance of certain export relationships between different countries.[3] The shortcoming of cartograms is an increased difficulty with specific location identification, particularly when the cartogram spans many different countries (Dorling, 1996; Dent, 1975). When a task requires high precision and accuracy for making inferences about data, maps with the least possible distortions are regarded as the most suitable (Peterson, 1996).

Visual representations can be very dense, cluttered, and/or hard to understand, particularly in the case of large volumes of information, and therefore not all patterns can be observed with the naked eye. This is often the case in IB research. For example, networks and maps can include thousands of nodes and relationships. For this reason, the latest visual representation tools permit users to interactively zoom in and zoom out on a representation. This allows for the filtering out of noise from the data and the re-classifying of entities into different subsets along time, space, or other relational dimensions.

2.3. Interactions

The simultaneous analysis of multiple visual representations is called visual interaction (Dörk, Carpendale, & Williamson, 2012; Parsons & Sedig, 2014; Self et al., 2014; Yi et al., 2008). Certain visual interactions, particularly animations and simulations, can help overcome cognitive limitations (Goldman, 1989; Liu & Stasko, 2010; Parsons & Sedig, 2014) and reveal subtle changes in patterns that are not otherwise detectable (MacEachren, Boscoe, Haug, & Pickle, 1998; Moody, McFarland, & Bender-deMoll, 2005). Interactive timelines in combination with network representations facilitate the detection of temporal patterns and the understanding of how clusters emerge and dissolve over time (Card, Suh, Pendleton, & Bodnar, 2006; Toyoda & Kitsuregawa, 2005). Interactive visualizations allow for analyzing a large number of variables simultaneously, making it easier to identify hidden data patterns within maps or other representations, including adjacency matrixes or chord diagrams (Andrienko & Andrienko, 2006; Fisher & Buchel, 2012; Guo, Gahegan, MacEachren, & Zhou, 2005; Jern, Thygesen, & Brezzi, 2009; MacEachren, 2013).

In the next section, we will apply interactive visualization tools using a series of IB sample datasets.[4] Following the logic laid out in our conceptual framework (Fig. 1), we selected these visualization tools because of their applicability for IB research contextualization and for their accessibility. We provide an extended list of tools, their visualization purposes, their most useful application in IB research,[5] and links to the relevant software online in our 'How to' section (https:// www. ivey. uwo.ca/ internationalbusiness/

[2] Note that in visualizations, the term "object" refers to the unit of analysis, including, for example, a firm, a country, a group, or a manager carrying geographic and non-geographic characteristics.

[3] www.ghemawat.com/Maps/ShowMaps.aspx?MapName=EUSA.

[4] In order to illustrate some visualization methodologies, we utilize a series of datasets with different data structures in the online IB Toolbox, including (1) the Toyo Keizai Inc. dataset on Japanese MNE FDI (2014 edition); (2) the SDC Platinum Dataset of IJV

[5] See also the online IB Toolbox: http://ec2-54-149-181-220.us-west-2.compute.amazonaws.com/IBToolbox/#home.

research/ibvisualizationtoolbox/). We acknowledge that the number of interactive visualization tools available is growing continuously. Thus, an even more extensive list would have gone beyond the space limitations of this journal. We start with the Japanese FDI datasets and interactive maps, the most foundational visualization tools for IB research. For further exploratory contextualization, we will then introduce hexbinning, heat maps, raster models, filtering, and interactive lenses. Drawing on the global IJV and political violence datasets, we will introduce interactive dashboards, adjacency matrices, chord diagrams, and standard deviational ellipses with interactive timelines.

3. Interactive visualization tools for IB contextualization

3.1. Interactive mapping

To put IB data on a map, datasets require references to geographic locations. These references can be precise in the form of exact addresses or less precise in the form of country names, provinces, cities, or zip codes. Exact addresses can be geocoded (i.e., enriched with exact coordinates). Less precise references can be geo-referenced (i.e., represented through spatial polygons or lines) (Hill, 2006) or can be represented as central points within a specific country, province/state, or city.

Contextualization based on maps embodies mainly the interpretation of specific footprints and relationships between different footprints of linked objects, including MNEs (De Smith, Goodchild, & Longley, 2007). Analyses of footprints not only expose where MNEs are located, but also reveal spatial, temporal, and attributable patterns and constraints based on relationships with other objects that are not apparent without using map-based interactive visualizations. Spatial patterns may help in making inferences about socioeconomic and behavioral processes that may drive an MNE's location choice (Grossbart, Mittelstaedt, & Murdock, 1978). They may also reveal an MNE's neighbors and distances to other firms, as well as the detection of movements that are difficult to observe based on numeric data outputs in tables.

In Fig. 2, we show a screenshot of an interactive map that illustrates the expansion paths of Japanese MNEs in China based on the entry sequence of individual MNEs subsidiary by subsidiary over time. Red markers represent locations where MNEs opened a subsidiary. Lines connect sequential expansion locations. Different line colors represent the sequential order of each MNE's expansion path. This allows a researcher to get a sense of the prevalence of preferred entry locations, clusters, and expansion sequences from, for example, investment core locations to the periphery. It should now become apparent that even such a coarse initial visualization already advances research contextualization through systematic rather than random contextualization by identifying masked or weak patterns in complex data. One can clearly see that along the coastal belt certain investment hubs exist and that most of the movement is happening between these hubs. However, when looking at the map in Fig. 2, it becomes obvious that the patterns created by footprints are too cluttered and hard to understand without additional analyses. The researcher now has the option to refine the research question or to eliminate data that are not applicable in the context of her/his research with the help of additional interactive visualization tools.

3.2. Community detection

In network theory, communities are often referred to as clusters, cohesive groups, or modules (Palla, Derényi, Farkas, & Vicsek, 2005). Communities are central features of a network which we define as "*a collection of points/nodes linked through some type of association*" (McCulloh, Armstrong, & Johnson, 2013: 4). Communities are a priori unknown parts of a network in which nodes are more connected to each other than to the rest of the network. Identifying these a priori unknown communities is critical in network analysis in order to uncover meaningful contextual structures of networks (Leicht and Newman, 2008). Moreover, communities offer insights about how interactions in small group aggregates form larger-scale contextual patterns (Porter, Onnela, & Mucha, 2009).

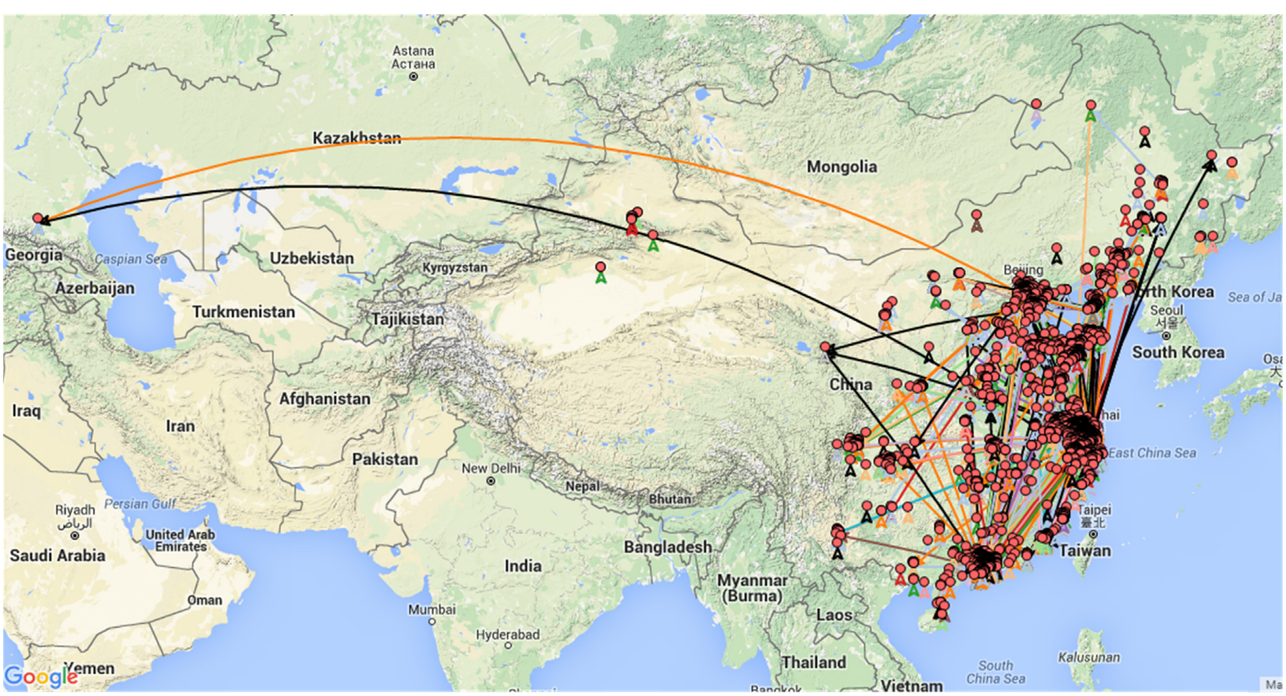

Fig. 2. Interactive map with vectors representing Japanese MNEs' expansion paths in China.

Please cite this article in press as: Schotter, A. P. J., et al. Interactive visualization for research contextualization in international business. *Journal of World Business* (2017), http://dx.doi.org/10.1016/j.jwb.2017.01.006

It is important to note that different community detection algorithms often yield different results for the same data sample. However, some communities do not vary under different community detection algorithms (Palla et al., 2005) and also remain constant over time (Gruzd, Wellman, & Takhteyev, 2011). These communities are called constant communities. If constant communities are missing in a network, it means that communities either do not exist or are highly overlapping (Leicht and Newman, 2008). We suggest using interactive visualization and geographic mapping combined with so-called spinglass network algorithms and major centrality metrics to visualize communities in networks.

Spinglass algorithms are based on the Potts model, the most popular model in statistical mechanics (Potts, 1952, Fortunato, 2010; Wu, 1982). To divide the countries into communities, the spinglass algorithm iteratively removes the edges from the network based on the betweenness centrality metric, which is recalculated after each removal of the edges.

The Potts model defines an object (i.e., node) to which the total of q spin states corresponds, and also defines interactions between the objects of the network, each of which can have up to q spin states (Araújo, Andrade, & Herrmann, 2010; Reichardt & Bornholdt, 2004).

Under the spin state of an IB environment, we understand the combination of government policies, the existing competitive environment, and many other characteristics specific to a country at time t. The maximum number of spin states in our IJV sample corresponds to the number of countries in the world, because each country could have its own unique IB environment spin state.

Spinglass models are particularly effective for exploring why and how certain characteristics spread throughout a sample (Minniti, 2004) and for modeling node or community interdependencies in networks. Thus, visualizing temporal directed networks interactively based on the entire data available, instead of pre-defined subsets, enhances the understanding of the phenomenological context in which communities emerge.

3.3. Hexbinning

For large datasets, like in the case of our Japanese FDI data, hexbinning, a point analysis technique, can be applied to investigate geographic patterns (Fig. 3). Hexbinning is a grouping technique that aggregates data into hexagons. It was first introduced in statistics by Carr, Littlefield, Nicholson, and Littlefield (1987). Hexbinning is considered the most efficient tool for detecting communities and their boundaries across two-dimensional spaces (Carr et al., 1987). It allows researchers to overcome the limitations of scatterplots and manual maps. Hexbinning reveals densities, highlights real-time empirical contours, and visualizes hotspots of activities — in our case, the concentration of Japanese MNE subsidiaries in China. We applied hexbinning to identify specific investment cores and peripheries for further analysis. We decided to investigate the Shanghai region in more detail, as it showed us the greatest density levels and spread as illustrated by the red colors of the hexagons. However, we also noted that several other hotspots prevail, including Beijing, Tianjin, and Shenzhen. While the interior provinces did not show densities at quite the level of the aforementioned locations, several locations showed increased density levels. An interesting research context derived from this hexbinning application could be a comparison of investment locations of similar densities.

