A TALE OF (SIXTY) TWO CITIES:

EXPLORING THE ROOTS AND NATURE OF THE CHANGING STRUCTURE OF KNOWLEDGE CONNECTIONS

By

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ABSTRACT OF THE DISSERTATION

A TALE OF (SIXTY) TWO CITIES:

EXPLORING THE ROOTS AND NATURE OF THE CHANGING STRUCTURE OF KNOWLEDGE CONNECTIONS

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In today's globalized knowledge economy, technological knowledge plays an increasingly important role. Nowadays, cities and clusters cannot rely exclusively on local knowledge sources, but they need to combine local with complementary geographically distant (trans-local) knowledge sources. This dissertation contributes to the literature on the changing geographic composition of knowledge connections, and the complementarity of distant and local connections. We do this by providing a more detailed picture of how the spatial distribution of these connections is changing, and how they interact with one another across a mix of developed and developing country cities. In particular, we look at 62 cities to see how the geographic structure of their knowledge sourcing has been changing, both at the level of city dyads and in the overall structure of the worldwide knowledge network between cities.

Using US patent citation data for patents invented in these 62 cities worldwide, our first study explores the nature of the association between local, trans-local and international citations. Our results show that in all cities there is a significant association between international and local citations, and that an increase in international citations leads to an

increase in local connections. We also find that this effect is accentuated in highly innovative cities when compared to relatively lower innovative cities in our dataset.

Our second study looks at dyadic relationships for all possible city pairs in our city dataset, and examines the determinants of the level of knowledge outflows and knowledge inflows between them. Our results show that knowledge sourcing patterns between individual cities have varied with the extent of their co-specialization of activities, their relative position in the international knowledge network and their degree of engagement with general purpose technologies.

Using social network analysis techniques, we construct a unidirectional network of cities in our third study, since backward citations point in just one direction to prior knowledge sources. We observe how this network changes during our time period both in the aggregate and at the level of five selected sectors. The nodes in our network represent cities while the edges represent citations from one city to another. We calculate network statistics such as degree strength and eigenvector centrality to determine which cities have gained influence over time and which cities have become relatively less important. We find some developing cities have gained substantial influence over time especially in the network of patents in the ICT and other electrical equipment technological fields.

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Dedication

To my son, Khizar, who was only two when I started this journey and has shown, through his patience and understanding, maturity beyond his years, and my daughter Inaya, who was born during my third year and has brought nothing but good luck since. You both have made me better, stronger and more fulfilled than I could have ever imagined.

Table of Contents

List of Tables

List of Illustrations

Chapter 1: Introduction

In this increasingly globalized world, geography still continues to play a vital role (Hotz-Hart, 2000; Scott, 2001). Globalization reinforces economic specialization since innovation capabilities are distributed unequally between regions. The innovation potential of regions depends on internationally immobile factors including research institutions, highly skilled labor and niche markets (Hotz-Hart, 2000). Hence, locations specialize around their national knowledge base and comparative advantages. With increasing globalization, factors of production move towards regions which are the most efficient for certain activities thereby reinforcing their specialization (Hotz-Hart, 2000). This increases the possibility of heightened geographic differentiation and locational specialization (Scott, 2001).

Contrary to popular belief, improvements in transport and communication have always tended to reinforce the clustering of economic activity by widening the range of accessible markets for any given region and by helping to spur new rounds of specialization in established urban areas (Scott and Storper, 2003). Despite the lowered costs of communication, importance for face to face contact for the transmission of complex and ambiguous messages still exists (Leamer and Storper, 2001). This idea has been proven by a number of scholars. Jaffe (1989) and Jaffe et al. (1993) use patent citations to show how distance limits the flow of ideas. Audretsch and Feldman (1996) show that intellectual innovations are strong concentrated in urban areas. The recent growth of Silicon Valley further shows that spatial agglomeration is conducive to creating cutting edge technology (Saxenian, 1994). Often face to face meetings are still necessary to establish mutual confidence and trust and to accurately evaluate potential partners in constantly changing business relationships (Storper and Venables, 2002).

In fact, with increasing globalization, large city regions or 'super agglomerations' are coming into being which play a foundational role in the new world system that has been taking place since the 1970s (Veltz, 1996; Scott, 1988; Scott, 2001). Often dubbed as 'global cities', these large cities possess some similar characteristics. They typically consist of several urban areas and extended suburban surroundings (Hall 2001; Scott et al., 2001; Scott and Storper, 2003). They are also characterized by high degrees of centrality and influence in the global economy and are interconnected in the global networks that provide an infrastructure for the global economy (Sassen, 1991, 2012; Wall & van der Knaap, 2011, Goerzen et al, 2013).

Our aim in this dissertation is to study these cities of today and their changing geography of knowledge connections. We study cities in our dissertation because of their relative economic importance in the world today. These metropolitan regions are the most important foci of national growth (Scott, 1998, 2002) in that they are places of dense interrelated economic activities and also typically have high levels of productivity by reason of their agglomeration economies and their innovation potential (Scott and Storper, 2003). In many developed countries, evidence shows that major metropolitan areas are growing faster than the other areas within the same country. This phenomenon is seen even in those countries where there appeared to be a turn toward a dominant pattern of non-metropolitan grown for a brief period in the 1970s (Frey and Speare, 1988; Forstall, 1993; Summer et al, 1993; Scott and Storper, 2003). In emerging countries too, economic growth is seen at very rapid rates in the large metropolitan areas (Scott and Storper, 2003).

The success and importance of cities today is often attributed to agglomeration economies (for e.g. Marshall, 1920). Although agglomeration economies discussed in previous literature (for e.g. Marshall, 1920; Markusen, 1996) focused on advantages brought by proximity to inputs for production and access to markets, these economies have lost importance because of diminishing transport and communication costs. Other advantages such as how cities enable making the most of capital intensive infrastructure, which is especially scarce in developing nations are now more relevant (Scott and Storper, 2003).

In addition, geographical concentration also brings together various people communities and this has additional effects on economic performance (Storper, 1997; Temple and Johnson, 1998; Woolcock, 1998). In these clusters, workers may increase their skill set by participation in work related networks (Grabher, 1993). Often, firms in these locations encourage socialization in both formal and informal ways to help streamline their interactions, to escalate information transfer, to build trust and to promote joint interests (Becattini, 1990; Asheim, 2000; Scott and Storper, 2003). Formal and informal relationship such as these add to the collective assets in any given region.

There is increasing evidence that creativity and learning have a distinctive geography, with regions playing active roles in sites of continuous and informal but significant improvement in industrial products and processes (Russo, 1985; Jaffe et al., 1993; Saxenian, 1994; Scott 1999; Feldman 2000; Dunning, 2002; Scott and Storper, 2003). A classic example of the phenomenon of localized innovation is Silicon Valley. The spatial proximity of large number of actors in a city provides the necessary ingredients for many exchanges of information to occur and out of which new understandings about process and product possibilities are constantly generated. Specialized regional economies raise the rate of innovation and promote long term grown because of the intense knowledge spillovers that may occur within them (Jaffe at al., 1993; Antonelli, 1994; Audretsch and Feldman, 1996; Nooteboom, 1999; Scott and Storper, 2003).

Cities themselves are not empty and analogous containers within which these agglomeration economies tend to occur. Each city with its unique geography, history and culture plays a role in significantly shaping the course of innovation (Schoenberger and Walker, 2016). The patterns of agglomeration vary from city to city depending on local conditions such as the local mix of sectors. This diversity is further enhanced by the role that historical path dependencies play in the evolution of regional economies (Fujita et al, 1999). This is why, there are many variations in the characteristics of urban systems in both developing and developed countries (Scott and Storper, 2003).

Agglomeration economies in a city are ample to offset the rising costs of urban concentration due to congestion, pollution, high land prices, pollution, etc. Such costs are especially high in developing countries but still fail to inhibit city growth (Azzoni, 1986; Storper 1991). In fact, problems associated with high density living often act as a catalyst to innovation. Innovations such as the elevator, which made skyscrapers and tall buildings possible and aqueducts which provided clean drinkable water to all city occupants were made to address problems caused by agglomeration. Problems that are faced by city occupants require creativity and solutions that often go beyond the means of an individual or a firm. Scientists, engineers and state actors often have to work together to come up with solutions. Additionally, due to historical and geographical factors, innovations are city specific and difficult to apply to other cities (Schoenberger and Walker, 2016).

According to scholars in the field of urban planning and policy, a new world order exists today with a new geography of city centrality and marginality that cuts across national boundaries and the north south divide (Friedman, 1986; Sassen, 1991). Friedman (1995) describes the current world system as a dynamic hierarchy in which ranks and entrance criteria of cities are open. Cities that attract investment and possess more of the command control functions of the world economy will be higher up in the urban hierarchy and their ranking may change with time. Sassen (1994) also paints a similar picture of these cities today and claims that areas that were once considered core are now considered peripheral whereas peripheral areas are now joining the core city system. The intensity of transaction between these successful cities, specifically transactions through the financial market, transaction in services and investments have increased sharply (Sassen, 1999). At the same time, there has been a sharpening of inequality between the concentration of strategic resources and activities in each of these cities and others in the same country (Sassen, 1999).

These major cities of today have been of interest to many scholars from a variety of fields and they are often described using labels including global cities, world cities, great industrial cities, global capitalist cities, primate cities (Goerzen et al., 2013). Early scholars studied cities using mainly demographic data to develop an understanding of urban primacy or hierarchy. This branch of literature is mainly focused on the implications of large human populations such as “mega cities” (Gilbert, 1996). These cities were then later interpreted in terms of their function in the global economy, first as international financial centers (Cohen 1981) and then as world cities (Friedmann 1986; Friedmann and Wolff 1982) and further as global cities (Sassen 1991). Our dissertation is firmly concerned with the functional definition of the city as opposed to the demographic one. According to this literature, three main characteristics can be attributed to the major cities today: a high degree of interconnectedness to local and global markets (e.g. Jacobs et al, 2010), a cosmopolitan environment (e.g. Hall, 1966) and high levels of advanced producer services (e.g. Sassen, 1991, 1994).

We use the GaWC (Globalization and World Cities) network together with levels of patenting to select our list of sixty two cities. Cities are assessed in the GaWC network in terms of their advanced producer services and their network connectivity. We selected cities that jointly met the criteria of having more than a certain threshold level of patents granted in the USA (by the US Patent and Trademark Office, or USPTO) for their inventions, and which were also included in the GaWC classification of global cities. The patenting threshold we used in determining which cities to include in our research varied for developing and developed cities. Our selection consists of cities from all around the world and from developing and developed cities. In particular, our cities include: thirteen US cities (Seattle, Austin, San Diego, Pittsburgh, New York City, Los Angeles, Boston, Chicago, the Bay Area, Miami, Atlanta, Houston and Dallas), Canadian cities (Toronto, Vancouver and Montreal), European cities (London, Manchester, Birmingham, Glasgow, Paris, Lyon, Grenoble, Berlin, Frankfurt, Munich, Hamburg, Stuttgart, Dusseldorf, Eindhoven, Vienna, Zurich, Basel, Stockholm, Copenhagen, Madrid, Barcelona, Brussels, Milan, Rome, Dublin, Helsinki, Moscow and Oslo), Asian cities (Tokyo, Osaka, Nagoya, Taipei, Singapore, Seoul, Hong Kong, Beijing, Shanghai, Guangzhou, Mumbai, Delhi and Bangalore), South American cities (Mexico City, Sao Paulo, Buenos Aires), Auckland, New Zealand and Sydney, Australia.

1.1 Aim of this Dissertation

In our dissertation, we are interested in studying the changing geographic composition of knowledge connections at the city level, the complementarity of distant and local connections. In particular we look at our sixty two cities to see how the geographic structure of their knowledge sourcing has been changing, both at the level of city dyads and in the overall structure of the worldwide knowledge network between cities.

Using US patent citation data for patents invented in these 62 cities worldwide, our first study, titled "Connecting Local and Global Technological Sourcing" explores the nature of the association between local, trans-local and international citations. We borrowed the definition of local, trans-local and international from Turkina and Van Assche (2018). Our results show that in all cities there is a significant association between international and local citations, and that an increase in international citations leads to an increase in local connections. We also find that this effect is accentuated in highly innovative cities when compared to relatively lower innovative cities in our dataset.

Our second study, "Exploring the Determinants of the Extent of Knowledge Connectivity between Two Cities" looks at dyadic relationships for all possible city pairs in our city dataset, and examines the determinants of the level of knowledge outflows and knowledge inflows between them. Our results show that knowledge sourcing patterns between individual cities have varied with the extent of the technology gap between them and their degree of engagement with general purpose technologies. We also see that for some cities, that play a leadership role in our overall network of cities, technological co-specialization plays less of a role in determining their knowledge sourcing patterns. Using social network analysis techniques, we construct a unidirectional network of cities in our third study, "Connecting the Nodes: Using SNA to Determine the Evolving Network of Cities over Time", since backward citations point in just one direction to prior knowledge sources. We observe how this network changes during our time period both in the aggregate and at the level of five selected sectors. The nodes in our network represent cities while the edges represent citations from one city to another. We calculate network statistics such as degree strength and eigenvector centrality to determine which cities have gained influence over time and which cities have become relatively less important. We find some developing cities have gained substantial influence over time especially in the network of patents in the ICT and other electrical equipment technological fields.

For all three studies, we use patent data from the US Patent Office (USPTO data) from the year 1976 – 2016 as our main data source. Patent citations are used to show knowledge sourcing, where the citing city is the recipient of the knowledge and the cited city is the source of the knowledge. The first named inventor address is used to identify the location of the patent. For each city, we used metropolitan areas in our study and not just the central city and define the boundaries of each metropolitan area using the respective governments' own definition. Details about the data are given in Chapter 3 of our dissertation.

1.2 Proposed Contributions

We aim to make several contributions in this dissertation:

In the International Business literature, the period after the 1970s is regarded as a true period of globalization where we expect to see greater interdependence between different regions. Therefore, we expect the time period included in our dissertation to be one of increasing internationalization of knowledge sources. Our first contribution is to explore if this is true and if it is to see to which extent it is across our selected sixty two cities. Additionally, the necessity of complementing 'global pipelines' and 'local buzz' has been emphasized in previous literature by many scholars (for example: Uzzi, 1997; Bramanti and Ratti, 1997; Maillat 1998; Scott 1998; Bresnahan et al 2001; Bathelt, 2007). Our dissertation looks at innovative cities around the world to see the extent to which they rely on external knowledge sources and the influence of these knowledge sources on the 'local buzz'. Previous literature predicts that external knowledge sources also increase 'local buzz' (Owen-Smith and Powell, 2004) and thereby stimulate innovation. In our dissertation we provide empirical evidence of this claim using patent citations. Furthermore, we look at each city individually in detail. We study the changes in its specialization and how its knowledge sourcing patterns change over the course of our time period. In this dissertation we will develop a better understanding of the knowledge sourcing patterns of cities with respect to their specialization, technological capabilities and network centrality.

Finally, using network analysis we will show how the relative importance of cities change over time. Our dissertation shows the increasing role of developing cities in the overall network of cities and how cities shift in rank, with respect to network centrality over time.

Our dissertation is structured as follows: chapter 2 summarizes previous related literature and chapter 3 describes our data sources. Chapter 4 contains our first study, chapter 5 our second study and chapter 6 our third study. We present our final conclusions and contributions in the last chapter, chapter 7.

Chapter 2: Literature Review

2.1 Benefits of Agglomeration

In the field of economic geography, many researchers have analyzed the benefits that arise from agglomeration of economic actors in a region and the resulting exchange of technological knowledge. Throughout the 20th century, a literature emerged which contributed to our understanding of why industry agglomerations emerge and the benefits that proximity can offer.

The concept of agglomeration has two different meanings in the literature (Estall and Buchannnan, 1961; Malmberg and Maskell, 2002). One stream of literature concerns itself with the phenomenon that people and economic activity in general tend concentrate in cities or industrial core regions. The advantages gained from this are generally referred to as urbanization economies. Jacobs (1969) has been one of the pioneers in this research area. She advanced the idea that cities enjoy an advantage because of their economic and social diversity. This diversity, because it is highly packed into limited space, facilitates haphazard serendipitous contact among people. According to Jacobs, it is the exchange of complementary knowledge sources across diverse firms and economic agents which yields a greater return on new economic knowledge. She postulates that the variety of industries within a geographic region promote knowledge externalities and eventually innovative activity and economic growth. Florida (2002) has also contributed to this field of research and argued that cosmopolitan cities facilitate creativity not only because of the diversity they offer but also because of the openness of their networks.

The other stream of literature concerns itself with the phenomenon that firms within the same or closely related industries tend to gather at certain places. These places are oft referred to as clusters in the related literature. In recent work, Porter (2000) defined cluster as “a geographically proximate group of interconnected companies and associated institutions in a particular field, linked by commonalities and complementarities”. He also stated that the geographic scope of cluster can “range from a single city or state to a country or even a group of neighboring countries”. The benefits that arise from locating in such cluster are referred to as localization economies. Economic geographers have utilized this definition of clusters in their research and analyzed how localized clusters of similar and related firms may facilitate knowledge spillovers and stimulate learning and innovation. Marshall (1890) was a pioneer in this field of literature. Marshall (1927) introduced the famous notion of ‘industrial atmosphere’ as being something that is ‘in the air’ and is only limited to the people within a particular region or place. Many other scholars have contributed to this field during the 1990s (Porter, 1990; Malmberg et al, 1996; Maskell et al, 1998; Maskell and Malmberg, 1999a; 1999b).

The general argument that is presented by this literature is that a local industrial structure with many firms competing in the same industry or collaborating across related industries tends to trigger processes which create not only dynamism and flexibility in general but also enhance learning an innovation. In clusters, the flow of industry-related information and knowledge is generally more abundant to the benefit of all the firms involved (Bathelt et al, 2004). The shared knowledge enables cluster firms to continuously combine and recombine similar and non-similar resources to produce new knowledge innovation. This in turn stimulates economic specialization within the cluster and results in the development of localized capabilities (Maskell and Malmberg, 1999a; 1999b). A local culture with specific norms, values and informal and formal institutions make it possible to transfer tacit forms of knowledge from one actor to another (Maskell and Malmberg, 2002).

Both streams of literature related to advantages of agglomeration disagree with what the nature of useful technological knowledge flows may be since the thread discussing urbanization economies generally advocates for the benefits of the congregation of diverse actors in a region, while the thread discussing clusters advocates for the benefits of related or similar technological knowledge flows. However, it can be seen that both these different streams emphasize the importance of localized technological knowledge flows in bringing about increased innovation and learning. We can also conclude from Beaudry and Schiffauerova (2009) that both Marshall and Jacobs effects apply in a large city context and the measurement of their relative significance is a statistical artifact of the degree of aggregation or disaggregation used.

There is also a stream of literature in the field of economic geography which focuses on the kind of technological knowledge that is transmitted within a region. In this thread, Storper and Venables (2002) have recently identified and touted for the importance of local 'buzz'. He uses the term buzz to label the technological knowledge and communication ecology created by face to face contact, and by co-presence and co-location of people in a region. The buzz consists of specific information and continuous updates of this information, organized and accidental meetings resulting in intended and unanticipated learning, the application of the same interpretative schemes and mutual understandings of new knowledge and technologies as well as shared cultural traditions and habits within a particular technology field, which stimulate the establishment of conventions and other institutional arrangements (Bathelt at al., 2004). Actors continuously contribute to and benefit from the diffusion of information, news and gossip by just 'being there' (Gertler, 1995). In similar fashion, Owen-Smith and Powell (2002) use the notion of 'local broadcasting', Grabher (2002) uses the term 'noise' to denote something similar.

The advantage of buzz is that it does not require particular investments. Any actor located within the region who participates in the region's various social and economic spheres can benefit from this local buzz (Bathelt et al., 2004). Hence, we can say that actors are not deliberately 'scanning' the environment in search for some technological knowledge but rather they are surrounded by a plethora of information which includes rumors, impressions, recommendations and strategic information amongst other things (Grabher 2002). Merely the co-location within same economic and social context generates various opportunities for communication. As Uzzi (1997) points out, the network ties can link actors in multiple ways, which allows them to exchange relevant information from one relationship to another.

Though management literature does not mainly concern itself with geography, a stream of literature focuses on which type of technological knowledge may be difficult to transfer across large distances. This literature builds upon the classification of knowledge into two broad categories which was introduced by Polanyi (1958). He distinguished between explicit (or codifiable) knowledge and tacit knowledge. Explicit knowledge is easier to transfer since it can be communicated in formal systematic language in formats such as blueprints or operating manuals (Howells, 2002). On the other hand, tacit knowledge is the type of knowledge that concerns itself with direct experience that is acquired by the informal take up of learned behavior and procedures (Howells, 2002).

Tacit knowledge is associated with learning without awareness, a process termed as subception by Polyani (1966). Spender (1996) suggested that tacit knowledge can be understood best as knowledge that has not yet been transformed into practice. According to Nonaka (1994), it refers to knowledge that has become habit and is highly context-specific and has personal quality. While tacit knowledge is deemed important, it is difficult to transfer because complex forms of knowledge are more difficult to communicate across space (Sorenson, 2005). However, it may possible to transfer this knowledge via face to face interaction and through frequent and repeated contact (von Hippel, 1994). Close and face to face interactions among the actors reduce uncertainty associated with the transfer of tacit knowledge, and embeddedness in the local environment helps companies to come up with context-specific solutions (Perez-Aleman, 2011).

In the management literature, there has been some studies done at the firm level which corroborates the importance of proximity. This literature uses patents and shows that firms tend to cite each other's patents more frequently (Almeida, 1996; Frost, 2001) and that knowledge moves beyond geographic boundaries slower (Baum and Haveman, 1997). They have also built upon studies by Arrow (1962) and Romer (1968) that discuss the externalities stemming from co-location by showing that these benefits are intensified by several other interrelated elements including the dense linkages among co-located buyers, suppliers and customers (Porter, 1998).

Economists have also contributed to this field of economic geography and studied the way in which a territory shapes innovative processes and co-determines their evolution (Crevoisier, 2004). Economists define territory as a space made up of a set of relationship between players and between players and their material environment (Crevoisier, 2004). Some economists have adopted an ‘innovative milieus’ approach which is based on the idea that a territory is a matrix of economic development and that economic mechanisms transform space (Crevoisier, 2004). The GREMI research program takes up this line of reasoning to advance our understanding of local and regional development processes. They emphasize the importance of dynamic collective learning processes in supporting innovation and growth within the local milieu (Camagni, 1991; Capello, 1999; Keeble at al., 1999; Mackinnon et al., 2002). In his work, Camagni (1991) treats the local milieu as an ‘operator’ between markets and organization to reduce uncertainties by supporting the organized interdependence between local firms. Spatial proximity is deemed important in this approach and is the main reason why the learning process of firms and other players remains dynamic since it allows for the easy exchange of information, similarity of cultural and psychological attitudes, frequency of interpersonal contacts and cooperation and density of factors mobility within the limits of the local area (Camagni, 1991). The research by GREMI has given sufficient evidence of a positive role of the local environment in providing the main four determining factors which influence knowledge flow between two or more cooperative partners: openness, channel of interaction, trust and prior experience (Wathne et al., 1996). The concept of local milieu is an evolutionary one, which emphasizes interaction between the actors and places importance on incremental forms of innovation involving relatively minor improvements in the design and operation of products (Freeman, 1994; Mackinnon et al., 2002).

All these different streams emphasize the importance of local networks on innovation. Local networks are seen to provide the type of technological knowledge, such as local buzz and other tacit knowledge, which might not be available elsewhere. However, relatively few empirical work has actually been done to prove the importance of local over trans-local interaction (Bathelt et al, 2004). An increasing number of studies have questioned the seemingly dominant local learning processes (Malecki and Oinas, 1999; Bathelt, 2001; Gertler, 2001; Vatne, 2001). Much of this literature points to the importance of combining both close and distant interactions for the creation of new technological knowledge (Uzzi, 1997; Bramanti and Ratti, 1997; Oinas, 1999; Maillat, 1998; Bresnahan et al, 2001; Bathelt, 2007).

2.2 The Advantages of External Linkages

In the economic geography literature, these external linkages are often referred to as 'pipelines', a term coined by Owen-Smith and Powell (2002). These pipelines are considerably different from local buzz which is characterized as largely unstructured, frequent and broad. The knowledge transferred over pipelines is much more planned, with the amount to be disclosed being decided beforehand (Bathelt et al, 2004). Unlike in the case of local network ties, there is no shared trust at the beginning but rather trust is built in a systematic and conscious way. This process of building trust is costly and usually takes time (Harrison 1992). Typically, in a pipeline procedural rules are set out in the beginning and initial small risks are taken. If things go well, these small risks are followed by larger risks and commitments (Lorenz, 1999). The knowledge that is transferred through these pipelines are rather decisive, non-incremental knowledge flows rather than the undirected, spontaneous 'local broadcasting' that occurs at a regional level (Owen-Smith and Powell, 2002).

These external knowledge connections are important because they offer actors within a region knowledge from disperse sources. When knowledge is continuously reused in different contexts, new knowledge generation processes may be triggered. Geographical separation may, therefore, be conducive to innovation (Bathelt and Glucker, 2011).

It should be noted however that these external knowledge flows are dependent on the local networks of a region. Studies, such as those of Hollywood, advertising industry in London and high technology industry in Silicon Valley have demonstrated that the two are mutually reinforcing (Bathelt at al., 2004). The more actors within a region engage in external knowledge sources, the more information they have to pump into the local networks, and therefore the more dynamic the local buzz (Bathelt et al., 2004). Since global pipelines may intensify local interaction they may result in increasing cluster cohesiveness and strengthen the internal translation processes between cluster actors (Murdoch 1995). On the other hand, in the absence of local connections, these external connections are of limited use. Local knowledge assists firms in sifting through the large volume of available information in order to isolate the knowledge that is particularly important for the development of technologies while discarding that which has little chances of success (Bathelt and Gluckler, 2011).

The GREMI approach also emphasizes the importance of actors in a local milieu establishing external systematic linkages with external technological knowledge sources to maintain its dynamism (Perrin 1991, Quevit, 1991), otherwise the milieu might stagnate (Maillat, 1998).

Another stream of literature emphasizes the need for external knowledge sources by discussing dangers of local networks that are too closed, exclusive and rigid (for e.g.

Kern, 1996). Such social relations can effect the competitiveness of actors in the region (Bathelt et al., 2004). Uzzi (1996, 1997) coined the term ‘over-embeddedness’ to describe the resulting technological lock in that occurs when groups of suppliers are embedded with the same set of customer for long periods of time. Burt (1992) discusses ‘structural holes’ that exist within any region that can only be overcome by non-redundant linkages to external sources of technological knowledge. He refers to these network relations as ‘plumbing’ through which information and resources are being transmitted.

Hence, it can be argued that both local buzz and global pipelines offer particular advantages for actors within a region and can lead to greater innovation and knowledge creation. Local buzz is beneficial to the innovation process because it generates opportunities for actors in a region to interact and form interpretative communities (Nanoka et al., 2000). Global pipelines are also advantageous since they allow the integration of multiple select environments that feed the local network with knowledge residing elsewhere. Malecki (2000) sums this line of reasoning well when stating that “Some places are able to create, attract and keep economic activity…because people in those places ‘make connections’ with other places…”.

2.3 Barriers to the Transfer of Knowledge:

Previous literature points to the conclusion that maintaining local and external knowledge connections are important for the innovativeness of a region. However, previous work by scholars also points to the difficulties in establishing these connections. Breschi and Malerba (2001) point to the fact that it is not just proximity that is sufficient for localized knowledge spillovers but they are in fact contingent upon embeddedness of the actors in the network. This embeddedness is achieved through close social interactions and by institutions building trust and encouraging informal relations among actors (Breschi and Malerba, 2001).

These difficulties are further compounded when knowledge is being transferred across national borders. This is because national boundaries are often proxies for cultural and language barriers. In addition, the standards and methods of measurement also vary across national boundaries (Teece, 1977), which increases the likelihood of incompatibility of knowledge structures or misunderstandings. The likelihood of having important knowledge contacts also decreases as distance increases which also leads to spatial concentration of knowledge (Fujita and Thisse, 2002). Also, trust between the sender and receiver may be less if they are in different countries, which may inhibit the transfer process (Szulanski, 1996; Wathne et al, 1996; Albino et al., 1998).

The literature in economic geography also states the difficulties involved in building global ‘pipelines’. Developing a successful pipeline is costly since it involves the development of a shared institutional context between partners which would enable shared learning and joint problem solving since actors are spread out in different cultural and institutional contexts (Owen-Smith and Powell, 2002). Unlike local buzz, establishing external knowledge connections is more difficult because it requires conscious efforts. Knowledge flows and interactions in a pipeline are often targeted towards a specific, pre-defined goal. As a result, these knowledge flows are usually more focused. Unlike local buzz, knowledge that flows through global pipelines is filtered and knowledge of failures are generally removed, despite how useful this information may be (Bathelt et al., 2004). In addition, building pipelines is not an automatic process like building contacts in local network may be. Hence, the process behind building pipelines must be planned in advance and may require investments. This is a complex and costly process. The first decision in building a pipeline involves choosing potential partners. This is made difficult by the fact that information about potential partners and their actual capabilities is usually incomplete (Malmgren, 1961).

The literature on global value chains and production networks have also emphasized the challenges and complexities in organizing and maintaining knowledge linkages that cut across national boundaries (Humphrey and Schmitz, 2002; Gereffi et al, 2005; Coe et al, 2010).

However, knowledge transfer across national boundaries remains feasible, even if challenging. Despite initial context specificity, tacit knowledge may flow both locally and across longer distances (Brannen, 2004). While studying the impact of trade-weighted R&D of other countries on a country's productivity growth, Park (1995) and Coe and Helpman (1995) found a positive effect. This can be regarded as evidence of knowledge spillovers across international borders. Jaffe and Trajtenberg (1996) also show that domestic inventors' citation probabilities are particularly high in the early years after an invention is made but decreases over time.

In our dissertation, we hope to build upon this literature in a number of ways. Firstly, we will provide empirical evidence for the complementarity between local and trans-local technological connections. We hope to achieve this using patent data from the United States Patent Office (USPTO) as our main data source. The first named inventor on the patent is used to determine the location of the patent, the citing patent is regarded as the recipient of the technological knowledge while the cited patent is regarded as the source. We observe using this data initially, if the number of trans-local data sources are increasing our sixty two cities. If they are, we hope to show the positive impact of this increase in the local network.

Secondly, even though global pipelines are important to enhance the innovativeness of the region, scholars have also shown that building these pipelines are costly. Hence, a region can have only a limited number of successful pipelines. We will analyze using our data, which cities most successfully engage in the exchange of technological knowledge and explore the factors that contribute to this success.

Since our dataset consists of patents from 1976-2016, we expect our knowledge sources to become more trans-local at an accelerated rate. This is because this time period is a part of the current information age, the characteristics of which are summed in the next section.

2.4 The current information age:

By the late 1970s, the old science-based and oil-driven era was gradually replaced by the present information age. While the previous era was based on mass production, economies of scale and specialized in-house corporate R&D, the new era is characterized by economies of scope with a greater diversity and geographic dispersion of search in R&D (Cantwell and Santangelo, 2002). In this new age, we believe that forming international or trans-local connections has become easier and also more necessary.

The advancements in ICT have lowered transport and communication costs thereby accelerating the process of knowledge creation and diffusion (Foss and Pederson, 2004). In addition, ICT have made previously distant technological combinations possible (Cantwell and Santangelo, 2002). It is now possible for firms to develop technological competences in new areas. Their existing technological competencies may also have multiple uses both within and outside their primary sector of activity (Robertson and Langlois, 1995). Therefore this age is characterized by an increase in inter-organizational collaboration and openness (Chesbrough, 2003).

In this current age, technology is becoming increasingly complex in character and firms must now possess a wider range of technological skills (Feldman and Audretsch, 1995). As a consequence, technological interrelatedness is also rising. There is also evidence that industrialized countries are becoming more technologically specialized and differentiated from each other over time (Cantwell and Vertova 2004), thereby increasing the importance of international linkages.

Because of these changes in the current information age, we expect that despite barriers to knowledge, there should be an increase in trans-local knowledge sourcing.

In our dissertation, we have chosen to conduct our study on a selection of cities. We chose cities with relatively high economic importance in the world today.

2.5 Present Day City Regions:

Previous scholars from various other disciplines have taken up interest in major cities. Their work can be split into two different branches: a demographic branch (e.g. Gilbert, 1996) and a functional branch. The demographic tradition has mainly concerned itself with problems arising because of large human populations.

Our dissertation adds to the literature pertaining the functional branch. Researchers in this branch have analyzed the global economic role of these cities (for e.g. Cohen, 1981; Friedmann, 1986; Sassen, 1991) and the characteristics and interconnections of these cities (e.g. Taylor, 2004). This earlier work on has converged on three key attributes that characterize major cities: a high degree of interconnectedness to local and global markets, a cosmopolitan environment and high levels of advanced producer services (Goerzen et al., 2013).

Sassen (1991, 1994) suggested that these cities emerge since internationalizing firms need a global supply of business services to support their foreign operations. These business services tend to be highly localized in their agglomeration patterns (Arzaghi and Henderson, 2008). Dunning and Norman (1983) also found that international business service firms located close to their customers which were generally MNEs. This means that both MNEs and their business service providers tend to co-locate. Sassen (1991, 1994) argued that today's major cities are therefore agglomeration of advanced producer services such as finance, law, accounting and advertising. These producer services are inputs to the global operations of complex organizations and are therefore command control points in the organization of the world economy (Sassen, 2012).

According to Hall (1966), certain cities develop a cosmopolitan environment because of social factors such as politics, communications, education and culture. Such an environment is interlinked with factors such as the pooling of specialized managerial capabilities required by MNEs (Dunning and Norman, 1983), the use of expatriates for coordination and control mechanism (Martinez and Jarillo, 1989) and coordination through local linkages through face to face communication (Storper and Venables, 2004). These cities also tend to form global linkages (Lorenzen and Mudambi, 2013). The cosmopolitan environment is complemented with an infrastructure that are conducive to inward and outward labor mobility (Bel and Fageda, 2008) and to the establishment of personal relationships between them across geographic space (Bathelt et al., 2004).

Hence, putting all previous work together, we can say that the attributes of successful cities today are: a high degree of interconnectedness to local and global markets, a cosmopolitan environment and high levels of advanced producer services (Goerzen et al., 2013).

Hence we can conclude that the successful cities today are more likely to utilize international knowledge sources because of their greater connectivity to global markets. Therefore, despite barriers to knowledge transfer between national boundaries, we can expect to see some internationalization of knowledge sources in these cities. As a result, we would expect to see an impact on the local knowledge sourcing as well in each of our cities.

Recently literature in economic geography has moved away from studying how these cities are formed to studying city network formation (Taylor, 2004). According to Friedman (1986) and Sassen (1991) a new geography of city centrality and marginality exists today that cuts across national boundaries and the north south divide. Friedman (1995) describes the current world system as a dynamic hierarchy in which ranks and entrance criteria of cities are open. Cities that attract investment and possess more of the command control functions of the world economy will be higher up in the urban hierarchy and their ranking may change with time. Sassen (1994) also paints a similar picture of successful cities today and claims that areas that were once considered core are now considered peripheral whereas peripheral areas are now joining the core city system. The intensity of transaction between these cities, specifically transactions through the financial market, transaction in services and investments have increased sharply (Sassen, 1999). At the same time, there has been a sharpening of inequality between the concentration of strategic resources and activities in each of these cities and others in the same country (Sassen, 1999).

Although Friedmann (1995)'s work on cities (or world cities as he labelled them) has been cited and built upon by many, he has not provided empirical support for his hypotheses. He rightly notes that such a dataset which encompasses information, people and services between cities is very difficult.

Chapter 3: Data

3.1 Patent Data:

Our main source of data are patents and their information extracted from the United States Patent and Trademark Office (USPTO) database. We prefer to use the USPTO database over other patent databases such as European Patent Office (EPO) and Japanese Patent Office (JPO), because the USPTO database is the easiest to use because of its superior organization. From all the databases, it is also known that the USPTO provides the richest information. This has been corroborated with studies such as Kim and Lee (2015). The USPTO data is rich because it offers a disaggregation by cross-country, cross-firm, structural and historical dimensions (Cantwell, 2006). Additionally, the US patent office imposes common screening and legal procedures which provides a benchmark for comparison (Pavitt, 1988). Furthermore, since the US is the largest single market in the world, it is more likely that even international players will register for a patent there after their home country even if they are not producing for the market (Archibugi, 1992; Cantwell, 2006).

The patents in the USPTO database provide comprehensive information of the patents. This includes the patent grant date, the technological classes, information about the inventor, information about the assignees and patent citation information. For our purpose, we extracted the patent grant date, the first technological class, first inventor location and patent citation information.

We extracted patent information for the years 1976 – 2016 from the electronic files made available by the USPTO office. These files are in different formats, such as XML, SGML and regular text. We designed specific programs in C++ for each of these different formats in order to extract the relevant data. In addition, there were slight changes in the files from year to year during our time period which required further customization of our programs.

The total number of patents in our patent database is 5.5 million. Since we are looking at patent and their citations, we constructed tables in which each observation was a different citing patent-cited patent pair. For example if patent A cites patent 1,2 and 3, we had three different observations corresponding to Patent A. In the first row was information related to cited patent 1, in the second row, information related to cited patent 3, and in the third row information related to cited patent 3. Therefore, even though we had a total of around 5.5 million patents, the total observations in our dataset were 59,575,219.

To get an idea of what our database looked like, we have included a few sample rows in Table 3.1.

pyear	pnumber	Hcity	Hstate	hcountry	tech	syear	refnumber	Scity	Sstate	scountry
1984	4423523	Agoura	CA	US	48	1981	4306316	Snyder	NY	US
1984	4423524	Rolla	MO	US	48	1980	4223409	Chia Yi	-	TW
1984	4423524	Rolla	MO	US	48	1978	4106127	Pittsburgh	PA	US
1984	4423524	Rolla	MO	US	48	1981	4286339	Caldwell	NJ	US

Table 3.1 Sample columns and rows from our database

In Table 3.1, pyear refers to the year in which the patent was granted, pnumber refers to the patent number, hcity refers to the host city(or the citing city), hstate refers to the host state(or the citing state), hcountry refers to the host country (or the citing country), syear refers to the year in which the source patent was granted, refnumber refers to the cited patent number, scity refers to the city of the source (or the cited patent's city), sstate refers to the state of the source (or the cited patent's state) and the scountry refers to the country of the source (or the cited patent's country).

After the initial extraction, considerable cleaning must be done to make the data in a useable format. An example of this is the country codes, which varied from year to year. We developed a comprehensive list of the country codes and how they changed from year to year. In addition, there were several patents (around a 100 every year) for which the country information was missing. To fix this, we accessed the original image files of the patent grants available at the USPTO website to find the respective countries and add them to our database.

A further complication were the typing errors and lack of consistency in city names. For example, New York City was written in a total of 20 different ways. This is excluding those patents that had written the name of the borough such as Queens or Brooklyn instead of New York City. To make sure we included all of the relevant patents, we went through each patent in the respective states and verified whether it was included in the city region or not. For example, in the case of New York City, we went through all patents belonging to the states of New York, Pennsylvania, Connecticut and New Jersey to check if they belonged to the New York metropolitan area or not. For certain large cities, such as the US cities, Japan and London, we actually double checked the dataset and ensured we did not leave anything out.