3.4. Vector models, interactive lenses, and filtering

Although the Japanese MNE subsidiaries in Fig. 2 were assigned specific coordinates, the representation shows footprints consisting of both investment locations and multi-colored vectors that connect different locations while indicating entry sequences. Zooming in on certain locations with the help of interactive lenses and selecting entry vector sequences enabled us to identify contextual characteristics of Japanese MNEs' co-ethnic investment agglomerations and expansion paths across these agglomerations in China (Stallkamp, Pinkham, Schotter, & Buchel, 2017). The visualization shows Japanese MNEs as sets of footprints consisting of multi-colored segmented lines and points. Each color represents a certain sequence in which an MNE entered the Chinese market and then expanded. However, when looking at the map it becomes apparent that patterns created by footprints are too cluttered and hard to understand or make sense of without filtering. Interactive visualization allowed us to manipulate the representation in real time without having to re-run statistical models based on predetermined locations or sets of preselected MNEs. If we had tested for the significance of hubs and their development and/or

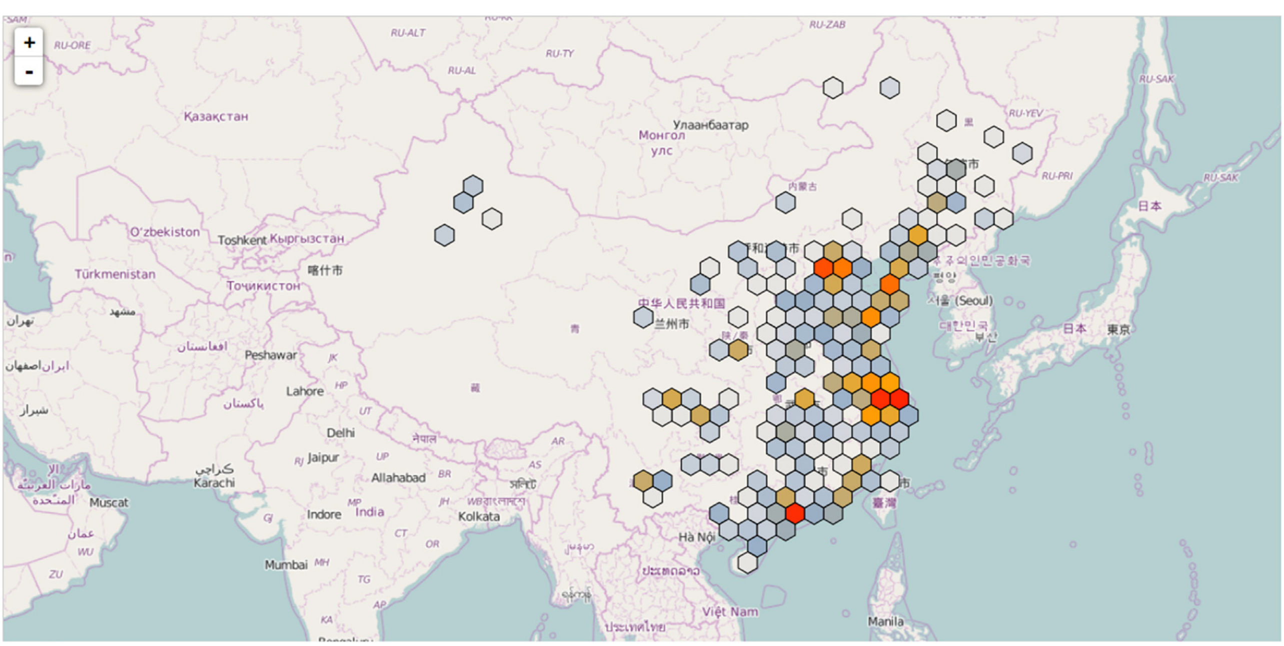

Fig. 3. Hexbin representation of Japanese FDI distribution analysis in China.

Please cite this article in press as: Schotter, A. P. J., et al. Interactive visualization for research contextualization in international business. *Journal of World Business* (2017), http://dx.doi.org/10.1016/j.jwb.2017.01.006

hub-interrelatedness based on predefined locations (e.g., administrative boundaries, including major cities or provinces), the likelihood of missing some of the less obvious hubs and the relationships between those hubs would have been high. In addition, a traditional statistical approach would have been very time consuming. One important observation from this initial visualization analysis was that Japanese MNEs have so far not expanded homogenously across all of China, despite several institutional changes that the Chinese government implemented to promote inland investments (reference anonymized). This is surprising, because much of the extant MNE location literature (e.g., Goodman, 2004; Naughton, 2007) suggests that after an initial entry in a country, national expansion is inevitable for most foreign MNEs.

As noted, we zoomed in on the Shanghai region and applied an interactive lens technique to analyze contextual properties of this region on the map. The purpose of interactive lenses is to provide "*an alternative visual representation of the data underlying a local area on the screen*" (Tominski, Gladisch, Kister, Dachselt, & Schumann, 2014: 43). The interactive lens technique allowed us to eliminate potential masking effects systemically and with relative ease. Particularly useful was the interactive lens approach for filtering at a level smaller than the administrative boundaries level, the common approach in extant IB research. Several investment hotspots spanned across administrative provincial and city boundaries. However, we found that Japanese MNEs collocate in much smaller areas than previously assumed. We found that co-ethnic effects drive co-location over and above investment incentives linked to predefined boundaries. By manipulating the visualization, we could test if this observation prevailed over time or not. This example highlights how interactive visualization allows for simultaneously displaying and analyzing an IB phenomenon in spatial, temporal, and other contexts. From a theory development perspective, this relatively simple example of interactive visualization allowed us to develop several linkages to different IB literatures, including the literature on subnational expansion and location choices (e.g., Mudambi & Santangelo, 2014), sequential entry decisions, co-ethnic theory (e.g., Hernandez, 2014; Kim, 2015), and regional clusters (e.g., Enright, 2003; Flores, Aguilera, Mahdian, & Vaaler, 2013).

3.5. Raster models

Next, we explored the Japanese FDI data with the help of a raster model. Raster models are matrixes where each cell is assigned a single data value describing a property of a geo-referenced object at a specific location (Campbell & Shin, 2012). Such a data structure simplifies geospatial analyses (reclassifying, overlay merging, and mathematical transformations, as well as cost-path, density, and neighborhood detection (Campbell & Shin, 2012)). Cells and their values are building blocks for deriving density distribution surfaces from data, which cannot be effectively represented in vector form. In econometrics, surfaces are commonly used for representing financial risks and firm clusters (Arbia, Espa, & Quah, 2008; Bera, Ivliev, & Lillo, 2015; Maoh & Kanaroglou, 2004). These surfaces often take the form of heat maps, which are created with additional models, including kernel density estimation. Kernel density estimation helps identify clusters of similar values in raster grids, represent their density, and smooth the contours of their density distribution surface (Silverman, 1986). Despite obvious advantages over vector models, raster models currently have shortcomings. For example, raster files are typically very large and their visualizations look less appealing than vector layers. They are often produced as single, inflexible, non-interactive representations (Antoniou & Morley, 2008) in which objects cannot be further analyzed based on emerging visual identification.

Unlike the vector representation in Fig. 3, a raster representation (Fig. 4) shows a more accurate (so-called) landscape of MNEs. Irregularly shaped landscapes are most promising for IB research contextualization, as they show variations in spatial coverage. The color codes on the heat map in Fig. 4 visualize cores and peripheries of Japanese MNE FDI in the greater Shanghai region. Reds are cores, represented by greater densities, and blues are peripheries with lower densities. The markers underneath the raster layer show how the raster and vector models overlap. The raster model approach is a significant improvement over statistical tests that rely on manually derived geographic spaces for identifying potential investment cores or peripheries (e.g., Schotter & Beamish, 2011). A very promising contextualization could be a focus on investigations that compares primary and secondary core locations

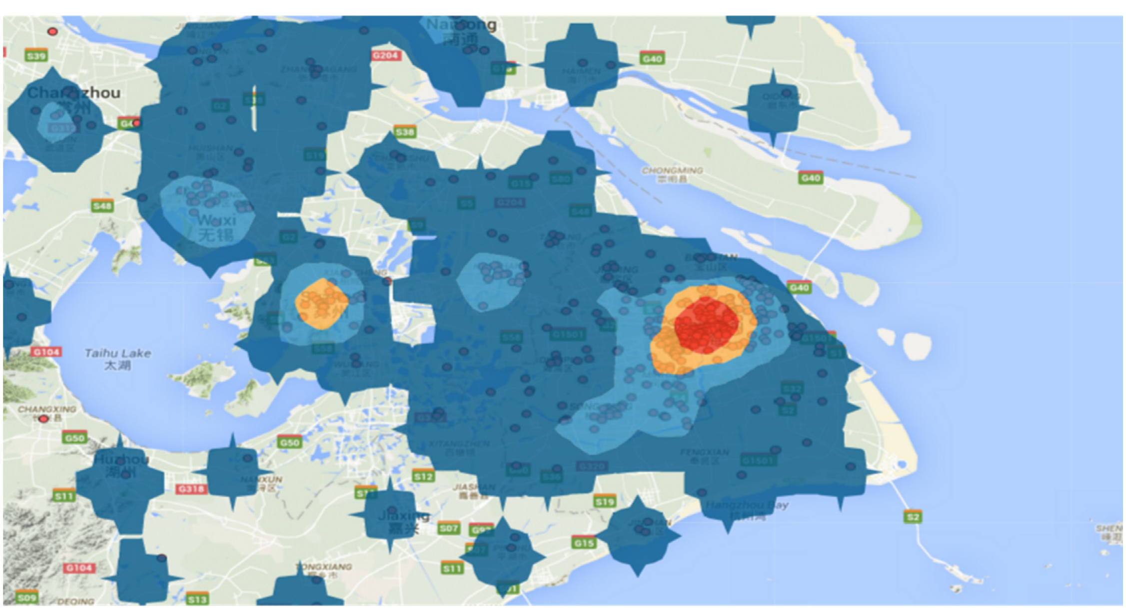

Fig. 4. Kernel density heat map representing Japanese FDI core and periphery locations in the greater Shanghai area.