After the data was extracted, cleaned and sorted according to metropolitan areas, we used the help of SAS and STATA to conduct our basic analysis.

The first inventor location was used to determine the location of the patent. The reason for not using assignee location is that assignee location corresponds to the location of the headquarters of the organization rather than where the patented invention was actually developed. Hence, since we are interested in the geography of innovations, it is necessary to look at the inventor locations.

We then used backward citations to identify the location of the knowledge source and recipient. The cited patent is regarded as the knowledge source while the citing patent is the recipient. The location of the patents are determined by first inventor locations. This method of using patent citation data to identify knowledge flow has been commonly used in previous literature (Jaffe et al., 1993; Jaffe and Trajtenberg, 1999; Singh, 2004).

There has been some research criticizing use of patent data to measure technological knowledge flows. Some scholars have suggested that since some patent citations are added by examiners, they therefore may not accurately reflect the actual technological flows (Alcacer and Gittelman, 2006). We respond to this claim by two arguments. Firstly, we believe that innovators may not be themselves aware of origins of the knowledge they use for their innovation. Therefore, the examiners actually make our data more objective by making sure all sources left out by the applicants are included. Additionally, we are looking at changes in trends. Any ‘noise’ by the patent citations should not matter for our analysis.

We also use technological class to identify the nature of knowledge flow between cities and to calculate the revealed technological advantage (RTA) index for our cities. The 6 digit technological classes are divided in to 56 technological fields (as done in Cantwell, 1995). These fields are listed in table 3.2. The RTA index is calculated to find which of these 56 fields each city is specialized in. This index was developed by Soete (1987), Cantwell (1989, 1991) and Patel and Pavitt (1991). This index is designed to normalize for cross-field and cross-national variations in the propensity to patent as well as the variations over time (Cantwell, 1991).

The RTA index for tech field *i* in city *j* is defined as:

$$RTA_{ij} = {}^{P_{ij}/\sum_j P_{ij}}\Big/_{\sum_i P_{ij}/\sum_{ij} P_{ij}}$$

Where P_{ij} is the number of patents of tech field i from country j, $\sum_j P_{ij}$ is the total number of patents from all countries for the tech field i, $\sum_i P_{ij}$ is the total number of all patents in all tech fields from city j and $\sum_{ij} P_{ij}$ is the number of all patents from all cities. The index varies around one, so a value greater than one suggests that the city may be relatively specialized in that particular tech field, compared to other tech fields. A value less than one would indicate that the city has a comparative disadvantage in that particular tech field.

Tech Field	**Description**	**Tech Field**	**Description**
1	Food and Tobacco Product	**29**	Other General Industrial Equipment
2	Distillation Processes	**30**	Mechanical Calculators and Typewriters
3	Inorganic Chemicals	**31**	Power Plants
4	Agricultural Chemicals	**32**	Nuclear Reactors
5	Chemical Processes	**33**	Telecommunications
6	Photographic Chemistry	**34**	Other Electrical Communication Systems
7	Cleaning Agents and Other Compositions	**35**	Special Radio Systems
8	Disinfecting and Preserving	**36**	Image and Sound Equipment
9	Synthetic Resins and Fibers	**37**	Illumination Devices

10	Bleaching and Dyeing	**38**	Electrical Devices and Systems
11	Other Organic Compounds	**39**	Other General Electrical Equipment
12	Pharmaceuticals and Biotechnology	**40**	Semiconductors
13	Metallurgical Processes	**41**	Office Equipment and Data Processing Systems
14	Miscellaneous Metal Products	**42**	Internal Combustion Engines
15	Food, Drink and Tobacco Equipment	**43**	Motor Vehicles
16	Chemical and Allied Equipment	**44**	Aircraft
17	Metal Working Equipment	**45**	Ships and Marine Propulsion
18	Paper Making Apparatus	**46**	Railways and Railway Equipment
19	Building Material Processing Equipment	**47**	Other Transport Equipment
20	Assembly and Material Handling Equipment	**48**	Textiles Clothing and Leather
21	Agricultural Equipment	**49**	Rubber and Plastic Products
22	Other Construction and Excavating Equipment	**50**	Non-Metallic Mineral Products
23	Mining Equipment	**51**	Coal and Petroleum Products
24	Electrical Lamp Manufacturing	**52**	Photographic Equipment
25	Textile and Clothing Machinery	**53**	Other Instruments and Controls
26	Printing and Publishing Machinery	**54**	Wood Products
27	Woodworking Tools and Machinery	**55**	Explosive Compositions and Charges
28	Other Specialized Machinery	**56**	Other Manufacturing and Non-Industrial

Table 3.2 List of the 56 Technological Fields

3.2 City Definitions:

Our research study consists of a total of 62 cities. We used metropolitan areas and not just the central city to determine the number of patents for every city. The reason behind this is, since we are using first inventor's address to determine the location of the patent, we have to cater for the fact that the inventor can live anywhere that is a drivable distance to the central city. We use government defined metropolitan areas to mark the boundaries of our cities. This information is commonly available on local government websites. Although the government defines metropolitan areas and makes this information readily available, we still faced some complications while consolidating city data. Inventors sometimes write names of towns or small cities that are too small to be included in the definition provided by the government. Therefore, we had to additionally use google maps to see where these towns were located. Additionally, we would check driving times provided by google maps by public transport or by driving for places that seemed to close to the boundary to ensure that all the places we included were actually at drivable distance.

For the European patents, we additionally used a database developed by Dr. John Cantwell while he was at the University of Reading (and used in Cantwell and Iammarino, 2005) to determine the city boundaries. This database was developed by a team of expert geographers who went through the entire patent database and determined which locations should be included in the city region. In addition, we rechecked the data in the database and matched it with city boundaries defined by the European Union.

3.2.1 Selection of Cities

For selecting our cities, we first looked at the comprehensive list provided by GaWC (Globalization and World Cities Research Network). The GaWC chooses city on the basis of their connectivity and concentration of producer services. In these cities, the trends we want to observe will be heightened because of their characteristics. However, since we are using patent citations for our data source, we wanted to include those cities that had enough patents for us to conduct meaningful research. Therefore, we set a threshold for number of patents and selected cities that were above that threshold. This threshold was lower for those cities that were from developing countries.

GaWC ranks cities into categories based on their connectivity and concentration of producer services. These categories include: alpha ++, alpha+, alpha, alpha- and beta+ cities. We made sure that we included in our sample, cities from each category. We also tried to include cities from all over the world, and not just from particular regions. Therefore our sample includes cities from North America, South America, Europe, South East Asia, Asia, and Oceania. In addition, we wanted to insure that our database contained cities from different stages of development, so we included developed and emerging cities in our sample.

Our complete selection of cities is shown in Table 3.3.

City Name	Country Name	City Name	Country Name
	North America		
Seattle	United States	Boston	United States
Austin	United States	Chicago	United States
San Diego	United States	The Bay Area	United States
Pittsburgh	United States	Miami	United States
New York City	United States	Atlanta	United States
Los Angeles	United States	Toronto	Canada
Dallas	United States	Vancouver	Canada
Houston	United States	Montreal	Canada
	South America		
Mexico City	Mexico	Sao Paulo	Brazil
Buenos Aires	Argentina		
	Europe		
London	UK	Paris	France
Glasgow	UK	Lyon	France
Manchester	UK	Grenoble	France

Birmingham	UK	Eindhoven	Netherlands
Berlin	Germany	Vienna	Austria
Frankfurt	Germany	Zurich	Switzerland
Munich	Germany	Basel	Switzerland
Hamburg	Germany	Stockholm	Sweden
Stuttgart	Germany	Copenhagen	Denmark
Dusseldorf	Germany	Brussels	Belgium
Madrid	Spain	Milan	Italy
Barcelona	Spain	Rome	Italy
Dublin	Ireland	Oslo	Norway
Helsinki	Finland	Moscow	Russia
Asia			
Mumbai	India	Nagoya	Japan
Delhi	India	Beijing	China
Bangalore	India	Shanghai	China
Tokyo	Japan	Guangzhou	China
Osaka	Japan		
Oceania			
Sydney	Australia	Auckland	New Zealand

Table 3.3 Our Selection of Cities

Chapter 4: Connecting Local and Global Technological Knowledge Sourcing

4.1 Introduction

In today's globalized information age, knowledge plays an increasingly important role. According to Grant (2002), the role of knowledge in today's economy corresponds to that of land in agrarian economies and that of capital in the early industrial economies. Today, cities and clusters cannot rely exclusively on local knowledge sources, but they need to combine "local buzz" (Storper and Venables, 2004) with "global pipelines" (Bathelt et al., 2004).

The current information age, with its advances in information and communication technologies (ICT), has facilitated the diffusion of knowledge across regions by lowering transport and communication costs (Foss and Pederson, 2004). In addition, contemporary ICT technologies have allowed combinations of previously separate lines of technological development (Santangelo, 2002). Since individual locations are increasingly specialized in their activity (Cantwell and Vertova 2004), international connections are generally necessary for such new combinations of innovative activity. Because of these changes in the environment for innovation, we would expect innovative cities to be progressively more connected with each other than ever before.

This study contributes to the literature on the changing nature of knowledge connections and the complementarity of external and local connections. We do so by providing a detailed picture of how the structure of connections is changing, and how intra- and inter-regional knowledge sources influence each other across our mix of developed and developing cities. In particular, we look at 62 cities to see how their international citations have affected their local citations. These include thirteen US cities (Seattle, Austin, San Diego, Pittsburgh, New York City, Los Angeles, Boston, Chicago, the Bay Area, Miami, Atlanta, Houston and Dallas), Canadian cities (Toronto, Vancouver and Montreal), European cities (London, Manchester, Birmingham, Glasgow, Paris, Lyon, Grenoble, Berlin, Frankfurt, Munich, Hamburg, Stuttgart, Dusseldorf, Eindhoven, Vienna, Zurich, Basel, Stockholm, Copenhagen, Madrid, Barcelona, Brussels, Milan, Rome, Dublin, Helsinki, Moscow and Oslo), Asian cities (Tokyo, Osaka, Nagoya, Taipei, Singapore, Seoul, Hong Kong, Beijing, Shanghai, Guangzhou, Mumbai, Delhi and Bangalore), South American cities (Mexico City, Sao Paulo, Buenos Aires), Auckland, New Zealand and Sydney, Australia. We selected cities above a certain threshold level of patenting from the Globalization and World Cities Research Network (GaWC) classification of global cities. Our database consists of USPTO patents from the years 1976–2016. Patent citations were used to identify the location of knowledge sources and recipients by using the inventor locations of cited (source) and citing (recipient) patents. We found that in all cities there is a significant correlation between international and local citations. These changes are more apparent in the later years, which are characterized by the diffusion phase of the information age across a wider variety of industries and activities (Alcacer et al, 2016). This is consistent with the stream of literature that emphasizes that external and local knowledge connections complement each other and are necessary for the innovativeness of a particular region (Uzzi, 1997; Bramanti and Ratti, 1997; Maillat 1998; Scott 1998; Bresnahan et al 2001; Bathelt, 2007). Cities from developing countries were already highly internationalized at the beginning of our time period, which illustrates the reliance of emerging markets in the current era on global knowledge sources for development. This is also consistent with the literature which shows that actors in emerging markets benefit from greater global knowledge connectivity (e.g. Cantwell and Zhang, 2013).

The rest of the study is structured as follows. In the next section, we develop the hypothesis. After that, we discuss the data and methodology. The final section contains the conclusion and discussion of the results.

4.2 Hypotheses Development

Previous literature has stressed that an innovative region will be one in which actors benefit from their local linkages and in which there are plenty of knowledge spillovers. Complex and valuable knowledge is transmitted through local linkages because geographical proximity is necessary for transfer of tacit and complex knowledge (Giuliani, 2013). This is because complex forms of knowledge are more difficult to communicate over distance (Sorenson, 2005).

However, there is a limit to the effectiveness of local linkages. For a region to be truly innovative, these local linkages must be complemented with global ones (Uzzi, 1997; Bramanti and Ratti, 1997; Maillat 1998; Scott 1998; Bresnahan et al 2001; Bathelt, 2007). One benefit of external knowledge connections is that they aid in the diffusion of knowledge within a cluster, which in turn stimulates additional local knowledge creation (Owen-Smith and Powell, 2004).

Conversely, if there is an increase in local linkages we can also expect to find an increase in the external knowledge connections. Local knowledge is needed to help firms shift through large volumes of available opportunities in order to identify the knowledge that is particularly important for solving local problems or moving into new domains of application, while discarding that which has little local relevance (Bathelt and Gluckler, 2011). Therefore, more local knowledge leads to a better ability of firms to utilize external knowledge. Hence, we hypothesize:

Therefore, we can hypothesize that

H1: An increase in international (or trans-local) citations is associated with an increase in local citations.

We also expect that the impact of international citations on local citations will be greater in innovative cities. Therefore we can hypothesize:

H2: The impact of international (or trans-local) citations on local citations is correlated with the innovativeness of the city.

4.3 Data and Methodology

In this study, we divide the cities into two clusters depending on their level of growth during our time period (1976-2016). We put cities with a high level of growth into cluster one and cities with relatively lower levels of growth in cluster two. Since we are interested in innovation led growth, we use indicators constructed using patenting shares and growth of patenting shares to assess the growth of a city. We do not use economic indicators such as GDP growth rate because growth at the level of the city does not always imply rising innovative activity there (Awate et al., 2012).

We rank every city on two dimensions: the share of the city's patents with respect to the total country patents, and the growth of the city's share of patents during the time period 1976 – 2016. By looking at city's share of country patents rather than the patenting levels, we are able to control for country differences. Cities that represent a high share of their country's patents or cities that show high growth of patent shares will be categorized into cluster one. Cities that represent a small share of their country's patents and cities that show slow growth of patent shares will be categorized into cluster two.

When calculating the share of city patents with respect to the total number of country patents, we looked at the sum of all of the country's patents and not just of the cities in our dataset. Hence, theoretically it is possible that all of the cities in our dataset exhibit an increase in shares throughout our time period.

The time period used starts from 1976. During the earlier years, patents from China, Taiwan and Hong Kong were all grouped under China. Therefore when calculating shares of cities from China and Taiwan and when calculating shares of Hong Kong we calculated the share with respect to the total number of patents of China, Taiwan and Hong Kong. Additionally, in the beginning of our time period Russia was still part of the Soviet Union. Therefore for consistency, even after the fall of the Soviet Union, when Russian patents were filed separately in the USPTO, we still calculated Moscow shares by using the total Soviet Union patents and not just patents from Russia. Moreover, when calculating shares of Singapore's patents, we calculated shares with respect to total patents from Singapore and Malaysia combined. This is because Singapore is a small country and the total country consists of a single city. Therefore, to calculate the total shares, we included patents from the neighboring country Malaysia.

A city's patenting growth rate is influenced by its current stage of development. We would expect cities from emerging economies to have a higher percentage increase in their share of patents as compared to cities from developed economies. Emerging countries also tend to have fewer innovative cites as compared to large developed countries, therefore cities from emerging countries are expected to have higher shares with respect to their total country patents than cities from developed countries. Thus, when comparing innovativeness of cities, we compare cities from emerging markets separate from cities from developed markets. We use the UN categorization of developed and developing cities in 1976 to determine which cities in our dataset are developing and which cities are developed.

We also separate the US cities from the rest of our cities when analyzing the percentage increase in patenting shares. This is because, the US is a large innovative country containing many innovative and dynamic cities. Therefore, even highly innovative cities tend to represent lesser shares of their total country patents than cities from other developed countries.

Hence, we divide our cities into three categories: the US cities, cities from other developed countries and cities from emerging countries. We look at the cities in each category separately and divided cities into cluster one and cluster two, where cluster one consists of highly innovative cities and cluster two consists of relatively lower innovative cities.

4.3.1 Category 1: The US cities

The US is a large and highly innovative country that contains a greater number of innovative cities than any other country in the world. Therefore, we would expect that even a very innovative city in the US would tend to represent a smaller share of their country patents than a city with similar innovativeness in another country. For this reason, we analyze the innovativeness of these cities separately from the other cities in our dataset.

We divided our time period into 8 blocks of 5 years and one block containing only the year 2016. We calculated the shares for our respective cities in each of these blocks. The shares of all US cities in our dataset throughout these 9 periods are shown in Table 4.1.

	1	2	3	4	5	6	7	8	9	*Average*
The Bay Area	0.047	0.048	0.057	0.067	0.105	0.136	0.157	0.173	0.183	0.108
New York City	0.150	0.135	0.125	0.111	0.101	0.088	0.083	0.082	0.075	0.106
Los Angeles	0.070	0.063	0.066	0.062	0.056	0.057	0.056	0.055	0.052	0.060
Boston	0.045	0.044	0.046	0.049	0.050	0.052	0.053	0.055	0.055	0.050
Chicago	0.066	0.057	0.051	0.045	0.039	0.032	0.029	0.029	0.028	0.042
Seattle	0.009	0.010	0.013	0.013	0.017	0.020	0.039	0.040	0.042	0.023
Houston	0.020	0.023	0.027	0.026	0.021	0.020	0.020	0.021	0.023	0.022
San Diego	0.010	0.011	0.014	0.017	0.020	0.024	0.026	0.035	0.038	0.022
Dallas	0.015	0.016	0.019	0.021	0.024	0.024	0.022	0.022	0.021	0.020
Austin	0.003	0.005	0.006	0.010	0.018	0.021	0.024	0.020	0.020	0.014
Pittsburgh	0.024	0.020	0.019	0.013	0.010	0.008	0.007	0.006	0.006	0.012
Atlanta	0.006	0.007	0.009	0.011	0.014	0.014	0.015	0.017	0.016	0.012
Miami	0.010	0.011	0.013	0.015	0.013	0.010	0.009	0.010	0.010	0.011

Table 4.1 Shares of patents of all US cities

To calculate the growth rate, we divided the time period (1976-2016) into 9 blocks again. 8 of these blocks consist of 5 years, whereas the last time block contains the year 2016. We then looked at the change of shares between each of these time blocks. Our selected US cities and their respective growth rates for each of these time periods is given in Table 4.2.

	2	3	4	5	6	7	8	9	*Average*
Austin	0.706	0.375	0.629	0.716	0.194	0.135	-0.145	0.000	0.326
Seattle	0.125	0.311	0.047	0.248	0.210	0.938	0.005	0.063	0.244
The Bay Area	0.023	0.208	0.162	0.566	0.296	0.160	0.099	0.058	0.197
San Diego	0.074	0.247	0.212	0.217	0.148	0.093	0.378	0.069	0.180
Atlanta	0.287	0.301	0.182	0.226	-0.001	0.134	0.116	-0.090	0.144
Dallas	0.116	0.193	0.097	0.122	-0.004	-0.083	0.006	-0.022	0.053
Boston	-0.025	0.055	0.058	0.027	0.029	0.015	0.038	0.006	0.025

Houston	0.150	0.185	-0.066	-0.182	-0.037	0.011	0.031	0.082	0.022
Miami	0.051	0.263	0.098	-0.082	-0.256	-0.052	0.060	0.016	0.012
Los Angeles	-0.107	0.049	-0.062	-0.087	0.018	-0.015	-0.023	-0.056	-0.035
New York City	-0.098	-0.070	-0.119	-0.089	-0.125	-0.061	-0.004	-0.087	-0.082
Chicago	-0.136	-0.114	-0.108	-0.137	-0.174	-0.107	0.000	-0.037	-0.102
Pittsburgh	-0.174	-0.029	-0.308	-0.253	-0.225	-0.110	-0.068	-0.029	-0.149

Table 4.2 Patent share growth rates of all US cities

We plotted the cities on the basis of their average patent shares and their average patent share growth rate in the figure below. Cities which ranked comparatively high on average patent share or average patent share growth rate are categorized as cluster 1. All other cities are categorized as cluster 2.

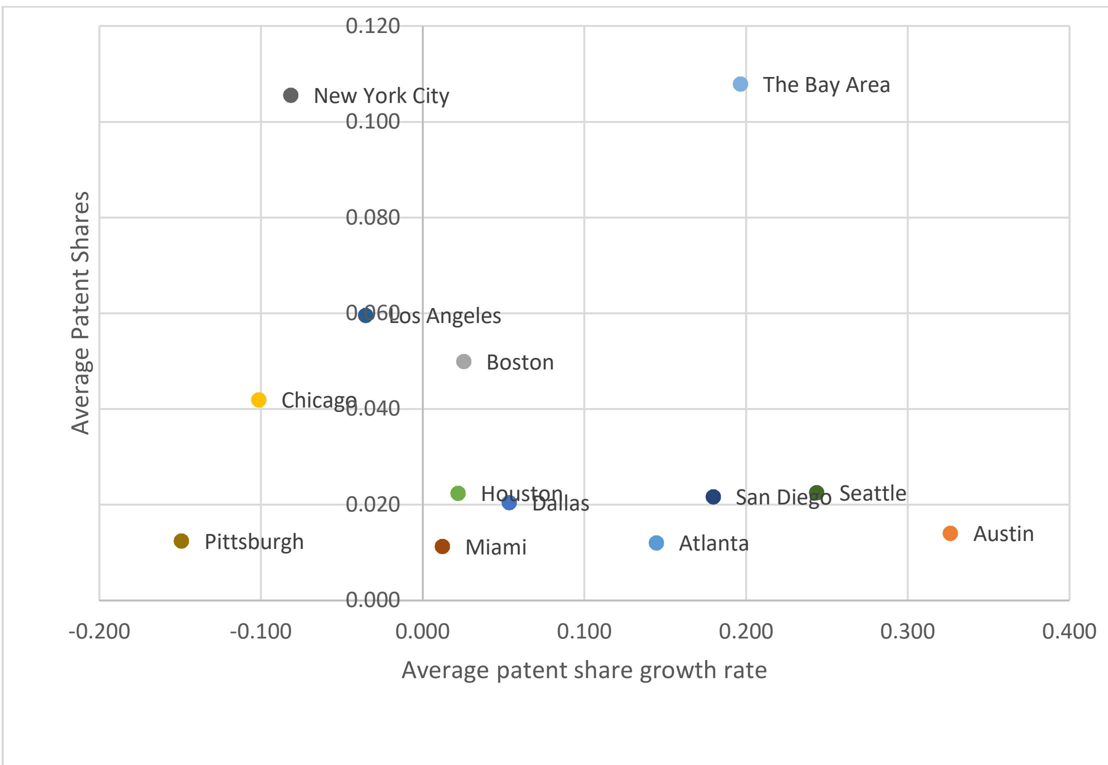

Figure 4.1 Average patent shares and patent share growth of US cities

Based on figure 4.1, we categorize the Bay Area, New York City, Los Angeles, Boston, Seattle and Austin as cluster 1 cities. We categorized the Bay Area, New York City, Los Angeles and Boston as cluster 1 cities because of their relatively high patent shares and

Austin and Seattle as cluster 1 cities because of their comparatively high average patent share growth rate. On the other hand, Chicago, Pittsburgh, Houston, Dallas, Miami, Atlanta and San Diego are categorized as cluster 2 cities because of their relatively low average patent shares and average patent share growth rate.

4.3.2 Category 2: Developed Cities

We can expect that innovative cities that were already developed in the beginning of our time period, i.e. 1976, will have a lesser percentage increase in their share of patents than cities from emerging countries. Therefore, we keep them in a separate category from cities that are from emerging economies. We also expect them to have a higher percentage increase in their share of patents than US cities. This is because the US is a large country with a greater number of innovative cities than US cities. Because of these reasons, we analyze the innovativeness of these cities separately from other cities in our dataset.

Just like we did with the US cities, we divided our time period into 8 blocks of 5 years and one block containing only the year 2016. We calculated the shares for our respective cities in each of these blocks. The shares of all developed cities in our dataset throughout these 9 periods are shown in Table 4.3:

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	***Average***
Tokyo	0.578	0.590	0.595	0.597	0.609	0.605	0.614	0.614	0.580	0.598
Copenhagen	0.503	0.490	0.466	0.530	0.603	0.586	0.537	0.489	0.480	0.520
Oslo	0.481	0.511	0.402	0.439	0.451	0.379	0.468	0.469	0.428	0.448
Helsinki	0.392	0.390	0.426	0.373	0.430	0.440	0.502	0.532	0.511	0.444
Dublin	0.396	0.512	0.477	0.440	0.470	0.398	0.389	0.423	0.485	0.443
Auckland	0.315	0.390	0.368	0.508	0.479	0.500	0.453	0.505	0.452	0.441
Barcelona	0.448	0.483	0.397	0.409	0.396	0.412	0.397	0.368	0.371	0.409
Paris	0.528	0.516	0.435	0.408	0.393	0.355	0.324	0.299	0.286	0.394

Sydney	0.261	0.285	0.264	0.256	0.273	0.400	0.596	0.441	0.317	0.343
Eindhoven	0.342	0.322	0.367	0.307	0.326	0.333	0.398	0.340	0.327	0.340
Stockholm	0.310	0.291	0.245	0.323	0.333	0.270	0.261	0.324	0.359	0.302
Vienna	0.413	0.396	0.348	0.295	0.291	0.236	0.224	0.220	0.179	0.289
London	0.311	0.298	0.275	0.255	0.259	0.247	0.226	0.219	0.228	0.257
Milan	0.389	0.315	0.290	0.255	0.242	0.210	0.189	0.172	0.180	0.249
Toronto	0.225	0.204	0.247	0.240	0.246	0.208	0.227	0.220	0.227	0.227
Madrid	0.245	0.203	0.221	0.221	0.224	0.177	0.206	0.268	0.243	0.223
Zurich	0.203	0.211	0.231	0.212	0.193	0.186	0.238	0.246	0.245	0.218
Osaka	0.185	0.172	0.180	0.196	0.163	0.158	0.146	0.151	0.160	0.168
Basel	0.289	0.249	0.201	0.162	0.123	0.112	0.114	0.101	0.100	0.161
Brussels	0.235	0.178	0.157	0.157	0.124	0.147	0.120	0.119	0.118	0.151
Montreal	0.184	0.153	0.119	0.118	0.112	0.119	0.104	0.099	0.111	0.124
Dusseldorf	0.163	0.166	0.152	0.147	0.118	0.082	0.063	0.063	0.061	0.113
Stuttgart	0.080	0.103	0.102	0.111	0.117	0.123	0.106	0.098	0.110	0.106
Vancouver	0.071	0.070	0.074	0.091	0.095	0.093	0.098	0.099	0.111	0.089
Nagoya	0.083	0.091	0.090	0.075	0.084	0.084	0.090	0.097	0.101	0.088
Grenoble	0.035	0.039	0.060	0.057	0.069	0.085	0.113	0.112	0.119	0.077
Rome	0.070	0.073	0.051	0.057	0.046	0.048	0.051	0.069	0.064	0.059
Lyon	0.071	0.063	0.066	0.064	0.055	0.054	0.045	0.048	0.049	0.057
Munich	0.050	0.054	0.051	0.039	0.041	0.034	0.063	0.056	0.058	0.050
Birmingham	0.080	0.063	0.051	0.045	0.046	0.038	0.028	0.026	0.032	0.046
Manchester	0.052	0.041	0.035	0.039	0.028	0.027	0.020	0.020	0.026	0.032
Berlin	0.020	0.019	0.019	0.018	0.025	0.023	0.025	0.029	0.031	0.023
Hamburg	0.018	0.018	0.018	0.014	0.014	0.015	0.019	0.021	0.024	0.018
Glasgow	0.015	0.013	0.010	0.012	0.016	0.013	0.010	0.011	0.015	0.013
Frankfurt	0.016	0.014	0.013	0.014	0.011	0.012	0.009	0.011	0.013	0.013

Table 4.3 Patent shares of all developed cities apart from the US cities

To calculate the growth rate, we divided the time period (1976-2016) into 9 blocks again. 8 of these blocks consist of 5 years, whereas the last time block contains the year 2016. We then looked at the change of shares between each of these time blocks. Our selected developed cities and their respective growth rates for each of these time periods is given in Table 4.4.

	2	3	4	5	6	7	8	9	*Average*
Grenoble	0.126	0.525	-0.044	0.210	0.233	0.324	-0.008	0.064	0.179
Berlin	-0.018	-0.029	-0.039	0.379	-0.079	0.119	0.138	0.060	0.066
Vancouver	-0.012	0.065	0.224	0.050	-0.028	0.053	0.012	0.119	0.060
Sydney	0.093	-0.075	-0.028	0.066	0.464	0.490	-0.260	-0.280	0.059
Auckland	0.241	-0.057	0.379	-0.057	0.044	-0.095	0.115	-0.105	0.058
Munich	0.072	-0.059	-0.235	0.041	-0.152	0.842	-0.122	0.037	0.053
Stuttgart	0.295	-0.009	0.090	0.048	0.058	-0.144	-0.075	0.127	0.049
Hamburg	0.006	-0.030	-0.206	-0.008	0.036	0.281	0.125	0.160	0.046
Helsinki	-0.006	0.091	-0.124	0.155	0.022	0.141	0.060	-0.040	0.038
Dublin	0.294	-0.068	-0.079	0.068	-0.152	-0.025	0.089	0.146	0.034
Stockholm	-0.059	-0.158	0.315	0.030	-0.187	-0.033	0.242	0.106	0.032
Zurich	0.044	0.090	-0.079	-0.090	-0.037	0.278	0.036	-0.006	0.029
Nagoya	0.102	-0.013	-0.167	0.116	0.000	0.073	0.083	0.037	0.029
Glasgow	-0.113	-0.187	0.190	0.254	-0.144	-0.215	0.038	0.363	0.023
Madrid	-0.169	0.088	0.000	0.012	-0.208	0.162	0.299	-0.094	0.011
Toronto	-0.092	0.209	-0.031	0.028	-0.156	0.094	-0.034	0.033	0.006
Rome	0.037	-0.300	0.125	-0.204	0.056	0.061	0.351	-0.078	0.006
Eindhoven	-0.058	0.139	-0.163	0.062	0.021	0.197	-0.147	-0.038	0.001
Tokyo	0.021	0.008	0.003	0.020	-0.007	0.015	0.000	-0.055	0.001
Copenhagen	-0.025	-0.048	0.136	0.137	-0.027	-0.084	-0.089	-0.017	-0.002
Oslo	0.062	-0.213	0.091	0.027	-0.159	0.233	0.003	-0.087	-0.005
Frankfurt	-0.084	-0.104	0.079	-0.178	0.009	-0.200	0.207	0.160	-0.014
Osaka	-0.071	0.047	0.087	-0.168	-0.032	-0.074	0.034	0.059	-0.015
Barcelona	0.079	-0.178	0.028	-0.031	0.040	-0.037	-0.072	0.007	-0.020
London	-0.041	-0.076	-0.074	0.016	-0.048	-0.086	-0.028	0.039	-0.037
Lyon	-0.116	0.047	-0.026	-0.134	-0.022	-0.162	0.068	0.011	-0.042
Montreal	-0.170	-0.219	-0.008	-0.050	0.057	-0.128	-0.047	0.122	-0.055
Manchester	-0.207	-0.145	0.113	-0.282	-0.051	-0.245	-0.004	0.295	-0.066
Brussels	-0.241	-0.118	0.000	-0.209	0.183	-0.185	-0.010	-0.003	-0.073
Paris	-0.024	-0.157	-0.062	-0.037	-0.097	-0.086	-0.078	-0.042	-0.073
Milan	-0.190	-0.080	-0.119	-0.050	-0.135	-0.098	-0.089	0.046	-0.089
Vienna	-0.040	-0.121	-0.153	-0.015	-0.189	-0.051	-0.018	-0.184	-0.096
Birmingham	-0.217	-0.189	-0.111	0.012	-0.173	-0.259	-0.067	0.219	-0.098
Dusseldorf	0.020	-0.084	-0.032	-0.195	-0.305	-0.231	-0.001	-0.031	-0.107
Basel	-0.138	-0.195	-0.195	-0.241	-0.090	0.023	-0.120	-0.003	-0.120

Table 4.4 Patent share growth rates of all developed cities apart from the US cities

We plotted the cities on the basis of their average patent shares and their average patent share growth rate in the figure below. Cities which ranked comparatively high on average patent share or average patent share growth rate are categorized as cluster 1. All other cities are categorized as cluster 2.

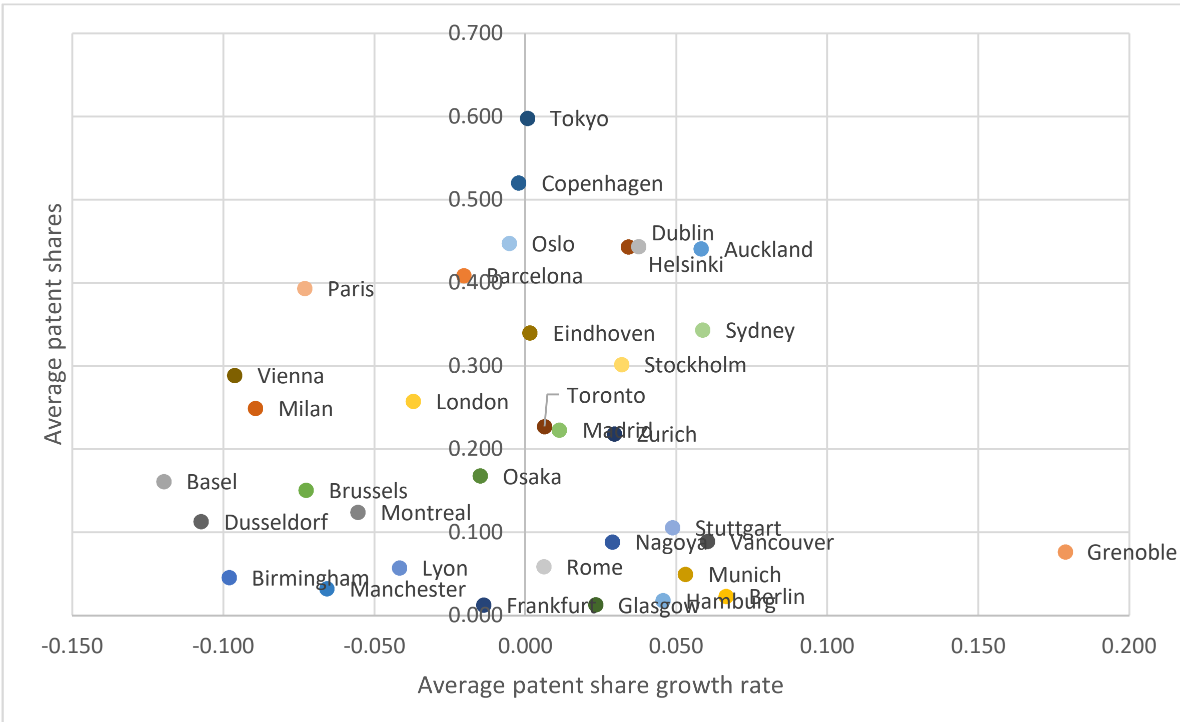

Figure 4.2 Average patent shares and patent share growth of all developed cities except the US cities

Based on figure 4.2, we categorize Tokyo, Copenhagen, Dublin, Auckland, Helsinki, Oslo, Barcelona, Paris and Grenoble as cluster 1 cities. We categorized Tokyo, Copenhagen, Dublin, Auckland, Helsinki, Oslo, Barcelona and Paris as cluster 1 cities because of their comparatively high average patent shares and Grenoble as cluster 1 because of its exceptionally high average patent share growth rate. The rest of the cities, Sydney, Eindhoven, Vienna, London, Milan, Toronto, Stockholm, Madrid, Zurich, Osaka, Brussels, Basel, Dusseldorf, Montreal, Birmingham, Lyon, Manchester, Frankfurt, Rome, Glasgow, Nagoya, Munich, Hamburg, Berlin, Vancouver and Stuttgart are classified as category 2 cities because of their relatively low average patent shares and average patent share growth rate.

4.3.3 Category 3: Developing Cities

We expect emerging cities to exhibit a larger increase in patent shares than both the category 1 and category 2 cities. This is because they have such low patenting levels in the beginning of our time period that even if they register one additional patent, the resulting increase in patent share would be quite high. Also, emerging countries usually have a fewer number of innovative cities when compared to developed cities. Therefore one innovative city is likely to be responsible for a larger share of country patents in an emerging economy than in a developed economy. Hence, we examine developing cities separately.

Most emerging cities in our dataset had 0 or fewer than 5 patents in the beginning of our time period. There are also a lot of fluctuations where more emerging market cities may have 2 patents in one year and then 0 patents in the next few years. Therefore, we look at the increase in patent share starting from the year 2000 in the case of developing cities rather than from 1976.

We divided our time period into 3 blocks of 5 years and one block containing only the year 2016. We calculated the shares for our respective cities in each of these blocks. The list of our selected developing cities in the third category and their shares with respect to their respective country patents in the USPTO are shown in Table 5.

	1	**2**	**3**	**4**	**Average**
Seoul	0.796	0.867	0.898	0.917	0.869
Singapore	0.862	0.750	0.810	0.790	0.803

Buenos Aires	0.751	0.774	0.744	0.603	0.718
Moscow	0.568	0.565	0.563	0.525	0.555
Taipei	0.394	0.391	0.303	0.224	0.328
Bangalore	0.181	0.312	0.369	0.415	0.319
Sao Paulo	0.212	0.306	0.271	0.319	0.277
Mexico City	0.143	0.201	0.298	0.263	0.226
Delhi	0.135	0.099	0.068	0.057	0.090
Guangzhou	0.008	0.056	0.125	0.115	0.076
Beijing	0.012	0.039	0.084	0.150	0.071
Shanghai	0.009	0.030	0.070	0.104	0.053
Mumbai	0.068	0.048	0.041	0.041	0.049
Hong Kong	0.043	0.039	0.031	0.029	0.035

Table 4.5 Patent shares of all developing cities

To calculate the growth rate, we divided the time period (2000-2016) into 4 blocks again. 3 of these blocks consist of 5 years, whereas the last time block contains the year 2016. We then looked at the change of shares between each of these time blocks. Our selected developing cities and their respective growth rates for each of these time periods is given in Table 4. 6.

	2	3	4	Average
Guangzhou	5.691	1.224	-0.083	2.277
Shanghai	2.550	1.313	0.489	1.451
Beijing	2.188	1.171	0.791	1.384
Bangalore	0.718	0.185	0.125	0.342
Mexico City	0.401	0.488	-0.117	0.257
Sao Paulo	0.446	-0.115	0.178	0.169
Seoul	0.089	0.036	0.021	0.049
Singapore	-0.130	0.081	-0.026	-0.025
Moscow	-0.005	-0.003	-0.068	-0.026
Buenos Aires	0.030	-0.038	-0.190	-0.066
Hong Kong	-0.101	-0.205	-0.079	-0.128
Mumbai	-0.294	-0.149	0.008	-0.145
Taipei	-0.009	-0.225	-0.261	-0.165
Delhi	-0.267	-0.314	-0.151	-0.244

Table 4.6 Patent share growth rates of all developing cities

We plotted the cities on the basis of their average patent shares and their average patent share growth rate in the figure below. Cities which ranked comparatively high on average patent share or average patent share growth rate are categorized as cluster 1. All other cities are categorized as cluster 2.