Please cite this article in press as: Schotter, A. P. J., et al. Interactive visualization for research contextualization in international business. *Journal of World Business* (2017), http://dx.doi.org/10.1016/j.jwb.2017.01.006

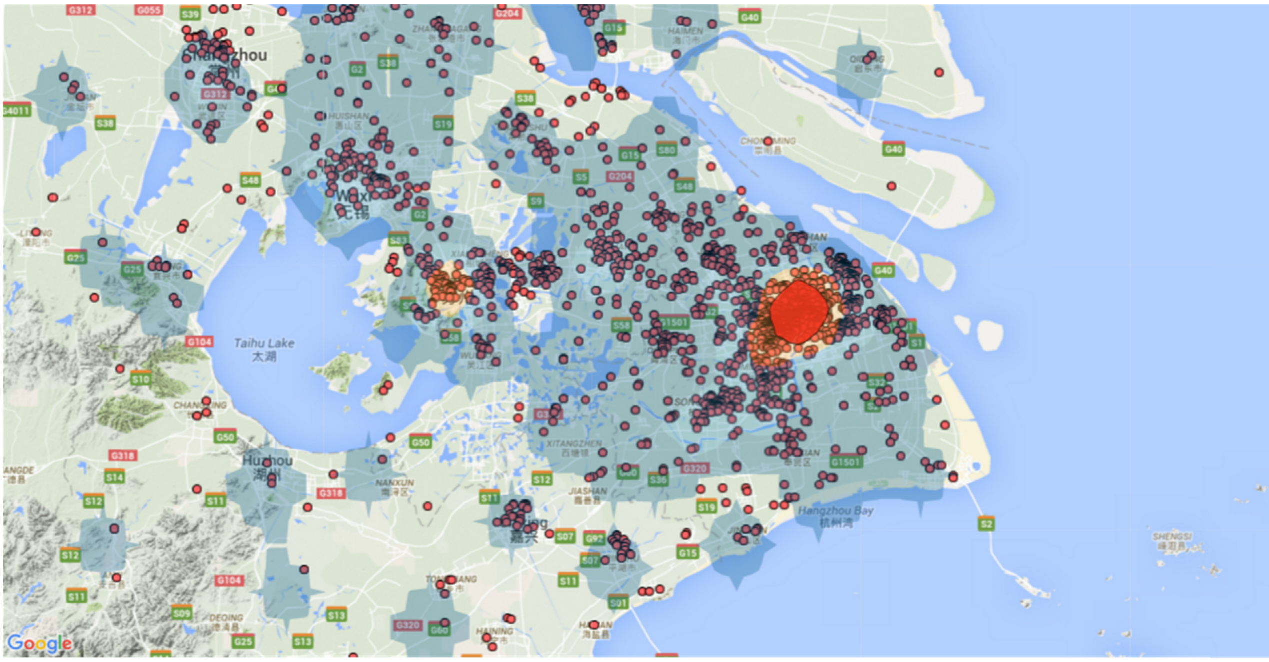

Fig. 5. Interactive heat map of Japanese MNE core and periphery investments in greater Shanghai.

(the darker blue peripheral areas around the cores in Fig. 4). Such an approach is not possible based on statistical techniques, as these secondary cores are not visually detectable without guesses by the researcher.

However, raster layers are usually generated as fixed layers. To make the heat map raster visualization interactive, we extracted the kernel density values assigned by the QGIS software (Quantum GIS Development Team, 2011) from the grid and drew contours around similar values using a contouring algorithm (Bourke, 1987). From the contours, we determined the dimensions and boundaries of polygons corresponding to each surface value on the raster map. This allowed us to represent polygons on Google Maps as separate objects that we could then interactively analyze. Fig. 5 shows this approach for the Shanghai region. It allowed us not only to select cores and peripheries but also to access points from the vector layer. We were able to analyze properties and behaviors of MNEs that started in either cores or peripheries discreetly, over time, or dynamically without having to reconfigure the underlying statistical data structure. The value for theory development in IB is that such an approach results in a more accurate representation of actual MNE investment paths across time and space. Such an approach also improves the ability to develop more defined hypotheses. In our case (reference anonymized), we developed new theory on co-ethnic agglomeration (e.g., Levitt, 2004; Polanyi, Arensberg, & Pearson, 1957; Portes & Sensenbrenner, 1993) linked this with institutional and MNE agglomeration logics (e.g., Beugelsdijk & Mudambi, 2013; Cano-Kollmann, Cantwell, Hannigan, Mudambi, & Song, 2016; Klier & McMillen, 2008). We found that co-ethnic effects are sensitive to much shorter physical distances than previously assumed. We found that co-ethnic MNE investment communities (e.g., Hernandez, 2014; Kim, 2015) form within a few city blocks of each other only. The implication is that in order for MNEs to capture co-ethnic benefits, it is not only important to be located within a certain city or province, but to pay attention to the sub-region or district for choosing an investment location.

3.6. Interactive dashboards

Due to advances in visualization technologies, we are now witnessing the emergence of new types of so-called interactive dashboards. Interactive dashboards utilize information visualization, geo-visualization, visual analytics, and geospatial analytics dynamically and often in real time. This makes them suitable for exploring the contextual properties of an object and its interactions with other objects across time and space on one unified screen. Interactive dashboards allow for rapid sub-group analyses without having to manually parse out a dataset. An interactive dashboard is also the central feature of our online visualization toolbox (see link above). Fig. 6 shows a screenshot of the dashboard applied to the IJV sample dataset.

The central feature of the dashboard is a geographic map with countries represented as network nodes and connected by lines (edges) denoting the presence of IJV formation relationships between different countries. Right below the geographic map is a double-layered timeline for the entire sample period. The timeline on the bottom shows the intensity of annual IJV formation in the form of circles of different sizes. The upper timeline shows thumbnails as indicators of the presence of certain IJV formation communities and highlights some relational association between countries if the underlying area shows a grey marking. In our IJV dashboard, we use spinglass models and simulated annealing for community detection based on the igraph R package (Csardi & Nepusz, 2006).[6] From the upper timeline in the dashboard, we see that there are only a few significant communities over the sample period. From here, a researcher can dive deeper into the data and narrow, expand, or change the contextualization of her/his IJV research project. It should be apparent that the interactive visual approach allows for more refined hypotheses development and for accounting of all three of the interactive visualization dimensions and their manipulations depicted in Fig. 1.

The legend in the top-right corner of the dashboard includes two components: (1) the map legend and filters and (2) the representation of the centrality metrics. Centrality metrics display

[6] We chose this algorithm because spinglass models have been widely adopted in economic analysis and business (see, e.g., Palmer, 1988; Minniti, 2004). In a recent comparative study on the performance of community detection algorithms in artificial networks, spinglass models performed better than Louvain's algorithm as described in Blondel et al., 2008. The Reichardt and Bornholdt (2006) spinglass model relies on an analogy between statistical mechanics and network structure. It can detect communities with both hierarchical and overlapping structures.

Please cite this article in press as: Schotter, A. P. J., et al. Interactive visualization for research contextualization in international business. *Journal of World Business* (2017), http://dx.doi.org/10.1016/j.jwb.2017.01.006

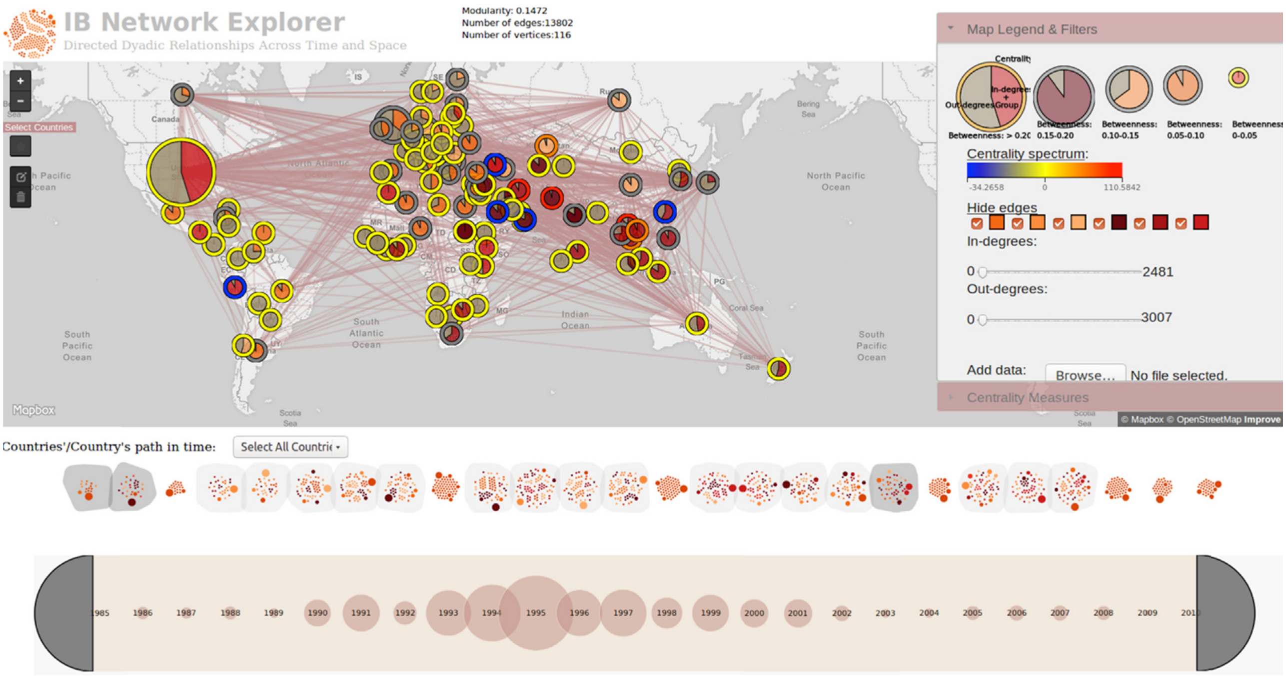

Fig. 6. Interactive dashboard and community timelines for global IJV formation analyses.

calculated centrality indices related to network footprint characteristics, which quantify different aspects of the centrality of a node's position within a network or a particular community as well as the centrality propensity of the entire network (Freeman, 1978). Betweenness centrality represents the extent to which a node lies on the path between other nodes (Newman, 2010). In-degree centrality and out-degree centrality refer to the ingoing or outgoing connections of a node within the network. Closeness centrality represents a network's density compared to other connected nodes and, finally, alpha-centrality reflects the importance of endogenous adjacent communities. Appendix II provides a more technical introduction to the different centrality metrics.

On the map, each country node is represented as a pie chart. The diameter of each pie chart represents the betweenness of the related node within the network. The map legend and filters show pie charts with different diameters associated with different betweenness intervals (0–0.05, 0.05–0.1, 0.1–0.15, 0.15–0.20, >0.20). This allows a researcher to understand which countries are high or low on IJV formation betweenness. Countries with the highest betweenness have the largest diameters of nodes, which means that they are highly influential in the IJV formation network. Such countries are 'in between' many other pairs of countries. The United States and China are such countries, which is common knowledge. However, when we interactively filter for time or for a specific global region, different high betweenness countries emerge. It should be apparent that the exploratory power of these visualization tools lies in their interactivity. Researchers can now, for example, explore whether and/or under which conditions countries that show more betweenness interact with other countries or perhaps only with some other countries within their respective network communities. If new contextual patterns emerge, a more refined research question and guiding hypothesis can be developed.

The individual slices of each pie-chart represent the in-degrees and out-degrees in the total number of IJV formations of MNEs from a particular country. The khaki-colored slices represent out-degrees, or the relative number of IJVs formed of MNEs from a particular country in other countries. The other, non-khaki-colored slices represent in-degrees or the relative number of IJVs formed within a country by MNEs from other countries. The non-khaki colors are assigned by igraph automatically and suggest in cases of similarities that a set of countries is connected through a potentially important underlying contextual characteristic, which a researcher may want to investigate further.