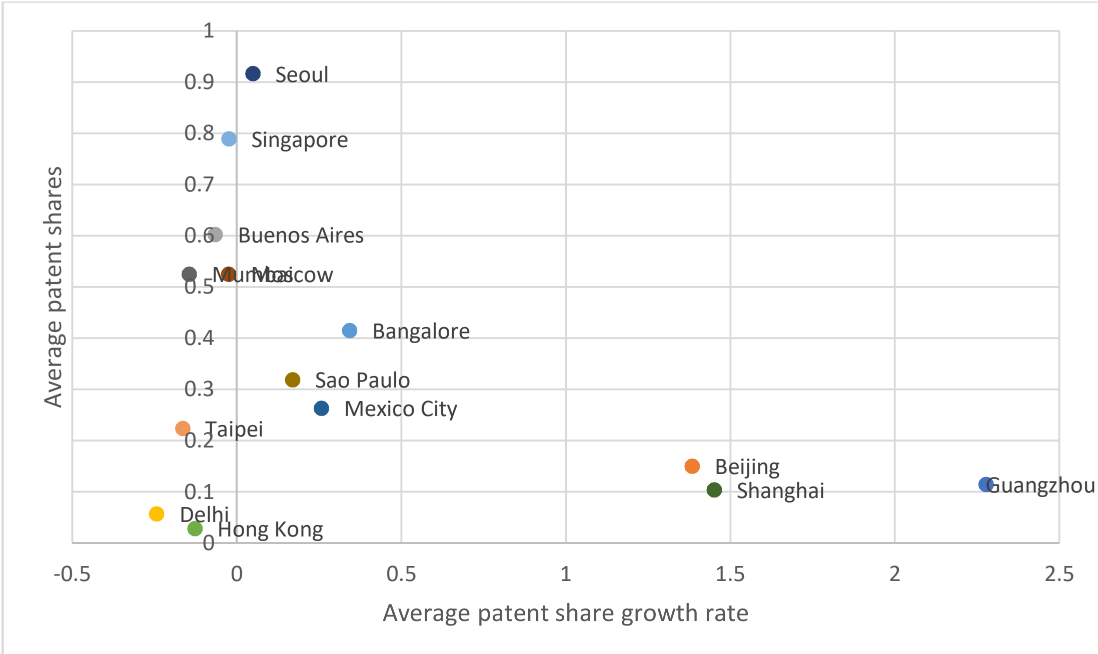

Figure 4.3 Average patent shares and patent share growth of all developing cities

Based on the figure 4.3, we categorize Seoul, Singapore, Beijing, Shanghai and Guangzhou as cluster 1 cities. We categorized Seoul and Singapore as cluster 1 cities because of their comparatively high average patent shares and Beijing, Shanghai and Guangzhou as cluster 1 because of their exceptionally high average patent share growth rate. The rest of the cities, Buenos Aires, Munich, Moscow, Bangalore, Sao Paulo, Mexico City, Taipei, Delhi and Hong Kong are classified as category 2 cities because of their relatively low average patent shares and average patent share growth rate.

4.3.4 Categorization of cities in clusters

Our final cluster 1 and 2 cities are shown in table 4.7 below:

Cluster	**Cities**
Cluster 1	Bay Area, New York City, Los Angeles, Boston, Seattle, Austin, Tokyo, Copenhagen, Dublin, Auckland, Helsinki, Oslo, Barcelona, Paris, Grenoble, Seoul, Singapore, Beijing, Shanghai and Guangzhou
Cluster 2	Chicago, Pittsburgh, Houston, Dallas, Miami, Atlanta, San Diego, Sydney, Eindhoven, Vienna, London, Milan, Toronto, Stockholm, Madrid, Zurich, Osaka, Brussels, Basel,

	Dusseldorf, Montreal, Birmingham, Lyon, Manchester, Frankfurt, Rome, Glasgow, Nagoya, Munich, Hamburg, Berlin, Vancouver, Stuttgart, Moscow, Bangalore, Sao Paulo, Mexico City, Taipei, Delhi, Hong Kong and Buenos Aires

Table 4.7 Final division of cities into cluster 1 and cluster 2

We postulate that in both clusters we will see that international connections impact local connections in a positive way and vice versa. However, since cluster 1 consists of more innovative cities than cluster 2, we expect that the impact of international connections on the local connections would be higher in cluster 1 than in cluster 2.

In the proposal we conducted a study in which we analyzed the impact of international citations on local citations. Our dataset contained panel data ranging from the years 1976 – 2016. In our study, we used Least Squares regression with Dummy Variables (LSDV) with fixed effects for each city. The rationale for choosing fixed effects for cities was that they would help us control for those factors that are characteristic of each city and otherwise hard to control for. This could include culture, business practices, etc. Since these factors can be assumed to be largely consistent from year to year, fixed effects are the appropriate method to use. To further justify our use of a fixed effects model instead of a random effects model, we conducted a Hausman test. In the Hausman test, the null hypothesis is that the random effects model is appropriate, while the alternative hypothesis is that the fixed effects model is appropriate. We ran the Hausman test and obtained a significant p value of 0.0002. Therefore, we reject the null hypothesis and accept the fixed effects model as better suited for our purpose.

4.3.5 Definition of Variables

We defined our variables as follows:

Dependent Variable:

Share of local citations

Our dependent variable L_{it} was calculated as follows:

$$L_{it} = \frac{Number\ of\ local\ citations\ by\ city\ i\ in\ year\ t}{Total\ number\ of\ all\ local\ citations\ across\ all\ cities\ in\ year\ t} * 10{,}000$$

In this equation local citations are those cited patents in which the first inventor location is in the same city region as the citing patent. For example: for a patent whose first inventor's address is in the New York City region, a local citation would be a cited patent whose first inventor's address is also in the New York City region.

We divided the total number of local citations for each city in a certain year by the total number of all citations in that year to control for the increasing number of citations. Our data shows that in 1980 the total number of citations for all USPTO patents were 348,010 while in 2016 the total number of citations for all USPTO patents were 9,803,647. Hence, we need to control for this exponential rise in citations.

Independent Variable:

Share of international citations

Our independent variable I_{it} was calculated as follows:

$$I_{it} = \frac{Number\ of\ international\ citations\ by\ city\ i\ in\ year\ t}{Total\ number\ of\ all\ international\ citations\ across\ all\ cities\ in\ year\ t} * 10{,}000$$

In this equation international citations are those cited patents in which the first inventor location is in a different country than the first inventor of the citing patent. For example: for a patent whose first inventor's address is in the New York City region, an international citation would be a cited patent whose first inventor's address is outside of the United States.

Moderating Variable:

Share of ICT (International Communication Technology) citations

Since ICT technologies act as connectors to link previously unrelated technologies (Cantwell and Santangelo, 2000), we expect that the effect of the international citations on local citations to be amplified by the proportion of ICT technologies. Therefore we calculated the share of ICT citations and add this as a moderating variable in our model. The share of ICT patents is calculated as follows:

$$IICT_{it} = \frac{Number\ of\ international\ ICT\ citations\ by\ city\ i\ in\ year\ t}{Total\ number\ of\ all\ international\ ICT\ citations\ across\ all\ cities\ in\ year\ t} * 10{,}000$$

To categorize patents as ICT patents, we first classified patents using their USPTO classes and sub-classes into 56 technological fields (as set out in Cantwell, 1995). The 6 technological fields (out of 56) that are recognized as ICT fields are as follows: telecommunications, other electrical Communication systems, special radio systems, image and sound equipment, semiconductors and office equipment and data processing systems (see Cantwell and Santangelo, 1999).

We also ensured our model was robust and controlled for heteroscedasticity and autocorrelation.

Defining C_{it} as City i at year t, the model we estimate is:

$$L_{it} = \beta_0 + \beta_1 I_{it} + \beta_2 IICT_{it} + \beta_3 (I_{it} * IICT_{it}) + \beta_4 \sum_{i=2}^{33} C_{it}$$

Taking the Seattle region as the reference city, we obtained the results displayed in the appendix, table A-1.

The 13 US cities in our dataset are different from other cities because even though they demonstrate a lesser amount of internationalization than other cities, they are increasingly citing other cities in the US. To cater for this, we developed another model. In this model we defined our dependent variable, the share of local citations as we did in the previous model. However, our independent variable is the share of trans-local citations, which includes those citations that are within the same country but outside the area of the focal city. This definition of trans-local is borrowed from Turkina and Van Assche (2018).

The new independent variable N_{it} was calculated as follows:

$$N_{it} = \frac{Number\ of\ trans - local\ citations\ by\ city\ i\ in\ year\ t}{Total\ number\ of\ all\ trans - local\ citations\ across\ all\ cities\ in\ year\ t} * 10{,}000$$

In this equation trans-local citations are those cited patents in which the first inventor location is not in the same city region as the first inventor location of the citing patent. That is, this includes domestic patents that are not in the same city. For example: for a patent whose first inventor's address is in the New York City region, a trans-local citation could be a cited patent whose first inventor's address is outside of the United States or in a different city in the United States.

Just like in the previous model we included the share of ICT citations as a moderating variable. In this model, instead of calculating the share of ICT international citations we calculated the share of ICT trans-local citations. The formula for the moderating variable in this case is:

$$NICT_{it} = \frac{Number\ of\ non - local\ ICT\ citations\ by\ city\ i\ in\ year\ t}{Total\ number\ of\ all\ non - local\ citations\ across\ all\ cities\ in\ year\ t} * 10{,}000$$

This revised model becomes:

$$L_{it} = \beta_0 + \beta_1 N_{it} + \beta_2 NICT_{it} + \beta_3 (N_{it} * NICT_{it}) + \beta_4 \sum_{i=2}^{33} C_{it}$$

The results of our regression are displayed in the appendix in table A-2.

We have now finished collecting data for 62 cities. We run both models again with our complete dataset of 62 cities and see if we still get the same results as we did when we used 33 cities.

Like we did before, defining C_{it}as City i at year t, the first model we estimate with the 62 cities is:

$$L_{it} = \beta_0 + \beta_1 I_{it} + \beta_2 IICT_{it} + \beta_3 (I_{it} * IICT_{it}) + \beta_4 \sum_{i=2}^{62} C_{it}$$

We use San Diego as the base case, since San Diego was the most typical of our cities. While using San Diego, we got the least number of significantly different cities. The results are displayed in the appendix in table A-3.

We also repeat the second regression model using trans-local citations as an independent variable instead of international citations. The updated model is:

$$L_{it} = \beta_0 + \beta_1 N_{it} + \beta_2 NICT_{it} + \beta_3 (N_{it} * NICT_{it}) + \beta_4 \sum_{i=2}^{62} C_{it}$$

We can see in table A-3 and A-4 that after we add all 62 cities to both models we get similar and significant results again. Table A-3 means that even after adding all 62 cities to the model, the impact of international citations on local citations is still significant. In addition, the ICT international citations also exhibit a significant effect on the local citations. Table A-4 shows that after adding the 62 cities the impact of trans-local citations on local citations is still also significant. The ICT trans-local citations also have a significant effect on local citations.

We repeat both models after adding a lag to remove path dependency. We add a lag of two years and assess the impact of international and trans-local knowledge connections on local connections two years later. In addition, we also modify our method of calculating the independent variable, the share of international (or trans-local) citations by subtracting the international (or trans-local) ICT citations from it. This is because, international (or trans-local) citations are being used as a moderating effect so there might be multicollinearity if we include it in the independent variable as well.

The independent variable in the first model thus becomes:

$$NewI_{it} = \frac{\begin{gathered} Number\ of\ international\ citations\ by\ city\ i\ in\ year\ t - \\ Number\ of\ international\ ICT\ citiations\ by\ city\ i\ in\ year\ t \end{gathered}}{\begin{gathered} Total\ number\ of\ all\ international\ citations\ across\ all\ cities\ in\ year\ t - \\ Total\ number\ of\ international\ ICT\ citations\ by\ all\ cities\ in\ year\ t \end{gathered}} * 10{,}000$$

Defining C_{it}as City i at year t, the new model we estimate is:

$$L_{it+2} = \beta_0 + \beta_1 NewI_{it} + \beta_2 IICT_{it} + \beta_3 (NewI_{it} * IICT_{it}) + \beta_4 \sum_{i=2}^{62} C_{it}$$

The results are displayed in the appendix in table A-6.

We repeat the regression using trans-local citations as our independent variable. Just like we did previously when using international citations as our independent variable, we subtract the trans-local ICT citations. This is because, trans-local citations are used as a moderating effect in our model and we want to eliminate any multicollinearity.

The new independent variable in this model thus becomes:

$$NewN_{it} = \frac{\begin{array}{c}Number\ of\ non-local\ citations\ by\ city\ i\ in\ year\ t -\\ Number\ of\ non-local\ ICT\ citiations\ by\ city\ i\ in\ year\ t\end{array}}{\begin{array}{c}Total\ number\ of\ all\ non-local\ citations\ across\ all\ cities\ in\ year\ t -\\ Total\ number\ of\ non-local\ ICT\ citations\ by\ all\ cities\ in\ year\ t\end{array}} * 10{,}000$$

Defining C_{it}as City i at year t, the new model we estimate is:

$$L_{it+2} = \beta_0 + \beta_1 NewN_{it} + \beta_2 NICT_{it} + \beta_3(NewN_{it} * NICT_{it}) + \beta_4 \sum_{i=2}^{62} C_{it}$$

The results for the model are displayed in the appendix in table A-7.

We also hypothesized, that the relationship between international (or trans-local) and local citations will vary depending on the innovativeness of the city. We conduct another regression analysis to assess whether the impact of the international citations on local citations varies between clusters. We define our dependent variable as we did earlier as the share of local citations. The dependent variable L_{it} is calculated as follows:

$$L_{it} = \frac{Number\ of\ local\ citations\ by\ city\ i\ in\ year\ t}{Total\ number\ of\ all\ local\ citations\ across\ all\ cities\ in\ year\ t} * 10{,}000$$

The independent variable, share of international citations I_{it} is calculated as follows:

$$I_{it} = \frac{Number\ of\ international\ citations\ by\ city\ i\ in\ year\ t}{Total\ number\ of\ all\ international\ citations\ across\ all\ cities\ in\ year\ t} * 10{,}000$$

Defining C_{it}as City i at year t and CLUSTER as a dummy variable which takes the value of 1 when the city belongs to the highly innovative sector, the new model we estimate is:

$$L_{it+2} = \beta_0 + \beta_1 I_{it} + \beta_2 CLUSTER + \beta_3(I_{it} * CLUSTER)$$

4.4 Results

The results of our model are displayed in table 4.8.

Source	SS	df	MS
Model	520584322	3	173291674
Residual	58722262.8	2,318	25639.156
Total	579306585	2,321	249593.53

Number of obs	2,322
F(3, 2318)	6849.84
Prob > F	0
R-squared	0.8986
Adj R-squared	0.8985
Root MSE	159.16

Share of local Citations (with two year lag)	Coefficient	Std. Err.	T	P>t	[95% Conf. Interval]	
Share of International Citations	0.7197266	0.032492	22.15	0	0.65601	0.783443
CLUSTER	-57.53554	8.580491	-6.71	0	-74.3618	-40.7093
CLUSTER * Share of International Citations	0.7706818	0.03436	22.43	0	0.703302	0.838062
_cons	-11.47799	5.161436	-2.22	0.026	-21.5995	-1.35648

Table 4.8 Regression results with international citations as independent variable and using CLUSTER as an interactive variable

We repeat the regression using trans-local citations as the independent variable. This new independent variable is calculated as follows:

$$N_{it} = \frac{Number\ of\ non-local\ citations\ by\ city\ i\ in\ year\ t}{Total\ number\ of\ all\ non-local\ citations\ across\ all\ cities\ in\ year\ t} * 10{,}000$$

Defining C_{it}as City i at year t and CLUSTER as a dummy variable which takes the value of 1 when the city belongs to the highly innovative sector, the new model we estimate is:

$$L_{it+2} = \beta_0 + \beta_1 N_{it} + \beta_2 CLUSTER + \beta_3 (N_{it} * CLUSTER)$$

The results we obtained are displayed in table 4.9.

Source	SS	Df	MS
Model	546862614	3	182287538
Residual	32443970.7	2,318	13996.5361
Total	579306585	2,321	249593.53

Number of obs	2,322
F(3, 2318)	13023.76
Prob > F	0
R-squared	0.944
Adj R-squared	0.9439
Root MSE	118.31

Share of local Citations (with two year lag)	Coefficient	Std. Err.	T	P>t	[95% Conf. Interval]	
Share of Trans-local Citations	0.4207791	0.011716	35.92	0	0.397805	0.443754
CLUSTER	-85.27418	6.294021	-13.55	0	-97.6167	-72.9317
CLUSTER * Share of Trans-local Citations	0.3107469	0.012376	25.11	0	0.286478	0.335015
_cons	-13.45553	3.619546	-3.72	0	-20.5534	-6.35764

Table 4.9 Regression results with trans-local citations as independent variable and using CLUSTER as an interactive variable

We can see from our results that the impact of international citations on local citations is significant. In addition, the ICT international citations also exhibit a significant effect on the local citations. We also show that the impact of trans-local citations on local citations is also significant. The ICT trans-local citations also have a significant effect on local citations. This effect is still visible after catering for path dependency.

We also see that highly innovative cities are more internationally connected than others. This is in line with the economic geography literature and the international business literature that stresses the importance of connectivity for the innovativeness of a region. We also see that the effect of these international connection on the local connections is greater in innovative cities than in less innovative cities. This implies that in innovative cities the local connections increase more because of the international connections when compared to less innovative cities.

Chapter 5: Exploring the Determinants of the Extent of Knowledge Connectivity between Two Cities

5.1 Introduction

Previous literature on global value chains and global production networks have emphasized the challenges and complexities in organizing and maintaining knowledge linkages that cut across national boundaries (Humphrey and Schmitz, 2002; Fuijita and Thisse, 2002; Gereffi et al, 2005; Coe et al, 2010). Adding to this literature, Jaffe and Trajtenberg (1999) find that patents whose inventors reside within the same country are typically 30 – 80 percent more likely to cite each other than inventors from other countries.

In particular, the tacit component of knowledge is not easy to replicate across different contexts (Polanyi, 1966; Von Hippel 1994; Szulanski and Jensen 2004) since it is embodied in large part in localized organizational routines and the collective expertise of specific production teams (Nelson and Winter, 1982).

We expect that in this current information age, with its advances in information and communication technologies (ICT), an increase in the diffusion of knowledge across regions. The developments in ICT have led to the lowering of transport and communication costs (Foss and Pederson, 2004). In addition, contemporary ICT technologies have allowed combinations of previously separate lines of technological development (Santangelo, 2002). Since individual locations are increasingly specialized in their activity (Cantwell and Vertova 2004), international connections are generally necessary for such new combinations of innovative activity. Because of these changes in the environment for innovation, we would expect innovative cities to be progressively more connected with each other than ever before.

However, our previous study showed that the levels of internationalization of knowledge sources varied greatly across the cities in our dataset. This study explores possible reasons for these differences. We aim to look at each city pair in our dataset and understand the factors that determine the likelihood of two cities sourcing knowledge from each other. Our goal is to look at all the 62 cities in our dataset, and therefore 1,891 pairs to determine knowledge sourcing patterns.

Just like our previous study, the 62 cities included in our research include thirteen US cities (Seattle, Austin, San Diego, Pittsburgh, New York City, Los Angeles, Boston, Chicago, the Bay Area, Miami, Atlanta, Houston and Dallas), Canadian cities (Toronto, Vancouver and Montreal), European cities (London, Manchester, Birmingham, Glasgow, Paris, Lyon, Grenoble, Berlin, Frankfurt, Munich, Hamburg, Stuttgart, Dusseldorf, Eindhoven, Vienna, Zurich, Basel, Stockholm, Copenhagen, Madrid, Barcelona, Brussels, Milan, Rome, Dublin, Helsinki, Moscow and Oslo), Asian cities (Tokyo, Osaka, Nagoya, Taipei, Singapore, Seoul, Hong Kong, Beijing, Shanghai, Guangzhou, Mumbai, Delhi and Bangalore), South American cities (Mexico City, Sao Paulo, Buenos Aires), Auckland, New Zealand and Sydney, Australia.

Our database consists of USPTO patents from the years 1976–2016. Patent citations were used to identify the location of knowledge sources and recipients by using the inventor locations of cited (source) and citing (recipient) patents.

The rest of the study is structured as follows. In the next section, we develop the hypothesis. After that, we discuss the data and methodology. The last section in this chapter contains results and a discussion.

5.2 Hypotheses Development:

The concept of absorptive capacity has been studied extensively at the firm level. As argued by Cohen and Levinthal (1990), the ability of a firm to evaluate and utilize external knowledge is dependent on the level of previous related knowledge. In this study, we extend this argument to the level of the location (as has been done previously for e.g. Criscuolo and Narula, 2008) and assert that the 'absorptive capacity' of a location determines which external knowledge sources it can use and exploit. We contend that a city is more likely to source knowledge from a city that is closer to it in terms of technological development. The amount of knowledge sourced is likely to increase with a decrease in technological level. However, we expect this to be a curvilinear relationship, which means that the increase in knowledge sourcing resulting from a decrease in technological gap will be more if the technological gap is larger.

Therefore we hypothesize:

H1: The extent of knowledge sourced by one city from another initially rises with the technological gap between them, and then falls as the technological gap becomes larger, in an inverse U-shaped relationship.

The evolutionary perspective of economic development states that a firm is bounded in its search for new knowledge to proximate neighborhoods. This means that they are more likely to search those locations that are close location wise or have similar technological knowledge (March and Simon, 1958; Nelson and Winter, 1982). Therefore, if similar or ‘related’ knowledge is present, the possibility of firms being able to utilize the knowledge in its own contexts greatly increases (Castaldi et al 2015). This has been corroborated by Freken et al. (2007) who showed that related but different knowledge improved the ‘opportunities to interact, copy modify and recombine ideas, practices and technologies across industries’. Taking this argument to a location level, we would expect that locations would be more likely to source knowledge from those locations that are specialized in related knowledge.

However, in our selection of cities, certain cities play a more influencing role than others in the knowledge network between them. These central cities are more likely to source knowledge from cities regardless of their technological co-specialization. Sassen (1991, 1994) argued that these cities are agglomeration of advanced producer services such as finance, law, accounting and advertising. We expect that these cities, especially the high influencers, will therefore benefit from a variety of knowledge sources rather than only those that are close to them in terms of technological specialization.

Therefore, we hypothesize:

H2: The extent of knowledge sourced by one city from another city will depend less on technological co-specialization for those cities that are more central to the network.

We believe that the tendency for knowledge to be transmitted across cities depends on its technological classification. We believe that those fields that belong to General Purpose Technology (GPT) fields will be more pervasive than others. GPTs are unique in that they may be used across several industries and are therefore more pervasive than other technological fields (Helpman and Trajtenberg, 1998). GPTs are also considered to be the ‘carrier branches’ of knowledge diffusion (Freeman and Perez 1988) and catalysts which allow fusion of previously separate branches of technology. Qiu and Cantwell (2018) conduct a study at the industry level which shows that international knowledge connectivity is most likely to take place in those industries that are GPT based such as industries in the biotechnology and electronics sectors. We extend the argument to the level of the city and hypothesize that cities that are specialized in GPT technologies tend to exhibit more internationalization than others. Hence, we hypothesize:

H3: A city that specializes in General Purpose Technologies (GPTs) is more likely to have higher knowledge flows.

5.3 Data and Methodology:

For the purpose of this study, we use patents granted by the USPTO as our primary data source. Patent citations are used to identify the location of knowledge sources and recipients by using the first named inventor locations of cited (source) and citing (recipient) patents.

We will conduct our analysis on all of the 62 cities in our dataset. We look at knowledge outflow and inflow between each city pair in our dataset. The number of pairs in our dataset are:

$$62C2 = \frac{62!}{2!(62-2)!} = 1891.$$

However, since we are considering the case of knowledge outflow from any city *a* to another city *b* and knowledge inflow in City *a* from City *b* as separate observations, the total number of observations in our dataset are:

$$P(62,2) = \frac{62!}{(62-2)!} = 3782.$$

We will observe these 3,782 instances over the period 1981 – 2016. Our main aim is trying to predict the extent of knowledge flow to any city *a* from city *b*.

We divide our time period (1981-2016) into seven different time periods. The first six time periods, consist of five consecutive years each whereas the last time period (2011-2014) consist of the last four consecutive years. We observe how our dependent and independent variables change from one period to another.

We use least squares regression with dummy variables (LSDV) with fixed effects for each city. The reason, we chose fixed effects for cities was to control for factors that are characteristic of each city and hard to control for. Examples of these factors include culture and business practices. As these factors can be assumed to largely consistent from year to year, fixed effects are the appropriate method to use.

5.3.1 Variable Definition

Our variables are defined as follows:

Dependent Variable:

Knowledge Inflow to Host City *a* from Source City *b*:

Our dependent variable is the total knowledge inflow to city *a* from city *b* in a time period. In terms of patents, this will be the total number of patents filed by first named inventors in city *a* that cite city *b* in a time period.

We define knowledge inflow at time period *t* as:

$$K_{ab} = Number\ of\ patent\ citations\ by\ first\ named\ inventors\ in\ city\ a\ to\ city\ b.$$

Independent Variables:

Technological Gap:

The technological gap between cities is calculated for the five broad streams of classifications separately. These five broad streams of classification are transport, mechanical, chemical, information communication technologies (ICT) and other electrical equipment. The details of the tech56 fields in each of the classification fields is given in the appendix in table B-1.

The classification of the knowledge flow is determined by the technological field of the citing patent. The difference in eigenvector centrality of each city in these categories is then used to determine the technological gap. We calculate eigenvector centrality using STATA. As an example, if the citing patent's primary technological field belongs to the chemical category, then the technological gap between the cited and citing locations is determined by their difference in eigenvector centrality in the network of patents that belong to the chemicals category.

Hence we define our variable technological gap between city *a* and *b* for classification *c* in time period *t* as:

$$TG_{abc} = Eigenvector\ Centrality_{bc} - Eigenvector\ Centrality_{ac}$$

If the knowledge recipient, i.e. city *a* has a higher eigenvector centrality than the source, i.e. city *b* then the technological gap will be negative. However, if the source has a higher eigenvector centrality than the recipient city, the value of technological gap will be positive. A large positive technological gap will indicate that the source, city *b,* is a lot more technologically advanced than the recipient. We would hence expected limited knowledge inflow to city *a* be limited because city *a* would not have the necessary absorptive capacity to absorb more knowledge from city *b*.

Within our measure of technological gap we control for technological co-specialization as well. The higher the technological co-specialization the smaller will be the technological gap between cities.

Degree of Technological Co-Specialization:

We first divided each city's patents in to 56 technological fields (as done in Cantwell, 1995). We then calculate the specialization of each city in each of these technological fields. This is done by calculating the Revealed Technological Advantage index (RTA) as developed by Soete (1987), Cantwell (1989, 1991) and Patel and Pavitt (1991).

The RTA index for tech field *i* in city *j* is defined as:

$$RTA_{ij} = {}^{P_{ij}/\sum_j P_{ij}}\Big/_{\sum_i P_{ij}/\sum_{ij} P_{ij}}$$

Where P_{ij} is the number of patents of tech field i from country j, $\sum_j P_{ij}$ is the total number of patents from all cities for the tech field i, $\sum_i P_{ij}$ is the total number of all patents in all tech fields from city j and $\sum_{ij} P_{ij}$ is the number of all patents from all cities. The index varies around one, so a value greater than one suggests that the city may be relatively specialized in that particular tech field, compared to other tech fields. A value less than one would indicate that the city has a comparative disadvantage in that particular tech field.

However, there are some difficulties faced when constructing RTA index for developing cities that have small number of patents. Since Beijing and Bangalore have a small number of patents in the US, they show substantial inter-industry variation in the RTA index and sometimes very high and low values. To counter for this we adjust the RTA using the following equation:

$$AdjRTA = \frac{(RTA-1)}{(RTA+1)} + 1$$

For the rest of our analysis, we divide our time period into 8 groups. Each group consists of 5 years, except the last which consists of 4. We do cross-section regressions on the adjusted RTA calculated for each city with adjusted RTAs of every other city to assess the degree of specialization. We do these regressions for every time period in our dataset. The regression equation is as follows:

$$AdjRTA_{ia} = \propto + \beta_1 AdjRTA_{ib} + \varepsilon$$

Where a and b are two different cities in our dataset. This regression is run for every unique city pair for every time period. The resulting coefficient is used as the degree of technological co-specialization. This technique to calculate technological co-specialization is borrowed from Cantwell and Janne (1999).

Network Centrality:

We determine the centrality of a city in our network by using the eigenvector centrality measure. We use STATA to calculate the eigenvector of each city. This value is calculated by assigning scores to all the cities in our network. Connections to high scoring cities contribute more to the score of the city in question than equal connections to low scoring cities (Grund, 2015).

The eigenvector centrality for each city in time period t is the average eigenvector centrality of the city throughout the period. Based on their eigenvector centrality each city is divided into a cluster. Cluster 1 consists of cities with a relatively higher value of eigenvector centrality, while cluster 2 consists of cities with relatively low values. Figure 5.1 below displays eigenvector centrality for each city for each time period.

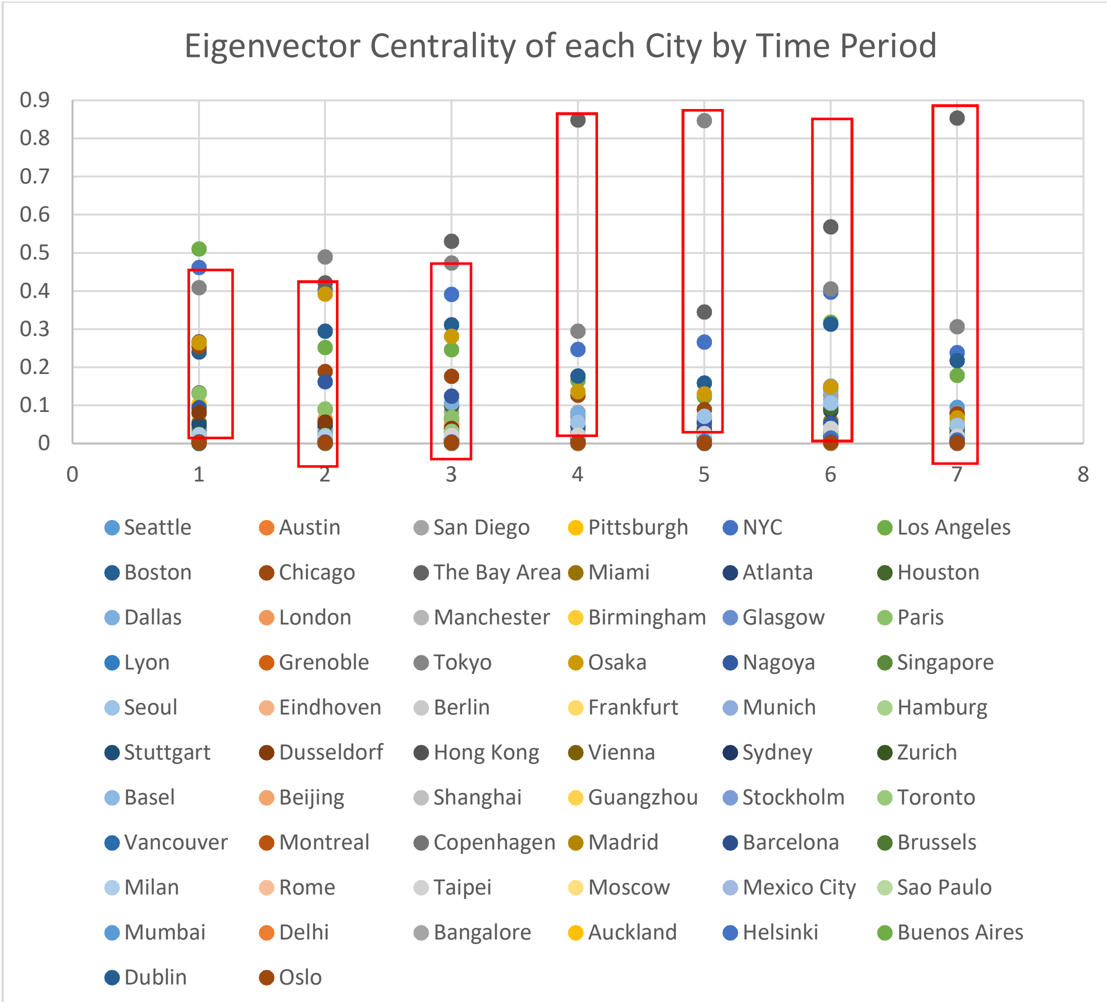

Figure 5.1 Eigenvector centrality of each city by time period

In figure 5.1, cities inside the red box are those that we included in cluster 1. The table below gives the list of cities in cluster 1 in each time period.

	Cluster 1 cities
1981-1985	Los Angeles, New York City, Tokyo, Osaka, Chicago and Boston
1986-1990	Tokyo, The Bay Area, New York City, Osaka, Boston, Los Angeles, Chicago and Nagoya
1991-1995	The Bay Area, Tokyo, New York City, Boston, Osaka, Los Angeles and Chicago
1996-2000	The Bay Area, Tokyo and New York City
2001-2005	Tokyo, The Bay Area and New York City
2006-2010	The Bay Area, Tokyo, New York City, Los Angeles and Boston

2011-2014	The Bay Area, Tokyo, New York City, Boston and Los Angeles

Table 5.1 List of cluster 1 cities by time period

<u>Specialized in General Purpose Technology Fields:</u>

To determine the relative specialization a city in general purpose technology fields (GPTs), we calculate the RTA of each city in each of the technological fields that belong to the GPT category (as defined by Qiu and Cantwell, 2015). The tech 56 fields that are categorized as GPT are given in table 5.2.

Tech field	Tech 56 Description
5	Chemical Processes
9	Synthetics resins and Fibers
11	Other Organic Compounds
16	Chemical and allied equipment
29	Other general industrial equipment
38	Electrical devices and systems
39	Other general electrical equipment
41	Office equipment and data processing systems
50	Non-metallic mineral products
53	Other instruments and controls

Table 5.2 GPT fields

We then calculated a weighted average of each city's RTA in each of these technological fields. The weights for each technological field are calculated by its relative share of the total number of patents filed in that year. This means that those technological fields that have higher number of patents will have a higher weight assigned and those with lower number of patents will have a lower weight assigned.

$$GPT_a = Weighted\ Average(AdjRTA_a\ GPT\ techfields)$$

Control Variables:

<u>Annual merchandise trade:</u>

Since trade statistics are available at the country level and not at the city level, we control for the imports coming into the country city *a* is situated in from the country city *b* is situated in. This is because, previous literature has shown that knowledge transfer is associated with the amount of trade (Sjöholm, 1996). For the years 1981- 2000, we used the United Nations trade data, assembled by Robert Feenstra and Robert Lipsey, under a grant from the National Science Foundation to the NBER[1]. Trade data from 2001 – 2014 was downloaded from WITS (World Integrated Trade Solution), a project by World Bank[2].

If city *a* and city *b* are in the same country, we set the value for annual merchandise trade greater than the maximum trade between any countries. This also allows us to control for cities being in the same country, which is important since inventors residing within the same country are typically 30 – 80 percent more likely to cite each other than inventors from other countries (Jaffe and Trajtenberg, 1999).

<u>Number of Patents by Host City *a:*</u>

If city *a* has a high propensity to patent and has a high number of patents, we would expect that citations to city *a* would also be high. Therefore, we control for the number of patents by city *a*.

<u>Number of Patents by Source City *b:*</u>

If city *b* has a high number of patents, than the number of times it cites patents from any source city *a* are likely to be high as well. Therefore, we control for patenting levels of city *b*.

<u>Technological Co-specialization at the beginning of our time period:</u>

[1] This data was downloaded from: The Center of International Data < http://cid.econ.ucdavis.edu/nberus.html>

[2] This data was downloaded from: WITS, World Bank Group <https://wits.worldbank.org/countrystats.aspx?lang=en>

We use technological co-specialization at the beginning of our time period as a control variable. Since cities have tend to be path dependent in their trajectory of technological development, we feel it is important to control for technological co-specialization at the beginning of our time period as well.

Our final model is:

$$K_{abt} = \alpha + \beta_1 TG_{abt} + \beta_2 TCO_{abt} * Cluster_{at} + \beta_3 TCO_{abt} + \beta_4 Cluster_{at} + \beta_5 GPT_{at} + \beta_6 GPT_{bt} + \beta_7 \sum_{i=2}^{62} a_i$$

Where K_{abt} refers to knowledge inflow to city *a* from city *b* at time period *t,* TG_{abt} refers to technological gap between city *a* and *b* at time period *t,* TCO_{abt} refers to the degree of technological co-specialization between cities a and b at time period *t*, $Cluster_{at}$ refers to the cluster the recipient city *a* belongs to *,* GPT_{at} refers to the mean RTA of city *a* in GPT fields and GPT_{bt} refers to the mean RTA of city *b* in GPT fields.