3.7. Graduated symbols, histograms, and timelines with interactive sliders

Next, we deployed the IJV dataset and the dataset on political violence together to illustrate a more complex contextualization approach. The dashboard in Fig. 7 allows for the analysis of the spatial distribution of IJVs and political events on macro and micro levels, simultaneously (see also Fig. 1). The representation shows so-called graduated symbols in the form of blue cluster bubbles on a world map. The bubbles visualize the global distribution of IJVs. The visualization makes it easy to identify IJV formation intensities globally (larger bubbles mean more IJV formations). In addition to the bubbles, the underlying green, yellow, and red areas on the map show the distribution and intensity of political violence events[7] in the world. At the top of the dashboard, we see an interactive time slider that shows a histogram of aggregated annual IJV formations and a histogram of aggregated political violence events. The histograms allow for comparing the temporal distribution of IJVs in the world (blue color) and the total number of political violence events in the world (red color) for a selected time period. Reducing or increasing the time range on the time slider interactively changes the representation of the bubbles on the map. The map shows the macro level. Additional representations in the form of timeline graphs and histograms linked to bubbles can be produced with the help of the selection tool on the right side of the representation. They can show IJV and political events at the level of an individual country or a group of countries. The data show that in the middle of the 1990s, the total number of political events in the world was minimal and, at the same time,

[7] We define political violence as part of "contentious politics" or collective political struggle, which includes such things as revolutions, civil war, riots and strikes, but also more peaceful protest movements (O'Neil, 2015).

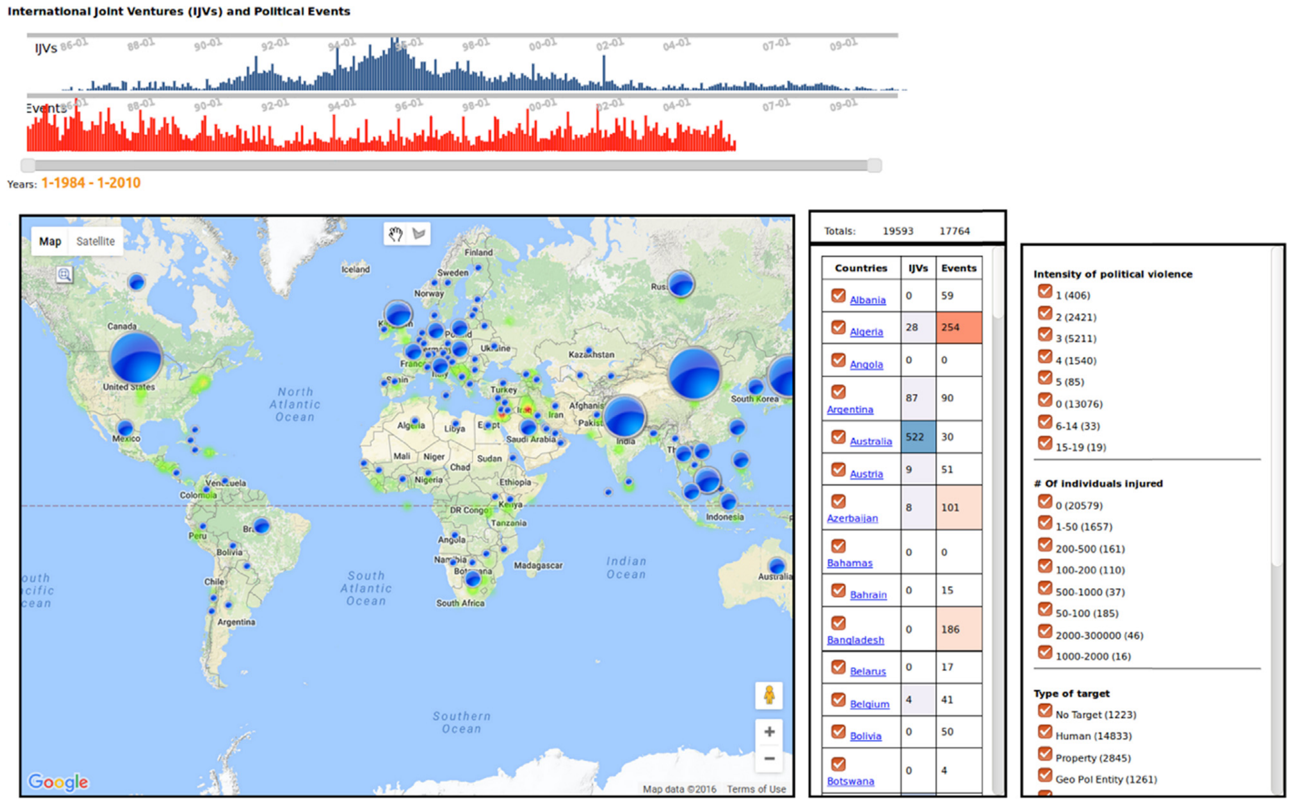

Fig. 7. Graduate symbols on dashboard, combining geographic IJV formation and political violence map with interactive timelines and dashboard selection tool.

the total number of IJV formations reached its maximum. From here, researchers can go deeper and investigate a particular context interactively. Time-based, regional, or local contextualization becomes more nuanced. However, given that the IJV context has been widely researched, a more thorough, iterative approach of going back and forth between the extant IJV literature and the interactive visualization would be required. The dashboard allows for this in an easy way.[8]

3.8. Standard deviational ellipses

A representation of IJVs aggregated by countries does not allow researchers to carry out any point pattern analyses, which is common in exploratory spatial data analysis. To make sense of patterns, standard deviational ellipse analysis (Fig. 8) is the appropriate interactive visualization technique (Friendly, Monette, & Fox, 2013). A standard deviational ellipse is a two-dimensional (spatial) equivalent of standard descriptive statistics for a single variable (O'Sullivan & Unwin, 2003). Standard deviational ellipses are often used for comparing two or more data distributions with each other and are the representations of underlying centrographic statistics of distributions of points in space. The ellipse is centered at the geographical centroid of the set of points specified through the drawing of a polygon on the map. Applying standard deviational ellipses to the exploration of the spatial and temporal patterns of the number of IJVs formed in different countries is helpful for gaining insights about statistically significant clusters of countries that are particularly attractive for IJV formation. Through the examination of the sizes, shapes, and spatial orientations of the ellipses, which represent various standard deviations, we are able to identify these patterns. The axes lengths of ellipses are determined by the standard deviation in the north–south and east–west dispersion of the observation area. Thus, the area of the ellipses indicates the spread of the IJV formation phenomenon (e.g., Gong, 2002). The orientation of the ellipses is based on the cross-correlations of the x-coordinates away from the center (Mitchell, 2005). The orientation suggests which areas are most likely to see a rise in future IJV formation activities (here, IJV formation) (Taniar, Gervasi, Murgante, Pardede, & Apduhan, 2010). Ellipses can be drawn for one, two, or three standard deviations,[9] though some studies suggest that ellipses with one standard deviation (the smallest one in our representation) are the most appropriate, as they represent higher statistical power (Sherman, Spencer, Preisser, Gesler, & Arcury, 2005).

Standard deviational ellipses have some advantages over non-spatial descriptive statistics for summarizing distributions because they condense data across space and time. In our case, they are useful for developing a better understanding of location effects on the formation of IJVs. Standard deviational ellipse analysis allows us to gradually zoom in and out to detect statistically significant groups. This is particularly useful for locations represented by greater variance, a greater annual change rate, or a smaller sample size, like in the case of Africa.

In our example (Fig. 8), the ellipse is stretched more in a north–south direction, with the one standard deviation ellipse (the smallest one) located closer to the South of Africa, which indicates that most IJVs were formed in the South of the continent. The slider on top of the figure allows for interactive manipulation of the visualization. Interactive visualizations of standard deviational ellipses raise additional, potentially novel questions that are useful for contextualization, such as: If one of the countries in a region becomes an attractive destination for IJVs, could this effect and

[8] We provide an additional interactive dashboard tool for the analysis of IJV formations and political risk in our online toolbox (http://ec2-54-149-181-220.us-west-2.compute.amazonaws.com/IBToolbox/#risks).

[9] One standard deviation includes approximately 68 percent of the data points, two standard deviations contain approximately 95 percent of the points, and three standard deviations cover approximately 99 percent of the points.

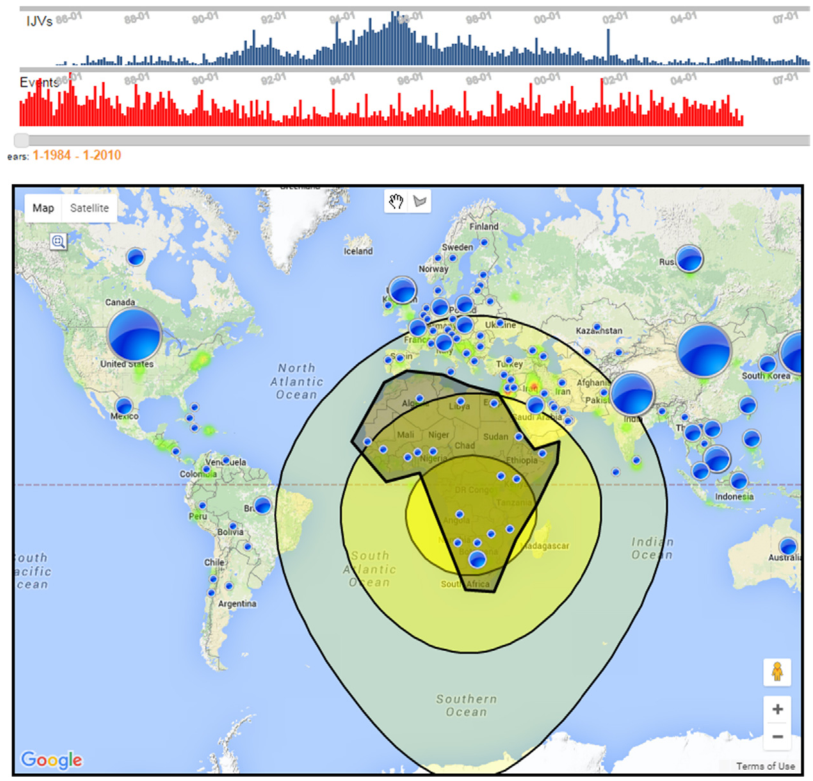

Fig. 8. Standard deviational ellipses for the analysis of political violence and IJV formation relationships in Africa.

lead to the regional spread of international IJV activities? Interactive visualization based on standard deviational ellipse analysis allows for exploring such questions.

3.9. Adjacency matrices

Besides map-based representations, it can be useful to analyze communities in networks with the help of a so-called adjacency matrix (Fig. 9) (Anderson & Armen, 1998; Anderson & McCartney, 1995; Bertin, 1983). In Fig. 9, each matrix row *i* and column *j* corresponds to the link between a node *i* and a node *j* characterized by the IJV home and host country. Color and saturation encodings created by the underlying community detection algorithm show IJV formation patterns. Adjacency matrices have a number of advantages over vector representations on maps. As vector representations grow in size, they become too cluttered and difficult to understand. In matrix views, however, links in the form of edges are absent, and groups are easier to identify and explore.

Adjacency matrices have three main features useful for the deeper exploration of network structures and their underlying dyadic relationships, including (1) a color scheme that helps to distinguish groups of countries; (2) variations in color intensity to differentiate between more or less tightly connected country communities; and (3) the use of various grey shades for identifying relationships and their strengths between countries belonging to different communities.

The underlying matrix algorithm automatically reorders countries on both axes and forms communities with blue, orange, red, and green colors based on data associations between countries. The black-colored rectangles represent interactions between members of different communities. Abundant black rectangles would suggest that members of all communities interact with members of other groups equally well, and do not strongly interact within communities.

For the IJV sample data, the adjacency matrix allows for exploring the distribution of countries within communities along with the corresponding community characteristics, such as the number of countries per community, their geographic distribution, and changes to the particular communities over time. At the country dyadic level, the adjacency matrix visualizes the intensity of IJV formation relationships between the country dyads belonging to the same community. Interactively manipulating time periods to explore the dynamics of particular community and dyadic relationships enhances research contextualization. It allows the researcher to zoom in on a sub-sample of the data in a way that is difficult to accomplish without the visualization.

3.10. Chord diagrams

Chord diagrams are another non-map-based visualization technique. The advantage of chord diagrams is an underlying hierarchical edge-bundling mechanism that reduces the visual complexity of dyadic relationships in communities (Holten, 2006). The representation takes the form of a circle diagram with objects (countries in our IJV example) ordered around the outer perimeter (Fig. 10a & b). The arc length of each country along the perimeter is automatically scaled to the share of IJVs that a country has within the data sample. A chord's width between the arcs shows the number of IJVs for a particular country dyad. If a chord has a wider width on one side and a narrower one on the other side, it means that relatively more IJVs from that country were formed in the other country. In addition to the presence and the magnitude of the relationships that can be discovered by other visualization means, the chord's width demonstrates the dyadic symmetries and asymmetries in relationships. At the country level, through selecting one of a country's arcs by pointing a cursor on it, invisible IJV relationships of that country with the rest of the sub-sample selected for the chord diagram can be visualized (Fig. 10b represents the chord diagram for IJV formation in Africa only). The advantage of chord diagrams over other relational models is the underlying hierarchical edge-bundling technique, which reduces the analytic complexity when analyzing contextual relationships

Please cite this article in press as: Schotter, A. P. J., et al. Interactive visualization for research contextualization in international business. *Journal of World Business* (2017), http://dx.doi.org/10.1016/j.jwb.2017.01.006

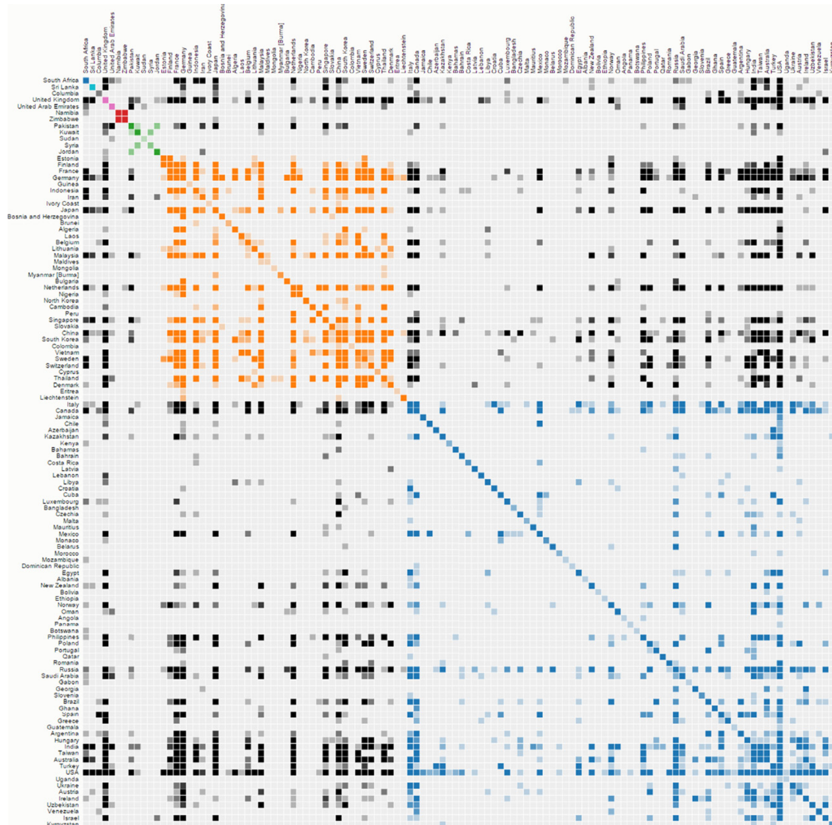

Fig. 9. Adjacency matrix, visualizing IJV formation for the purpose of community detection.

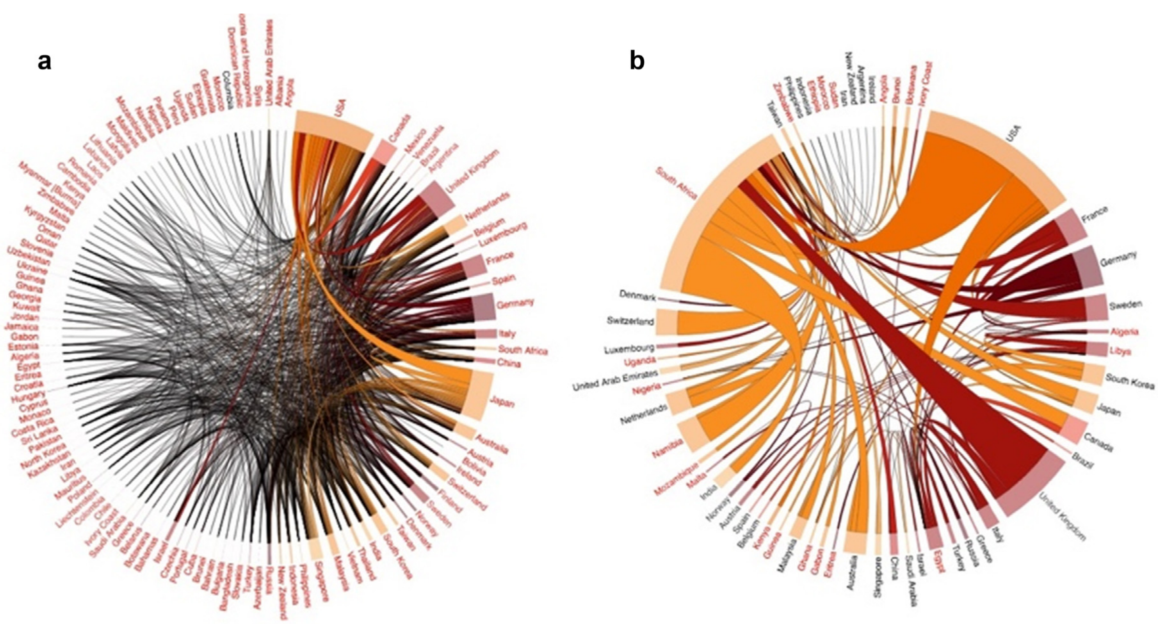

Fig. 10. (a) and (b) Chord diagrams for visualizing IJV formation intensity and IJV home- and host-country relationships — (a) shows all formation relationships globally; (b) shows only formations in/with Africa.

(Holten, 2006). Width encoding allows researchers to discover not only relationships, but also symmetries and asymmetries in relationships.

4. Discussion and conclusions

There has been a growing interest in IB to understand the true validity of empirical results and its meaningfulness for theory development. Ellis (2010) argued that when one looks at the material impact of hypothesized variables in IB studies published in leading journals, there is much to be concerned about. Other researchers have shown similar results for other areas of management (e.g., Aguinis, Beaty, Boik, & Pierce, 2005). Part of the response to concerns like these has been editorials to highlight best practices. This is seen in recent articles on the use of control variables and alternative explanations, endogeneity

(Reeb, Sakakibara, & Mahmood, 2012), and experimentation (Zellmer-Bruhn, Caligiuri, & Thomas, 2016). However, problems do not arise from a lack of empirical sophistication but from a lack of understanding the foundations of scientific testing and the experimental basis of nearly all empirical research programs (reference anonymized). The implication is that IB scholars should focus on improving research program designs and particularly research contextualization by following the logic and experimental basis of the philosophy of science.

In this paper, we introduced interactive visualization to IB with the purpose of advancing research contextualization and the experimental toolkit of researchers in the field. Interactive visualization is particularly helpful for abductive research and research that deploys a grounded theory approach (Dougherty, 2002; Eisenhardt, 1989). Interactive visualization enables researchers to go beyond traditional multivariate and other statistical approaches when examining phenomena at multiple levels of granularity or scale, and/or across rich contextual settings. The power of interactive visualization for IB contextualization lies in its ability to explore and detect patterns in data by examining the characteristics of a sample interactively and simultaneously across multiple dimensions, along with accounting for different data dependence structures (e.g., spatial, temporal, relational, etc.). We argue that this is particularly helpful for moving IB research beyond current theory development gridlocks. In addition, interactive visualization supports dialogue amongst researchers from different disciplines by providing visual artifacts for cross-domain sense making (Spee & Jarzabkowski, 2009). Interactive mapping can extend earlier economic geography approaches for identifying weak MNE FDI patterns (e.g. Dicken, 2010; McCann & Iammarino, 2013).

For IB research in particular, this introduction to interactive visualization aids the contextualization of various IB phenomena such as foreign entry by MNEs and more fine grained analyses of internationalization dynamics. Useful areas include for example, (a) the 'real option' approach to FDI (Buckley, Casson, & Gulamhussen, 2002; Rugman & Li, 2004); (b) the emerging research on the motives of emerging market MNEs and their resulting sequence of foreign entry (Ramamurti, 2012); (c) the regional multinationals research agenda (Verbeke, Kano, & Yuan, 2016); or (d) the subnational expansion of foreign MNEs (e.g., Stallkamp et al., 2017). Further research investigating the impact of diverse political and institutional factors on various outcomes associated with MNEs can benefit from not only much richer politico-economic context-related data that have become recently available, but also from applying interactive visualization to synthesize those large volumes of information. Research on political risk (e.g., Kobrin, 1979), political behavior of MNEs (e.g., Boddewyn, 1988), political domestic institutions (e.g., Henisz et al., 2009), interstate conflict and interstate alliances (e.g., Li & Vashchilko, 2010), as well as institutional voids (e.g., Khanna & Palepu, 2010) demonstrate multidimensionality of political context with significant variations across time and space.

Thus, interactive visualization enriches contextualization in IB in four ways: (1) visualizing data across more than one dimension interactively and in more than one layout enables the identification of additional contextual concepts, new and relevant communities, and links among them; (2) interactive visualization facilitates the identification of implicit (tacit) patterns in research datasets in ways not possible with the use of traditional statistical analyses; (3) interactive visualization facilitates interdisciplinary research by providing a 'common' language for the diverse interpretation of visualized patterns; and (4) interactive visualization allows for more extensive examinations of previously weak empirical results through interactive visualization tools (see online IB toolbox).

Finally, we acknowledge some limitations. When we decided to write this introduction, we were aware of the challenges that reproducing interactive visualizations in paper format presents. Regardless, we hope that this introduction is comprehensible and we encourage researchers to explore the numerous links that we have provided. A similar challenge was to dig deeper into the individual sample data used for our exemplary illustration. We realize that we did not go into great depth conceptually in every example. We regarded this as a worthwhile tradeoff and instead chose to provide an introduction to a certain breadth of interactive visualization tools relevant to IB scholars instead.

Appendix I

Previous research in IB utilizing visualization.