Our regression yields the results displayed in the table below:

Source	SS	df	MS
Model	9.23E+11	71	1.30E+10
Residual	1.71E+12	84,786	20126084
Total	2.63E+12	84,857	30980782

Number of observations	*84,858*
F(71, 84786)	*645.6*
Prob > F	*0*
R-squared	*0.3509*
Adj R-squared	*0.3504*
Root MSE	*4486.2*

Total number of citations to city *a*	**Coefficient**	**Std. Err.**	**t**	**P>t**	**[95% Conf.**	**Interval]**
Independent Variables:						
Technology gap	-730.808	167.8409	-4.35	0	-1059.77	-401.841
Technology gap ^{2}	-4184.55	267.5319	-15.64	0	-4708.91	-3660.19
Technological co-specialization	254.5937	68.68924	3.71	0	119.9633	389.224
Cluster	-656.927	97.85471	-6.71	0	-848.721	-465.132
cluster * technological co-specialization	7222.183	167.8263	43.03	0	6893.245	7551.121

City *a* GPT specialization	4834.35	401.9701	12.03	0	4046.492	5622.208
City *b* GPT specialization	743.7634	233.568	3.18	0.001	285.9721	1201.555
Control Variables:						
Total number of patents by city *a*	0.041568	0.000717	58.02	0	0.040163	0.042972
Total number of patents by city *b*	0.04076	0.000429	94.98	0	0.039919	0.041601
Imports from city *b to* a	9.37E-06	1.09E-07	85.94	0	9.16E-06	9.59E-06
City fixed effects:						
Seattle	404.9209	140.0228	2.89	0.004	130.4774	679.3644
Austin	-464.636	146.7024	-3.17	0.002	-752.171	-177.1
Pittsburgh	-992.82	144.4188	-6.87	0	-1275.88	-709.76
New York City	-2229.01	165.8948	-13.44	0	-2554.16	-1903.86
Los Angeles	-1049.72	150.0298	-7	0	-1343.78	-755.663
Boston	-942.516	151.6141	-6.22	0	-1239.68	-645.354
Chicago	-604.081	141.5608	-4.27	0	-881.539	-326.624
The bay Area	1139.48	175.6219	6.49	0	795.2621	1483.697
Miami	-302.852	143.974	-2.1	0.035	-585.04	-20.6644
Atlanta	-247.304	142.698	-1.73	0.083	-526.991	32.38329
Houston	-536.725	141.1957	-3.8	0	-813.467	-259.982
Dallas	-365.072	140.3939	-2.6	0.009	-640.243	-89.9009
London	339.5298	143.8881	2.36	0.018	57.51029	621.5493
Manchester	-165.464	176.2829	-0.94	0.348	-510.977	180.049
Birmingham	44.74695	166.9308	0.27	0.789	-282.436	371.93
Glasgow	-278.106	193.9463	-1.43	0.152	-658.239	102.0276
Paris	212.6069	141.6765	1.5	0.133	-65.0779	490.2917
Lyon	466.1842	175.5238	2.66	0.008	122.159	810.2094
Grenoble	-221.248	162.072	-1.37	0.172	-538.908	96.41216
Tokyo	-2740.18	192.1889	-14.26	0	-3116.87	-2363.49
Osaka	-334.41	145.742	-2.29	0.022	-620.063	-48.7569
Nagoya	-291.721	144.9345	-2.01	0.044	-575.791	-7.65005
Singapore	429.6097	171.5299	2.5	0.012	93.4125	765.8069
Seoul	258.0793	149.8838	1.72	0.085	-35.6918	551.8504
Eindhoven	493.9821	160.9752	3.07	0.002	178.472	809.4921
Berlin	-501.704	163.45	-3.07	0.002	-822.065	-181.344
Frankfurt	9.627277	184.0967	0.05	0.958	-351.201	370.4553
Munich	-277.321	151.0301	-1.84	0.066	-573.339	18.69671
Hamburg	-185.766	165.1604	-1.12	0.261	-509.479	137.9476
Stuttgart	9.685274	146.5268	0.07	0.947	-277.506	296.8767
Dusseldorf	656.3303	161.1991	4.07	0	340.3814	972.2791
Hong Kong	407.8189	195.4116	2.09	0.037	24.81377	790.8241
Vienna	678.7066	171.8842	3.95	0	341.815	1015.598

Sydney	742.3874	157.5811	4.71	0	433.5298	1051.245
Zurich	210.3595	157.672	1.33	0.182	-98.6765	519.3954
Basel	1477.946	216.6558	6.82	0	1053.303	1902.59
Beijing	-432.625	186.0178	-2.33	0.02	-797.218	-68.0312
Shanghai	-540.538	191.0901	-2.83	0.005	-915.073	-166.003
Guangzhou	-336.629	202.5295	-1.66	0.096	-733.585	60.32686
Stockholm	417.3975	153.6856	2.72	0.007	116.1751	718.62
Toronto	274.2896	146.0045	1.88	0.06	-11.8781	560.4573
Vancouver	132.9878	153.368	0.87	0.386	-167.612	433.5879
Montreal	233.3125	151.5895	1.54	0.124	-63.8016	530.4266
Copenhagen	933.8322	169.9675	5.49	0	600.6973	1266.967
Madrid	203.0908	189.3867	1.07	0.284	-168.106	574.2871
Barcelona	606.9262	186.9832	3.25	0.001	240.4406	973.4118
Brussels	509.3577	185.9641	2.74	0.006	144.8696	873.8459
Milan	300.624	155.6605	1.93	0.053	-4.46928	605.7174
Rome	450.6973	183.7806	2.45	0.014	90.48883	810.9057
Taipei	1381.66	198.8881	6.95	0	991.8409	1771.479
Moscow	-4.68753	194.0718	-0.02	0.981	-385.067	375.6916
Mexico City	128.0904	245.7715	0.52	0.602	-353.62	609.8006
Sao Paulo	414.2603	220.843	1.88	0.061	-18.5902	847.1108
Mumbai	272.4817	252.6339	1.08	0.281	-222.679	767.642
Delhi	9.357009	236.1595	0.04	0.968	-453.514	472.2278
Bangalore	127.3877	202.8037	0.63	0.53	-270.106	524.8814
Auckland	456.3835	191.1122	2.39	0.017	81.80506	830.9619
Helsinki	456.9102	160.8748	2.84	0.005	141.5968	772.2235
Buenos Aires	524.213	209.0965	2.51	0.012	114.3857	934.0404
Dublin	140.7235	186.1037	0.76	0.45	-224.038	505.4852
Oslo	650.6474	172.8357	3.76	0	311.8907	989.404
_cons	-6718.49	430.3488	-15.61	0	-7561.97	-5875.01

Table 5.3 Regression results

We also generated a graph using STATA to show the relationship between technology gap and the knowledge transfer. We see as predicted that the extent of knowledge sourced decreases first with the increase in technology gap and then increases in an inverted U shape. This further confirms our hypothesis 1.

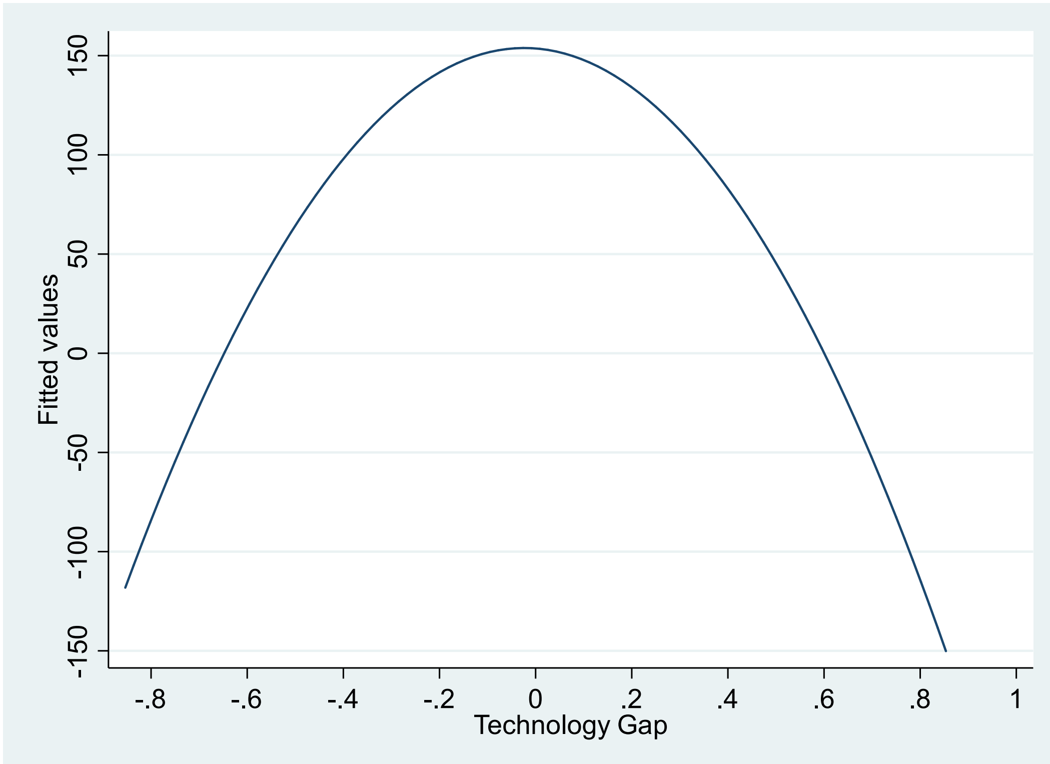

Figure 5.2 Relationship between Knowledge Transfer and Technology Gap

5.4 Results:

As we predicted in our first hypothesis, a city is likely to source technological knowledge from a city that is closer to it in terms of technological level. As the technological gap increases, the number of citations to the source city *b* decrease. We also see find a significant curvilinear effect which means that the relationship between technological gap and knowledge sourcing is not linear.

We find that technological co-specialization has a positive independent effect on the extent of knowledge sourcing. This is in line with the literature on the evolutionary perspective of economic development which states that firms are bound in their search for new knowledge to proximate neighborhoods in terms of distance and technological specialization (March and Simon, 1958; Nelson and Winter, 1982). We expected that this will also hold at a location level and our results show that it does.

We also find that if the recipient city *a* belongs to the cluster of cities with high eigenvector centrality, this negatively effects the extent of knowledge sourced from any source city *b.* This is in line with what we found in study 1. Cities that have high eigenvector centrality coincide with the highly innovative cities distinguished in study 1. In study 1, we found that the impact of trans-local citations on local citations are greater in these cities. Therefore, these cities make more use of their local technological networks than the less innovative ones.

We had predicted in hypothesis 2 that cities with higher eigenvector centrality are less likely to source knowledge from those cities that are closer to them in terms of technological co-specialization. We find that this is not true and that the interactive effect of cluster and technological co-specialization is highly significant and positive. This might be because the cities that are in the cluster are those that are specialized in multiple areas and so are technologically closer to a greater number of cities in our dataset.

As predicted in hypothesis 3, we also find a positive and significant effect on the extent of knowledge sourced if either the recipient city or the source city is specialized in a greater number of GPT technologies. This effect is more if the recipient city *a* is specialized in GPT technologies than when source city *b* is.

We also find that there is city to city variations and most cities exhibit significant fixed effects. Cities that rely more on trans-local sources than our base city, San Diego, such as London has a positive significant effect on the extent of trans-local knowledge sourcing.

Chapter 6: Connecting the Nodes: Using SNA to Determine the Evolving Network of Cities over Time

6.1 Introduction

Since the late twentieth century, an information based and internationally networked capitalism has emerged and replace the old science-based and managerially coordinated capitalism (Cantwell, 2014; Freeman and Louca, 2001). Alcacer et al. (2016) contend that there are two stages to every historical phase. In the first phase lead industries emerge and grow rapidly in isolation, while in the second stage, dubbed the 'diffusion' phase, the technologies and methods that characterize the current techno-economic paradigm have widespread applications across all industries. We have now entered the diffusion phase of the information age (Alcacer et al., 2016).

Because of the current general purpose technologies, such as IT, new technology markets have emerged (Athreye, 1997; Arora et al., 2001). Scholars in this area postulate that because of the emergence of generic technologies, we observe technological convergence and the rise of large scale markets. The lowered cost of experimentation, because of computer aided simulation, and the emergence of new languages that allow previously tacit knowledge to be codified, have also stimulated the growth of these markets. Because of these larger markets, a new division of labor exists in which nations can narrowly specialize and emerge as technology producers. Cantwell and Vertova (2004) also came up with a similar conclusion, arguing that because the technological diversification of nations had declined in recent years, emerging countries can now catch up through a much narrower specialization.

In addition, increased globalization entails a more open economy, which means an increase in foreign direct investment across all countries. When studying patents Athreye and Cantwell (2005) found that inward foreign direct investment led to emergence of new technology producers.

Because of this, we can expect that in our time period, we will observe new cities emerging as significant knowledge sources. We also expect that these new emerging cities may have more of a narrower focus in specialization, at least initially.

Since current information and communication technologies allow for a more geographic dispersal of activities, we may find that in this diffusion stage of the current information age, that there is wider geographic dispersion of the IB network (Torre and Moxon, 2001; Zaheer and Manrakhan, 2001). Therefore, we can expect the technological knowledge network between our cities to get denser with time.

We explore these trends by using social network analysis to construct a network of technological knowledge network between our cities. The details of our methodology are given in the next section.

6.2 Methodology:

In this study we aim to present an overall picture of the network of technological knowledge between our cities and how it has changed throughout our time period, 1981-2014. To achieve this, we calculated network statistics from the years 1981 to 2014 for the 62 cities in our study. Though we have patent data from the year 1976, the years before 1981 were excluded from our network analysis because we do not have information for a substantial number of cited patents for those years.

We divided our time period (1981-2014) into six time periods of five consecutive years each, except the last year, 2011-2014, which consists of the four consecutive years. We calculated the average node strength and eigenvector centrality for each of the time periods. We ranked each city in terms of average degree outdegree strength, indegree strength and eigenvector centrality for each of the time periods and observed how the rankings of cities changed over time.

Using cities as nodes and unidirectional arrows representing citations from one city to another, we calculated the following network statistics:

Node Strength: This refers to the strength of ties of each node. In our case, the strength of the tie refers to the number of times a location is cited by another. Because we have a directed network, we distinguish between indegree node strength and outdegree node strength. Indegree node strength of a location refers to the number of times it is cited by other locations and the outdegree node strength of a location refers to the number of times it cites other nodes.

Eigenvector Centrality: Eigenvector centrality is the measure of the influence of a node in the network. It assigns relative scores to all nodes in the network based on the concept that connections to high scoring nodes contribute more than equal connections to low scoring nodes. In our case, this implies that locations connected to other high influencing locations will have a greater score than locations connected to less influencing locations.

The overall network of technological knowledge between our cities:

Because of the current wave of globalization and because of facilitating ICT technologies, we expect to see developing cities emerging as important contributors and recipients of technological knowledge in our network. We hope that observing the change in network over our time period will help us understand which developing cities are becoming more important to the network and the extent of their success. We expect that not all developing cities will succeed in becoming more central to the network and the degree of their success will also vary.

We also expect that some old technology leaders will lose their centrality in the network during our time period. Because innovation is cumulative (Pavitt 1987), it is liable to lock in to a particular industrial pattern or configuration in any location and this pattern is only likely to change gradually over time since a shift to a sector in which technological opportunities are rising most rapidly might not be easy to achieve (Cantwell, 1991). Therefore, we can anticipate that some cities might be still locked in to the old technologies of the science paradigm which preceded this current information age and will gradually lose their importance in the network of technological knowledges.

6.3 Data Analysis

6.3.1 Outdegree Strength:

We first observe how the cities change with regards to their outdegree strength throughout our time period. We ranked each city according to how they rank in terms of their average outdegree strength in each of our time periods, where rank 1 is the city with the highest outdegree strength and 62 is the one with the lowest. The outdegree strength will tell us which cities have the most trans-local knowledge sources within our dataset. We see that New York City, Los Angeles, The Bay Area and Tokyo, Boston remain amongst the top cities with the most outdegree strength throughout our time period. Even though there is less shifting amongst the top few cities, we see developing cities such as Beijing, Taipei, Seoul and Bangalore gaining considerably in terms of outdegree strength.

We show in table 6.1 the cities which have shown the greatest increase in rank by the end of our time period. The exact values of the average outdegree strength of our cities in each of our time periods can be found in the appendix in table C-1.

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
Seoul	56	48	31	19	14	13	13
Taipei	50	40	27	23	18	18	19
Singapore	57	57	53	45	33	31	32
Helsinki	49	43	42	37	32	29	27
Beijing		59	58	57	55	47	38
Guangzhou		62	61	62	60	57	44
Seattle	23	18	17	15	12	10	6
Austin	26	21	20	13	10	12	11
Bangalore	59	61	62	60	56	54	47
Stockholm	36	25	26	26	25	23	24

Table 6.1 Cities which showed the most improvement in terms of relative outdegree strength

As expected, we also see that some cities have considerably decreased in terms of their outdegree strength. Table 6.2 depicts which cities have decreased the most in their ranks in terms of outdegree strength by the end of our time period.

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
Frankfurt	46	38	41	46	46	50	56
Milan	25	27	25	28	30	32	35
Munich	19	19	23	25	26	30	30
Dusseldorf	15	14	16	20	23	25	28
Manchester	35	31	36	41	43	43	49
Rome	37	45	46	48	48	49	51
Mexico City	45	50	52	55	58	61	61
Oslo	28	44	45	44	45	45	45
Toronto	5	22	21	22	21	21	22
Birmingham	29	29	33	39	39	42	48
Basel	21	26	28	32	36	40	43

Table 6.2 Cities which showed the most decline in terms of relative outdegree strength

In our case, outdegree strength represents the number of citations made by the city to other cities. Therefore we can conclude from our calculation of outdegree strengths, at the end of our time period a lot of developing cities have become bigger recipients of technological knowledge compared to the beginning of our time period. Previously large recipients of technological knowledge have declined relative to other cities in our network.

6.3.2 Indegree Strength:

We then observe how the cities change with regards to their indegree strength throughout our time period. The indegree strength will tell us which cities are the most important sources of technological knowledge in our network. We ranked each city according to how they rank in terms of their average indegree strength in each of our time periods, where a rank of 1 indicates the highest indegree strength while 62 marks the lowest. We show in the table below the cities which have shown the greatest increase in rank by the end of our time period. The ranks of all cities and the exact values of their average indegree strength in each of our time periods can be found in the appendix.

We see that in the beginning of our time period, New York City, Toronto, Los Angeles, the Bay Area, Chicago and Tokyo have the highest indegree strength in our network. However, in the later periods Osaka, Seattle and Houston also occupy the spots of the five highest indegree strength at one period or another.

	Period 1	**Period 2**	**Period 3**	**Period 4**	**Period 5**	**Period 6**	**Period 7**
Seoul	55	38	19	11	13	8	9
Guangzhou		61	62	62	54	33	26
Singapore	58	53	46	33	23	23	27
Bangalore	59	62	60	59	50	37	29
Shanghai		58	57	60	53	40	30

Taipei	45	28	23	19	16	16	18
Beijing		54	56	53	51	30	31
Seattle	22	15	12	13	12	6	5
Copenhagen	47	42	38	37	37	36	33
Auckland	54	52	55	54	52	53	42
Austin	23	21	16	9	9	10	11
San Diego	19	14	11	10	7	9	7
Helsinki	48	40	36	32	31	29	37

Table 6.3 Cities which showed the most improvement in terms of relative indegree strength

Interestingly, we can see that developing cities have improved more in terms of their indegree strength as compared to their outdegree strength. As an example, we can see that Seoul is ranked 13 according to its outdegree strength but 9 according to its indegree strength. This means that these new emerging cities are better sources of knowledge than they are recipients when compared to other cities in our network.

While some cities show improvement in their relative indegree strength, we also see that some cities have considerably decrease in their relative indegree strength. The table below depicts which cities have decreased the most in their ranks in terms of indegree strength by the end of our time period.

	Period 1	**Period 2**	**Period 3**	**Period 4**	**Period 5**	**Period 6**	**Period 7**
Basel	24	26	32	41	42	52	52
Rome	32	43	45	50	55	57	57
Dusseldorf	14	13	18	23	24	31	34
Mexico City	41	56	58	57	60	62	61
Mumbai	42	59	59	61	61	61	62
Manchester	40	39	39	45	44	51	58
Milan	27	25	26	29	34	41	45
Oslo	28	44	44	44	43	43	46
Toronto	2	20	22	20	20	19	19
Birmingham	33	33	37	40	39	47	49
Lyon	36	31	33	39	40	48	51
Sao Paulo	46	55	54	56	62	59	60

Table 6.4 Cities which showed the most decline in terms of relative indegree strength

6.3.3. Eigenvector Centrality:

Lastly, we also observe how cities change with respect to their eigenvector centrality. This measure helps us determine which cites have the most influence in the network since it assigns higher weights to those cities that have more influence in the network. We ranked each city according to how they rank in terms of their average eigenvector centralities in each of our time periods, where a rank of 1 indicates the highest eigenvector centrality while 62 marks the lowest.

We see that the cities with highest eigenvector centralities change throughout the period. In our first time period, the Bay Area, New York City, Los Angeles, Chicago and Boston have the highest eigenvector centralities. In the later periods, Tokyo and Osaka exhibit increased eigenvector centralities and rank in the top five cities with the highest eigenvector centralities in some of our periods.

We show in the table below the cities which have shown the greatest increase in rank by the end of our time period. The ranks of all cities and the exact values of their average eigenvector centralities in each of our time periods can be found in the appendix.

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
Seoul	56	46	28	21	8	19	18
Singapore	57	57	50	49	38	36	30
Austin	27	26	23	23	16	11	1
Bangalore	59	62	62	59	57	49	33
Stockholm	48	25	24	28	25	25	26
Guangzhou		61	61	62	61	53	40
Taipei	43	38	26	20	14	21	22
Seattle	23	17	10	15	17	16	4
Shanghai		58	58	58	56	50	44

Table 6.5 Cities which showed the most improvement in terms of relative eigenvector centrality

While some cities show improvement in their relative eigenvector centrality, we also see that some cities have considerably decrease in their relative eigenvector centrality. The table below depicts which cities have decreased the most in their ranks in terms of eigenvector centrality by the end of our time period.

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
Birmingham	25	30	37	40	39	46	50
Basel	26	28	40	32	43	42	46
Manchester	38	39	41	41	44	47	55
Mexico City	46	55	56	57	59	62	62
Frankfurt	39	41	42	45	45	43	54
Rome	37	45	44	48	49	56	52
Vienna	34	35	35	39	40	45	48

Table 6.6 Cities which showed the most decline in terms of relative eigenvector centrality

As we anticipated our results show that some cities from emerging countries now play a more central role in our network of cities. On the other hand, we see some cities especially those from developed countries show considerable decline throughout our timer period.

The network of our cities in 2014 is displayed in the figure below. The size of the node represents the eigenvector centrality of each city in 2014.

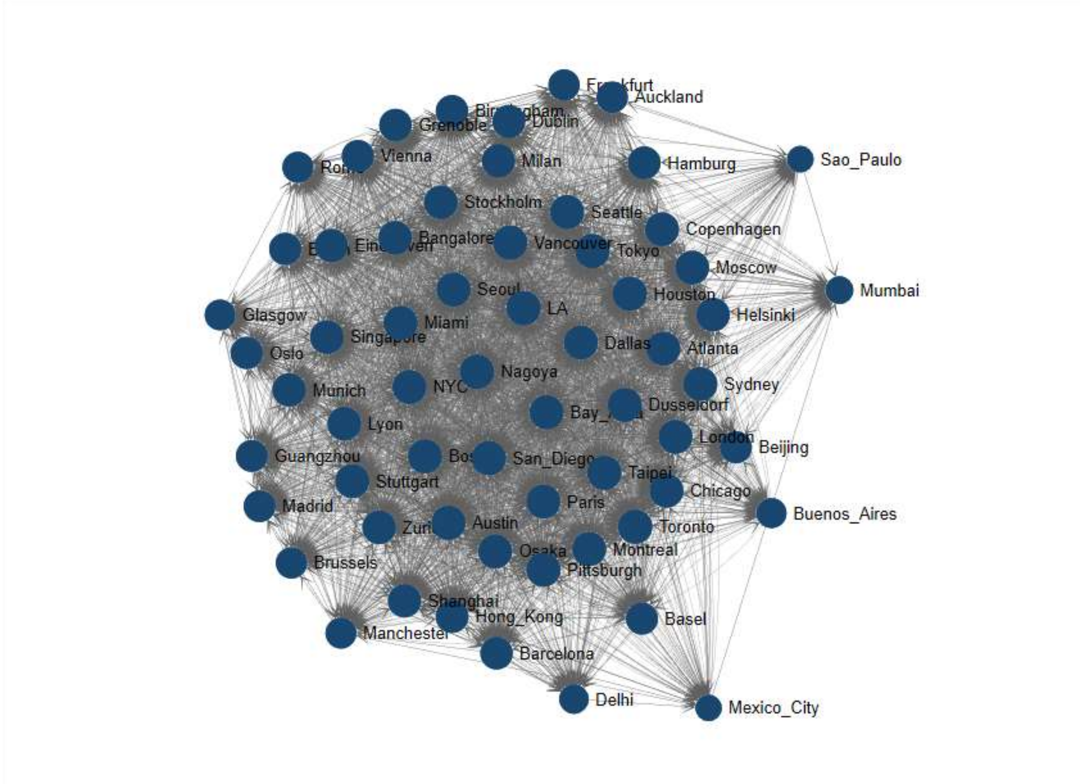

Figure 6.1 The network of our cities in 2014

We explore further by separating patents on the basis of their primary technological field into five broad classification fields: chemical, information and communication technologies (ICT), mechanical, other electrical equipment and transport. We then analyzed the network separately for different classification fields and calculated the same network statistics outdegree strength, indegree strength and eigenvector centrality for each classification field. The details of the tech56 fields that belong in each of these category were discussed in the previous study.

6.4 Data Analysis on the Network of Chemical Patents:

6.4.1 Outdegree Strength:

Just like we did with the overall network of cities, we rank each city according to how they rank in terms of their average outdegree strength in each of our time periods, where rank 1 is the city with the highest outdegree strength and 62 is the one with the lowest. In the Chemical network, we observe that those cities that ranked highest based on outdegree strength continue to rank high throughout our time period. These cities are New York City, Tokyo and the Bay Area.

We show in the table below the cities which have shown the greatest increase in rank by the end of our time period. The exact values of their average outdegree strength in each of our time periods can be found in the appendix.

	Period 1	**Period 2**	**Period 3**	**Period 4**	**Period 5**	**Period 6**	**Period 7**
Seoul	49	48	45	31	23	21	21
Taipei	55	51	48	45	35	32	35
Seattle	28	24	19	17	15	11	10
Vancouver	42	43	36	28	28	26	24
Atlanta	30	26	21	22	17	18	15
Helsinki	46	38	41	35	27	28	32
San Diego	17	14	15	10	9	7	6

Table 6.7 Cities which showed the most improvement in terms of relative outdegree strength in the chemical network

We can see that in the chemical network only Seoul and Taipei have improved considerably in their outdegree strength. The rest of the cities that show improvement are developed cities.

The table below depicts the cities that have declined the most in terms of their outdegree strength.

	Period 1	**Period 2**	**Period 3**	**Period 4**	**Period 5**	**Period 6**	**Period 7**
Manchester	20	22	24	27	37	35	40
Frankfurt	21	28	30	34	34	34	39
Mexico City	45	50	51	54	55	60	60
Birmingham	34	37	40	43	39	44	47

Milan	14	17	18	21	22	24	26
Brussels	27	34	34	38	38	36	38
Glasgow	41	44	46	48	49	52	52
Eindhoven	33	31	33	41	45	43	43

Table 6.8 Cities which showed the most decline in terms of relative outdegree strength in the chemical network

We see that mostly developed cities, with the exception of Mexico City, have declined in terms of outdegree strength in the chemical network.

6.4.2 Indegree Strength:

We then observe how which cities ranked the highest in terms of indegree strength. We see that cities such as New York City and the Bay Area are the only ones who are consistently amongst the top ranked cities for indegree strength. We ranked each city according to how they rank in terms of their average indegree strength in each of our time periods, where a rank of 1 indicates the highest indegree strength while 62 marks the lowest.

Cities such as Chicago which had the third highest indegree strength in the first time period had only the eight highest at the end of our time period. Similarly Dusseldorf which had the fifth highest indregree strength in the first two time periods had only the fourteenth highest by the end of our time period and Tokyo which had the second highest indegree strength in the first two time periods had only the seventh highest at the end of our time period.

This indicates that different knowledge sources are gaining importance in the chemical network.

We show in the table below the cities which have shown the greatest increase in rank by the end of our time period. The exact values of their average indegree strength in each of our time periods can be found in the appendix.

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
Seoul	53	46	24	21	17	13	13
Shanghai		56	59	60	59	43	26
Taipei	49	51	36	29	25	26	28
Guangzhou			61	62	62	51	41
Singapore	59	60	51	47	31	35	40
Vancouver	42	41	30	24	22	22	23
Seattle	28	22	18	15	15	12	9
Beijing		53	53	45	41	41	38
Dublin	46	43	48	48	53	55	32

Table 6.9 Cities which showed the most improvement in terms of relative indegree strength in the chemical network

We can see that cities such as Shanghai, Guangzhou and Beijing which did not show considerable improvement in terms of outdegree strength, still show considerable improvement in indegree strength. This implies that these cities have become important sources of knowledge for those patents that belong to the chemical classification, but have not become significant recipients of technological knowledge.

The table below depicts the cities that have declined the most in terms of their indegree strength.

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
Frankfurt	23	28	31	38	42	36	49
Birmingham	36	42	43	46	49	62	61
Munich	21	24	33	30	44	38	44
Rome	31	39	46	42	48	52	52
Stuttgart	30	29	32	36	35	44	50
Manchester	26	26	25	39	43	46	46
Milan	14	18	21	23	24	29	34
Basel	13	10	17	22	27	28	27

Table 6.10 Cities which showed the most decline in terms of relative indegree strength in the chemical network

We can see that there is a decline in a lot of developed cities in terms of indegree strength. This shows that their relative importance as sources of technological knowledge for chemical patents has decreased throughout our time period.

6.4.3 Eigenvector Centrality:

We ranked each city according to how they rank in terms of their average eigenvector centrality in each of our time periods, where a rank of 1 indicates the highest eigenvector centrality while 62 marks the lowest.

Eigenvector centrality is a measure of influence a node has on the network. We see a slight shift in the cities with the highest eigenvector centralities in the network of chemical patents. In the beginning of our time period, New York City, Tokyo and Chicago had the three highest eigenvector centralities. By the end of our time period, Boston, Los Angeles and Chicago have the three highest eigenvector centralities while Tokyo has the fifth highest eigenvector centrality and New York City has the sixth highest.

We show in the table below the cities which have shown the greatest increase in rank by the end of our time period. The exact values of their average eigenvector centrality in each of our time periods can be found in the appendix.

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
Seoul	53	47	31	26	20	16	18
Shanghai		58	59	60	56	51	31
Taipei	52	51	44	39	36	29	28
Seattle	28	24	14	18	16	13	8
Singapore	58	60	52	49	44	42	41
Vancouver	43	42	32	27	27	22	27
Toronto	29	19	20	17	19	17	15

Table 6.11 Cities which showed the most improvement in terms of eigenvector centrality in the chemical network

We can see that developing cities such as Seoul, Shanghai, Taipei and Singapore have gained considerably more influence in our network throughout our time period.

The table below depicts the cities that have declined the most in terms of their eigenvector centrality.

	Period 1	**Period 2**	**Period 3**	**Period 4**	**Period 5**	**Period 6**	**Period 7**
Birmingham	30	41	38	44	43	48	52
Manchester	23	28	34	38	40	39	43
Rome	36	39	43	41	46	46	51
Frankfurt	25	30	33	36	37	31	39
Stockholm	20	27	30	32	30	36	34
Buenos Aires	46	54	57	54	59	59	59
Mexico City	49	52	50	57	57	61	60

Table 6. 12 Cities which showed the most decline in terms of relative eigenvector centrality in the chemical network

We see that a lot of developed have declined considerably in terms of eigenvector centrality in the chemical network. Some developing cities such as Buenos Aires and Mexico City have also shown considerable decline.

The network of patents with chemical as their primary classification in 2014 is given in the figure below. The size of the node represents the eigenvector centrality of each city.

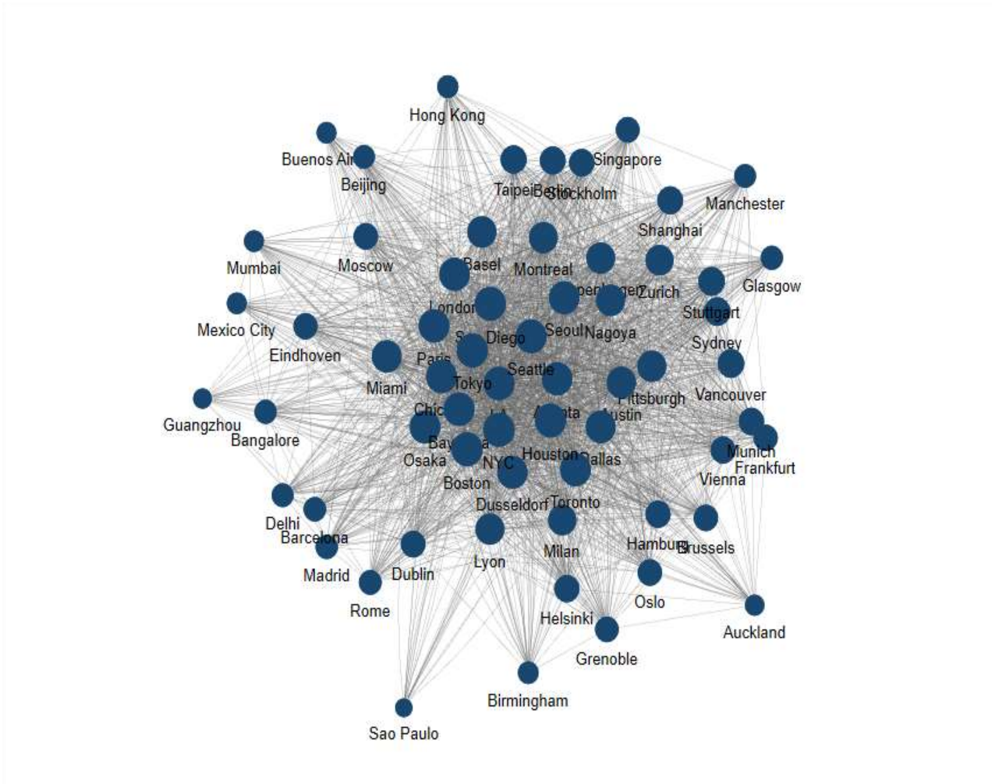

Figure 6.2 The network of patents classified as chemical in the year 2014

6.5 Data Analysis on the Network of ICT patents:

6.5.1 Outdegree Strength:

We ranked each city according to how they rank in terms of their average outdegree strength in each of our time periods, where rank 1 is the city with the highest outdegree strength and 62 is the one with the lowest.

In the ICT network, we see cities that had the highest outdegree strength, New York City, the Bay Area and Tokyo, continued to have the highest outdegree strength throughout our time period.

We show in the table below the cities which have shown the greatest increase in rank by the end of our time period. The exact values of their average outdegree strength in each of our time periods can be found in the appendix.

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
Seoul	52	42	22	14	11	12	12
Singapore		56	46	34	29	27	29
Beijing		57	55	53	50	35	32
Bangalore		58	60	50	48	41	34
Sydney	42	37	39	32	33	30	19
Helsinki	43	45	41	31	27	24	22
Taipei	41	35	28	25	22	20	21
Guangzhou				61	61	55	43

Table 6. 13 Cities which showed the most improvement in terms of relative outdegree strength in the ICT network

We see that a lot of developing cities have shown considerable improvement in terms of outdegree strength in the ICT network. This time the developing cities that show considerable improvement in outdegree strength also include cities such as Bangalore, Beijing and Guangzhou which did not show such improvement in the network of chemical patents. We also see that cities such as Guangzhou which did not have any ICT patent in the first three time period was able to catch up and move up the rankings very quickly.

The table below shows the cities which have declined the most in terms of outdegree strength in the network of ICT patents.

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
Birmingham	29	32	37	41	42	46	50
Vienna	28	33	35	42	45	49	47
Brussels	34	34	36	40	44	45	52
Frankfurt	39	44	47	52	54	54	56
Hamburg	27	29	33	36	41	42	44
Manchester	31	31	30	38	37	44	48
Milan	23	24	25	28	32	33	39
Rome	35	38	40	43	47	50	51

Table 6. 14 Cities which showed the most decline in terms of relative outdegree strength in the ICT network

We see that a lot of developed cities have shown considerable decline in terms of relative outdegree strength in the ICT network. We see cities such as Milan and Rome also show considerable decline in their relative outdegree strength in the ICT network although they didn't show a decline in the overall network of patents or in the network of chemical patents.

6.5.2 Indegree Strength:

We ranked each city according to how they rank in terms of their average indegree strength in each of our time periods for the ICT patent network, where rank 1 is the city with the highest indegree strength and 62 is the one with the lowest.

In the ICT network, we see that cities that had the highest indegree strength, New York City, the Bay Area and Tokyo, in our first time period continue to have the highest indegree strength throughout our time periods.

We show in the table below the cities which have shown the greatest increase in rank by the end of our time period. The exact values of their average indegree strength in each of our time periods can be found in the appendix.

	Period 1	**Period 2**	**Period 3**	**Period 4**	**Period 5**	**Period 6**	**Period 7**
Seoul	46	26	11	9	10	8	8
Bangalore		57	51	51	33	29	21
Guangzhou				62	57	36	29
Sydney	41	34	31	33	26	19	13
Beijing		51	55	50	41	25	27
Taipei	40	27	24	20	17	15	16
Shanghai		54	60	61	54	40	31
Singapore		47	35	31	21	23	28
Barcelona	54	56	56	53	45	35	36

Table 6.15 Cities which showed the most improvement in terms of relative indegree strength in the ICT network

We see that cities such as Bangalore and Guangzhou have increased even more in terms of indegree strength than they did in terms of outdegree strength. This means that these cities have become even more important sources of technological knowledge than recipients.

The table below shows which cities have declined the most in terms of relative indegree strength in the ICT network.

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
Milan	25	24	26	30	32	44	50
Vienna	27	32	39	43	44	50	52
Brussels	29	43	42	48	43	55	53
Manchester	35	37	40	45	48	51	55
Eindhoven	15	15	19	21	27	31	34
Glasgow	38	44	45	46	49	54	57
Zurich	22	23	28	36	36	37	41

Table 6. 16 Cities which showed the most decline in terms of relative indegree strength in the ICT network

A lot of developed cities have declined in terms of relative indegree strength throughout our time period. Hence we can infer that now different cities are becoming more vital sources of technological knowledge in the ICT network while older cities are declining in importance.

6.5.3 Eigenvector Centrality:

We ranked each city according to how they rank in terms of their average eigenvector centralities in each of our time periods for the ICT patent network, where rank 1 is the city with the highest eigenvector centrality and 62 is the one with the lowest.

When calculating eigenvector centrality, we observed that the cities with the highest influence in the beginning of our time period, Tokyo, the Bay Area and New York City continued to have the highest influence till the end of our time period.

We show in the table below the cities which have shown the greatest increase in rank by the end of our time period. The exact values of their average eigenvector centralities in each of our time periods can be found in the appendix.

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
Seoul	49	37	17	12	9	11	12
Bangalore		59	58	49	47	34	28
Guangzhou				62	60	48	33
Beijing		55	56	51	48	32	29
Singapore		53	44	33	29	30	30
Shanghai		57	60	58	57	47	36
Taipei	39	30	27	23	20	18	18

Table 6.17 Cities which showed the most improvement in terms of relative eigenvector centrality in the ICT network

As expected, we see a lot of developing cities show considerable improvement in terms of their eigenvector centralities throughout our time period. Even Guangzhou which had no patents in the first three time periods managed to considerably increase eigenvector centrality.

The table below shows the cities which have declined considerably in terms of their eigenvector centrality in the ICT network throughout our time period.

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
Birmingham	27	33	34	37	40	51	50
Manchester	32	31	37	41	45	46	53
Hamburg	29	27	35	38	43	44	47
Vienna	30	35	36	39	38	40	48
Brussels	35	41	40	44	44	50	52
Milan	24	25	26	30	35	39	40
Glasgow	41	45	47	47	46	54	56

Table 6.18 Cities which showed the most decline in terms of relative eigenvector centrality in the ICT network

The network of patents with ICT as their primary classification in 2014 is given in the figure below. The size of the node represents the eigenvector centrality of each city.

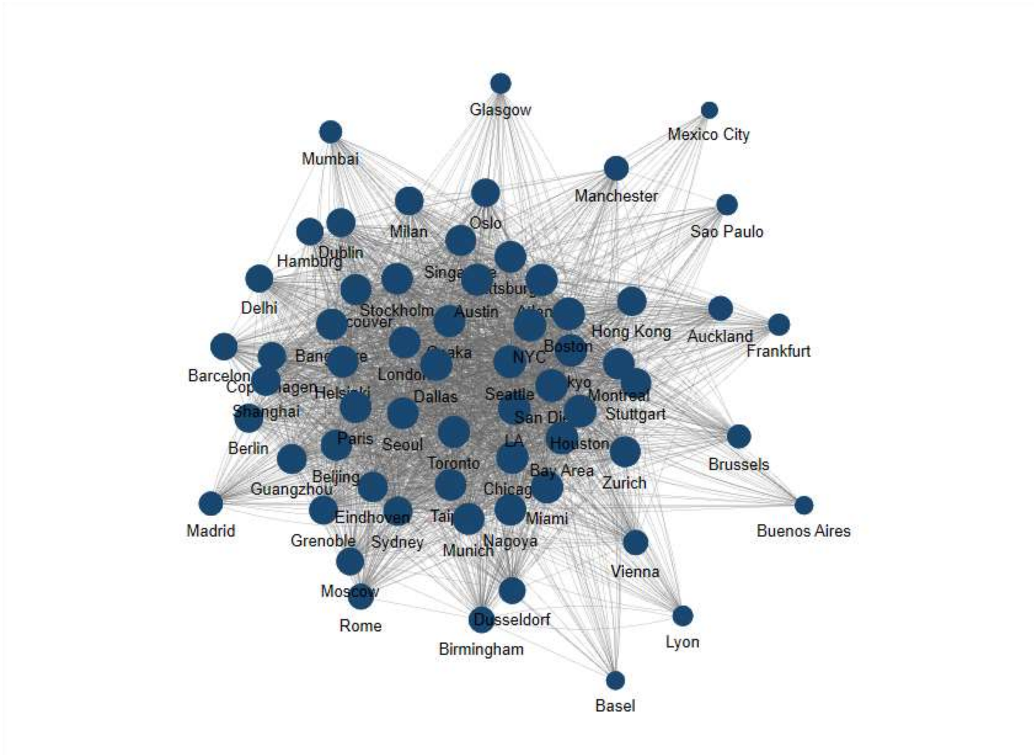

Figure 6.3 The network of patents classified as ICT in the year 2014

6.6 Data Analysis on the Network of Mechanical Patents:

6.6.1 Outdegree Strength:

We ranked each city according to how they rank in terms of their average outdegree strength in each of our time periods for the mechanical patent network, where rank 1 is the city with the highest outdegree strength and 62 is the one with the lowest.

We see that in the beginning of our time period, New York City, Tokyo and Los Angeles have the highest outdegree strength. However, by the end of our time period we see that the Bay Area has the highest outdegree strength while Los Angeles and New York City have second and third highest outdegree strengths respectively. Tokyo is still ranked high and has the fourth highest outdegree strength.

We show in the table below the cities which have shown the greatest increase in rank by the end of our time period. The exact values of their average outdegree strength in each of our time periods can be found in the appendix.

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
Seoul	53	50	51	26	20	17	18
Taipei	46	37	10	21	19	19	19
Dublin	55	55	40	52	53	43	35
Austin	31	28	30	22	21	18	17
Copenhagen	38	41	44	37	33	31	24
Singapore	56	56	50	53	47	42	43
Sydney	39	32	35	30	29	23	26
Guangzhou		61	56	60	60	57	51

Table 6.19 Cities which showed the most improvement in terms of relative outdegree strength in the mechanical network

We see that some developing cities have gradually increased in terms of relative outdegree strength in the network of mechanical patents. However, the increase is less than what we saw in the network of ICT patents. Some developed cities such as Dublin, Austin, Copenhagen and Sydney have also increased considerably in terms of outdegree strength.

The table below shows the cities which have declined considerably in terms of their outdegree strength in the mechanical network throughout our time period.

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
Birmingham	25	25	33	33	34	40	41
Manchester	30	33	47	42	43	44	45
Frankfurt	41	38	49	44	45	51	54
Mexico City	47	49	32	55	58	60	60
Milan	26	27	27	29	31	35	39
Basel	37	36	46	41	44	47	49
Vienna	33	40	34	39	42	41	44
Zurich	19	22	22	25	27	30	30

Table 6.20 Cities which showed the most decline in terms of relative outdegree strength in the mechanical network

We see a lot of developed cities have decreased in terms of relative outdegree strength in the mechanical network.

6.6.2 Indegree Strength:

We ranked each city according to how they rank in terms of their average indegree strength in each of our time periods for the mechanical patent network, where rank 1 is the city with the highest indegree strength and 62 is the one with the lowest.

In the beginning of our time period, we see that Tokyo, New York City and Chicago have the highest indegree strength. The top three cities keep on changing throughout our time period. At the end of our time period, the Bay Area, Boston and Los Angeles are the top three cities with the highest indegree strength. This shuffling indicates that the most central sources to the network of mechanical networks changed by the end of our time period.

We show in the table below the cities which have shown the greatest increase in rank by the end of our time period. The exact values of their average indegree strength in each of our time periods can be found in the appendix.

	Period 1	**Period 2**	**Period 3**	**Period 4**	**Period 5**	**Period 6**	**Period 7**
Seoul	50	42	28	16	14	10	15
Guangzhou		59	55	59	55	35	28
Dublin	54	53	37	45	47	42	26
Shanghai		58	60	58	53	38	32
Singapore	56	52	50	42	26	31	31
Taipei	41	26	8	20	16	18	19
Copenhagen	42	41	43	32	34	30	25
Austin	28	28	22	18	19	19	12
Sydney	30	33	32	24	22	13	14

Table 6.21 Cities which showed the most improvement in terms of relative indegree strength in the mechanical network

We see that a mix of developing and developed cities have increase in terms of their indegree strength. Developing cities are ranked higher when it comes to indegree strength compared to outdegree strength. This means that these cities are more vital sources of technological knowledge for mechanical patents but are still behind when it comes to the extent of trans-local connections their mechanical patents have.

The table below shows the cities which have declined considerably in terms of their indegree strength in the mechanical network throughout our time period.

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
Dusseldorf	13	15	20	22	24	29	33
Manchester	38	40	48	47	44	50	56
Vienna	32	35	40	43	46	51	50
Birmingham	27	29	39	34	38	40	44
Hamburg	29	32	41	38	39	41	46
Rome	44	46	27	53	57	59	60
Stockholm	23	25	23	25	28	33	39

Table 6.22 Cities which showed the most decline in terms of relative indegree strength in the mechanical network

As expected, we see a lot of developed cities show a decline in their indegree strength throughout our time period.

6.6.3 Eigenvector Centrality:

We ranked each city according to how they rank in terms of their average eigenvector centrality in each of our time periods for the mechanical patent network, where rank 1 is the city with the highest eigenvector centrality and 62 is the one with the lowest.

The cities with the highest eigenvector centrality in the beginning of our time period were New York City, Chicago and Tokyo. We see that throughout our time period the cities with three highest eigenvector centrality keeps changing. At the end of our time period, the cities with the highest eigenvector centrality are Seattle, Houston and Boston. Even though Chicago had the second highest eigenvector centrality in the beginning of our time period, it onlyhad the sixth highest by the end.

We show in the table below the cities which have shown the greatest increase in rank by the end of our time period. The exact values of their average eigenvector centrality in each of our time periods can be found in the appendix.

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
Seoul	51	49	39	22	20	19	9
Singapore	56	56	54	52	43	37	32
Austin	37	34	24	24	23	23	14
Taipei	42	36	17	21	19	17	21
Guangzhou		60	59	59	59	48	42
Seattle	16	17	15	13	12	9	1
Shanghai		58	57	58	57	49	43

Table 6.23 Cities which showed the most improvement in terms of relative eigenvector centrality in the mechanical network

We see a mix of developed and developing cities improving in terms of their relative eigenvector centrality.

The table below shows the cities which showed the most decline in terms of their relative eigenvector centrality throughout our time period.

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
Basel	36	40	40	43	45	47	51
Manchester	34	37	41	44	41	43	49
Brussels	43	45	48	47	52	53	57
Moscow	30	41	51	40	42	41	44
Birmingham	26	25	31	38	38	40	39
Frankfurt	40	42	42	46	46	54	53
Mexico City	48	52	53	56	58	60	60
Rome	45	44	37	49	50	57	56

Table 6.24 Cities which showed the most decline in terms of relative eigenvector centrality in the mechanical network

The network of patents with Mechanical as their primary classification is shown in the figure below. The size of the node refers to the city's eigenvector centrality.

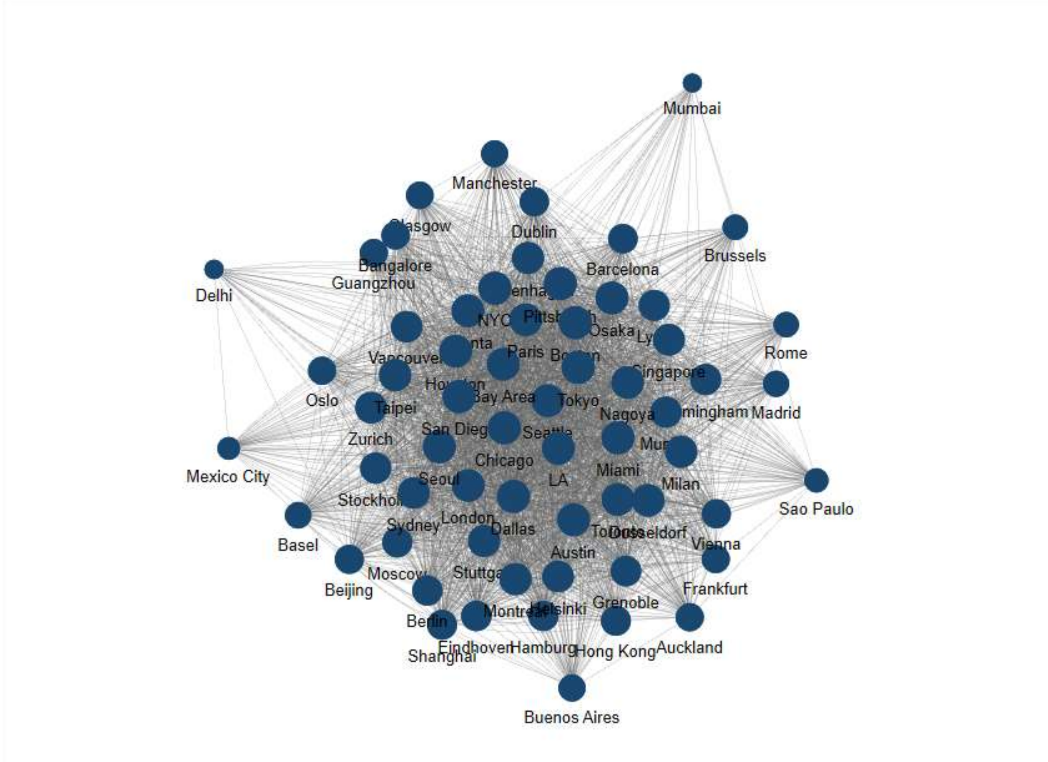

Figure 6.4 The network of patents classified as mechanical in the year 2014

6.7 Data Analysis on the Network of Other Electrical Equipment Patents:

6.7.1 Outdegree Strength:

We ranked each city according to how they rank in terms of their average outdegree strength in each of our time periods for the other electrical equipment patent network, where rank 1 is the city with the highest outdegree strength and 62 is the one with the lowest.

We see that Tokyo has the highest outdegree strength throughout our time period. However, the cities with the second and third highest outdegree strength keep changing throughout our time period. At period two, even an emerging city like Taipei had the third highest outdegree strength. Other cities that in one period or another have been amongst the highest three include the Bay Area, New York City, Osaka and Boston.

We show in the table below, the cities which have shown the greatest increase in rank by the end of our time period. The exact values of their average outdegree strength in each of our time periods can be found in the appendix.

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
Seoul	54	47	25	11	11	7	8
Taipei	46	3	22	12	12	9	7
Guangzhou				62	51	32	26
Singapore	57	34	43	29	24	22	21
Shanghai		57	57	57	56	43	36
Beijing		58	58	51	53	48	43
Hong Kong	42	33	32	34	29	30	29
Bangalore			60	58	57	55	48

Table 6.25 Cities which showed the most improvement in terms of relative outdegree strength in the other electrical equipment network

In terms of outdegree strength, we see that developing cities have increased considerably in their rank throughout our time period.

The table below contains cities which have shown the most decline in terms of their outdegree strength though out our time period.

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
Brussels	32	41	47	47	48	47	53
Zurich	19	23	27	27	34	33	38
Frankfurt	37	43	44	45	47	56	55
Basel	39	42	46	44	45	54	56
Birmingham	26	32	35	35	38	40	41
Paris	10	12	10	15	15	18	24
Vienna	36	31	36	40	44	46	50
Manchester	34	38	39	38	40	42	46

Table 6.26 Cities which showed the most decline in terms of relative outdegree strength in the other electrical equipment network

As expected, we see that developed cities have declined considerably in terms of their outdegree strength.

6.7.2 Indegree Strength:

We ranked each city according to how they rank in terms of their average indegree strength in each of our time periods for the other electrical equipment patent network, where rank 1 is the city with the highest indegree strength and 62 is the one with the lowest.

During the beginning of our time period, Tokyo had the highest indegree strength. However, at the end of our time period, the Bay Area had the highest indegree strength and Tokyo moved to the second place. Other cities that were amongst the three highest cities with the most indegree strength at some period or another include Boston, Taipei, Osaka and New York City.

We show in the table below, the cities which have shown the greatest increase in rank by the end of our time period. The exact values of their average indegree strength in each of our time periods can be found in the appendix.

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
Guangzhou				62	37	17	15
Seoul	48	28	11	6	7	6	6
Taipei	43	2	13	12	8	7	7
Shanghai		52	53	50	39	28	20
Singapore	49	34	33	21	14	14	17
Bangalore			58	59	40	40	30
Beijing		54	43	55	56	39	31
Vancouver	41	39	28	31	27	24	26

Table 6.27 Cities which showed the most improvement in terms of relative indegree strength in the other electrical equipment network

As we can see, developing cities have shown considerable improvement in terms of their indegree strength. Guangzhou has no patents classified as other electrical equipment but ends our time period with the 15^{th} highest indegree strength. Other developing cities have also shown considerable improvement in indegree strength.

The table below shows the cities that have declined considerably in terms of indegree strength throughout our time period.

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
London	13	16	23	24	22	30	35
Rome	40	41	44	53	57	58	61
Manchester	34	45	45	37	43	54	53
Moscow	32	48	36	36	38	43	51
Paris	10	12	15	19	24	32	29
Lyon	31	38	35	38	50	53	49
Pittsburgh	9	11	17	17	21	29	27
Basel	42	49	54	56	51	61	57
Birmingham	30	37	40	40	47	49	45
Frankfurt	39	42	42	51	46	56	54
Stockholm	27	22	31	30	32	36	42

Table 6.28 Cities whish showed the most decline in terms of relative indegree strength in the other electrical equipment network

We see that quite a few developed cities have shown considerable decrease in their relative indegree strength during our time period. Since indegree strength refers to the number of citations to a city, this implies that these cities are no longer as vital a source of technological knowledge for other electrical equipment patents as they were in the beginning of our time period.

6.7.3 Eigenvector Centrality:

We ranked each city according to how they rank in terms of their average eigenvector centrality in each of our time periods for the other electrical equipment patent network, where rank 1 is the city with the highest eigenvector centrality and 62 is the one with the lowest.

Throughout our time period, either New York City or Tokyo had the highest eigenvector centrality. Other cities which are amongst the top 3 cities at some period or the other include Boston, the Bay Area, Los Angeles and Osaka.

We show in the table below, the cities which have shown the greatest increase in rank by the end of our time period. The exact values of their average eigenvector centrality in each of our time periods can be found in the appendix.

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
Seoul	49	38	23	12	9	6	8
Guangzhou				62	45	34	25
Taipei	46	10	19	17	12	13	9
Singapore	50	32	36	34	33	24	22
Shanghai		56	55	55	49	38	30
Bangalore			59	59	51	43	37
Beijing		55	51	52	56	47	40
Hong Kong	42	35	32	33	30	28	27
Austin	27	22	17	15	14	11	13

Table 6.29 Cities which showed the most improvement in terms of relative eigenvector centrality in the other electrical equipment network

We see that developing cities have increased considerably in terms of their eigenvector centrality. This means that developing cities are gradually becoming more central to the network than older developed cities.

Cities that showed the greatest decline in terms of eigenvector centrality are given in the table below.

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
Brussels	34	46	49	50	48	55	54
Manchester	33	41	38	37	41	50	52
Basel	39	47	47	53	52	59	57
Zurich	17	24	27	30	34	35	35
Birmingham	25	34	35	36	40	40	41
London	12	13	15	22	19	22	28
Stockholm	22	19	26	26	27	32	38
Moscow	31	39	42	41	39	46	46
Rome	43	45	45	49	50	57	58

Table 6.30 Cities which showed the most decline in terms of relative eigenvector centrality in the other electrical equipment network

We can see that developed cities have decreased in terms of eigenvector centrality in the network of other electrical equipment patents.

The network of patents with other electrical equipment as their primary classification is shown in the figure below. The size of the node refers to the city's eigenvector centrality.

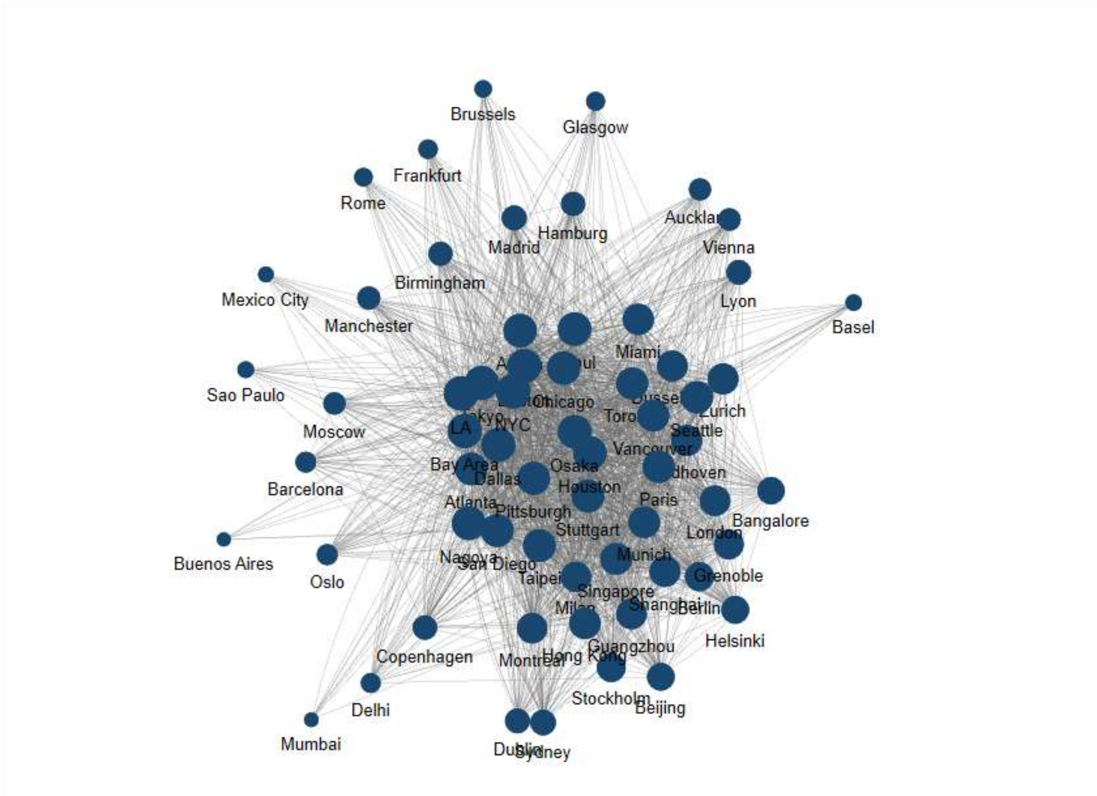

Figure 6.5 The network of patents classified as other electrical equipment in the year 2014

6.8 Data Analysis on the Network of transport patents:

6.8.1 Outdegree Strength:

We ranked each city according to how they rank in terms of their average outdegree strength in each of our time periods for the transport patent network, where rank 1 is the city with the highest outdegree strength and 62 is the one with the lowest.

We observe that in the beginning of our time period, Nagoya, Tokyo and Stuttgart have the three highest outdegree strength. However, even though Nagoya and Tokyo maintain high rankings throughout our time period, Stuttgart decreases in rank substantially. Other cities that were ranked in the top three at one period or another include Los Angeles and New York City.

We show in the table below, the cities which have shown the greatest increase in rank by the end of our time period. The exact values of their average outdegree strength in each of our time periods can be found in the appendix.

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
Seoul	56	49	42	27	24	20	20
Taipei	40	35	25	22	17	17	15
Grenoble	48	39	34	28	29	30	35
Singapore	57	54	45	56	56	46	45
Frankfurt	53	40	30	42	37	44	42
Atlanta	26	24	24	16	18	16	17
Austin	30	38	33	32	28	28	21
Miami	22	16	17	15	15	13	13
Sydney	45	32	39	35	34	32	36

Table 6.31 Cities which showed the most improvement in terms of relative outdegree strength in the transport network

We see that with that with the exception of Seoul, Taipei and Singapore the rest of the cities that have risen in rank throughout our time period include developed cities. In the transport network, we see that cities from emerging countries have not risen in rank as much as in the other networks.

In the table below, we show the cities that have shown the most decline in terms of relative outdegree strength throughout our time period.

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
Mexico City	39	52	54	55	57	53	60
Manchester	34	37	44	38	46	48	52

Vienna	17	17	18	31	32	35	32
Birmingham	14	15	22	23	23	27	28
Brussels	36	45	47	52	43	51	49
Barcelona	31	31	41	37	36	40	43
Lyon	25	25	26	34	35	37	37
Paris	7	9	11	12	14	15	19
London	11	12	14	19	21	22	22

Table 6.32 Cities which showed the most decline in terms of relative outdegree strength in the transport network

6.8.2 *Indegree Strength:*

We ranked each city according to how they rank in terms of their average indegree strength in each of our time periods for the transport patent network, where rank 1 is the city with the highest indegree strength and 62 is the one with the lowest.

Just as the with the indegree strength, Nagoya, Tokyo and Stuttgart have the three highest indegree strength. However, even though Nagoya and Tokyo maintain high rankings throughout our time period, Stuttgart decreases in rank substantially. Other cities that were ranked in the top three at one period or another include Osaka, Los Angeles and Boston.

We show in the table below, the cities which have shown the greatest increase in rank by the end of our time period. The exact values of their average indegree strength in each of our time periods can be found in the appendix.

	Period 1	**Period 2**	**Period 3**	**Period 4**	**Period 5**	**Period 6**	**Period 7**
Seoul	48	36	27	18	18	16	9
Madrid	53	44	50	34	49	35	31
Guangzhou			58	60	40	36	38
Hong Kong	46	55	43	40	36	32	29
Bangalore						47	32
Berlin	49	47	48	36	32	29	34
Taipei	38	29	22	22	17	19	23
Sydney	42	34	36	32	28	24	28

Table 6.33 Cities which showed the most improvement in terms of relative indegree strength in the transport network

Even though we did not see a lot of developing cities improving in terms of outdegree strength, we see that is not the case with indegree strength. Cities like Guangzhou and Bangalore also show considerable improvement in terms of indegree strength. This means that even though patents classified as transport within these cities may not use trans-local links as much as other cities, they still are becoming important sources of technological knowledge in this network.

The table below shows the cities which have declined the most in terms of relative indegree strength in the transport network.

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
Helsinki	32	41	41	48	39	44	61
Vienna	15	16	21	35	35	34	42
Birmingham	20	21	23	27	27	30	43
Rome	37	39	35	54	50	56	58
Barcelona	34	32	45	46	58	45	54
Lyon	25	30	31	39	43	41	44
Manchester	35	45	54	49	41	48	53
Moscow	41	56	46	33	33	55	56
London	12	14	20	21	20	23	26

Table 6.34 Cities which showed the most decline in terms of relative indegree strength in the transport network

As expected, we see a lot of previously developed cities decline in terms of relative indegree strength.

6.8.3 *Eigenvector Centrality:*

We ranked each city according to how they rank in terms of their average eigenvector centrality in each of our time periods for the transport patent network, where rank 1 is the city with the highest eigenvector centrality and 62 is the one with the lowest.

We see that almost throughout our time period, Tokyo has the highest eigenvector centrality. However, at the very end of our time period, Los Angles has the highest eigenvector centrality. Other cities that were amongst the top three at one period or the other include New York City and Boston.

We show in the table below, the cities which have shown the greatest increase in rank by the end of our time period. The exact values of their average eigenvector centralities in each of our time periods can be found in the appendix.

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
Seoul	51	40	33	23	23	16	13
Bangalore						62	37
Taipei	32	30	21	21	19	19	15
Guangzhou			57	61	54	42	41
Beijing		57		56	55	53	44
Hong Kong	44	51	46	37	39	33	32
Grenoble	46	33	34	30	33	32	36

Table 6.35 Cities which showed the most improvement in terms of relative eigenvector centrality in the transport network

Surprisingly, we see that developing cities have risen substantially in terms of eigenvector centrality in the transport network. This is despite the fact that Beijing, Guangzhou and Bangalore did not rise considerably in terms of their outdegree strength.

In the table below, we display cities that show considerable decline in terms of eigenvector centrality throughout our time period.

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
Mexico City	38	48	56	57	57	58	60
Barcelona	36	38	41	38	47	39	52
Birmingham	16	22	22	24	26	27	31
Rome	39	44	38	44	48	54	54
London	11	12	16	20	16	22	20
Lyon	25	29	31	34	35	36	34

Manchester	40	35	49	40	41	49	49
Pittsburgh	12	18	17	19	20	21	21
Vienna	29	26	32	35	36	41	38

Table 6.36 Cities which showed the most decline in terms of relative eigenvector centrality in the transport network

As expected, we see a lot of developed cities declining considerably in terms of relative eigenvector centrality throughout our time period.

A snapshot of what the network looked like in 2014 is shown below. The size of the node represents the eigenvector centrality of the city.

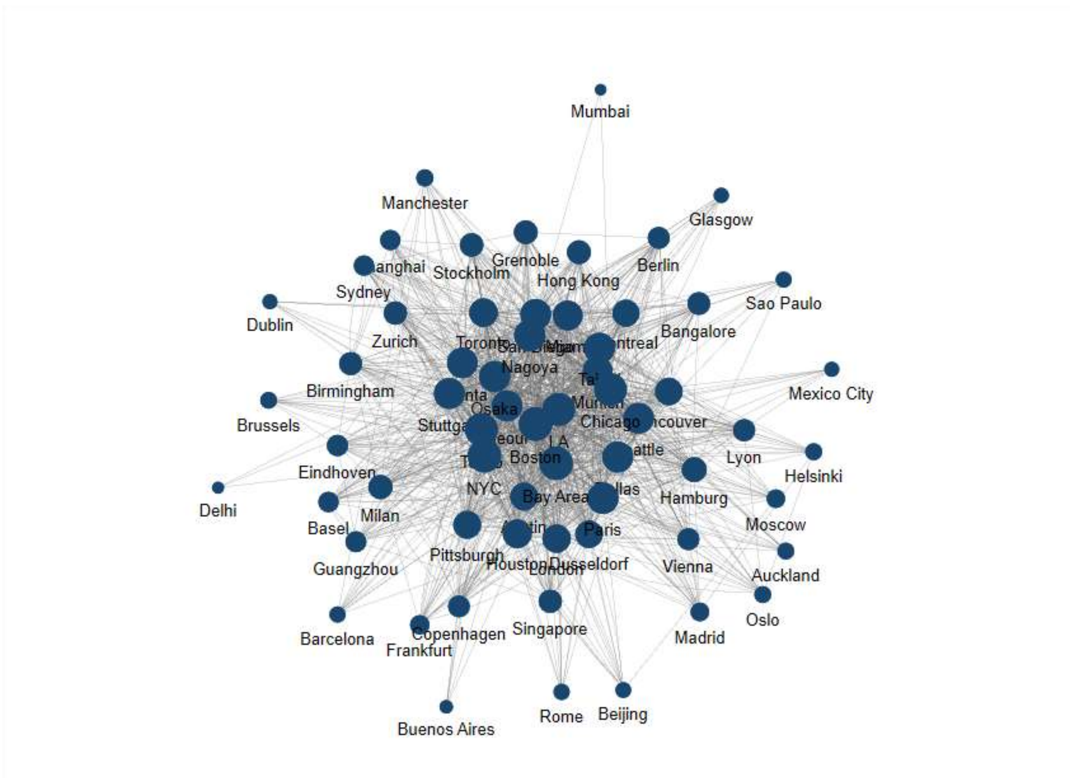

Figure 6.6 The network of patents classified as mechanical in the year 2014

We can see from the figure above that the network of patents classified as transport is not as dense as the other networks displayed before.

6.9 Some Conclusions:

In all of our networks, we see developing cities showing considerable improvements in their rankings in terms of outdegree strength, indegree strength and eigenvector centrality. However, there are some developing cities which show tremendous improvement in all of the networks. These cities are Seoul and Taipei. Singapore and Hong Kong also show improvement in all the networks but to a lesser extent. Developing cities such as Shanghai, Beijing, Guangzhou and Bangalore also show considerable improvement but to a lesser degree than Hong Kong and Singapore.

When we look at individual networks, we see cities such as Guangzhou, Beijing and Bangalore have improved considerably in all networks. However, at the end of the time period, all three of these cities show the most improvement in their network of ICT patents. In addition, Bangalore and Guangzhou also shows considerable improvement in the other electrical equipment.

A reason why we might see more improvement in the centrality of developing cities compared to developed cities, is the centrality argument presented by Awate and Mudambi (2018). They show that older established locations remain focused more on older existing technologies while newer emerging locations are able to develop new technologies quicker which are more central to the network.

We see that there is little mobility in the cities that are amongst the top influences in all networks. Cities that were the most central to our networks, remain more or less central throughout our time period. When divided by classification, we see that these cities are central to all networks. There are some exceptions to this. An example of this is Stuttgart, which was central only in the transport network and gradually declined throughout our time period.

We also see that there are cities who consistently rank low in all of our networks. These include Mexico City, Buenos Aires, Moscow and Sao Paulo.

We also observe that there is more change in the cities in terms of indegree strengths when compared to outdegree strengths. This indicates that emerging cities are gradually becoming more important sources of knowledge, but they have not started receiving technological knowledge at the same rate.

6.10 US Cites:

To further understand our network, we separated US cities from all others. We kept any point in the network where either the source or the recipient was a US city. We then calculated the degree strength for each city in our network. This would help us understand which cities are increasingly being cited by US cites and which cities are citing US cities.

6.10.1 Outdegree Strength:

The outdegree strength in this case will show us which cities are citing US cities the most. We ranked the cities in terms of their outdegree strength after an interval of five years throughout our time period.

We found that in the beginning of our time period, in 1981, most of the non- local linkages to the US cities included citations from Tokyo, Osaka, Dusseldorf and London. In 1990, the picture was more or less the same except Paris and Toronto showed a greater increase in outdegree strength than before. However, we see a change in 1995, when Seoul, a developing city, increased in outdegree strength more than the other European cites in our network. We further see in 2000 that Taipei also has more outdegree strength than other European cities in our network. In 2010, we see that Sydney is also one of the top five non US cites in terms of outdegree strength. By the end of our time period, 2014, many developing cities become significant in our network. These cities include

Bangalore, Beijing, Guangzhou, Seoul, Shanghai, Singapore and Taipei. In addition, developed cities like Vancouver, Sydney and Dublin have become increasingly important in the network.

The cities which showed the most increase in outdegree strength by the end of our time period are shown below:

	1981	1985	1990	1995	2000	2005	2010	2014
Bangalore			47	44	48	26	19	11
Seoul	35	38	14	5	3	2	2	2
Guangzhou				46	49	35	18	15
Shanghai	44		41	45	47	32	22	14
Dublin	45	41	33	40	27	25	29	18
Taipei	34	24	11	8	4	4	6	7
Singapore	39	43	39	32	16	9	12	13
Sydney	26	21	21	16	10	10	5	3
Beijing			40	35	42	29	14	19
Vancouver	29	25	15	12	11	11	8	9

Table 6.37 Cities in the US network which showed the most improvement in terms of relative outdegree strength

The cities which showed the most decline in outdegree strength by the end of our time period are shown below:

	1981	1985	1990	1995	2000	2005	2010	2014
Basel	11	15	18	31	35	40	36	36
Lyon	18	16	20	24	28	33	40	42
Birmingham	16	27	23	21	29	41	34	39
Dusseldorf	4	6	7	10	15	19	27	25
Milan	9	14	10	18	20	24	31	27
Berlin	17	19	24	23	23	23	24	34
Hamburg	21	23	22	25	31	37	30	38
Vienna	23	29	29	28	34	36	38	40

Table 6.38 Cities in the US network which showed the most decline in terms of relative outdegree strength

As we can see, European cities are gradually declining as important recipients of knowledge from the US cities.

6.10.2 Indegree Strength:

In this case, indegree strength will refer to the number of citations by US cities to other cities. Therefore, it will help us understand which cities are being increasingly cited by the US. We ranked the cities in terms of their indegree strength after an interval of five years throughout our time period.

In the beginning of our time period, in 1981, we see that Japanese cities and European cities, including Tokyo, Osaka, London and Dusseldorf were amongst those with the highest indegree strength. In 1985, Paris rose quite a bit in ranks and became the city with the second highest indegree strength. We see some change in the year 2000, when Seoul and Taipei rise substantially in ranks. This trend continues till the end of our time period and Seoul has the third highest indegree strength by 2014.

Although, developing cities such as Bangalore and Beijing are substantially increasing in rank, but their ranks at the end of the time period are not as high as they were in the case of outdegree strength.

	1981	1985	1990	1995	2000	2005	2010	2014
Seoul	39	39	33	18	7	3	3	15
Taipei	37	37	18	11	8	8	7	20
Singapore	45	44	42	38	29	21	19	32
Beijing			45	44	43	41	32	37
Bangalore			47	48	45	43	37	42
Helsinki	28	31	30	28	22	16	13	23
Dublin	42	34	44	39	39	34	29	39

Table 6.39 Cities in the US network which showed the most improvement in terms of relative indegree strength

Cities which show the most decline in their relative indegree strength in the US network are displayed in the table below.

	1981	1985	1990	1995	2000	2005	2010	2014
Birmingham	18	17	19	25	28	27	34	50

Basel	14	14	15	17	19	28	28	45
Manchester	16	18	22	29	26	30	31	47
Mexico City	30	36	36	43	44	47	48	61
Brussels	25	23	27	34	35	31	35	51
Glasgow	31	32	32	41	37	38	40	57
Milan	10	12	14	15	16	19	22	35
Frankfurt	34	27	29	33	36	36	43	58
Dusseldorf	5	5	6	6	9	12	14	28
Eindhoven	8	9	12	10	13	15	16	31

Table 6.40 Cities in the US network which showed the most decline in terms of relative indegree strength

As we can see, European cities are no longer as important sources of technological knowledge as they were in the beginning of our time period for the US cities.

We then divided the patents from the US cities network into categories based on their primary field of classification. These categories are: chemical, transport, ICT, mechanical and transport. We then observed network statistics for each of these categories in the year 2014.

6.10.3 Outdegree Strength by Classification:

When we look at the outdegree strength, we can understand to which extent each city is receiving knowledge from US cities.

We see that in those patents that belong to the chemical classification, Seoul has the second highest outdegree strength while Shanghai has the twelfth highest. Otherwise the cities with the highest outdegree strengths are mainly developed cities from Japan and Europe.

In the case of ICT patents, Seoul again has the second highest outdegree strength. However, we see many more developing cities amongst the top spots in this case. Bangalore has the fifth highest outdegree strength, Taipei has the eighth highest outdegree strength and Beijing has the thirteenth highest.

When we look at those patents in the US network from the mechanical network we see only a few developing cities amongst the cities with the highest outdegree strength. Seoul has the eighth highest while Taipei has tenth highest. Interestingly Sydney has the second highest outdegree strength, while Tokyo had the highest.

In the patents from the network of US cities that belong to the category of other electrical equipment, many developing cities are amongst those with the highest outdegree strength. Taipei has the second highest outdegree strength, while Seoul has the third highest. We see that Guangzhou has the seventh highest, Shanghai has the ninth highest, Singapore has the tenth highest and Hong Kong has the eleventh highest outdegree strength.

When we look at those patents that are primarily classified as Transport, we see that from the developing cities Seoul has a high outdegree strength which is the fourth highest in the network. Apart from Seoul, Canadian cities, Japanese cities and European cities are amongst those with the highest outdegree strength.

The cities and their ranking in terms of their outdegree strength in the network of US cities for every category is displayed in the table below.

	Chemical	ICT	Mechanical	Other Electrical Equipment	Transport
Auckland	39	19	28	36	42
Bangalore	40	5	39	18	20
Barcelona	46	29	42	32	39
Basel	10	49	31	47	18
Beijing	28	13	32	15	30
Berlin	26	32	30	28	32
Birmingham	49	33	33	33	35
Brussels	27	39	47	38	31
Buenos Aires	41	47	44	48	43

Copenhagen	9	31	12	30	26
Delhi	37	30	49	37	45
Dublin	16	20	13	25	44
Dusseldorf	6	37	22	24	10
Eindhoven	20	24	17	8	21
Frankfurt	44	43	16	44	38
Glasgow	32	45	21	39	19
Grenoble	38	27	27	12	27
Guangzhou	31	15	24	7	33
Hamburg	29	34	37	35	6
Helsinki	33	14	35	23	46
Hong Kong	30	22	25	11	16
London	5	6	4	21	14
Lyon	21	46	36	40	29
Madrid	43	40	43	26	17
Manchester	35	42	41	34	36
Mexico City	47	44	46	42	40
Milan	25	48	19	19	23
Montreal	7	7	3	22	9
Moscow	17	25	29	46	47
Mumbai	42	38	48	49	48
Munich	36	10	18	16	13
Nagoya	24	21	15	6	7
Osaka	3	11	7	4	8
Oslo	23	28	34	29	34
Paris	4	9	9	17	5
Rome	18	35	45	45	49
Sao Paulo	48	36	38	43	41
Seoul	2	2	8	3	4
Shanghai	12	17	20	9	28
Singapore	34	16	14	10	24
Stockholm	22	18	26	27	15
Stuttgart	45	23	11	14	11
Sydney	13	3	2	31	25
Taipei	19	8	10	2	12
Tokyo	1	1	1	1	3

Toronto	8	4	6	13	1
Vancouver	11	12	5	5	2
Vienna	15	41	40	41	37
Zurich	14	26	23	20	22

Table 6.41 The rankings of cities in terms of outdegree strength by classification in the US network

6.10.4 Indegree Strength:

When we look at indegree strength, we can know to which extent each city is being used as a source of knowledge by US cities.

In the network of patents that belong to the chemical category, we see that from the developing cities, only Seoul is ranked highly in terms of indegree strength. Otherwise cities from Japan, Canada and Europe are amongst those with the highest indegree strength.