Publication Detail	Visualization Type	Purpose	Theories used	Datasets used	Key Findings
Johansson and Nebenzahl (1986)	Distribution of points on a 2D plane	To communicate and analyze the effects of production shifts	Theories on brand name value specifying brand image as a multi-dimensional product space	Survey data collected by the paper's authors	1. Better economic development of a home country improves brand image; 2. Better economic development of a host country producing a particular product adds value to the brand image
Koschat and Swayne (1996)	Interactive simple linked plots	To communicate and analyze customer panel data	Previous research on exploratory data analysis to demonstrate how the use of simple displays can represent complex data	Panel data consisting of records of shopping trips and purchases for about 3500 households in 1986-1988 years	A novel way of screening, structuring, and exploring panel data (e.g., combination of information across panel sections and over time
Serrano-Cinca (1998)	Neural networks	To communicate and analyze the data on the distribution of savings banks in Spain	Strategic group theory (Hunt, 1972)	Dataset on Spanish banks in 1990-1992 (30 financial ratios)	Detection of seven strategic groups in Spanish banking sector that correspond to seven Spanish macro-regions

Appendix I (*Continued*)

Publication Detail	Visualization Type	Purpose	Theories used	Datasets used	Key Findings
Porembski, Breitenstein, & Alpar (2005)	Sammon's non-linear mapping algorithm as feature space transformation for high-dimensional data	To explore and analyze a lot of information on the productivity of the branches of a German bank "with just one glance"	Use of Sammoon's mapping (Sammon, 1969) to visualize the reference and efficiency relations among the homogeneous Decision Making Units (DMUs)	Data of approximately 140 branches of a German bank	Identification of the outliers among the branches of a German bank as well as modeling the characteristics of its inefficient branches
Roijakkers and Hagedoorn (2006)	Networks; temporal 2D graphs	To explore and analyze the major long-term trends and patterns in R&D partnering between companies in the high-tech pharmaceutical biotechnology industry	R&D partnership growth and inter-firm cooperation (e.g., Hladik, 1985)	Inter-firm R&D partnerships in 1975-2000 (source: MERIT-CATI information system)	Cyclical growth pattern in many new partnerships; increased complexity and size of R&D networks; increased variety of the cooperation modes over time
Nerur, Rasheed, & Natarajan (2008)	Distribution of points on a 2D plane; networks	To visualize the intellectual structure of the strategic management field	An author co-citation analysis (ACA), multidimensional scaling, factor analysis, and pathfinder network analysis	Papers published by 62 top-ranked authors in Strategic Management Journal (SMJ) in 1980-2000	Graphical map of the intellectual structure in a two-dimensional space to visualize spatial distances between intellectual themes within the field
Basole (2009)	Networks	To explore relations between current and emerging segments of the mobile ecosystem; to discover the impact of convergence (technology, product, and service) on the mobile ecosystem and identify key players and segments, and their roles	Theories of network science, complex systems, inter-firm links, and the science of visualization	Data on existing and newly formed inter-firm relationships in 2006–2008 (Sources: Thomson's Financial SDC Platinum database; the Connexiti database)	The mobile ecosystem is growing and increasing in complexity; visualization confirmed the prior understanding of the mobile ecosystem's technological foundations along with providing a context for strategy
Acosta, Kim, Melzer, Mendoza, & Thelen (2011)	Map; heat map	To illustrate the extent of the challenges and potential opportunities to grow more inclusive markets for the poor	Market inclusiveness	Secondary survey data on access to water in Haiti in 2001, access to credit in Guatemala in 2000, and access to mobile phones in South Africa in 2006	Visualized market access to three markets in three countries across geographic and income dimensions
Tarakci et al. (2014)	Bubbles; circular diagram, 2D plots	To visualize the degree and locus of between- and within-group consensus as well as the degree and content of strategic consensus	Strategy formation and implementation processes, strategic consensus (e.g., Markoczy, 2001)	Author-collected survey data	A novel analytical approach to analyze strategic consensus within and between groups, Strategic Consensus Mapping, that includes intuitive visualizations
Berry, Guillen, & Hendi (2014)	Calculation and visualization of a minimum volume ellipsoid	To analyze the convergence across countries over 1960–2009 as a result of globalized forces	Theories on modernization, dependency, the world-system, political trade blocs, and the world-society	Data on main economic, demographic, knowledge, financial, and political dimensions of countries, 1960-2009 (e.g., World Development Indicators)	Limited evidence of convergence within clusters of countries (e.g., trade blocs); consistent evidence of divergence across countries that is driven by divergence between group of countries
Schotter and Beamish (2013)	Map; spider chart	Understanding the effects of managerial influences on MNE foreign location decisions.	Foreign location choice theories, Theory of the MNE	Author-built database of managerial travel hassles from multiple sources	Novel metric, ranking of 131 countries based on the hassle factor; higher hassle travel score to a potential FDI site decreases the likelihood of choosing it for FDI
Beugelsdijk and Mudambi (2013)	Bubbles to visualize frequencies; histogram along with a trend line	To compare the effect of distance on space and geography as an illustration of a gap in IB research at the subnational level	A review of IB theories on space and geography	1291 papers published in the JIBS over the period 1990–2012	Demonstrate increased volume of publication on space and geography in IB since 1990

Appendix I (*Continued*)

Publication Detail	Visualization Type	Purpose	Theories used	Datasets used	Key Findings
Flores et al. (2013)	Iterative scheme	To illustrate the application of regional grouping scheme refinement as an iterative process	A new theory of comparative regional scheme assessment for model-building purposes of MNC location choices	US MNC subsidiary's location (Angel, 2001), ROI, size and industry (Fortune, 2001; World Investment Report); World Development Indicators	Ex-post analytical approach to evaluate the similarities between different regional groupings of countries based on geography, broad cultural traits and trade or investment patterns
Alcácer, Dezső, & Zhao (2013)	Scheme for an extensive form of a game; 2D area graphs	To illustrate (1) the moves of firms in a game theory model and (2) equilibrium strategies of the firms by displaying their marginal costs	Strategic interaction among MNEs and location decisions (e.g., Knickerbocker, 1973) and game theory models of oligopolistic competition	A set of parameters for computational solution of a game theory model to identify the equilibrium strategies of rival firms expanding across time and markets	In oligopolistic industries, limiting competitors' growth potential and increasing their own competitive advantages are the main drivers of firms' location choices

Appendix II

B.1. Centrality metrics

To display centrality metrics in interactive visualization for a country and for the entire time period, a user needs to select the appropriate tool, including 'betweenness', 'in-degree', 'out-degree', 'closeness', or 'alpha-centrality'.

The betweenness of a node (or a country in our *IB Network Toolbox*) refers to the extent to which a node lies on the path between other nodes (Newman, 2010, p. 186). The betweenness metric, x_i, is calculated as in Newman (2010, p. 187, formula 7.36) and in the igraph R package in the following way (this formula is equally suitable for the calculation of betweenness for directed and non-directed networks):

$$x_i = \frac{2}{n*n-3*n-2)} \sum_{\substack{i \neq j \\ i \neq v \\ j \neq v}} \frac{g_{ivj}}{g_{ij}},$$

where g_{ivj} is the number of shortest paths from a node i to a node j that pass through a node v, g_{ij} is the total number of shortest paths from a node i to a node j, and n is the number of vertices or nodes in the network.

In non-directed networks, degrees of a node refer to "*the number of edges connected to it*" (Newman, 2010, p. 135), in directed networks, two degrees characterize each node's, in-degree and out-degree. To express in- and out-degrees of a node mathematically, we need to define the adjacency matrix, A_{ij}, as in Newman (2010, p. 115, formula 6.5):

$$A_{ij} = \begin{cases} 1 & \text{if there is an edge from j to i} \\ 0 & \text{otherwise} \end{cases}$$

In-degree, k_i^{in}, refers to "*the number of ingoing edges connected to a vertex*" (Newman, 2010, p. 136), the normalized value of which is calculated as:

$$k_i^{in} = \frac{1}{n-1} \sum_{j=1}^{n} A_{ij}$$

Out-degree, k_i^{out}, refers to "*the number of outgoing edges*" (Newman, 2010, p. 136), the normalized value of which is calculated as:

$$k_i^{out} = \frac{1}{n-1} \sum_{i=1}^{n} A_{ij}$$

The closeness of a node i, C_i', is the inverse of the harmonic mean distance between vertices i and j, d_{ij}, which is "*the average of the inverse distances*," as defined in Newman (2010, p. 185, formula 7.30), which correspond to the "normalized" specification of the "closeness" function in R's igraph package:

$$C_i' = \frac{1}{n-1} \sum_{j(\neq i)} \frac{1}{d_{ij}}$$

The closeness will have greater values for those nodes that are "closer" to i than those that are further away from i.

Alpha-centrality, α, is "a generalized eigenvector measure of centrality" (Bonacich & Lloyd, 2001, p. 199). The R's function to calculate alpha-centrality is based on Bonacich and Lloyd (2001). The matrix solution for the parameter α reflects the importance of the endogenous, adjacency matrix, A with elements A_{ij} defined above, versus exogenous factors, which are denoted as vector e in the determination of centrality:

$$x = \left(I - \alpha A^T\right)^{-1} e$$

References

Acosta, P., Kim, N., Melzer, I., Mendoza, R. U., & Thelen, N. (2011). Business and human development in the base of the pyramid: Exploring challenges and opportunities with market heat maps. *Journal of World Business, 46*(1): 50–60.

Aguinis, H., Beaty, J. C., Boik, R. J., & Pierce, C. A. (2005). Effect size and power in assessing moderating effects of categorical variables using multiple regression: A 30-year review. *Journal of. Applied Psychology, 90*(1): 94.

Alcácer, J., Dezső, C. L., & Zhao, M. (2013). Firm rivalry, knowledge accumulation, and MNE location choices. *Journal of International Business Studies, 44*(5): 504–520.

Anderson, M., & McCartney, R. (1995). Inter-diagrammatic reasoning. In *Proceedings of the 14th international joint conference on artificial intelligence* (vol. 1, pp. 878–884). San Francisco: Morgan Kaufmann Publishers Inc..

Anderson, M., & Armen, C. (1998). Diagrammatic reasoning and color. In *Formalization of reasoning with visual and diagrammatic representations, papers from the 1998 Fall Symposium, Technical Report FS-98-04* (pp. 13–22). Menlo Park: AAAI Press.