In the case of those patents that are classified as ICT, we see that although a lot of developing cities were receiving knowledge from the US, they are not amongst the top sources of knowledge for the US cities. The only two developing cities that are ranked highly in terms of indegree strength are Seoul, which has the second highest indegree strength and Taipei which has the ninth highest indegree strength.

When we look at those patents classified as mechanical, we see that the only developing cities amongst the ones with the highest indegree strength are Taipei and Seoul. Additionally even though Sydney had the second highest outdegree strength, it only has the eleventh highest outdegree strength. Tokyo has both the highest indegree and outdegree strength.

In the case of those patents classified as other electrical equipment, we see that Seoul, Taipei and Singapore have high indegree strengths. Even though Guangzhou and Beijing were ranked high with regards to their outdegree strength, we see that they do not rank so highly with regards to indegree strength. Cities with high indegree strength include those cities from Canada, Europe and Japan.

When we look at those patents that are primarily classified as transport, we see that cities that rank the highest in indegree strength are European cities, Japanese cities and Canadian cities. The only exception is Seoul which has the eleventh highest indegree strength.

The cities and their ranking in terms of their indegree strength in the network of US cities for every category is displayed in the table below.

	Chemical	ICT	Mechanical	Other Electrical Equipment	Transport
Auckland	42	38	37	27	29
Bangalore	46	20	45	29	39
Barcelona	40	40	40	39	42
Basel	12	46	36	41	28
Beijing	33	18	43	31	48
Berlin	15	28	23	24	21
Birmingham	37	42	29	28	17
Brussels	26	39	35	40	26
Buenos Aires	38	45	27	47	43
Copenhagen	9	23	10	26	34
Delhi	47	33	48	45	45
Dublin	34	25	18	37	27
Dusseldorf	5	26	14	25	12
Eindhoven	35	16	26	6	36
Frankfurt	28	43	39	42	40
Glasgow	39	41	38	43	41
Grenoble	30	19	22	15	22
Guangzhou	49	29	46	17	37
Hamburg	27	31	24	33	13
Helsinki	19	6	20	20	35
Hong Kong	43	22	30	14	18
London	3	4	4	8	8

Lyon	14	47	19	34	24
Madrid	36	36	42	30	31
Manchester	31	37	31	36	46
Mexico City	44	49	47	48	44
Milan	13	30	25	19	15
Montreal	11	11	12	16	10
Moscow	24	27	21	32	25
Mumbai	41	48	49	46	49
Munich	17	17	16	13	16
Nagoya	10	8	5	5	3
Osaka	2	3	2	2	2
Oslo	25	24	34	35	23
Paris	4	7	3	11	7
Rome	32	35	33	44	32
Sao Paulo	48	44	44	49	47
Seoul	6	2	8	3	11
Shanghai	45	32	41	22	33
Singapore	29	15	32	7	38
Stockholm	16	10	13	21	14
Stuttgart	22	12	9	10	6
Sydney	21	14	11	18	19
Taipei	20	9	6	4	4
Tokyo	1	1	1	1	1
Toronto	7	5	7	9	5
Vancouver	8	13	15	12	9
Vienna	23	34	28	38	20
Zurich	18	21	17	23	30

Table 6.42 The rankings of cities in terms of indegree strength by classification in the US network

In conclusion, we see similar patterns for the US cities as we did for the entire network of cities. The only exception is, when looking at the entire network of cities, we see that developing cities show an increase in both indegree and outdegree strength. However, in the case of the network of US cities, we see that the outdegree strength of developing cities have increase more than their indegree strength. This implies, that although these developing cities use US cities as sources of technological knowledge, the reverse is true to a lesser extent. The developing cities have not improved by the same amount as sources of knowledge.

Chapter 7: Conclusion

7.1 Overview

In this dissertation, we studied the changing geographic composition of knowledge connections at the city level and the complementarity of trans-local and local connections. We looked at 62 cities to see how the geographic structure of their knowledge sourcing has been changing both at the level of city dyads and in the overall structure of the worldwide knowledge network between cities.

Using US patent citation data for patents invented in these 62 cities worldwide, our first study, titled "Connecting Local and Global Technological Sourcing" explored the nature of the association between local, trans-local and international citations. Our results showed that in all cities there is a significant association between international and local citations, and that an increase in international citations leads to an increase in local connections. We also find that this effect is accentuated in highly innovative cities when compared to relatively lower innovative cities in our dataset.

Our second study, "Exploring the Determinants of the Extent of Knowledge Connectivity between Two Cities" looked at the dyadic relationships for all possible city pairs in our city dataset, and examined the determinants of the level of knowledge outflows and knowledge inflows between them. Our results showed that knowledge sourcing patterns between individual cities have varied with the extent of the technology gap between them and their degree of engagement with general purpose technologies. We were expecting that for cities that have high network centrality, degree of technological co-specialization will matter less, but we find that this is not the case.

Using social network analysis techniques, we constructed a unidirectional network of cities in our third study, “Connecting the Nodes: Using SNA to Determine the Evolving Network of Cities over Time”, since backward citations point in just one direction to prior knowledge sources. We observed how this network changed during our time period both in the aggregate and at the level of five selected sectors. The nodes in our network represented cities while the edges represent citations from one city to another. We calculated network statistics such as degree strength and eigenvector centrality to determine which cities have gained influence over time and which cities have become relatively less important. We find some developing cities have gained substantial influence over time especially in the network of patents in the ICT and other electrical equipment technological fields.

For all three studies, we used patent data from the US Patent Office (USPTO data) from the year 1976 – 2016 as our main data source. Patent citations are used to show knowledge sourcing, where the citing city is the recipient of the knowledge and the cited city is the source of the knowledge. The first named inventor address is used to identify the location of the patent. For each city, we used metropolitan areas in our study and not just the central city and define the boundaries of each metropolitan area using the respective governments’ own definition. Details about the data are given in Chapter 3 of our dissertation.

7.2 Contributions

We believe we made several contributions in this dissertation:

In the International Business literature, the period after the 1970s is regarded as a true period of globalization where we expect to see greater interdependence between different regions. We showed that in this dissertation, that cities are now using more trans-local technological linkages than before. We also see that a lot of developing cities are now becoming more central to the network of technological knowledge sources.

Additionally, the necessity of complementing 'global pipelines' and 'local buzz' has been emphasized in previous literature by many scholars (for example: Uzzi, 1997; Bramanti and Ratti, 1997; Maillat 1998; Scott 1998; Bresnahan et al 2001; Bathelt, 2007). Our dissertation looked at innovative cities around the world to see the extent to which they rely on external knowledge sources and the influence of these knowledge sources on the 'local buzz'. Previous literature predicts that external knowledge sources also increase 'local buzz' (Owen-Smith and Powell, 2004) and thereby stimulate innovation. In our dissertation we provide empirical evidence of this claim using patent citations. We showed that cities in which trans-local citations have greater impact on the local knowledge network are in fact more innovative.

Furthermore, we looked at each city individually in detail. We studied the changes in their specialization and how their knowledge sourcing patterns changed over the course of our time period. In this dissertation we will develop a better understanding of the knowledge sourcing patterns of cities with respect to their specialization, technological capabilities and network centrality.

Finally, using network analysis we showed how the relative importance of cities changed over time. Our dissertation showed the increasing role of developing cities in the overall network of cities and how cities shifted in rank, with respect to network centrality over time.

7.3 Limitations:

One of the limitations in our work is that we use only USPTO patents in this dissertation. While using patent citations to measure technological knowledge flow have been used frequently in the past, it is not without its limitations. Even though patent data might be the best accessible source to measure knowledge flow, using it may understate the actual innovation of a city and the extent of knowledge transfer between cities.

Another limitation is that we only had patent data from 1976 onwards. Hence, we did not have citation data for quite a few years in the beginning of our time period. Although, we are confident that our trends would not have been effected much, it would have been better if we could have citation data for all patents in our dataset.

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Appendices

Appendix A: Study 1 Complete Regression Results

Source	SS	Df	MS
Model	913037.445	35	26086.7842
Residual	38908.6447	1,153	33.7455721
Total	951946.09	1,188	801.301423

Number of observations	1,189
F(35, 1153)	773.04
Prob > F	0
R-squared	0.9591
Adj R-squared	0.9579
Root MSE	5.8091

Share of Local Citations	Coefficient	Std. Err.	T	P>t	[95% Conf. Interval]	
Share of International Citations	1.4523	.0635252	22.86	0.000	1.327662	1.576938
Share of ICT International Citations	-1.714152	.153194	-11.19	0.000	-2.014722	-1.413582
Share of International Citations * Share of ICT Citations	.014855	.0004087	36.35	0.000	.014053	.0156569
City						
Austin	-1.553018	1.354018	-1.15	0.252	-4.209632	1.103597
San Diego	-3.629109	1.371169	-2.65	0.008	-6.319375	-.9388422
Pittsburgh	-2.520338	1.376312	-1.83	0.067	-5.220694	.1800176
NYC	2.239438	1.446315	1.55	0.122	-.5982669	5.077143
LA	.9960849	1.391244	0.72	0.474	-1.733569	3.725739
Boston	-6.513171	1.478834	-4.40	0.000	-9.414677	-3.611665
Chicago	-3.423472	1.403015	-2.44	0.015	-6.17622	-.6707238
SF (bay area)	11.93471	1.456484	8.19	0.000	9.077054	14.79237
Miami	-3.243976	1.369591	-2.37	0.018	-5.931146	-.5568051
Atlanta	-3.548404	1.369068	-2.59	0.010	-6.234547	-.862261
Houston	2.092523	1.414805	1.48	0.139	-.6833581	4.868404
Dallas	-2.944296	1.360858	-2.16	0.031	-5.614332	-.2742599
London	-6.496712	1.367496	-4.75	0.000	-9.179771	-3.813653
Paris	-6.291601	1.378204	-4.57	0.000	-8.995669	-3.587533
Tokyo	5.944818	1.490298	3.99	0.000	3.020817	8.868818
Osaka	-7.435171	1.401231	-5.31	0.000	-10.18442	-4.685924
Nagoya	-4.769985	1.399866	-3.41	0.001	-7.516555	-2.023415
Singapore	-4.193638	1.363178	-3.08	0.002	-6.868224	-1.519051
Seoul	-14.04513	1.362343	-10.31	0.000	-16.71808	-11.37218
Berlin	-2.963758	1.369394	-2.16	0.031	-5.650542	-.2769737
Frankfurt	-2.333463	1.369961	-1.70	0.089	-5.021358	.3544322
Munich	-3.649897	1.361133	-2.68	0.007	-6.320473	-.9793216
Hamburg	-2.526014	1.369606	-1.84	0.065	-5.213212	.1611847
Stuttgart	-5.50344	1.382046	-3.98	0.000	-8.215048	-2.791832

Hong Kong	-3.506257	1.370707	-2.56	0.011	-6.195616	-.8168978
Sydney	-7.437122	1.366517	-5.44	0.000	-10.11826	-4.755984
Beijing	-2.533294	1.410494	-1.80	0.073	-5.300717	.2341287
Shanghai	-3.560693	1.430376	-2.49	0.013	-6.367125	-.7542613
Guangzhou	-3.688572	1.455918	-2.53	0.011	-6.545117	-.8320265
Mumbai	-2.173915	1.3883	-1.57	0.118	-4.897792	.5499614
Delhi	-1.990016	1.406567	-1.41	0.157	-4.749734	.7697024
Bangalore	-2.330454	1.431066	-1.63	0.104	-5.138239	.4773312
_cons	1.825547	.9803071	1.86	0.063	-.0978391	3.748932

Table A.1 Regression results with international citations as the independent variable

Source	SS	Df	MS
Model	900116.835	35	25717.6239
Residual	51829.2549	1,153	44.9516521
Total	951946.09	1,188	801.301423

Number of observations	1,189
F(35, 1153)	572.12
Prob > F	0
R-squared	0.9456
Adj R-squared	0.9439
Root MSE	6.7046

Share of Local Citations	Coefficient	Std. Err.	T	P>t	[95% Conf. Interval]	
Share of Trans-local Citations	.827269	.0569273	14.53	0.000	.7155764	.9389617
Share of Trans-local ICT Connections	.0402061	.1411467	0.28	0.776	-.2367271	.3171394
Share of Trans-local Citations * Share of ICT Citations	.0049755	.0002745	18.12	0.000	.0044369	.0055142
City						
Austin	1.892671	1.571459	1.20	0.229	-1.190568	4.97591
San Diego	.8501066	1.631918	0.52	0.603	-2.351755	4.051968
Pittsburgh	4.580508	1.628466	2.81	0.005	1.385419	7.775597
NYC	5.360983	1.673449	3.20	0.001	2.077636	8.644329
LA	3.041311	1.715135	1.77	0.076	-.3238254	6.406447
Boston	-1.246958	1.746153	-0.71	0.475	-4.67295	2.179035
Chicago	2.572023	1.662461	1.55	0.122	-.6897644	5.83381
SF (bay area)	14.59104	1.694027	8.61	0.000	11.26732	17.91476
Miami	2.541927	1.616954	1.57	0.116	-.6305744	5.714428
Atlanta	1.311918	1.598252	0.82	0.412	-1.823891	4.447727
Houston	9.87211	1.694888	5.82	0.000	6.5467	13.19752
Dallas	1.439313	1.597354	0.90	0.368	-1.694734	4.573359
London	3.670205	1.614953	2.27	0.023	.5016282	6.838781
Paris	4.46898	1.620957	2.76	0.006	1.288623	7.649336
Tokyo	44.49381	1.619925	27.47	0.000	41.31548	47.67214
Osaka	4.903657	1.62265	3.02	0.003	1.719979	8.087336
Nagoya	5.721884	1.63769	3.49	0.000	2.508697	8.935071
Singapore	4.24319	1.61377	2.63	0.009	1.076935	7.409445
Seoul	2.704504	1.581782	1.71	0.088	-.39899	5.807999
Berlin	4.809741	1.618779	2.97	0.003	1.633658	7.985824
Frankfurt	4.987445	1.619286	3.08	0.002	1.810368	8.164522
Munich	4.257093	1.612493	2.64	0.008	1.093344	7.420842
Hamburg	4.934643	1.619006	3.05	0.002	1.758115	8.11117
Stuttgart	4.481945	1.62576	2.76	0.006	1.292165	7.671725
Hong Kong	4.690708	1.619202	2.90	0.004	1.513795	7.867621
Sydney	4.577658	1.611513	2.84	0.005	1.415831	7.739484

Beijing	4.638224	1.668261	2.78	0.006	1.365056	7.911392
Shanghai	4.514315	1.688083	2.67	0.008	1.202257	7.826373
Guangzhou	4.512775	1.717121	2.63	0.009	1.143743	7.881806
Mumbai	5.036419	1.639793	3.07	0.002	1.819106	8.253732
Delhi	5.022107	1.661476	3.02	0.003	1.762251	8.281962
Bangalore	4.377141	1.69023	2.59	0.010	1.06087	7.693413
_cons	-5.134625	1.184269	-4.34	0.000	-7.458188	-2.81106

Table A.2 Regression results with trans-local citations as the independent variable

Source	SS	Df	MS
Model	559162717	64	8736917
Residual	42634768.8	2,399	17771.89
Total	601797486	2,463	244335.2

Number of observations	2,464
F(64, 2399)	491.61
Prob > F	0
R-squared	0.9292
Adj R-squared	0.9273
Root MSE	133.31

Share of local Citations	Coefficient	Std. Err.	T	P>t	[95% Conf. Interval]	
Share of International Citations	1.496696	0.054359	27.53	0	1.390101	1.603291
Share of International ICT Connections	-0.3013479	0.049124	-6.13	0	-0.3976786	-0.20502
Share of International Citations * Share of ICT Citations	0.0000839	1.26E-05	6.66	0	0.0000592	0.000109
City						
Seattle	31.75758	29.51756	1.08	0.282	-26.12497	89.64014
Austin	32.60809	29.86897	1.09	0.275	-25.96356	91.17975
Pittsburgh	41.05385	29.73899	1.38	0.168	-17.26293	99.37062
NYC	460.5042	35.29355	13.05	0	391.2952	529.7132
LA	89.99025	30.87607	2.91	0.004	29.44371	150.5368
Boston	-24.53257	31.03289	-0.79	0.429	-85.38661	36.32147
Chicago	98.60314	30.16207	3.27	0.001	39.45673	157.7496
SF (bay area)	608.2334	36.2039	16.8	0	537.2392	679.2275
Miami	22.44947	29.5824	0.76	0.448	-35.56024	80.45919
Atlanta	-18.38157	29.5584	-0.62	0.534	-76.34422	39.58108
Houston	202.6677	29.76658	6.81	0	144.2968	261.0386
Dallas	18.26965	29.60921	0.62	0.537	-39.79263	76.33194
London	-169.4738	29.5237	-5.74	0	-227.3684	-111.579
Manchester	15.2502	29.83877	0.51	0.609	-43.26224	73.76264
Birmingham	3.985772	29.81792	0.13	0.894	-54.48578	62.45733
Glasgow	43.61877	30.1343	1.45	0.148	-15.47319	102.7107
Paris	-226.4057	29.80497	-7.6	0	-284.8519	-167.96
Lyon	12.45864	29.87812	0.42	0.677	-46.13096	71.04824
Grenoble	2.754443	29.73094	0.09	0.926	-55.54655	61.05543
Tokyo	59.26475	49.10558	1.21	0.228	-37.02899	155.5585
Osaka	-304.1786	31.59411	-9.63	0	-366.1332	-242.224
Nagoya	-119.8549	30.26111	-3.96	0	-179.1955	-60.5142
Singapore	-8.307465	30.25261	-0.27	0.784	-67.63142	51.01649
Seoul	-255.1487	30.90962	-8.25	0	-315.761	-194.536
Eindhoven	2.471539	29.75994	0.08	0.934	-55.88631	60.82939
Berlin	14.42145	29.79943	0.48	0.628	-44.01384	72.85673
Frankfurt	30.35793	29.91748	1.01	0.31	-28.30885	89.0247

Munich	-46.10308	29.54949	-1.56	0.119	-104.0483	11.84209
Hamburg	22.75875	29.84689	0.76	0.446	-35.76962	81.28711
Stuttgart	-112.6395	29.5478	-3.81	0	-170.5813	-54.6976
Dusseldorf	-109.1236	30.5217	-3.58	0	-168.9752	-49.272
Hong Kong	12.28792	30.17363	0.41	0.684	-46.88117	71.45701
Vienna	33.471	30.04077	1.11	0.265	-25.43755	92.37954
Sydney	-62.59159	29.70192	-2.11	0.035	-120.8357	-4.34751
Zurich	-12.46484	29.65398	-0.42	0.674	-70.61491	45.68523
Basel	22.60647	29.85945	0.76	0.449	-35.94653	81.15946
Beijing	30.74934	31.81585	0.97	0.334	-31.64005	93.13874
Shanghai	25.40541	32.12051	0.79	0.429	-37.5814	88.39222
Guangzhou	22.77256	32.71137	0.7	0.486	-41.37291	86.91803
Stockholm	-21.54318	29.78137	-0.72	0.47	-79.94305	36.8567
Toronto	-147.0974	29.60211	-4.97	0	-205.1458	-89.0491
Vancouver	-37.10854	29.79487	-1.25	0.213	-95.53488	21.3178
Montreal	-47.37403	29.5843	-1.6	0.109	-105.3875	10.6394
Copenhagen	11.08509	29.99819	0.37	0.712	-47.73996	69.91014
Madrid	44.99154	30.33537	1.48	0.138	-14.4947	104.4778
Barcelona	34.63161	30.08491	1.15	0.25	-24.3635	93.62672
Brussels	34.05239	30.09198	1.13	0.258	-24.95658	93.06136
Milan	-15.79023	29.66392	-0.53	0.595	-73.95979	42.37932
Rome	40.96177	30.11078	1.36	0.174	-18.08406	100.0076
Taipei	-113.2889	29.71057	-3.81	0	-171.5499	-55.0279
Moscow	28.26574	29.83828	0.95	0.344	-30.24574	86.77723
Mexico City	46.31813	29.97493	1.55	0.122	-12.4613	105.0976
Sao Paulo	48.38454	30.17125	1.6	0.109	-10.77988	107.549
Mumbai	51.1553	30.36895	1.68	0.092	-8.396783	110.7074
Delhi	51.02965	31.95041	1.6	0.11	-11.6236	113.6829
Bangalore	31.39442	32.38768	0.97	0.332	-32.11632	94.90515
Auckland	43.04626	30.13466	1.43	0.153	-16.0464	102.1389
Helsinki	9.157874	29.91577	0.31	0.76	-49.50555	67.82129
Buenos Aires	48.94233	30.16811	1.62	0.105	-10.21592	108.1006
Dublin	35.29539	30.07749	1.17	0.241	-23.68516	94.27593
Oslo	38.36872	29.90059	1.28	0.2	-20.26494	97.00237
_cons	-57.50463	21.63829	-2.66	0.008	-99.9363	-15.073

Table A.3 Regression results with 62 cities and international citations as the independent variable

Source	SS	Df	MS
Model	589056019	64	9204000
Residual	12741466.3	2,399	5311.157
Total	601797486	2,463	244335.2

Number of observations	2,464
F(64, 2399)	1732.96
Prob > F	0
R-squared	0.9788
Adj R-squared	0.9783
Root MSE	72.878

Share of local citations	Coefficient	Std. Err.	T	P>t	[95% Conf. Interval]	
Share of trans-local citations	0.6097208	0.014732	41.39	0	0.5808326	0.638609
share of trans-local ICT citations	-0.1992913	0.012608	-15.81	0	-0.2240141	-0.17457
Share of trans-local citations * share of ICT citations	0.0000588	2.17E-06	27.15	0	0.0000546	0.000063
City						
Seattle	30.63018	16.27342	1.88	0.06	-1.281238	62.54159
Austin	60.46154	16.54362	3.65	0	28.02027	92.90281
Pittsburgh	40.80261	16.37973	2.49	0.013	8.682732	72.92249
NYC	160.1961	22.53994	7.11	0	115.9964	204.3959
LA	-31.7595	18.50316	-1.72	0.086	-68.04332	4.524329
Boston	-58.46017	18.14004	-3.22	0.001	-94.03195	-22.8884
Chicago	19.11002	17.24336	1.11	0.268	-14.7034	52.92345
SF (bay area)	149.7351	21.71922	6.89	0	107.1447	192.3255
Miami	22.06572	16.27426	1.36	0.175	-9.847341	53.97879
Atlanta	-10.90192	16.20088	-0.67	0.501	-42.6711	20.86725
Houston	145.3084	16.39045	8.87	0	113.1675	177.4493
Dallas	26.8684	16.26845	1.65	0.099	-5.033265	58.77006
London	8.042977	16.27654	0.49	0.621	-23.87456	39.96052
Manchester	52.78933	16.9233	3.12	0.002	19.60353	85.97512
Birmingham	48.34258	16.90249	2.86	0.004	15.19758	81.48758
Glasgow	62.41353	17.11779	3.65	0	28.84633	95.98072
Paris	11.14556	16.14321	0.69	0.49	-20.51052	42.80163
Lyon	50.66791	16.93642	2.99	0.003	17.45638	83.87943
Grenoble	49.99459	16.8558	2.97	0.003	16.94114	83.04803
Tokyo	719.1509	23.78619	30.23	0	672.5073	765.7945
Osaka	-7.258424	16.54619	-0.44	0.661	-39.70472	25.18788
Nagoya	32.29571	16.2513	1.99	0.047	0.4276615	64.16376
Singapore	46.81577	17.12657	2.73	0.006	13.23135	80.40018
Seoul	5.430713	16.44806	0.33	0.741	-26.82316	37.68458

Eindhoven	71.38804	16.6576	4.29	0	38.72325	104.0528
Berlin	53.11367	16.90304	3.14	0.002	19.96761	86.25973
Frankfurt	55.48894	16.98102	3.27	0.001	22.18995	88.78793
Munich	38.11126	16.59043	2.3	0.022	5.578206	70.64431
Hamburg	55.10874	16.92779	3.26	0.001	21.91413	88.30334
Stuttgart	24.29218	16.37573	1.48	0.138	-7.819863	56.40423
Dusseldorf	28.56975	16.56484	1.72	0.085	-3.913134	61.05263
Hong Kong	52.53901	17.11401	3.07	0.002	18.97923	86.09879
Vienna	63.73219	17.04021	3.74	0	30.31713	97.14725
Sydney	38.67093	16.71274	2.31	0.021	5.898029	71.44384
Zurich	49.54607	16.76359	2.96	0.003	16.67344	82.41869
Basel	67.86691	16.853	4.03	0	34.81896	100.9149
Beijing	60.36979	17.98537	3.36	0.001	25.10132	95.63826
Shanghai	56.06652	18.15565	3.09	0.002	20.46413	91.66891
Guangzhou	55.86269	18.46358	3.03	0.003	19.65646	92.06891
Stockholm	45.55384	16.82783	2.71	0.007	12.55525	78.55243
Toronto	3.454149	16.45927	0.21	0.834	-28.82171	35.73
Vancouver	37.31994	16.8374	2.22	0.027	4.302587	70.33729
Montreal	34.08023	16.70257	2.04	0.041	1.327269	66.83318
Copenhagen	52.75199	17.0097	3.1	0.002	19.39676	86.10721
Madrid	62.83078	17.22766	3.65	0	29.04814	96.61341
Barcelona	59.81106	17.08682	3.5	0	26.3046	93.31752
Brussels	59.23379	17.08893	3.47	0.001	25.72319	92.74439
Milan	48.18998	16.76981	2.87	0.004	15.30516	81.0748
Rome	62.24301	17.10143	3.64	0	28.70791	95.77811
Taipei	19.18668	16.58951	1.16	0.248	-13.34458	51.71793
Moscow	59.44996	16.94032	3.51	0	26.23079	92.66913
Mexico City	63.44509	17.03607	3.72	0	30.03817	96.85202
Sao Paulo	63.78359	17.14392	3.72	0	30.16517	97.40201
Mumbai	64.83925	17.24865	3.76	0	31.01545	98.66304
Delhi	65.33969	18.08084	3.61	0	29.884	100.7954
Bangalore	61.12825	18.27484	3.34	0.001	25.29214	96.96435
Auckland	62.3617	17.12002	3.64	0	28.79013	95.93327
Helsinki	54.23628	16.95702	3.2	0.001	20.98436	87.48821
Buenos Aires	64.27768	17.14154	3.75	0	30.66392	97.89144
Dublin	60.45728	17.08004	3.54	0	26.96411	93.95045
Oslo	62.40431	16.98452	3.67	0	29.09845	95.71017
_cons	-67.29888	12.725	-5.29	0	-92.25201	-42.3458

Table A.4 Regression results with trans-local citations as the independent variable

Source	SS	df	MS
Model	543607139	64	8493862
Residual	35699445	2,257	15817.21
Total	579306585	2,321	249593.5

Number of obs	2,322
F(64, 2257)	537
Prob > F	0
R-squared	0.9384
Adj R-squared	0.9366
Root MSE	125.77

Share of local Citations (with two year lag)	Coefficient	Std. Err.	T	P>t	[95% Conf. Interval]	
Share of International citations	0.8755565	0.043829	19.98	0	0.7896063	0.961507
Share of International ICT citations	0.3374115	0.03737	9.03	0	0.2641292	0.410694
Share of International Citations * Share of ICT International Citations	0.0000799	1.35E-05	5.92	0	0.0000534	0.000106
City						
Seattle	26.57991	28.72904	0.93	0.355	-29.75819	82.918
Austin	-9.899642	29.00449	-0.34	0.733	-66.7779	46.97862
Pittsburgh	43.32302	29.54561	1.47	0.143	-14.61639	101.2624
NYC	382.5184	37.64877	10.16	0	308.6886	456.3483
LA	67.30433	31.73754	2.12	0.034	5.066519	129.5421
Boston	-33.16211	31.92814	-1.04	0.299	-95.7737	29.44947
Chicago	48.72887	30.89341	1.58	0.115	-11.85359	109.3113
SF (bay area)	636.3656	35.75789	17.8	0	566.2438	706.4874
Miami	-3.750146	28.80593	-0.13	0.896	-60.23902	52.73872
Atlanta	-19.54855	29.18614	-0.67	0.503	-76.78302	37.68593
Houston	215.067	29.9428	7.18	0	156.3487	273.7853
Dallas	-22.57313	28.72517	-0.79	0.432	-78.90364	33.75739
London	-185.9542	29.31658	-6.34	0	-243.4445	-128.464
Manchester	2.43266	29.17551	0.08	0.934	-54.78096	59.64628
Birmingham	-3.089478	29.20518	-0.11	0.916	-60.36129	54.18234
Glasgow	28.16131	29.34604	0.96	0.337	-29.38673	85.70935
Paris	-276.5709	29.90655	-9.25	0	-335.2182	-217.924
Lyon	6.870909	29.27251	0.23	0.814	-50.53293	64.27475
Grenoble	-12.20966	29.01697	-0.42	0.674	-69.11239	44.69307
Tokyo	-194.9267	51.21564	-3.81	0	-295.3614	-94.4921
Osaka	-327.1147	32.79225	-9.98	0	-391.4209	-262.809
Nagoya	-97.51361	31.0062	-3.14	0.002	-158.3172	-36.71
Singapore	-24.77397	29.72846	-0.83	0.405	-83.07195	33.52402

Seoul	-279.8906	29.9106	-9.36	0	-338.5458	-221.236
Eindhoven	-53.44735	28.66882	-1.86	0.062	-109.6674	2.772662
Berlin	1.589895	29.09899	0.05	0.956	-55.47367	58.65346
Frankfurt	19.49365	29.20204	0.67	0.504	-37.77201	76.75931
Munich	-80.01343	28.73222	-2.78	0.005	-136.3578	-23.6691
Hamburg	8.250351	29.14685	0.28	0.777	-48.90708	65.40778
Stuttgart	-127.1239	29.5111	-4.31	0	-184.9956	-69.2521
Dusseldorf	-71.29304	31.02192	-2.3	0.022	-132.1275	-10.4586
Hong Kong	-1.23974	29.47524	-0.04	0.966	-59.04114	56.56166
Vienna	20.01022	29.31434	0.68	0.495	-37.47566	77.4961
Sydney	-54.37423	29.25941	-1.86	0.063	-111.7524	3.003939
Zurich	-25.1459	29.06003	-0.87	0.387	-82.13307	31.84128
Basel	14.8492	29.3742	0.51	0.613	-42.75406	72.45247
Beijing	18.69226	31.05163	0.6	0.547	-42.20048	79.585
Shanghai	16.09462	31.75152	0.51	0.612	-46.1706	78.35985
Guangzhou	9.852349	32.78142	0.3	0.764	-54.43253	74.13723
Stockholm	-41.44031	29.07729	-1.43	0.154	-98.46134	15.58072
Toronto	-138.6054	29.60013	-4.68	0	-196.6518	-80.5591
Vancouver	-42.76691	29.23789	-1.46	0.144	-100.1029	14.56904
Montreal	-51.62285	29.0837	-1.77	0.076	-108.6564	5.410737
Copenhagen	0.3166322	29.35812	0.01	0.991	-57.2551	57.88836
Madrid	29.87277	29.54952	1.01	0.312	-28.07429	87.81983
Barcelona	21.97718	29.32183	0.75	0.454	-35.5234	79.47775
Brussels	19.70457	29.33743	0.67	0.502	-37.82659	77.23574
Milan	-28.6007	29.10174	-0.98	0.326	-85.66966	28.46826
Rome	25.50416	29.32694	0.87	0.385	-32.00643	83.01474
Taipei	-114.7667	29.53586	-3.89	0	-172.687	-56.8465
Moscow	9.856042	29.07325	0.34	0.735	-47.15705	66.86914
Mexico City	30.65726	29.19059	1.05	0.294	-26.58593	87.90045
Sao Paulo	34.1537	29.37892	1.16	0.245	-23.45883	91.76623
Mumbai	37.8965	29.97765	1.26	0.206	-20.89014	96.68313
Delhi	34.76295	32.44607	1.07	0.284	-28.8643	98.39021
Bangalore	14.90828	33.92723	0.44	0.66	-51.62356	81.44011
Auckland	28.70056	29.35118	0.98	0.328	-28.85755	86.25868
Helsinki	-4.40426	29.16088	-0.15	0.88	-61.5892	52.78068
Buenos Aires	33.49297	29.37192	1.14	0.254	-24.10583	91.09177
Dublin	18.89724	29.69445	0.64	0.525	-39.33403	77.12852
Oslo	21.80027	29.1197	0.75	0.454	-35.30392	78.90447
_cons	-41.07915	21.14182	-1.94	0.052	-82.53858	0.380291

Table A.5 Regression results with the international citations (after subtracting international ICT citations) as independent variables and a two year lag in the dependent variable.

Source	SS	df	MS
Model	567440455	64	8866257
Residual	11866130	2,257	5257.479
Total	579306585	2,321	249593.5

Number of obs	2,322
F(64, 2257)	1686.41
Prob > F	0
R-squared	0.9795
Adj R-squared	0.9789
Root MSE	72.508

Share of local Citations (with two year lag)	**Coefficient**	**Std. Err.**	**T**	**P>t**	**[95% Conf. Interval]**	
Share of Trans-local citations	0.4360823	0.026528	16.44	0	0.3840597	0.488105
Share of Trans-local ICT citations	0.1268746	0.010216	12.42	0	0.106841	0.146908
Share of Trans-local Citations * Share of ICT Trans-local Citations	0.0001528	5.61E-06	27.26	0	0.0001418	0.000164
City						
Seattle	12.82555	16.64377	0.77	0.441	-19.81314	45.46425
Austin	-1.129844	17.14672	-0.07	0.947	-34.75483	32.49514
Pittsburgh	79.00053	17.3141	4.56	0	45.0473	112.9538
NYC	165.6449	26.39704	6.28	0	113.8799	217.4099
LA	-12.09949	22.58454	-0.54	0.592	-56.38812	32.18914
Boston	-55.29027	21.52417	-2.57	0.01	-97.49951	-13.081
Chicago	48.08272	20.29276	2.37	0.018	8.288304	87.87713
SF (bay area)	147.2849	22.8638	6.44	0	102.4486	192.1211
Miami	-1.421149	16.7978	-0.08	0.933	-34.3619	31.5196
Atlanta	-3.014209	17.01208	-0.18	0.859	-36.37517	30.34675
Houston	232.3049	17.96325	12.93	0	197.0787	267.5311
Dallas	-29.47785	16.74818	-1.76	0.079	-62.32129	3.365594
London	13.29228	16.83334	0.79	0.43	-19.71817	46.30272
Manchester	39.12238	17.41011	2.25	0.025	4.980886	73.26388
Birmingham	39.95637	17.39841	2.3	0.022	5.837819	74.07493
Glasgow	44.66616	17.58744	2.54	0.011	10.17691	79.15541
Paris	1.931676	16.72703	0.12	0.908	-30.87029	34.73364
Lyon	43.43436	17.43984	2.49	0.013	9.234561	77.63416
Grenoble	36.14989	17.3168	2.09	0.037	2.191371	70.10841
Tokyo	834.8742	25.86374	32.28	0	784.155	885.5934
Osaka	22.77506	17.90809	1.27	0.204	-12.34298	57.89309
Nagoya	95.5749	17.28885	5.53	0	61.67121	129.4786
Singapore	31.89204	17.72214	1.8	0.072	-2.861345	66.64543

Seoul	-2.316544	16.76291	-0.14	0.89	-35.18887	30.55578
Eindhoven	32.6192	16.94939	1.92	0.054	-0.6188262	65.85722
Berlin	40.65881	17.3777	2.34	0.019	6.580872	74.73675
Frankfurt	42.22262	17.45976	2.42	0.016	7.983755	76.46149
Munich	15.48353	16.98095	0.91	0.362	-17.81638	48.78344
Hamburg	40.73819	17.40854	2.34	0.019	6.599763	74.87661
Stuttgart	37.63722	17.00361	2.21	0.027	4.292881	70.98156
Dusseldorf	87.95052	17.37871	5.06	0	53.8706	122.0305
Hong Kong	39.2762	17.60062	2.23	0.026	4.76112	73.79129
Vienna	50.80412	17.52486	2.9	0.004	16.4376	85.17064
Sydney	45.23057	17.27778	2.62	0.009	11.34858	79.11256
Zurich	42.27068	17.25075	2.45	0.014	8.441695	76.09967
Basel	66.29584	17.41776	3.81	0	32.13933	100.4523
Beijing	42.37764	18.5393	2.29	0.022	6.021776	78.7335
Shanghai	41.82422	18.91099	2.21	0.027	4.739476	78.90896
Guangzhou	41.54866	19.47458	2.13	0.033	3.358706	79.73861
Stockholm	30.82674	17.28458	1.78	0.075	-3.068587	64.72207
Toronto	22.08115	17.07434	1.29	0.196	-11.40191	55.5642
Vancouver	32.39938	17.34602	1.87	0.062	-1.616426	66.41519
Montreal	30.70198	17.21854	1.78	0.075	-3.063848	64.46781
Copenhagen	42.09956	17.50865	2.4	0.016	7.764818	76.43429
Madrid	44.89624	17.70491	2.54	0.011	10.17664	79.61585
Barcelona	43.52501	17.56484	2.48	0.013	9.080085	77.96994
Brussels	42.9832	17.56141	2.45	0.014	8.545002	77.4214
Milan	41.17755	17.26659	2.38	0.017	7.317498	75.03761
Rome	44.60518	17.5699	2.54	0.011	10.15035	79.06002
Taipei	32.19511	17.16598	1.88	0.061	-1.467647	65.85787
Moscow	41.53537	17.40474	2.39	0.017	7.404398	75.66634
Mexico City	44.96226	17.50445	2.57	0.01	10.63576	79.28876
Sao Paulo	45.89574	17.61661	2.61	0.009	11.34928	80.44219
Mumbai	46.81499	17.95729	2.61	0.009	11.60047	82.02951
Delhi	45.74995	19.33213	2.37	0.018	7.83934	83.66055
Bangalore	39.62121	20.14955	1.97	0.049	0.107626	79.1348
Auckland	45.06438	17.59302	2.56	0.01	10.56419	79.56457
Helsinki	39.18718	17.42656	2.25	0.025	5.01342	73.36094
Buenos Aires	46.01267	17.61159	2.61	0.009	11.47607	80.54926
Dublin	42.72454	17.77175	2.4	0.016	7.873851	77.57522
Oslo	44.20666	17.45135	2.53	0.011	9.984294	78.42903
_cons	-47.42743	13.13683	-3.61	0	-73.18897	-21.6659

Table A.6 Regression results with the trans-local citations (after subtracting trans-local ICT citations) as independent variable and a two year lag in the dependent variable

Appendix B: Definitions for Study 2

Category	Tech 56 Field Description	
Chemical	2	Distillation Processes
	3	Inorganic Chemicals
	4	Agricultural Chemicals
	5	Chemical Processes
	6	Photographic Processes
	7	Cleaning Agents and other compositions
	8	Disinfectants and Preservatives
	9	Synthetics resins and Fibers
	10	Bleaching and Dying
	11	Other Organic Compounds
	12	Pharmaceuticals and biotechnology
	51	Coal and petroleum products
	55	Explosive compositions and charge
Other Electrical Equipment	30	Mechanical Calculators and typewriters
	37	Illumination devices
	38	Electrical devices and systems
	39	Other general electrical equipment
	52	photographic equipment
Transport	42	Internal combustion engines
	43	Motor vehicles
	44	Aircraft
	45	Ships and marine propulsion
	46	Railways and railway equipment
	47	Other transport equipment
	49	Rubber and plastic products
Other	32	Nuclear reactors
	48	Textiles, clothing and leather
	54	Wood products
	56	Other manufacturing (non industrial)
	1	Food and Tobacco
Mechanical	13	Metallurgical Processes
	14	Miscellaneous Metal products
	15	Food drink and tobacco equipment
	16	Chemical and allied equipment
	17	Metal Working Equipment
	18	Paper making apparatus
	19	Building material and processing equipment
	20	Assembly and material handling equipment
	21	Agricultural equipment

	22	Other Construction and excavating equipment
	23	Mining equipment
	24	Electrical lamp manufacturing
	25	Textile and clothing machinery
	26	Printing and publishing
	27	Wood working tools and machinery
	28	Other specified machinery
	29	Other general industrial equipment
	31	Power plants
	50	Non-metallic mineral products
	53	Other instruments and controls
ICT	33	Telecommunications
	34	Other electrical communication systems
	35	Special radio systems
	36	Image and sound equipment
	40	Semiconductors
	41	Office equipment and data processing systems

Table B.1 Description of broad classification of technological fields

Appendix C: Additional Network Statistics for Study 3

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
Atlanta	247.4	599.6	1590.6	3685.8	6496.4	11986.8	24248.25
Auckland	7.2	23.4	48.4	86.2	170.6	321	868.5
Austin	211.2	650	1590.4	5687.8	12685	22246	38597.5
Bangalore	0.2	0.4	1	20	87.8	310.2	1260.25
Barcelona	16.8	46.4	74.8	141.8	217.6	364.8	810
Basel	313.4	469.2	562	879.2	894.6	906.2	1526.75
Bay Area	3084	6196.4	13817.4	40015.4	75706.6	167303.8	371918.8
Beijing		1.6	13	49.6	127.6	527.2	1908.75
Berlin	109.2	218.8	309.2	591.4	901	1351.4	2390.25
Birmingham	171.2	331.8	351.8	460.2	689.2	726.8	1181.75
Boston	1933.2	5527.2	10478.8	23876.8	37714.2	56928.4	119430.5
Brussels	76.4	113	145.6	244	336.2	522.6	933
Buenos Aires	7.6	23.8	36.6	149.6	271.4	304.4	754.5
Chicago	2672.6	5206.2	7909	16783	23297.4	31008.4	63291
Copenhagen	71.4	123.2	217	506	766.2	1537.2	3938.5
Dallas	764.6	2035.6	3886.4	10379.2	16733.6	29789.8	41324.25
Delhi	0.6	1	7.6	13.4	39	176.6	447.25
Dublin	82.8	20.8	49.8	123	245.6	580.6	1691
Dusseldorf	696	1516.4	2253.8	3207	3410.4	3438	5865.25
Eindhoven	310.8	808.8	1142.8	1828.4	2292.4	3441.8	5752.5
Frankfurt	59.8	142.2	203.8	262.2	358.4	391.2	705.75
Glasgow	36.6	52.4	74.4	157.2	235.4	345.2	634
Grenoble	78.8	228.2	457.4	941.2	1665.8	1819.6	3190.25
Guangzhou		0.2	1.4	3.6	42.6	274	1459.25
Hamburg	87.2	209.8	276.8	470.4	602.8	927.6	1696
Helsinki	38.6	101	191.8	499.6	1138.6	2779.6	6070.75
Hong Kong	201.2	66.6	126.6	305.4	705	1215	2472.75
Houston	1204.4	2706	4715.8	7658.4	12599.6	25135.4	37688
LA	3185	7016.6	11280.6	22451.8	37380.8	50716.8	130399.3
London	797.6	1725.6	2285.6	3852.2	5104.8	7714.2	14230.5
Lyon	116	256.4	377.6	570.6	640.6	826.4	1836.25
Madrid	30.6	26	38.8	73.8	158.6	293.8	685.25
Manchester	105.6	229.8	288	410.6	510	655.4	1180.5
Mexico City	62.2	28.2	46.2	57	59.4	70.8	159.5
Miami	381	1286.4	2472	6438	8298.2	12351.2	26439.25
Milan	223.8	441.8	728.4	1164	1504.4	1877	2542.75
Montreal	132.8	361.4	552.4	1168.8	1893.8	3184	6244
Moscow	71.4	129.4	172.2	290.2	580.2	930.2	1850
Mumbai	55.2	11.8	9.8	21	32.4	61.4	138.25
Munich	396.4	891.4	1121.8	1550.8	1982.4	2695.8	4643.5
Nagoya	1458	3136.4	3499	6780.6	10146.6	12629.2	21582.5
NYC	6357.2	13950.2	23954.2	42505.8	69367.2	99106	194444.3
Osaka	1503	4966	8572.6	21138.6	23220.4	34046	56855.25
Oslo	179	85	141.6	278.6	362.8	607.2	1318.5
Paris	1220.6	2584.8	3420.6	5596.6	7160.2	9114.6	15167.25
Pittsburgh	1023.4	1819.4	2323.6	3676.6	5190.6	6886.8	13158.75
Rome	96.8	79.6	138.2	226.8	286	398.4	871.75
San Diego	438	1335	2547.6	6660.6	13556	22872.2	46220.25
Sao Paulo	54.6	19	34.2	56	68.4	112.2	261
Seattle	271.2	923	2045.2	5262.8	10368.4	23773.8	67723.25

Seoul	5	47.4	400	3207.8	8574.8	16336.6	31096.75
Shanghai		2	14.4	24	50.6	185.8	832.5
Singapore	1.2	9	39.4	269.4	1084.2	2225.2	3873
Stockholm	98.2	484	611.2	1325.4	2246.4	3537	6503.5
Stuttgart	414.6	1266	1779.6	2964.8	3836.2	4529.2	7733.5
Sydney	416.4	153.6	263.8	641.8	982.2	3028	11987.5
Taipei	38.4	126.2	576.8	2122	5227.6	8746	13959
Tokyo	1708.8	15697.4	32861.8	56067.6	91769.2	153208.4	177386.5
Toronto	2331.8	633.6	1154.8	2580	3946.4	6821	11750.25
Vancouver	166.8	145.4	301	912.2	1890	3038	6169.5
Vienna	69	182	240.6	424.6	460.8	620	1289.25
Zurich	136.2	536	773.4	1104.6	1414.4	1850.4	3119.75

Table C.1 Outdegree strengths of all our cities in the overall patent network

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
Atlanta	390.6	997	2604.8	7490.4	10705	20726.4	37469.75
Auckland	13.2	26	38.6	103.8	284.4	400.6	1808.25
Austin	353.4	776.4	2513.2	9601.4	15677	25841.8	39253.25
Bangalore	0.4	0.6	8.6	32.2	318.4	1332.8	4938
Barcelona	19	53.6	101.2	207	359.6	786.6	1677
Basel	281.4	389.6	352.8	303.4	434.8	401.4	804.25
Bay Area	2773.2	5860	15415.4	55664	104805.8	214224.8	489324.5
Beijing		20	38.2	114.2	311.6	2153.2	4257.5
Berlin	110.4	207.8	267.2	572.6	928.8	1223.8	2304.75
Birmingham	121.2	203.6	238.4	357.4	462.6	512.4	957.25
Boston	1852	5531.2	11293.2	24956.2	42651.8	60544.6	126740.5
Brussels	43.6	78.8	106.4	218	349.8	395.4	593.75
Buenos Aires	10.4	16.8	46.8	89.8	167.6	148.6	495.5
Chicago	2748.6	4686.6	7000.2	16034.4	23010.4	24849	50012.5
Copenhagen	56	128.2	217.2	568.6	834.2	1370.4	3544.5
Dallas	756	2171.2	4375.6	11561.8	14989	17545.6	31561.75
Delhi	1.6	1.6	7.4	35.2	176	342.8	736.25
Dublin	117.2	43.8	59.8	205.4	372	675.2	3265
Dusseldorf	676.6	1468.8	1824	2333	2567.6	2077	3402.75
Eindhoven	246.2	671.4	754.4	1186.4	1672.4	3014.8	3994
Frankfurt	67.2	136.4	162.8	217.8	331.2	320	705.5
Glasgow	45.2	46.4	64.2	134.4	175	257	1066
Grenoble	89.8	291.8	404.6	837	1452.2	1823.8	2705.25
Guangzhou		1	7	12	198.2	1841.8	6048
Hamburg	82	194.2	204.6	297.6	440.8	766.6	1099.5
Helsinki	51.8	138.8	260.2	745.4	1432.4	2491.6	2972
Hong Kong	214.4	81.2	210.2	569	1288.2	2070.8	3060.25
Houston	1186.6	3336.8	5740.8	8153.6	14343	29696.8	39639.25
LA	2816	6285	10826.8	21353	38689.4	51056.8	122385.3
London	616.8	1297	1386.8	2455.8	3874.6	5560.2	9828.25
Lyon	101.8	241.2	339.2	372.8	444	461.6	813.5
Madrid	20.4	32.4	56	116	177	439.4	654.5
Manchester	77.6	161.4	216.6	221.8	387.4	403.4	546.5
Mexico City	73.8	17.2	18.4	35.4	77	85.4	345.75
Miami	452.2	1375.4	2644	4840.4	5859	9047.4	22773.75
Milan	196	458.2	633.4	863	1101.4	1069.2	1530
Montreal	130.4	305.2	529.6	1257.8	1991	3117.6	7488.25
Moscow	50.6	42.6	100.4	407.4	497.4	634.4	1564
Mumbai	72.6	3.8	14.6	23.4	72.8	106	281.25
Munich	425.2	718.8	692.6	1023	1301.4	3296.4	6153.25
Nagoya	1473.8	3509	3587.6	6696.2	8970	11050.4	15856.75
NYC	5850.6	11506.6	20738.8	34105.2	48743.8	69709.2	145680
Osaka	1741.4	6519	9896.6	16044.2	16657.2	19654.8	28312.5
Oslo	186	81.6	136.6	251.8	402	773.4	1332.5
Paris	1099.8	1917.4	2676.4	3698	4362.8	5259.8	9295
Pittsburgh	954.6	1941.2	2260.2	3276	4444.4	5668.6	10544.5
Rome	121.8	83.8	130.8	143.8	179	261.8	593.5
San Diego	414.6	1450.4	3169.4	8500.4	17627.4	28977	67700
Sao Paulo	62.4	19.8	42.4	61.4	61.4	151.4	375.75
Seattle	370.6	1376.6	2764	7955.6	13907	46791.8	96360.5
Seoul	13.2	178.2	1813.4	8385.8	13692.2	29183.6	42088.25

Shanghai		15.6	22.2	29.6	208.2	1208	4456
Singapore	1.6	22	120.6	600.4	3122.8	3894.6	5458.25
Stockholm	101.2	286	615.6	1472.4	1684	1539	2613.25
Stuttgart	407.4	1217	1713.2	2642.4	3755.4	3490	5390.5
Sydney	456.4	180.4	288.2	809.6	2344.8	7943.8	24445.25
Taipei	66	304.4	1092	3154.8	7733.6	10991.6	14747
Tokyo	2215.4	17226.6	30095.8	42546.2	69386.2	109178	88807.25
Toronto	2845.6	813.2	1386	2763.2	3877.8	7465.2	11821
Vancouver	143.6	203.6	555.6	1306.6	2175.2	3758.4	7934.5
Vienna	70.8	192.6	161.8	297.2	369.6	426.4	843.5
Zurich	129	463	557.6	589.2	869	1218.4	2251.25

Table C.2 Indegree strengths of all our cities in the overall patent network

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
Atlanta	0.155552	0.153974	0.151638	0.149911	0.145173	0.141344	0.134367
Auckland	0.043398	0.063226	0.075699	0.091745	0.101751	0.105128	0.118629
Austin	0.129765	0.137185	0.144615	0.144581	0.145087	0.141006	0.13553
Bangalore	0.002322	0.002875	0.015113	0.045298	0.081341	0.113368	0.129265
Barcelona	0.061444	0.08706	0.104125	0.109754	0.115544	0.119079	0.12181
Basel	0.132567	0.1312	0.12446	0.130747	0.117321	0.118293	0.122733
Bay_Area	0.184099	0.167121	0.159907	0.152784	0.14687	0.141801	0.13553
Beijing		0.044885	0.046965	0.079096	0.103154	0.120619	0.125465
Berlin	0.119818	0.123577	0.125681	0.125572	0.130941	0.128758	0.128975
Birmingham	0.132649	0.12997	0.127029	0.120799	0.121478	0.11707	0.120789
Boston	0.177767	0.167752	0.159654	0.154077	0.147219	0.140812	0.134369
Brussels	0.100717	0.10324	0.110958	0.111365	0.109049	0.112582	0.117138
Buenos_Aires	0.044467	0.065646	0.07522	0.097937	0.09176	0.09145	0.106591
Chicago	0.183078	0.166911	0.158771	0.152705	0.14744	0.14081	0.134934
Copenhagen	0.106419	0.124272	0.127507	0.128113	0.126041	0.131126	0.129467
Dallas	0.160653	0.160936	0.156257	0.151132	0.145097	0.141333	0.134397
Delhi	0.007319	0.007016	0.026654	0.045006	0.073349	0.09406	0.107694
Dublin	0.071041	0.06339	0.074193	0.100732	0.104036	0.107924	0.126548
Dusseldorf	0.16245	0.163024	0.152831	0.147553	0.143441	0.136612	0.133984
Eindhoven	0.125185	0.13402	0.134699	0.13363	0.13122	0.131904	0.127225
Frankfurt	0.107698	0.110214	0.118976	0.11201	0.116188	0.1178	0.115874
Glasgow	0.090724	0.086981	0.087248	0.097	0.103959	0.110194	0.110095
Grenoble	0.12434	0.125504	0.127171	0.127904	0.131489	0.131098	0.128503
Guangzhou		0.002986	0.021654	0.025421	0.070694	0.109511	0.126827
Hamburg	0.116251	0.126284	0.127604	0.124995	0.120317	0.125556	0.127773
Helsinki	0.09286	0.122178	0.131152	0.126654	0.131382	0.135006	0.128596
Hong_Kong	0.085119	0.091971	0.10619	0.113267	0.127914	0.130417	0.128719
Houston	0.17411	0.165613	0.157156	0.150915	0.145517	0.142352	0.134963
LA	0.183345	0.16882	0.159532	0.15314	0.147992	0.140812	0.134955
London	0.164278	0.159593	0.152995	0.147299	0.143872	0.141119	0.134934
Lyon	0.111859	0.129989	0.132099	0.130187	0.124127	0.122908	0.126217
Madrid	0.065148	0.076942	0.071183	0.092714	0.09915	0.099562	0.113691
Manchester	0.110264	0.122493	0.121846	0.115955	0.117226	0.116849	0.113836
Mexico_City	0.085702	0.058508	0.064554	0.071698	0.074721	0.066309	0.080754
Miami	0.163061	0.159867	0.156397	0.149552	0.145619	0.140557	0.134963
Milan	0.144698	0.146251	0.14558	0.14178	0.14002	0.13387	0.131478
Montreal	0.13988	0.141902	0.142836	0.142953	0.138489	0.137852	0.134061
Moscow	0.097391	0.10736	0.104617	0.113671	0.118902	0.11775	0.126508
Mumbai	0.049902	0.023561	0.031348	0.041276	0.064354	0.071627	0.091995
Munich	0.15329	0.152969	0.145502	0.139303	0.138477	0.135155	0.131259
Nagoya	0.170696	0.161131	0.153029	0.149897	0.144138	0.139987	0.134955
NYC	0.183997	0.168576	0.161027	0.153241	0.14741	0.141323	0.134934
Osaka	0.158474	0.168671	0.156467	0.153725	0.145261	0.140863	0.13553
Oslo	0.115575	0.103681	0.105639	0.115694	0.113768	0.113393	0.122509
Paris	0.176377	0.163995	0.157012	0.150368	0.145178	0.141295	0.134642
Pittsburgh	0.158158	0.160328	0.153884	0.147547	0.143397	0.141321	0.133801
Rome	0.110344	0.103089	0.107865	0.10893	0.104258	0.100079	0.117253
San_Diego	0.134216	0.1543	0.155331	0.14969	0.146419	0.14109	0.133822
Sao_Paulo	0.057442	0.05857	0.077536	0.076031	0.077765	0.083287	0.095356
Seattle	0.135809	0.1572	0.156412	0.149144	0.144801	0.140799	0.13553
Seoul	0.035735	0.092738	0.138689	0.146911	0.145801	0.140497	0.134359
Shanghai		0.034966	0.04089	0.050235	0.087664	0.112672	0.126202

Singapore	0.012	0.039054	0.084393	0.108082	0.122319	0.129188	0.131156
Stockholm	0.072487	0.140916	0.143423	0.137751	0.138647	0.13683	0.133087
Stuttgart	0.156861	0.157721	0.148721	0.14844	0.141565	0.138503	0.13259
Sydney	0.14085	0.128381	0.124756	0.131112	0.129356	0.136667	0.134735
Taipei	0.096901	0.122727	0.140957	0.146998	0.145162	0.139755	0.133822
Tokyo	0.124393	0.169736	0.16001	0.152137	0.146845	0.14234	0.133801
Toronto	0.170305	0.156583	0.14766	0.146843	0.14454	0.140702	0.134369
Vancouver	0.136347	0.122873	0.134389	0.13623	0.13848	0.136911	0.133592
Vienna	0.116013	0.123813	0.127339	0.121042	0.120892	0.117597	0.122468
Zurich	0.123536	0.146525	0.140322	0.13932	0.135002	0.131914	0.130528

Table C.3 Eigenvector centralities of all our cities in the overall network of patents

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
Atlanta	28.4	63.4	163.8	314.8	674.6	739.6	1617
Auckland	0.4	3	5.2	8.6	15.2	28	45
Austin	67	119.8	209	424.4	560.8	732.6	1223.5
Bangalore	0.2	0.4	0.2	1.4	4.4	21	44.75
Barcelona	2.8	3.6	9.6	35.8	42.8	50.4	129.25
Basel	246.8	443.8	486.4	711.2	567.2	564.6	965.25
Bay Area	567.4	1252.6	1939.2	4356.8	9202.2	9758.6	23166.25
Beijing		0.4	2.6	12	37	58.2	121.75
Berlin	29.6	52.8	110.4	174	158.2	206.6	437.75
Birmingham	22.4	29	39.2	71.6	109	90.8	139.5
Boston	301.8	754.2	1414.2	2980.4	4682.8	8075.6	15727
Brussels	32.6	34.6	61	90	111.4	149.2	250.5
Buenos Aires	1	1.8	4.2	5.6	7.2	17.4	64.75
Chicago	585.8	894.2	1454.2	2149	3064.6	2777.6	5527.25
Copenhagen	28.2	35.2	79.2	164.4	246.6	418.4	888.75
Dallas	80.4	160.4	282.4	589.6	911.8	914.2	1479.5
Delhi	0	0.4	2.6	5.4	9.6	19.2	44.25
Dublin	3	8	17.6	23.2	31.2	28.8	126.25
Dusseldorf	572.8	959	979.4	1642.8	1081.4	1149	2490.75
Eindhoven	24.8	46.2	61.2	78.8	70.8	94.8	174
Frankfurt	37.4	59	76.8	106.4	128.6	151.4	247.5
Glasgow	8.6	11.4	19.8	34.6	37.4	40.6	92.75
Grenoble	16	32.4	50.6	90.4	84.8	101.4	172
Guangzhou			0	0	1.2	3.4	8.5
Hamburg	14.2	23	42.6	88.6	114.2	127	213.25
Helsinki	4.6	25.6	35	90.6	210	255.2	353.75
Hong Kong	1.4	1	3	8	17.8	53.4	73.5
Houston	325.6	361.4	1066.4	1792	2274.8	2904.8	4382.25
LA	445.8	798.4	1046.6	3028.8	3336.8	4039.8	8151.25
London	279.6	405.4	564.2	832	966.6	1262.8	2271
Lyon	65.4	96.2	157.8	252.4	284.4	263.4	549.25
Madrid	2	4.8	6.4	12.2	27.6	51.4	119.75
Manchester	51.6	83.4	126.8	143.6	114	151	218.25
Mexico City	5.4	3.8	8	8.8	13	13.8	38.5
Miami	34.6	102.8	150.2	395.8	457.8	631.6	1399.5
Milan	108.4	128.6	203.6	341	411.8	461.2	668.75
Montreal	35.2	87	100.8	195.6	255.6	465.2	843.25
Moscow	17.8	24	32	49.4	108.4	140	302
Mumbai	2.2	10.4	8.6	14.4	10.2	18	41.75
Munich	34.8	63.4	100.6	140.8	138.4	199.4	360.75
Nagoya	87.8	217.6	423.8	769.6	887.6	831.6	1335.25
NYC	2781	4278.6	3496.8	8556.2	12470	11693.4	19063
Osaka	529.2	1009.6	1635.2	2872.4	3007.8	3290.2	5424.75
Oslo	7.4	11.2	23.4	77.4	70.2	86.6	193.25
Paris	276.4	392.4	723	1168.8	1358.8	1857.6	2566.75
Pittsburgh	284	371.4	482.8	836.6	943	967.6	1347.75
Rome	16.2	21	34	59	85.6	87.2	149.25
San Diego	80.4	219	287.6	1368	2167.2	2964.8	5680.75
Sao Paulo	0.8	2.4	3.2	5.6	6	7.6	20.5
Seattle	29.8	67.6	188.8	580.4	889.4	1549.4	3146.5
Seoul	2.6	7	23.2	132.2	388.6	586.6	1113

Shanghai		0.6	1.8	4.6	9.2	16	58.75
Singapore	0.6	0.4	1.6	13.4	54	82.2	145.75
Stockholm	28	51.8	62.2	128.6	161.2	172.2	358
Stuttgart	21.4	41.8	72.8	119.4	144.2	131.6	274.75
Sydney	8.2	19.6	40.2	84.6	102	142.4	308.5
Taipei	0.8	3.8	14.2	57.4	127.6	181.8	293.75
Tokyo	1054.4	2162.6	3693.8	6185.8	8200.4	7811.6	12585.5
Toronto	35.8	74.4	178.2	546.8	571.8	927.6	1652.25
Vancouver	8.4	18.8	47.2	142.8	201.4	370.2	871
Vienna	19.4	33.2	43.8	90.4	83.6	115.4	261.75
Zurich	36.2	63.6	97.8	140.6	160.8	197.2	372.5

Table C.4 Outdegree strength of all our cites in the chemical network

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
Atlanta	56.52857	164.2	338.4	1963.8	1938.4	1918.8	2512.75
Auckland	0.2	4.4	6.4	20.4	46.4	54.4	83
Austin	83.66895	142	372.8	647.8	1077.4	1028.2	2215.25
Bangalore	0.2	0.4	2	2.2	18.6	79.4	62.5
Barcelona	3.6	6.8	22.6	33.8	38	41.6	138.75
Basel	189.2315	374	337.8	260.6	231.2	232.6	453.5
Bay Area	558.37	1128.4	1964	5039.8	12198.6	12492.6	27470.75
Beijing		3.4	7.4	49	76.4	112	234.25
Berlin	27.2923	52.4	88.2	141.4	115.2	159.2	239
Birmingham	15.50077	18.2	27.8	48.4	59.8	18	54.25
Boston	335.3053	852.2	1663.8	4045.8	5891.6	9795.6	18949.5
Brussels	13.53049	26.4	54.4	76.8	125.4	121.2	236.75
Buenos Aires	4	2	3.4	18.8	21.4	31.4	79
Chicago	589.6151	873.2	1478.8	2329	3235	2561.8	5512
Copenhagen	21.07986	34	86	190	210.6	320.8	828
Dallas	66.92428	247.8	307.6	929.8	993.2	722.8	1329.75
Delhi	1.2	1.4	3	23.4	84	33.8	97.75
Dublin	4.4	17.4	17.2	43	39.8	42	297.25
Dusseldorf	477.3605	925.4	689	1125.6	808.4	673	1841.75
Eindhoven	17.6	26.8	28.6	34.8	51.4	67.8	146.5
Frankfurt	36.93486	47.6	69	69.2	76.4	151.2	133.25
Glasgow	7.902431	10.4	21.4	26.2	21.2	24.4	111.5
Grenoble	19.06524	32.4	40	49.8	68.4	117.4	177.25
Guangzhou			2.8	0.8	5.2	60.2	196.5
Hamburg	9.04	22	27	50.2	78.2	112	138.5
Helsinki	6.8	27.6	37.8	103.4	195.6	216	233.5
Hong Kong	0	2	4.6	20.4	102.2	163.8	110.75
Houston	291.5117	646	1579.8	2186.4	3030.4	4867	7619
LA	399.3767	815.6	1028.2	3438.6	3790.4	4074.6	8320.75
London	217.9574	285.2	398.2	580	695.8	795.8	1034.5
Lyon	48.4024	95.6	134.4	165.4	268.6	220.2	353.75
Madrid	2.4	6	15.8	19.8	41	79.2	114
Manchester	28.24438	53	105.6	68.2	73	84.2	144.5
Mexico City	2.2	3.4	7.4	10.2	21.2	41.2	81
Miami	34.1133	126.6	193.6	439	519.6	565.4	1462.25
Milan	96.02155	146.6	222.2	245.8	252.6	221.6	270
Montreal	26.28501	39.2	88.6	173.8	234.4	463.8	791.5
Moscow	13.19871	7.6	12.2	100.2	84.8	134.2	295.25
Mumbai	2.4	3.6	8.6	8.6	26.6	54.4	127
Munich	47.12253	60.6	59.6	120.2	73	126.2	173
Nagoya	78.25532	287.2	444	668.4	552.6	410.4	552
NYC	2415.528	4155.4	3218	7367	9835.4	9150.4	14844.25
Osaka	462.3695	1060	1537.6	2035.6	1827.8	1486.4	2058.25
Oslo	5.477778	9.8	29	61.8	69	85	180.75
Paris	207.825	301	605	980	1034.8	1433.4	1328
Pittsburgh	247.5678	342.8	535.8	843.2	1002.2	1103	1245.75
Rome	22.605	23.8	22.4	58	62.4	57.6	117.75
San Diego	74.87824	172.6	354.2	1971.8	2951.4	4634.4	10605.5
Sao Paulo	0.2	2.4	5.2	12.8	10.6	19.6	22.5
Seattle	27.08527	112.8	337	834.4	972.8	1350.4	3352.25
Seoul	1.4	9.8	129.6	431.2	782.4	1239	1908

Shanghai		2.2	3.2	8.4	21.2	102.4	461.75
Singapore	0	0.6	12.2	45.4	152.8	156.2	224
Stockholm	16.66534	25.2	37.6	104	121.4	253.4	299.25
Stuttgart	23.00356	41.2	64	81.8	118.2	87.4	133.25
Sydney	13.27	25	35.6	65.8	158.2	305.4	582.75
Taipei	3.6	3.8	40.4	135.8	252.6	279.6	440.75
Tokyo	979.9013	2102.6	3238.8	3599.8	4759.2	4355.6	6499.75
Toronto	42.49153	138.4	286.6	771.8	572.2	1040.8	1480.25
Vancouver	8.2	21.6	79.8	243.4	309.4	412	774.5
Vienna	9.8	29.4	41.4	82.4	63.8	79.8	250
Zurich	28.29223	53.8	83.4	102.6	122.8	178.2	362.5

Table C.5 Indegree strength of all cites in the chemical network

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
Atlanta	0.138851	0.154861	0.159832	0.15958	0.162572	0.159816	0.157938
Auckland	0.005644	0.015839	0.029373	0.049156	0.044962	0.066631	0.077491
Austin	0.130188	0.142643	0.147394	0.142258	0.156378	0.151716	0.145169
Bangalore	0.002447	0.005052	0.00886	0.013588	0.037928	0.075758	0.072942
Barcelona	0.034228	0.037476	0.062628	0.081515	0.08615	0.078271	0.097562
Basel	0.173098	0.17342	0.15758	0.154966	0.138227	0.137798	0.142507
Bay Area	0.220337	0.208419	0.196029	0.183451	0.182174	0.176392	0.163277
Beijing		0.016257	0.032222	0.0665	0.083026	0.092762	0.101609
Berlin	0.105458	0.114961	0.128319	0.123994	0.119936	0.124739	0.123235
Birmingham	0.111921	0.087573	0.102082	0.09804	0.098278	0.083877	0.091123
Boston	0.212577	0.205849	0.196769	0.183411	0.180247	0.179345	0.16544
Brussels	0.101793	0.092794	0.100765	0.113035	0.115804	0.109327	0.116838
Buenos Aires	0.035149	0.021539	0.028788	0.04979	0.042368	0.053885	0.070286
Chicago	0.225111	0.198532	0.191899	0.178136	0.178221	0.172049	0.164187
Copenhagen	0.100663	0.10082	0.126433	0.136363	0.132846	0.129948	0.140022
Dallas	0.147689	0.156934	0.161582	0.165165	0.161519	0.154418	0.15012
Delhi	0.008977	0.008173	0.015735	0.043482	0.071494	0.058966	0.076488
Dublin	0.031959	0.046632	0.050929	0.06832	0.071616	0.066721	0.097695
Dusseldorf	0.213293	0.204013	0.183639	0.17611	0.16946	0.162281	0.156459
Eindhoven	0.083993	0.090583	0.089464	0.093423	0.08554	0.083069	0.094413
Frankfurt	0.124146	0.11374	0.118298	0.11055	0.111879	0.122921	0.1129
Glasgow	0.066664	0.045508	0.076004	0.075759	0.071897	0.063564	0.096738
Grenoble	0.0962	0.110033	0.102356	0.101398	0.098917	0.099015	0.104332
Guangzhou			0.011644	0.003569	0.013492	0.041661	0.068921
Hamburg	0.083041	0.094193	0.104014	0.113078	0.099456	0.102865	0.102139
Helsinki	0.061096	0.090377	0.0952	0.110219	0.117045	0.121475	0.116106
Hong Kong	0.008064	0.015829	0.022243	0.051831	0.077965	0.089022	0.08584
Houston	0.195607	0.189956	0.189926	0.172423	0.171828	0.171139	0.15867
LA	0.214737	0.200387	0.189113	0.181197	0.176813	0.177123	0.164612
London	0.188269	0.191263	0.174482	0.168252	0.168044	0.163782	0.155877
Lyon	0.142824	0.142458	0.140216	0.138357	0.141435	0.12737	0.134552
Madrid	0.027797	0.042456	0.042902	0.055375	0.069654	0.070274	0.083715
Manchester	0.12647	0.119448	0.114956	0.108932	0.09962	0.107605	0.104636
Mexico City	0.030304	0.028351	0.043989	0.039005	0.048963	0.043028	0.069643
Miami	0.123499	0.138747	0.144029	0.151978	0.147314	0.146237	0.148509
Milan	0.15318	0.163147	0.151418	0.148762	0.146571	0.136116	0.136057
Montreal	0.123659	0.128129	0.130234	0.135985	0.136788	0.142399	0.143835
Moscow	0.103701	0.079763	0.077324	0.10827	0.103041	0.106471	0.114462
Mumbai	0.021165	0.035267	0.030765	0.036098	0.054587	0.055958	0.077578
Munich	0.124314	0.138355	0.130151	0.123759	0.11602	0.122915	0.122585
Nagoya	0.156112	0.166012	0.165955	0.161684	0.159432	0.148475	0.146812
NYC	0.237667	0.218605	0.197729	0.185411	0.183073	0.178104	0.162754
Osaka	0.213444	0.210985	0.194115	0.180167	0.17412	0.172695	0.159516
Oslo	0.055587	0.05808	0.074173	0.091699	0.092491	0.096208	0.108175
Paris	0.189814	0.190879	0.188078	0.175502	0.171455	0.166038	0.160079
Pittsburgh	0.199049	0.184304	0.172767	0.15865	0.155802	0.159795	0.150884
Rome	0.096401	0.090379	0.08707	0.106878	0.092388	0.090925	0.093359
San Diego	0.149539	0.159154	0.161733	0.174362	0.172347	0.172773	0.161675
Sao Paulo	0.007506	0.022602	0.029151	0.030843	0.035341	0.050918	0.049346
Seattle	0.116619	0.135504	0.162216	0.157505	0.158791	0.161933	0.160429
Seoul	0.013439	0.044253	0.120793	0.133507	0.152467	0.158443	0.149983

Shanghai		0.015085	0.017878	0.02951	0.051013	0.078166	0.122869
Singapore	0.003486	0.006592	0.034272	0.068612	0.094051	0.099138	0.108289
Stockholm	0.131692	0.122244	0.121744	0.115153	0.122635	0.11459	0.11967
Stuttgart	0.106028	0.113676	0.124982	0.126916	0.127731	0.115772	0.122836
Sydney	0.084604	0.099987	0.104369	0.110863	0.115474	0.122803	0.118382
Taipei	0.01951	0.032211	0.086472	0.108354	0.115047	0.123982	0.131734
Tokyo	0.227693	0.213737	0.198391	0.182114	0.181216	0.176188	0.163199
Toronto	0.115882	0.150425	0.150297	0.158568	0.15433	0.156296	0.154808
Vancouver	0.064134	0.087426	0.120307	0.130463	0.130458	0.143787	0.134088
Vienna	0.086303	0.097306	0.098046	0.106311	0.103397	0.111311	0.112437
Zurich	0.130417	0.132548	0.129654	0.129361	0.125422	0.123001	0.12673

Table C.6 Eigenvector centrality of all our cities in the chemical network

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
Atlanta	28.8	112.8	222.8	1106.6	2352	5476.8	12592
Auckland	0.2	3.2	4.4	9.4	21.2	81.4	201.25
Austin	69.4	359.2	915.8	3800	6799.6	15400.2	23968.5
Bangalore		0	0	13.6	36.2	197.2	986.5
Barcelona	0.6	1	1.4	2.8	15.2	68	281
Basel	2	5.6	6.4	9	19.2	32	81
Bay Area	832.8	2188.8	5009.2	15316.8	42748.4	81747.6	183427.8
Beijing		0.2	2.2	10.6	28.8	329.2	1365.75
Berlin	17	36	37.6	94.4	139	322	605.75
Birmingham	13.6	32.6	31.8	54.6	82	133.4	260.5
Boston	528.4	1430	3025.8	8532.8	13980.4	29484.2	51355.5
Brussels	8.4	22.6	33.8	58.8	76.4	145.2	248.5
Buenos Aires	1	4.8	4.2	19.6	20.8	37.6	65
Chicago	377.4	1028.8	1703.6	5098.6	7448.4	13668.6	26487.75
Copenhagen	4.2	10.2	18.2	33.6	77	268.8	682.25
Dallas	287	784	1482.8	4185.4	7484.8	14751.8	24471.75
Delhi			4	6.2	23.6	132.2	340.5
Dublin	0	1.8	13.2	44.6	112	269.6	529.75
Dusseldorf	10.2	34.4	41.2	85.4	139	308.4	590
Eindhoven	156.4	376.8	505.6	818.2	997.6	1749.2	2796
Frankfurt	4	7.2	9.6	12.8	21	44	145
Glasgow	2.2	4.8	8.8	36.4	65.4	133	218.5
Grenoble	6.4	39.2	87.6	207.6	356	761.2	1496.75
Guangzhou				0.6	3.4	39	416.75
Hamburg	15.6	35	39.4	76.6	82.6	190.2	391
Helsinki	2.8	6.8	19.4	143.6	563.6	1562.8	4169.25
Hong Kong	4	12.4	19.4	68	175.4	419.2	964.5
Houston	137.8	403.6	674.4	1974.4	3180.8	5602.6	9040.75
LA	665.4	1649.8	2130.6	5228.4	8655	17990.6	36555
London	164.4	374	528.2	1037	1580.4	3297.4	5878.25
Lyon	1	4.4	5	13	23.8	38.2	78.75
Madrid	0.4	1.4	4.2	17.8	35.8	89.8	228.75
Manchester	10.8	34	41.8	68.8	114.4	173	306.5
Mexico City	1.8	1.8	1.6	3	0.6	4.2	9.75
Miami	109	362.2	847.2	2640.6	3179.4	6152.2	11105
Milan	29.4	68	127.8	221.8	282.8	492	587
Montreal	12.4	35.2	67.8	275.8	617.6	1293.6	2632.75
Moscow	6.6	11.4	11.6	25.8	100	185.8	468.25
Mumbai				0.2	4.2	24.2	63
Munich	77.6	223	273	484.4	624	1026.4	1894.25
Nagoya	96.6	466.2	714.6	1394	2264.6	3643	6521.5
NYC	1222.8	3194	5297.8	13577.4	23298.4	47657.6	88817.25
Osaka	301.4	974	2635	6984.8	8664	14320.4	21074.25
Oslo	2.8	12	28.6	70.4	102.8	235.4	525.75
Paris	298.8	650.6	754.2	1295.8	1707	2733.4	4484
Pittsburgh	65.6	155.8	232.8	583.2	901.6	1938.4	4084.5
Rome	7.2	14.4	23.4	48.8	47	102.8	251.25
San Diego	137.6	346	694.2	2138.4	4442.4	10393	23087.5
Sao Paulo	0.8	0.8	1.4	4.4	8	37.4	67
Seattle	84	209.6	366.4	1984.8	6077	16207.4	34483
Seoul	0.6	10.6	203	1771.4	4539.2	10023.8	18963

Shanghai		0	0.8	3.8	6.6	31	335.75
Singapore		0.6	11	93.4	422.6	1176	2197.5
Stockholm	43.2	101.2	119.6	466.6	1096.4	2005	3596
Stuttgart	62.2	191.2	268.4	510.6	783.6	1395.2	2697
Sydney	3	15.6	27.8	128	256.2	960.2	4755.25
Taipei	3.8	22.4	77.6	368.2	942	2136.4	4473
Tokyo	1371.8	4164.2	16469.2	26835	32299	60952.4	113018.8
Toronto	16.2	54	143	552.4	1177.6	2676.4	5200.25
Vancouver	9.6	19.8	41	212.8	472.4	1147.4	2613
Vienna	15.2	31.2	35.8	52.4	74.4	132.2	333.5
Zurich	45.2	97	130.6	276.2	311.6	561.4	1019.5