Andrienko, N., Andrienko, G., & Gatalsky, P. (2003). Exploratory spatio-temporal visualization: An analytical review. *Journal of Visual Languages & Computing, 14*(6): 503–541.
Andrienko, N., & Andrienko, G. (2006). *Exploratory analysis of spatial and temporal data: A systematic approach*. Berlin: Springer Verlag.
Antoniou, V., & Morley, J. (2008). Web mapping and WebGIS: Do we actually need to use SVG? *SVG Open 2008: 6th international conference on scalable vector graphics* (pp. 26–28).
Arbia, G., Espa, G., & Quah, D. (2008). A class of spatial econometric methods in the empirical analysis of clusters of firms in the space. *Empirical Economics, 34*(1): 81–103.
Araújo, N. A. M., Andrade, R. F. S., & Herrmann, H. J. (2010). Q-state Potts model on the Apollonian network. *Physical Review E, 82*(4): 046109–54617.
Bartlett, C. A., & Ghoshal, S. (1989). *Managing across borders: The transnational solution*. Cambridge, MA: Harvard Business School Press.
Basole, R. C. (2009). Visualization of inter-firm relations in a converging mobile ecosystem. *Journal of Information Technology, 24*(2): 144–159.
Bell, E., & Davison, J. (2012). Visual management studies: Empirical and theoretical approaches. *International Journal of Management Reviews, 15*(2): 167–184.
Bera, A. K., Ivliev, S., & Lillo, F. (2015). *Financial Econometrics and Empirical Market Microstructure*. New York: Springer International Publishing.
Berry, H., Guillen, M. F., & Hendi, A. S. (2014). Is there convergence across countries? A spatial approach. *Journal of International Business Studies, 45*(4): 387–404.
Bertin, J. (1983). *Semiology of graphics: Diagrams, networks, maps*. Madison, WI: The University of Wisconsin Press, Ltd.
Beugelsdijk, S., & Mudambi, R. (2013). MNEs as border-crossing multi-location enterprises: The role of discontinuities in geographic space. *Journal of International Business Studies, 44*(5): 413–426.
Beugelsdijk, S., McCann, P., & Mudambi, R. (2010). Introduction: Place, space, and organization — Economic geography and the multinational enterprise. *Journal of Economic Geography, 10*(4): 485–493.
Blondel, V. D., Guillaume, J. L., Lambiotte, R., & Lefebvre, E. (2008). Fast unfolding of communities in large networks. *Journal of Statistical Mechanics: Theory and Experiment, 2008*(10): 100–108.
Birkinshaw, J. (1997). Entrepreneurship in multinational corporations: The characteristics of subsidiary initiatives. *Strategic Management Journal, 18*(3): 207–229.
Bodner, G., & Domin, D. (2000). Mental models: The role of representations in problem solving in chemistry. *University Chemistry Education, 4*: 24–30.
Boddewyn, J. J. (1988). Political aspects of MNE theory. *Journal of International Business Studies, 19*(3): 341–363.
Bonacich, P., & Lloyd, P. (2001). Eigenvector-like measures of centrality for asymmetric relations. *Social Networks, 23*: 191–201.
Bourke, P. (1987). A contouring subroutine. *Byte, 12*(6): 143–150.
Buckley, P. (2002). Is the international business research agenda running out of steam? *Journal of International Business Studies, 33*(2): 365–373.
Buckley, P. J., Casson, M. C., & Gulamhussen, M. A. (2002). Internationalisation – Real options, knowledge management and the Uppsala approach. In V. Havila, M. Forsgren, & H. Hakansson (Eds.), *Critical perspectives on internationalization* (pp. 229–261). Oxford: Pergamon.
Campbell, J., & Shin, M. (2012). *Geographic information system basics*. http://2012books.lardbucket.org/books/geographic-information-system-basics Accessed 10.11.15.
Cano-Kollmann, M., Cantwell, J., Hannigan, T. J., Mudambi, R., & Song, J. (2016). Knowledge connectivity: An agenda for innovation research in international business. *Journal of International Business Studies, 47*(3): 255–262.
Card, S., Mackinlay, J., & Shneiderman, B. (1999). *Readings in information visualization: Using vision to think*. San Francisco: Morgan Kaufmann Publishers.
Card, S. K., Suh, B., Pendleton, B. A., & Bodnar, J. W. (2006). TimeTree: Exploring time changing hierarchies. *IEEE symposium on visual analytics science and technology* (pp. 3–10).
Carr, D., Littlefield, R., Nicholson, W., & Littlefield, J. (1987). Scatterplot matrix techniques for large N. *Journal of the American Statistical Association, 82*(398): 424–436.
Csardi, G., & Nepusz, T. (2006). The igraph software package for complex network research. *InterJournal, Complex Systems, 1695*(5): 1–9.
Cheng, J. L. C., Guo, W., & Skousen, B. (2011). Advancing new theory development in the field of international management. *Management International Review, 51*(6): 787–802.
Chernoff, H. (1973). The use of faces to represent points in k-dimensional space graphically. *Journal of the American Statistical Association, 68*(342): 361–368.
Child, J. (2009). Context, comparison, and methodology in Chinese management research. *Management and Organization Review, 5*(1): 57–73.
Dent, B. D. (1975). Communication aspects of value-by-area cartograms. *The American Cartographer, 2*(2): 154–168.
De Smith, M. J., Goodchild, M. F., & Longley, P. (2007). *Geospatial analysis: A comprehensive guide to principles, techniques and software tools*. Leicester, UK: Troubador Publishing Ltd.
DeSarbo, W. S., & Grewal, R. (2008). Hybrid strategic groups. *Strategic Management Journal, 29*(3): 293–317.
DeSarbo, W. S., Grewal, R., Hwang, H., & Wang, Q. (2008). The simultaneous identification of strategic/performance groups and underlying dimensions for assessing an industry's competitive structure. *Journal of Modelling in Management, 3*(3): 220–248.
Dicken, P. (2010). *Global shift: Mapping the changing contours of the world economy*. New York: Guildford.
Dörk, M., Carpendale, S., & Williamson, C. (2012). Visualizing explicit and implicit relations of complex information spaces. *Information Visualization, 11*(1): 5–21.
Dorling, D. (1996). Area cartograms: Their use and creation. In C. Dunn (Ed.), *Concepts and techniques in modern geography series*. No 59 University of East Anglia: Environmental Publications.
Dougherty, D. (2002). Grounded theory research methods. In J. Baum (Ed.), *The Blackwell companion to organizations* (pp. 21–64). Oxford: Blackwell.
Dykes, J., MacEachren, A. M., Kraak, M.-J. (Eds.). (2005). *Exploring geovisualization*. New York: Elsevier Ltd.
Eisenhardt, K. M. (1989). Building theories from case study research. *Academy of Management Review, 14*(4): 532–550.
Ellis, P. D. (2010). *The essential guide to effect sizes: Statistical power, meta-analysis, and the interpretation of research results*. Cambridge, UK: Cambridge University Press.
Enright, M. J. (2003). Regional clusters: What we know and what we should know. In J. Bröcker, D. Dohse, & R. Soltwedel (Eds.), *Innovation clusters and interregional competition* (pp. 99–129). Berlin, New York: Springer.
Ferreira de Oliveira, M. C., & Levkowitz, H. (2003). From visual data exploration to visual data mining: A survey. *IEEE Transactions on Visualization and Computer Graphics, 9*(3): 378–394.
Fisher, E., & Buchel, O. (2012). Can interactive map-based visualizations reveal contexts of scientific datasets? http://www.cais-acsi.ca/ojs/index.php/cais/article/download/628/387 Accessed 30.09.15. *Presented at the 41st annual conference of the Canadian Association of Information Science (CAIS)*.
Flores, R., Aguilera, R. V., Mahdian, A., & Vaaler, P. M. (2013). How well do supranational regional grouping schemes fit international business research models. *Journal of International Business Studies, 44*(5): 451–474.
Fortunato, S. (2010). Community detection in graphs. *Physics Reports, 486*(3–5): 75–174.
Fortune (2001). The annual list of the largest US corporations. *Fortune, 143*(8): F1–F23.
Freeman, L. C. (1978). Centrality in social networks conceptual clarification. *Social Networks, 1*: 215–239.
Friendly, M., Monette, G., & Fox, J. (2013). Elliptical insights: Understanding statistical methods through Elliptical Geometry. *Statistical Science, 28*(1): 1–39.
Gilbert, J. K., Reiner, M., & Nakhleh, M. (2007). *Visualization: Theory and practice in science education*. Dordrecht: Springer Science & Business Media.
Goodman, D. S. (2004). The campaign to "Open up the West": National, provincial-level, and local perspectives. *China Quarterly, 178*: 317–334.
Goldman, A. I. (1989). Interpretation psychologized. *Mind and Language, 4*(4): 161–185.
Gong, J. (2002). Clarifying the standard deviational ellipse. *Geographical Analysis, 34*(2): 155–167.
Grossbart, S. L., Mittelstaedt, R. A., & Murdock, G. W. (1978). Nearest neighbor analysis: Inferring behavioral processes from spatial patterns. In K. Hunt (Ed.), *Advances in consumer research* (5, pp. 114–118). .
Gruzd, A., Wellman, B., & Takhteyev, Y. (2011). Imagining Twitter as an imagined community. *American Behavioral Scientist, 55*(10): 1294–1318.
Guo, D., Gahegan, M., MacEachren, A. M., & Zhou, B. (2005). Multivariate analysis and geovisualization with an integrated geographic knowledge discovery approach. *Cartography and Geographic Information Science, 32*(2): 113–132.
Hernandez, E. (2014). Finding a home away from home: Effects of immigrants on firms' foreign location choice and performance. *Administrative Science Quarterly, 59*(1): 73–108.
Hill, L. L. (2006). *Georeferencing: The geographic associations of information*. Cambridge, MA: MIT Press.
Hladik, K. J. (1985). *International joint ventures*. Lexington, MA: Lexington Books.
Holten, D. (2006). Hierarchical edge bundles: Visualization of adjacency relations in hierarchical data. *IEEE Transactions on Visualization and Computer Graphics, 12*(5): 741–748.
Hunt, M. S. (1972). *Competition in the major home appliance industry, 1960–1970* unpublished Doctoral Dissertation Cambridge, MA: Harvard University.
Hymer, S. (1976). *The international operations of national firms: A study of direct investment*. Cambridge, MA: MIT Press.
Hymer, S. H. (1979). In R. B. Cohen (Ed.), *The multinational corporation: A radical approach*. Cambridge, UK: Cambridge University Press.
Jern, M., Thygesen, L., & Brezzi, M. (2009). A web-enabled geovisual analytics tool applied to OECD regional data. *Reviewed Proceedings in Eurographics*, 137–144.
Johansson, J. K., & Nebenzahl, I. D. (1986). Multinational production: Effect on brand value. *Journal of International Business Studies, 17*(3): 1–27.
Khanna, T., & Palepu, K. G. (2010). *Winning in emerging markets: A road map for strategy and execution*. Cambridge, MA: Harvard Business Press.
Keim, D., Andrienko, G., Fekete, J.-D., Gorg, C., Kohlhammer, J., & Melancon, G. (2008). Visual analytics: Definition, process, and challenges. In A. Kerren, J. T. Stasko, J.-D. Fekete, & C. North (Eds.), *Information visualization: Human-centered issues and perspectives* (pp. 154–175). New York, NY: Springer-Verlag.
Klier, T., & McMillen, D. P. (2008). Clustering of auto supplier plants in the United States. *Journal of Business & Economic Statistics, 26*(4): 460–471.
Kim, H. (2015). Should birds of a feather flock together? Agglomeration-by-nationality trade-off in foreign markets. *Academy of Management Proceedings, 2015*(1): 14290.
Knickerbocker, F. T. (1973). *Oligopolistic reaction and multinational enterprise*. Boston.

Knigge, L., & Cope, M. (2006). Grounded visualization: Integrating the analysis of qualitative and quantitative data through grounded theory and visualization. *Environment and Planning, 38*(11): 2021–2037.
Kobrin, S. J. (1979). Political risk: A review and reconsideration. *Journal of International Business Studies, 10*(1): 67–80.
Kohlhammer, J., Keim, D., Pohl, M., Santucci, G., & Andrienko, G. (2011). Solving problems with visual analytics. *Procedia Computer Science, 7*: 117–120.
Koschat, M. A., & Swayne, D. F. (1996). Interactive graphical methods in the analysis of customer panel data. *Journal of Business & Economic Statistics, 14*(1): 113–126.
Levitt, P. (2004). Transnational ties and incorporation: The case of Dominicans in the United States. In D. G. Gutierrez (Ed.), *The Columbia history of Latinos in the United States since 1960*. New York: Columbia University Press.
Li, Q., & Vashchilko, T. (2010). Dyadic military conflict, security alliances, and bilateral FDI flows. *Journal of International Business Studies, 41*(5): 765–782.
Liu, Z., & Stasko, J. (2010). Mental models, visual reasoning, and interaction in information visualization: A top-down perspective. *IEEE Transactions on Visualization and Computer Graphics, 16*(6): 999–1008.
McCann, P., & Iammarino, S. (2013). *Multinationals and economic geography*. Cheltenham: Edward Elgar.
MacEachren, A. M. (2013). Visualizing uncertain information. *Cartographic Perspectives, 13*: 10–19.
MacEachren, A. M., Boscoe, F. P., Haug, D., & Pickle, L. W. (1998). Geographic visualization: Designing manipulable maps for exploring temporally varying georeferenced statistics. *Proceedings IEEE Symposium on Information Visualization* (pp. 87–94).
Maoh, H. F., & Kanaroglou, P. S. (2004). *Economic clustering and urban form: The case of Hamilton*. Ontario: Centre for Spatial Analysis Working Paper Series, CSpA WP 003, Centre for Spatial Analysis.
Markman, A. B. (2013). *Knowledge representation*. New York: Psychology Press.
Markoczy, L. (2001). Consensus formation during strategic change. *Strategic Management Journal, 22*(11): 1013.
McCulloh, I., Armstrong, H., & Johnson, A. (2013). *Social network analysis with applications*. New York: John Wiley & Sons.
Meyer, R. E., Höllerer, M. A., Jancsary, D., & van Leeuwen, T. (2013). The visual dimension in organizing, organization, and organization research: Core ideas, current developments, and promising avenues. *Academy of Management Annals, 7*(1): 489–555.
Minniti, M. (2004). Entrepreneurial alertness and asymmetric information in a spinglass model. *Journal of Business Venturing, 19*(5): 637–658.
Mitchell, A. (2005). *The ESRI guide to GIS analysis: Spatial measurements and statistics*. Redlands, CA: ESRI Press.
Moody, J., McFarland, D., & Bender-deMoll, S. (2005). Dynamic network visualization. *American Journal of Sociology, 110*(4): 1206–1241.
Morrow, R. A., & Brown, D. D. (1994). *Critical theory and methodology* (Vol. 3). Thousand Oaks, CA: Sage Publications.
Mudambi, R., & Santangelo, G. D. (2014). From shallow resource pools to emerging clusters: The role of multinational enterprise subsidiaries in peripheral areas. *Regional studies*,. http://dx.doi.org/10.1080/00343404.2014.985199
Naughton, B. (2007). *The Chinese economy: Transitions and growth*. Cambridge, MA: MIT Press.
Nerur, S. P., Rasheed, A. A., & Natarajan, V. (2008). The intellectual structure of the strategic management field: An author co-citation analysis. *Strategic Management Journal, 29*(3): 319–336.
Newman, M. E. J. (2010). *Networks: An introduction*. Oxford: Oxford University Press.
O'Neil, P. H. (2015). *Essentials of comparative politics*. New York: WW Norton & Company.
O'Sullivan, D., & Unwin, D. J. (2003). *Geographic information analysis*. New York: John Wiley & Sons.
Oesterle, M., & Wolf, J. (2011). 50 Years of management international review and IB/IM research. *Management International Review, 51*(6): 735–754.
Palla, G., Derényi, I., Farkas, I., & Vicsek, T. (2005). Uncovering the overlapping community structure of complex networks in nature and society. *Nature, 435*(7043): 814–818.
Palmer, R. (1988). Statistical mechanics approaches to complex optimization problems. In P. W. Anderson, K. J. Arrow, & D. Pines (Eds.), *The economy as an evolving complex system*. Reading: Addison-Wesley.
Parsons, P., & Sedig, K. (2014). Adjustable properties of visual representations: Improving the quality of human-information interaction. *Journal of the Association for Information Science and Technology, 65*(3): 455–482.
Peterson, D. (1996). *Forms of representation: An interdisciplinary theme for cognitive science*. Bristol, UK: Intellect Books.
Pickett, R. M., & Grinstein, G. G. (1988). Iconographic displays for visualizing multidimensional data. *Proceedings of the 1988 IEEE Conference on Systems, Man, and Cybernetics* (pp. 514–519).
Polanyi, K., Arensberg, C. M., & Pearson, H. W. (Eds.). (1957). *Trade and market in the early empires: Economies in history and theory* (pp. 243–269). Glencoe, IL: Free Press.
Porembski, M., Breitenstein, K., & Alpar, P. (2005). Visualizing efficiency and reference relations in Data Envelopment Analysis with an application to the branches of a German bank. *Journal of Productivity Analysis, 23*(2): 203–221.
Porter, M. A., Onnela, J. P., & Mucha, P. J. (2009). Communities in networks. *Notices of the AMS, 56*(9): 1082–1097.
Portes, A., & Sensenbrenner, J. (1993). Embeddedness and immigration: Notes on the social determinants of economic action. *American Journal of Sociology, 98*(6): 1320–1350.
Potts, R. B. (1952). Some generalized order-disorder transformations. *Mathematical Proceedings of the Cambridge Philosophical Society, 48*(1): 106–109.
Quantum GIS Development Team (2011). *Quantum GIS geographic information system: Open source geospatial foundation project*. http://qgis.osgeo.org Accessed 10.11.15.
Ramamurti, R. (2012). What is really different about emerging market multinationals? *Global Strategy Journal, 2*(1): 41–47.
Reeb, D., Sakakibara, M., & Mahmood, I. P. (2012). From the editors: Endogeneity in international business research. *Journal of International Business Studies, 43*(3): 211–218.
Reichardt, J., & Bornholdt, S. (2004). Detecting fuzzy community structures in complex networks with a Potts model. *Physical Review Letters, 93*(21): 218701–218704.
Reichardt, J., & Bornholdt, S. (2006). Statistical mechanics of community detection. *Physical Review E, 74*(1): 016110–016114.
Robinson, A. C. (2010). Supporting synthesis in geovisualization. *International Journal of Geographical Information Science, 25*(2): 211–227.
Roijakkers, N., & Hagedoorn, J. (2006). Inter-firm R&D partnering in pharmaceutical biotechnology since 1975: Trends, patterns, and networks. *Research Policy, 35*(3): 431–446.
Roth, R. E. (2012). Cartographic interaction primitives: Framework and synthesis. *Cartographic Journal, 49*(4): 376–395.
Rugman, A., & Li, J. (2004). *Real options and international investment*. Cheltenham: Edward Elgar.
Sammon, J. W., Jr. (1969). A nonlinear mapping for data structure analysis. *IEEE Transactions Computing, C-18*(5): 401–409.
Saraiya, P., North, C., & Duca, K. (2005). An insight-based methodology for evaluating bioinformatics visualizations. *IEEE Transactions on Visualization and Computer Graphics, 11*(4): 443–456.
Schotter, A., & Beamish, P. W. (2011). General manager staffing and performance in transitional economy subsidiaries: A subnational analysis. *International Studies of Management & Organization, 41*(2): 55–87.
Schotter, A., & Beamish, P. W. (2013). The hassle factor: An explanation for managerial location shunning. *Journal of International Business Studies, 44*(5): 521–544.
Self, M. W., Lorteije, J. A. M., Vangeneugden, J., van Beest, E. H., Grigore, M. E., Levelt, C. N., et al. (2014). Orientation-tuned surround suppression in mouse visual cortex. *Journal of Neuroscience, 34*(28): 9290–9304.
Serrano-Cinca, C. (1998). From financial information to strategic groups: A self-organizing neural network approach. *Journal of Forecasting, 17*(5–6): 415–428.
Shenkar, O., & Von Glinow, M. (1994). Paradoxes of organizational theory and research: Using the case of China to illustrate national contingency. *Management Science, 40*(1): 56–71.
Sherman, J. E., Spencer, J., Preisser, J., Gesler, W., & Arcury, T. (2005). A suite of methods for representing activity space in a healthcare accessibility study. *International Journal of Health Geographic, 4*(1): 24.
Shneiderman, B. (1996). The eyes have it: A task by data type taxonomy for information visualizations. *Proceedings of the IEEE Symposium* (pp. 336–343).
Silverman, B. W. (1986). *Density estimation for statistics and data analysis*. New York: CRC Press.
Spee, A. P., & Jarzabkowski, P. (2009). Strategy tools as boundary objects. *Strategic Organization, 7*(2): 223–232.
Spence, R. (2014). *Information visualization: An introduction*. New York: Springer International Publishing.
Stallkamp, M., Pinkham, B. C., Schotter, A., & Buchel, O. (2017). Core or periphery? The effects of country-of-origin agglomerations on the within-country expansion of MNEs. *Journal of International Business Studies* (forthcoming).
Sutton, R. I., & Staw, B. M. (1995). What theory is not. *Administrative Science Quarterly, 40*(3): 371–385.
Taniar, D., Gervasi, O., Murgante, B., Pardede, E., & Apduhan, B. O. (Eds.). (2010). *Computational science and its applications*. Heidelberg: Springer.
Tarakci, M., Ates, N., Porck, J., van Knippenberg, D., Groenen, P., & de Haas, M. (2014). Strategic consensus mapping: A new method for testing and visualizing strategic consensus within and between teams. *Strategic Management Journal, 35*(7): 1053–1069.
Teagarden, M. B., Von Glinow, M., Bowen, D. E., Frayne, C. A., Nason, S., Huo, Y. P., et al. (1995). Toward a theory of comparative management research: An idiographic case study of the best international human resources management project. *Academy of Management Journal, 38*(5): 1261–1287.
Thudt, A., Hinrichs, U., & Carpendale, S. (2012). The bohemian bookshelf: Supporting serendipitous book discoveries through information visualization. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, vol. 1* (pp. 1461–1470).
Tominski, C., Gladisch, S., Kister, U., Dachselt, R., & Schumann, H. (2014). A survey on interactive lenses in visualization. In R. Borgo, R. Maciejewski, & I. Viola (Eds.), *STAR – state of the art report, Eurographics conference on visualization* (pp. 435–462).
Toyo Keizai (2014). *Kaigai Shinshutsu Kigyo Souran*. Tokyo: Toyo Keizai.
Toyoda, M., & Kitsuregawa, M. (2005). A system for visualizing and analyzing the evolution of the web with a time series of graphs. *Proceedings of the Sixteenth ACM Conference on Hypertext and Hypermedia* (pp. 151–160).
Turkay, C., Jeanquartier, F., Holzinger, A., & Hauser, H. (2014). *On computationally-enhanced visual analysis of heterogeneous data and its application in biomedical informatics. Interactive knowledge discovery and data mining in biomedical informatics*. Heidelberg: Springer.

Verbeke, A., Kano, L., & Yuan, W. (2016). Inside the regional multinationals: A new value chain perspective on subsidiary capabilities. *International Business Review, 25*(3): 785–793.

Wehrend, S., & Lewis, C. (1990). A problem-oriented classification of visualization techniques. In *Proceedings of the 1st Conference on Visualization '90* (pp. 139–143). Los Alamitos, CA: IEEE Computer Society Press.

Wise, J. A., Thomas, J. J., Pennock, K., Lantrip, D., Pottier, M., Schur, A., et al. (1995). Visualizing the non-visual: Spatial analysis and interaction with information from text documents. *Information Visualization Proceedings* (pp. 51–58).

Wu, F. Y. (1982). The Potts model. *Reviews of Modern Physics, 54*(1): 235–268.

Yi, J. S., Kang, Y.-A., Stasko, J., & Jacko, J. A. (2008). Understanding and characterizing insights: How do people gain insights using information visualization? *Proceedings of the 2008 Workshop on Beyond Time and Errors: Novel Evaluation Methods for Information Visualization BELIV'08*.

Zellmer-Bruhn, M., Caligiuri, P., & Thomas, D. C. (2016). From the editors: Experimental designs in international business research. *Journal of International Business Studies, 47*(4): 399–407.