Table C.7 Outdegree strength of all cities in the ICT network

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
Atlanta	55.2	141.8	393	1373.4	3357	11032.2	23143.25
Auckland	1.6	2.2	0.6	5.6	31.2	133.6	1150.75
Austin	158.2	383.8	1159.2	6369	9029	17546	21908.5
Bangalore		0.2	3.8	19.2	218.6	1053.8	3904.75
Barcelona	0	0.4	1.6	10.4	79.8	508.2	1135.75
Basel	1	2.4	4.6	4.8	5.6	19.2	14.75
Bay Area	688.4	2001.6	5943.2	23170.2	54607.8	97328.4	228856.3
Beijing		2	2.6	22.6	105.4	1629.2	2991.75
Berlin	14.8	25.2	46.2	114.4	211.6	344.4	1072.75
Birmingham	11.4	23.6	36	50	49.8	98.8	358.5
Boston	422	1409.2	2952.8	7025.8	13856	23527.6	42241
Brussels	12.6	9.8	19.2	26.4	90.6	88.2	157.5
Buenos Aires	0.4	1.4	3.6	4.6	6	11.6	32
Chicago	406.2	992.8	1347.4	3830.4	6251.2	9415.8	18393.25
Copenhagen	4.8	16.8	9.6	48.4	174.6	383.4	475.25
Dallas	244.4	760.8	1585.6	4611.2	6729	9319.8	17212.75
Delhi			2.8	1.8	67.4	258.8	520
Dublin	1.4	7.2	18.6	57.6	173.4	304.8	873.25
Dusseldorf	10.2	22.2	29.6	80.4	175.8	309	287.25
Eindhoven	118.2	308.2	317.2	561	728.8	982.4	1159.75
Frankfurt	1.2	7.8	3	45	49.6	54	86.5
Glasgow	6.2	9.4	10.2	34.6	52.4	97.4	77.75
Grenoble	10	66.6	89	289.6	498.6	836.2	1076
Guangzhou				0.2	21.2	447.2	2155.5
Hamburg	11.4	31.6	29.8	41.8	73.6	245	300
Helsinki	3.2	13	26.2	277.4	800.6	1626.6	1839
Hong Kong	11	10.2	31.4	108	214.6	654.6	894
Houston	162	373.8	661.4	1851.6	2080.8	3260.8	5264
LA	559.8	1272.8	1833.8	4677.2	9518.6	19965	40289.25
London	98	267.4	323.2	653.4	1393.2	2928.8	4105.25
Lyon	2	3.8	4.6	11.2	23	11.8	42.75
Madrid	0.8	2	9	23.6	43.4	99	199.25
Manchester	10	22.2	27.6	36.6	54.8	107.2	99.25
Mexico City	0.6	0	1.6	1.4	6.2	9	17.75
Miami	122.6	373	1080	1762.6	1918.8	4250.8	10179.25
Milan	22	74.2	90.6	207.4	287.8	297.4	282.75
Montreal	22.8	40.2	64.8	429.8	695.6	1250.8	3839.5
Moscow	5.8	1.2	8	95.8	137.8	226.2	647.25
Mumbai				6	15.6	21	105.5
Munich	96.2	184.6	169.8	344.4	457.4	2009.6	3807
Nagoya	131.4	595.6	744	1247.8	2004	3069.8	4129.25
NYC	1077.4	2358.6	4017.4	9926	15345.6	34621.8	71350
Osaka	332.2	1493.8	3574.2	5135.6	6737.2	8993.4	9361.5
Oslo	4.6	20	44.8	77.6	100.6	388.2	636.75
Paris	266.2	413.2	525.6	730	1089	1780.8	3804.75
Pittsburgh	41.4	166	189.6	445	797.8	1661.8	3886.25
Rome	7.4	13.4	15.6	27.2	37.4	137.8	353.75
San Diego	146	345	637.6	2323.2	4734	10719.8	28034.75

Sao Paulo	0	0.2	1.2	2.4	4.4	51.4	64
Seattle	97.8	299	531.4	3347.6	8194.6	36507.8	58280.25
Seoul	1.8	59	914	4225.2	6381.2	17191.2	26244.5
Shanghai		1.4	0.6	0.8	34	367.8	1765
Singapore		4.6	33.2	171.6	1046.8	1778.6	2485.25
Stockholm	31.4	49.6	175.4	707.4	832	620	1411.75
Stuttgart	78.8	189.2	228.8	471.6	776	1009	1499.25
Sydney	5.2	24.4	48.4	110.2	764.4	2982.8	12808.75
Taipei	5.4	58	130.6	621.6	1573	3337.6	5522.25
Tokyo	1779.4	5243.2	15783.6	22385.8	25445.4	41632	67552.25
Toronto	19.6	95.6	125.6	478.4	1180.6	2996.8	5394.25
Vancouver	7.8	31.6	64.8	341.4	528.4	1486.8	3873
Vienna	15	28	29	42.2	82.2	132	168
Zurich	32.2	83.4	81	87	181.4	428.2	763.25

Table C.8 Indegree strength of patents in the ICT network

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
Atlanta	0.138776	0.155398	0.157118	0.160366	0.164338	0.157005	0.1485
Auckland	0.011744	0.028042	0.021252	0.041113	0.060362	0.075268	0.099395
Austin	0.15603	0.168421	0.174267	0.174195	0.167136	0.158635	0.149667
Bangalore		0.001431	0.013358	0.052595	0.082168	0.123903	0.139659
Barcelona	0.005218	0.0067	0.017023	0.027722	0.066065	0.110855	0.116119
Basel	0.023555	0.032234	0.037245	0.037979	0.040335	0.048585	0.057936
Bay Area	0.234616	0.207396	0.204065	0.186447	0.175526	0.16042	0.151598
Beijing		0.009766	0.015349	0.047162	0.081201	0.126201	0.137139
Berlin	0.096661	0.100014	0.099038	0.110999	0.121921	0.120564	0.122761
Birmingham	0.100934	0.095825	0.096971	0.097748	0.098037	0.094186	0.099668
Boston	0.220261	0.208001	0.198773	0.183889	0.173918	0.160252	0.150385
Brussels	0.068744	0.070938	0.082298	0.083148	0.092	0.094542	0.099062
Buenos Aires	0.012418	0.024759	0.024742	0.043911	0.051631	0.039002	0.055502
Chicago	0.223985	0.207552	0.196148	0.179508	0.171074	0.157304	0.149686
Copenhagen	0.054343	0.074133	0.076109	0.08258	0.109755	0.122314	0.120674
Dallas	0.209011	0.194824	0.192553	0.178955	0.169701	0.157185	0.149188
Delhi			0.025828	0.02543	0.064416	0.101727	0.115409
Dublin	0.010201	0.034517	0.065337	0.086512	0.102027	0.104934	0.119867
Dusseldorf	0.081423	0.105749	0.107031	0.125888	0.125075	0.119313	0.119494
Eindhoven	0.163561	0.16822	0.161881	0.153534	0.140873	0.142345	0.13426
Frankfurt	0.036234	0.053718	0.051059	0.050624	0.068697	0.073049	0.084939
Glasgow	0.049523	0.049156	0.05466	0.075131	0.089021	0.084417	0.081674
Grenoble	0.072802	0.116887	0.129034	0.129334	0.138485	0.140065	0.129616
Guangzhou				0.003423	0.035404	0.096131	0.132194
Hamburg	0.090101	0.114447	0.095827	0.097647	0.092191	0.102118	0.111055
Helsinki	0.035967	0.066254	0.084919	0.131822	0.144344	0.146054	0.140359
Hong Kong	0.064014	0.068846	0.085172	0.105661	0.117406	0.118861	0.124218
Houston	0.169212	0.167843	0.16915	0.167851	0.159097	0.154146	0.147674
LA	0.233646	0.212686	0.19732	0.181547	0.172383	0.159422	0.149808
London	0.198379	0.179992	0.175119	0.161483	0.160424	0.152062	0.146292
Lyon	0.019066	0.037583	0.038354	0.042703	0.062853	0.053812	0.067244
Madrid	0.008358	0.022194	0.035748	0.060318	0.077904	0.085811	0.092629
Manchester	0.076581	0.101004	0.087294	0.092858	0.090205	0.101444	0.093193
Mexico City	0.018068	0.01145	0.015276	0.011723	0.011976	0.019464	0.034735
Miami	0.177701	0.178972	0.187725	0.172522	0.163656	0.153809	0.147277
Milan	0.131864	0.14201	0.13122	0.131307	0.118698	0.116855	0.120285
Montreal	0.111562	0.114027	0.128654	0.135323	0.142483	0.141815	0.140155
Moscow	0.065675	0.045476	0.055009	0.076803	0.094281	0.095222	0.11578
Mumbai				0.011624	0.036657	0.046551	0.073821
Munich	0.180918	0.166367	0.153491	0.154581	0.144842	0.144942	0.140509
Nagoya	0.166411	0.183954	0.170201	0.158803	0.156827	0.148961	0.142577
NYC	0.23987	0.217277	0.206583	0.186351	0.173437	0.161014	0.151622
Osaka	0.208077	0.201265	0.195641	0.181797	0.167288	0.156869	0.147463
Oslo	0.031907	0.078516	0.08216	0.095096	0.09636	0.104619	0.112654
Paris	0.213224	0.196371	0.186017	0.169033	0.161185	0.152036	0.143898
Pittsburgh	0.168682	0.164537	0.14762	0.148193	0.142625	0.145045	0.143667
Rome	0.050622	0.079214	0.081794	0.086994	0.080283	0.085758	0.103033
San Diego	0.197541	0.179473	0.17733	0.174634	0.165696	0.159786	0.150878
Sao Paulo	0.006822	0.005817	0.012075	0.018504	0.024771	0.048935	0.050654
Seattle	0.175475	0.16738	0.166208	0.175016	0.171251	0.160072	0.149098
Seoul	0.017679	0.081486	0.16407	0.173308	0.168238	0.157129	0.148457

Shanghai		0.006371	0.006861	0.019253	0.043609	0.097141	0.129526
Singapore		0.014519	0.075805	0.115088	0.135156	0.139126	0.136846
Stockholm	0.149748	0.145814	0.139786	0.152235	0.148332	0.143971	0.142562
Stuttgart	0.165649	0.170292	0.158621	0.160829	0.151718	0.144221	0.140356
Sydney	0.042434	0.086186	0.113899	0.109025	0.124317	0.13677	0.136007
Taipei	0.050937	0.10418	0.130658	0.150513	0.154092	0.149301	0.14434
Tokyo	0.24488	0.217632	0.210097	0.186551	0.173137	0.160179	0.151413
Toronto	0.106972	0.146737	0.14233	0.149661	0.154314	0.148373	0.147286
Vancouver	0.069175	0.094204	0.116406	0.138662	0.132701	0.13946	0.143015
Vienna	0.086832	0.093444	0.093748	0.09664	0.103729	0.112707	0.105548
Zurich	0.13744	0.142307	0.140531	0.131464	0.124803	0.124147	0.130439

Table C.9 Eigenvector centrality of all cities in the ICT network

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
Atlanta	107	375.6	645.6	1585.4	2312	2865.8	6390
Auckland	4.8	13.8	25.6	48.8	89.4	128	432
Austin	42	110.4	237.8	631	1406	2468.8	5870.25
Bangalore	0		0.6	1	38	72.4	140.5
Barcelona	8.6	30	47	74.4	123.2	164.2	299.75
Basel	30.6	64.6	91	158.6	193.2	211.8	365.25
Bay Area	1004.2	2341.4	3948.6	9188.6	16997.4	28928	84322.5
Beijing		0.8	6.6	14.2	38.6	73.4	212.25
Berlin	36.4	61.4	111.2	222.2	346.2	559.8	932
Birmingham	84.8	200.2	202.8	250.4	348.8	359	580.5
Boston	817.6	1973.8	3790	7746	14014.4	20125.4	44929
Brussels	19.6	32.8	43	65.4	122.6	167.8	360.5
Buenos Aires	4	13.6	24.2	110	223	224	551.25
Chicago	1402.2	2418	3704.2	6784.6	8452.6	10169.4	19567
Copenhagen	29.6	57.6	98.2	208	394.6	757	2042
Dallas	302	824	1329.4	2799	4988	9565.4	9847.25
Delhi	0.2	0.6	2.8	0.8	1.6	9.2	20.25
Dublin	2.2	9	126.4	40	77.4	235	897
Dusseldorf	298	628.8	641.4	1065.8	1299.6	1441.4	2273.75
Eindhoven	101.8	211.4	239.4	398	561.4	829.4	1088
Frankfurt	20.8	61.8	78.8	106.6	147.4	151.4	269
Glasgow	11.4	29.6	52	62.4	89.4	125.2	320.75
Grenoble	35.2	85.4	130.4	290.8	454	557.8	887
Guangzhou		0.2	29.8	2.4	17.2	72.4	343.25
Hamburg	45.8	109.2	133.8	226	292.2	450.4	865
Helsinki	22.6	51.8	100	198.2	339.6	554.8	1059
Hong Kong	6.8	20	403.6	88.2	205.6	388.8	615.5
Houston	541.2	1231.6	2574.4	2741.2	3731.4	12025.4	24099.75
LA	1336.6	3345	4370.2	10251.6	17017.2	21053.8	57980
London	314.2	659.8	767	1354.4	1858.4	2191.6	3958.5
Lyon	42	100.2	114.4	219.8	284.6	448.8	1039.25
Madrid	3.2	10.4	35.2	29.6	64.2	88.8	173.75
Manchester	42.6	78.6	81.2	149.6	198.2	230	475.75
Mexico City	10.8	19.4	207.8	31.2	28.8	34	89.25
Miami	182.6	575.8	979.4	2298.2	3506	4227	10504.5
Milan	83.6	155.4	267.4	396.2	533.4	540	819.25
Montreal	70	165.2	242	466	758.8	938.2	1888.75
Moscow	48.2	76.8	94.4	177.2	308.2	498.6	866.25
Mumbai	0.6	0.8	80.2	4.4	7.2	9.4	13.25
Munich	138.6	383.4	597.8	598	724.2	884	1481.25
Nagoya	382.4	1045.6	2783.4	3126.2	3805	4824	6509
NYC	2442.4	4491.6	7541.8	13848.8	21900.4	28738.8	52182.25
Osaka	632	1460.6	2574.8	4892	6942.8	8466	14581.5
Oslo	12.4	32.8	269.2	90.4	134.4	214.2	436.25
Paris	429.4	1041.8	1266.8	1743	2728.4	3097	5938.75
Pittsburgh	377	787.6	1009.6	1815	2497.4	3367.6	6284.75
Rome	15.4	30.4	213.4	82	118	166.2	391.5
San Diego	245.2	568	933.8	2515.4	3846.8	7140.6	17393.75

Sao Paulo	2.8	10.8	145.6	35.6	42.4	61	138.5
Seattle	175.6	392.6	792.2	1988	2992	5074.4	11142.75
Seoul	3	17.6	68	506.6	1436.4	2786.8	4929
Shanghai		0.4	8.2	9	20.6	61.8	169
Singapore	0.8	5.6	70	37.6	134	258.4	537.5
Stockholm	101.8	239.4	470	561.8	735	1014.8	2018.25
Stuttgart	174.2	575	784.2	1409.6	1850.2	1836.2	3123.25
Sydney	28.2	85.2	166.4	338.2	598	1646	2012.5
Taipei	11	64	2444	699.6	1702.2	2411.8	4301.75
Tokyo	1790.6	6231.8	5712.2	18739.6	29045.4	26474.6	49421
Toronto	118.6	341.2	466.6	970	1387.2	1807	3189
Vancouver	30.8	73.6	140.6	329.4	707.2	862.2	1883.25
Vienna	41	58	189.2	182.6	203.6	268.8	521.25
Zurich	151.8	313.6	490	528.2	707.8	813.8	1256.75

Table C.10 Outdegree strength of all cities in the mechanical network

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
Atlanta	157	568.8	1152	3146.4	3994.8	3621	6615.5
Auckland	9.8	14.4	18.6	52.6	142.6	148.6	485.25
Austin	51	144.4	469.6	1112.2	1773.8	2284.2	6694.25
Bangalore	0.2		0.4	8.4	28.8	71.4	195.25
Barcelona	10.2	29.6	59.6	126.2	191.4	139	314.5
Basel	29	66.6	47.2	55.8	100.6	96	236.75
Bay Area	916.2	2350	4313.2	13897.2	27394	51920	140603.5
Beijing		10	16.8	33.2	101.2	264	487
Berlin	31.6	62.6	92.2	184.8	347.8	375	609.75
Birmingham	62	121.2	131.8	208	246.4	297.4	451
Boston	813.4	2032.8	4355.2	9012	16784.6	25432	53761
Brussels	10.4	24.8	26	85.2	96	139.6	148.75
Buenos Aires	5.2	10.2	26.2	57.8	113.6	67	277.25
Chicago	1405.2	1955.6	3109.6	7254.6	8865.2	8955	15255.5
Copenhagen	20.2	54.2	102.2	238.6	388.2	622.2	1993.75
Dallas	361.2	857	1506.2	3293.6	4349.2	4243.8	8720.75
Delhi	0.2	0.2	4.8	7.2	11.2	15	27
Dublin	5	12.4	142.4	87.2	126	280.2	1988.5
Dusseldorf	319	651.2	526.2	821.2	854.2	672.4	971.5
Eindhoven	79.8	173.6	190	259.2	385.2	810.4	1210.25
Frankfurt	25.6	63	53.2	89	119.6	83.6	436.75
Glasgow	11.6	24.8	39.6	40.2	72.4	97	891.25
Grenoble	37.2	95	111.8	203	498.4	379.2	526.75
Guangzhou		1	29.8	9.4	68.4	392.6	1453.75
Hamburg	43.4	94.6	116.2	149.8	194	289.8	354.5
Helsinki	29.2	72.2	136	258.8	389.4	400.6	500.75
Hong Kong	7.4	29.6	482.2	190.2	459.4	684.4	838.25
Houston	564.6	1485.2	2969.6	2975.4	5933.2	17319.2	27244.75
LA	1166	3259.8	4259.6	9708.2	16630.8	18717.6	46861.75
London	235.2	507.2	441.2	805	1159.6	1202.8	2746
Lyon	31.2	81.2	100.2	127.2	150.2	184.2	324
Madrid	6.6	14.6	35.2	37.6	52.6	92.2	125.5
Manchester	29.2	58.4	57.4	80.8	148	136.6	197.5
Mexico City	6	10	165.8	14.4	38.4	28.8	219.75
Miami	217.2	598.4	868.4	1663.4	2567.4	3233.4	7240.25
Milan	63.6	146.6	207	221	295.6	333.8	675.75
Montreal	69	157	248	400.2	668.6	837.4	1904.75
Moscow	30.4	32	43.4	146	180	153	336.75
Mumbai	0.6	0	59.2	3.8	18	20.2	37
Munich	153.6	290.2	429.6	301.4	398.6	679.8	1331.5
Nagoya	421	1174.8	2533.4	3021.6	3428	4258.2	4640.25
NYC	2146.6	3612.2	7091.8	11425.4	14030.8	18551.4	28991.75
Osaka	729.8	1722.8	2602.2	3590.2	4677	3950	5305.25
Oslo	15.8	22.8	215	75.2	170.4	239.4	335
Paris	391.6	804.6	1105.8	989.2	1500.4	1324.4	2577.75
Pittsburgh	339.4	872.4	1024.8	1683.6	2139.4	2664.2	4827.75
Rome	13.6	27.2	305.4	40.2	52.6	46.2	85.25
San Diego	219.2	702.6	1343.2	3441.8	6489.2	10368.6	27522.75

Sao Paulo	2.8	10	211.8	36	40	71.4	253.75
Seattle	243.8	661.8	1033	2575.4	3872.8	6619.8	14284.75
Seoul	7.4	46.4	261.6	1547.6	2802.2	4736.2	5961.25
Shanghai		6.8	14.6	10	77.4	335	1046.25
Singapore	1	12.6	49	101	670	582.4	1073.75
Stockholm	89.2	150.8	467.4	473.6	508.4	451.6	603
Stuttgart	224	564.8	750.4	1127.4	1794.4	1629	2508
Sydney	41.6	94.6	212.2	563.2	1268.2	4141.4	6139.25
Taipei	25.2	147.8	2705.8	986.2	2416.6	2628.4	3859.75
Tokyo	2163.2	6812.4	4825.6	14637.8	21138.4	14627.2	25687
Toronto	115.2	367.4	546.8	962.8	1358.8	1715.6	2873
Vancouver	40.8	96.4	255.2	466	798.4	961.2	2277
Vienna	40	76.8	130.4	92.8	128.6	130.4	317.75
Zurich	133.4	247	335.75	319.6	429.8	465.2	767

Table C.11 Indegree strength of our patents in the mechanical network

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
Atlanta	0.155411	0.157866	0.158088	0.161524	0.153691	0.152083	0.143255
Auckland	0.044116	0.056108	0.065344	0.080669	0.098376	0.102481	0.113098
Austin	0.104955	0.119883	0.140202	0.14235	0.14278	0.143652	0.143442
Bangalore	0.001027		0.003289	0.014936	0.044497	0.066026	0.099777
Barcelona	0.052923	0.08319	0.098503	0.108596	0.112154	0.102932	0.11037
Basel	0.106321	0.107685	0.108021	0.107068	0.110348	0.102193	0.104791
Bay Area	0.199595	0.178208	0.169812	0.164987	0.156821	0.155182	0.14579
Beijing		0.028773	0.035094	0.052966	0.08265	0.098637	0.114462
Berlin	0.106719	0.108742	0.11735	0.123049	0.129376	0.129646	0.127455
Birmingham	0.126709	0.137277	0.126245	0.120545	0.120092	0.117358	0.122434
Boston	0.195142	0.17811	0.170429	0.164127	0.158296	0.156098	0.14595
Brussels	0.071794	0.084434	0.088837	0.09601	0.087896	0.097369	0.096304
Buenos Aires	0.032879	0.051262	0.062984	0.085024	0.080516	0.08196	0.104724
Chicago	0.203082	0.180922	0.170789	0.165995	0.157704	0.155238	0.14528
Copenhagen	0.091267	0.113381	0.121491	0.12217	0.126471	0.122587	0.133875
Dallas	0.170747	0.16767	0.16065	0.160472	0.154196	0.152295	0.143786
Delhi	0.001569	0.002565	0.012349	0.011301	0.018328	0.024698	0.045874
Dublin	0.028037	0.046797	0.080492	0.087525	0.092033	0.098136	0.119972
Dusseldorf	0.176932	0.172121	0.150411	0.155392	0.149067	0.145214	0.140382
Eindhoven	0.122656	0.123204	0.125439	0.124454	0.126771	0.131449	0.126686
Frankfurt	0.092119	0.099028	0.102465	0.099537	0.10709	0.096291	0.102721
Glasgow	0.059151	0.07769	0.087304	0.083538	0.088161	0.098244	0.101152
Grenoble	0.11033	0.121985	0.100452	0.12544	0.134544	0.124391	0.126003
Guangzhou		0.003733	0.036818	0.024977	0.060477	0.099734	0.119908
Hamburg	0.125808	0.125037	0.122545	0.121836	0.121631	0.126859	0.127027
Helsinki	0.095509	0.120877	0.118549	0.124319	0.128583	0.125365	0.126675
Hong Kong	0.043251	0.070994	0.099775	0.109945	0.125427	0.127247	0.121823
Houston	0.179202	0.173705	0.16626	0.161488	0.154104	0.154878	0.146232
LA	0.200368	0.183833	0.167594	0.165586	0.158813	0.154797	0.145259
London	0.182489	0.168897	0.152526	0.153315	0.148917	0.149126	0.142765
Lyon	0.1123	0.126075	0.110512	0.123428	0.116749	0.122868	0.126457
Madrid	0.036037	0.060474	0.076359	0.067155	0.078902	0.079963	0.094568
Manchester	0.107114	0.113401	0.104947	0.105476	0.114748	0.106215	0.11081
Mexico City	0.047755	0.051876	0.076262	0.054782	0.064096	0.057495	0.077617
Miami	0.166339	0.161105	0.155549	0.158141	0.151072	0.152463	0.143125
Milan	0.132027	0.133879	0.139656	0.137552	0.131613	0.128229	0.133723
Montreal	0.136868	0.14028	0.136715	0.140713	0.141876	0.135982	0.137295
Moscow	0.116465	0.102489	0.080002	0.113296	0.1135	0.114027	0.116794
Mumbai	0.005974	0.003766	0.038591	0.018159	0.030842	0.038952	0.046403
Munich	0.148224	0.154923	0.148494	0.140149	0.1415	0.135686	0.13664
Nagoya	0.172179	0.165651	0.165995	0.160827	0.151515	0.153279	0.142408
NYC	0.204491	0.181388	0.171274	0.165489	0.157576	0.156036	0.14443
Osaka	0.190554	0.176062	0.150361	0.160739	0.156446	0.151905	0.143202
Oslo	0.069653	0.093771	0.099124	0.103753	0.101664	0.106003	0.115338
Paris	0.192619	0.175033	0.165639	0.156988	0.152372	0.150278	0.144297
Pittsburgh	0.180685	0.169094	0.143754	0.156721	0.151893	0.149012	0.144041
Rome	0.06718	0.086251	0.113428	0.087228	0.090223	0.080977	0.096811
San Diego	0.162747	0.16397	0.1399	0.159024	0.153588	0.153984	0.144908
Sao Paulo	0.024056	0.045169	0.089275	0.073073	0.07583	0.082258	0.095573
Seattle	0.166135	0.163583	0.152522	0.158876	0.153057	0.153635	0.146292
Seoul	0.037968	0.069549	0.109282	0.14458	0.149116	0.149402	0.144568

Shanghai		0.015011	0.040126	0.032047	0.073463	0.098892	0.117147
Singapore	0.008493	0.036772	0.075432	0.083361	0.112956	0.123338	0.128647
Stockholm	0.15115	0.147335	0.15473	0.139851	0.139721	0.135401	0.134118
Stuttgart	0.163319	0.165978	0.150763	0.155004	0.152015	0.149859	0.139611
Sydney	0.109148	0.120388	0.129009	0.134875	0.135343	0.139757	0.138195
Taipei	0.08175	0.115429	0.150709	0.14896	0.149868	0.150003	0.140538
Tokyo	0.200629	0.182914	0.166011	0.165021	0.15811	0.154103	0.14569
Toronto	0.149525	0.157861	0.148663	0.153516	0.150316	0.150247	0.142771
Vancouver	0.116604	0.123721	0.134899	0.138744	0.137803	0.135038	0.135238
Vienna	0.099801	0.117832	0.131217	0.114786	0.114993	0.107373	0.115117
Zurich	0.154705	0.154331	0.149571	0.142605	0.140409	0.136055	0.134984

Table C.12 Eigenvector centralities of all cities in the mechanical network

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
Atlanta	17.6	51.8	119.2	322.8	601.8	744.4	1124
Auckland	1	1.6	6	11.8	19.6	47.2	109
Austin	28.2	81.4	273.6	1041.6	2417.2	2611.6	3158.25
Bangalore			0.2	4	9.2	24.4	60
Barcelona	0.2	1.8	6.2	9.8	17.2	34.8	48.5
Basel	5	10.4	9	18.2	29.4	25.4	28
Bay Area	317	994.4	2091.6	5327.2	8754.8	12072.6	19850.25
Beijing		0.2	1	11.4	17.2	35.8	92.25
Berlin	20.8	42.8	48.6	90.8	156.8	178.2	277.25
Birmingham	19.8	26.6	30	46.8	57.8	62.6	106.75
Boston	489.4	849	1379.4	2365.2	3379.4	4689.2	7347
Brussels	11.6	12.2	7.8	14	23.2	36	35.25
Buenos Aires	0.2	0.4	2.4	5.2	6.2	11.2	12.25
Chicago	291.8	612.6	1046.6	1801	2606.6	2688.6	3732
Copenhagen	3.4	8	17.6	21.2	34.6	86.6	137
Dallas	101	274	702.4	1609.2	2706.2	3454.2	3280.5
Delhi			0.4	0.6	1.2	9.6	20.5
Dublin	0.8	2	5.6	7	16.6	32.6	47.5
Dusseldorf	21.6	44	59.8	110.6	158	176.2	229.75
Eindhoven	65.2	174	252	433.6	597.4	597.8	1425.75
Frankfurt	6	9.6	12	18	24.6	24.4	28.75
Glasgow	3.6	2.8	4.4	12	32.8	29.6	34.25
Grenoble	14.8	46	109.8	291.6	763.8	405.8	580.75
Guangzhou				0	18.2	183.6	589.5
Hamburg	5.2	14.2	19	28.2	42.4	56	60.25
Helsinki	4.8	13.8	14.8	30.6	124.2	380.2	293.75
Hong Kong	4	21.8	40.2	87.8	184.6	295.2	504
Houston	44.6	95	266	570.8	804.6	1024.6	1619.5
LA	360.2	775	1421.6	2563.6	4580.8	5981	8405
London	90	162.8	217	342.6	448.4	521.8	744.5
Lyon	6.8	18	30.2	40.4	53.2	47.2	82
Madrid	1	3.4	4.8	5.2	13.4	31.2	83.75
Manchester	8	14	18.6	35.6	44.2	54.8	62.75
Mexico City	0.6	0.6	5.2	4.8	5.6	6.8	13.25
Miami	44	117	268	527.4	758.6	824.8	1041.25
Milan	21.8	52.4	78.4	153.4	238.8	299	307.25
Montreal	15.2	34.8	56	98	161.2	277	419
Moscow	13	16.4	15.4	26.8	72	80.8	98.25
Mumbai	0.6	0.2	0	2	4.6	6.6	11.5
Munich	69.8	146.4	174.4	285.4	364.6	463.6	650.75
Nagoya	153.8	442.4	914.2	1347.8	2658.4	2955.6	4108
NYC	626.8	1662.8	2243.8	4376.2	7726.8	9054.2	11201.5
Osaka	296.2	1020.2	2381.8	4143.2	5348.6	5858.2	8081.5
Oslo	2.6	5.4	6.6	17	19	33.8	53
Paris	126.2	266.8	393.6	560.8	791.4	699	736.25
Pittsburgh	164.6	269.6	355	556	742.4	633.4	1199.75
Rome	1.2	7.6	10.8	12.6	26.4	19.4	24.75
San Diego	50.8	130.2	284.6	594.4	1251.4	1625	2048.25
Sao Paulo	0.4	2	2.4	2.8	3.6	3.6	10.5
Seattle	27.2	68.4	175.2	312.4	572	998.8	1450.25
Seoul	0.4	6	91.2	880.6	2334.8	3467.2	4690.25

Shanghai		0.4	2	4.8	12.8	54	229
Singapore	0.2	21.8	13.8	107.6	444.4	633.2	805.75
Stockholm	19.8	102.2	55.4	96.4	170	174.6	222.25
Stuttgart	78.6	89	221	356.2	579.8	636	916
Sydney	4.2	9.4	19.4	39.6	66.2	148	241.75
Taipei	1.6	1648.4	116.6	595.8	1772.2	2983.4	5333
Tokyo	971.2	2296.2	4806.2	11117.4	21894.6	22074.2	27794
Toronto	26.4	40.6	107	223.4	416.4	684.4	740.25
Vancouver	9.6	13	33	96.6	262.2	303.6	571.75
Vienna	6.8	33.4	23.2	29.6	31.6	40.4	51.75
Zurich	30.6	64.5	70.6	120.6	148.2	180	217.5

Table C.13 Outdegree strength of all patents in the other electrical equipment network

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
Atlanta	33.2	98.8	161.4	509.8	628.2	870.6	1532.75
Auckland	0.6	3.6	5.6	14.6	30.4	40	46.5
Austin	38.4	121.2	523	1637.4	2293.8	3756	4072.5
Bangalore			2.4	2.4	50.8	104.2	452
Barcelona	0.6	3.4	6.8	14.2	43.8	59.8	53.25
Basel	3.6	5.2	3.4	4.2	22.4	4.4	18.5
Bay Area	284	943.4	2285.2	7368.4	12452.4	17332.4	28088
Beijing		3.2	9.8	4.4	19.2	111.2	350.5
Berlin	25.4	44	41.6	94.8	144.2	228.6	236.75
Birmingham	13.4	17.8	16	30.6	33.2	34.4	53.5
Boston	478.8	723.4	1297.6	2485.2	4122.6	6770.8	9981
Brussels	1	6	6.2	12.6	39.4	34	21
Buenos Aires	1	1.2	4	3	4.6	14.2	13.75
Chicago	308	610.4	975.6	1546.4	2540.8	2403.6	3364.25
Copenhagen	2.8	9	17	21.6	50.6	58.8	72.75
Dallas	72.2	314.8	823.6	1470	2175.4	1859.6	2040.5
Delhi			1	1.2	9.8	27	36.5
Dublin	0	6.6	3.2	5.8	22.4	42.2	51.75
Dusseldorf	23.4	34.2	54	70	95.8	137.4	156
Eindhoven	50.4	160.2	157.2	247	458.6	1018.8	1229.25
Frankfurt	5.2	10.8	12.6	8.8	38.4	19.2	30
Glasgow	2	3.2	3.4	26.8	22.2	27.4	19
Grenoble	15.6	65.6	89	223	377.6	511.8	906.5
Guangzhou				1	83.6	879.4	1916.25
Hamburg	5.4	12.4	13	27	32.8	52.8	74.25
Helsinki	5.8	19.4	18	59.4	110.8	210.8	292
Hong Kong	5.4	29.2	57	147.8	345.2	518	803.75
Houston	35.4	160.6	282.2	467.8	659.2	805	1331.75
LA	289.4	617.4	1320.2	2060.6	4947.8	6338.6	6944.5
London	69.4	137.6	127	226.6	405.8	307	253.5
Lyon	10.2	17.4	29.8	36.4	30.4	27.4	49
Madrid	2.6	3.2	2.8	14.6	22	140.8	112.25
Manchester	5.6	8.2	8.8	36.6	43.2	27.2	32
Mexico City	0.6	0.8	0.6	3.8	5.6	3.2	11.25
Miami	59	131.6	286.6	375.4	475	494.4	906.5
Milan	20.6	62	78.2	154	235.8	168.8	187.75
Montreal	18.4	35.2	46.4	156.8	269.8	286.6	259.5
Moscow	9.6	6	23	49	74.8	59.8	37.25
Mumbai	0	0	0.8	2.2	4.4	6.2	1
Munich	63	118.8	113.6	238.6	275.4	413.6	522
Nagoya	199	606	1085.8	1628.4	2687	3019.2	3634.75
NYC	563.2	1195.8	1571.4	3460.8	6146.4	6530.4	9779.75
Osaka	358	1640	2663.4	3144	3894.4	3288.8	3899.5
Oslo	2.4	8.4	6.4	10.8	20	34.4	94
Paris	124.2	215.4	283.2	324.4	365	261.8	488.5
Pittsburgh	159	263.8	281.6	401.4	443.8	337.2	562
Rome	4.2	11.8	9.8	5.8	17.6	9.2	10.75
San Diego	48.2	144.8	373.2	710	1561.4	1773	3336.75
Sao Paulo	0.6	3.8	4.4	5.4	4	7.6	18
Seattle	37.6	118.2	264.2	705	961.8	1131	2314.25
Seoul	2	48.8	441.6	2167	3697.8	6239.2	6141

Shanghai		3.6	3.8	9.6	60.8	343.2	1054.75
Singapore	1.6	28.2	43	248.6	1193.6	1221.6	1499.75
Stockholm	19.2	96.6	53.4	128	167.2	143.6	83.75
Stuttgart	89.4	68	217.4	321.4	502.4	530	756.5
Sydney	5.4	24	18.4	32	185.4	373.2	284.25
Taipei	3	1654	292.4	1012.4	2826.4	3833	5776.25
Tokyo	1069	2079.8	4329	9354	18409.2	15185.2	19660
Toronto	27.4	55.4	141.6	226.6	360.4	754.8	703.25
Vancouver	3.8	14.2	58.6	117.6	288.2	499.8	600.25
Vienna	5.4	37.4	8	20.8	41.8	46.6	49.75
Zurich	25.2	73	84.4	74.2	91.4	104.2	170

Table C.14 Indegree strength of all cities in the other electrical equipment network

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
Atlanta	0.128577	0.155255	0.149204	0.161838	0.151754	0.155585	0.15471
Auckland	0.011726	0.029545	0.037148	0.057393	0.062722	0.071259	0.086144
Austin	0.119724	0.149588	0.164259	0.165888	0.163757	0.164776	0.157241
Bangalore			0.008586	0.01811	0.064811	0.088257	0.119616
Barcelona	0.005262	0.024187	0.044194	0.055783	0.073362	0.090971	0.081608
Basel	0.051601	0.055992	0.046969	0.039822	0.062912	0.043219	0.056721
Bay Area	0.227137	0.213268	0.202229	0.189783	0.180584	0.175825	0.168571
Beijing		0.018152	0.03248	0.042147	0.058239	0.081194	0.10674
Berlin	0.115276	0.121602	0.112605	0.125634	0.133805	0.133179	0.134159
Birmingham	0.125279	0.095563	0.090368	0.105984	0.095041	0.09315	0.101917
Boston	0.237477	0.210601	0.199082	0.190082	0.178859	0.17411	0.16683
Brussels	0.070797	0.060057	0.03873	0.052715	0.071812	0.068038	0.062548
Buenos Aires	0.007026	0.007973	0.021692	0.025917	0.026987	0.049369	0.036757
Chicago	0.233731	0.209379	0.197739	0.185048	0.178746	0.16983	0.164777
Copenhagen	0.035594	0.063068	0.073088	0.074616	0.099171	0.096004	0.096443
Dallas	0.180596	0.174491	0.180553	0.178069	0.169726	0.166338	0.161096
Delhi			0.007598	0.008401	0.027926	0.056228	0.057413
Dublin	0.006496	0.030918	0.030871	0.039784	0.058731	0.074001	0.081576
Dusseldorf	0.12752	0.134291	0.129389	0.132192	0.135986	0.129468	0.131049
Eindhoven	0.149263	0.157217	0.151751	0.147689	0.148516	0.139193	0.144639
Frankfurt	0.04804	0.068926	0.06727	0.05704	0.082331	0.068462	0.068207
Glasgow	0.034707	0.029348	0.03147	0.066976	0.074756	0.068712	0.061917
Grenoble	0.116664	0.123203	0.149052	0.147272	0.138826	0.13844	0.146283
Guangzhou				0.00415	0.076292	0.126747	0.14392
Hamburg	0.067806	0.068048	0.067114	0.074107	0.084553	0.092113	0.09671
Helsinki	0.058443	0.077383	0.078173	0.111298	0.108093	0.117947	0.123586
Hong Kong	0.041049	0.089423	0.114382	0.125401	0.135307	0.135852	0.143121
Houston	0.149462	0.161423	0.172534	0.162414	0.15734	0.156714	0.152332
LA	0.229595	0.211386	0.200761	0.1885	0.182948	0.175655	0.167188
London	0.182305	0.168841	0.167904	0.155025	0.154295	0.145785	0.142165
Lyon	0.077997	0.084952	0.101702	0.101912	0.105099	0.07979	0.095744
Madrid	0.02081	0.033287	0.027778	0.050758	0.057316	0.087092	0.099701
Manchester	0.071949	0.075715	0.079769	0.104362	0.09043	0.073498	0.078517
Mexico City	0.008655	0.006867	0.01347	0.026782	0.03025	0.025659	0.031379
Miami	0.151654	0.16718	0.170577	0.162374	0.153254	0.149524	0.150409
Milan	0.124194	0.14635	0.131526	0.132913	0.136597	0.134742	0.132146
Montreal	0.116319	0.12667	0.124129	0.129661	0.137894	0.138043	0.134978
Moscow	0.08329	0.077554	0.069437	0.079562	0.096811	0.085658	0.092502
Mumbai	0.005096	0.001193	0.004036	0.01372	0.026176	0.032299	0.028212
Munich	0.175281	0.168639	0.156089	0.160113	0.144591	0.143844	0.143468
Nagoya	0.185	0.19443	0.183782	0.178272	0.17095	0.168138	0.160717
NYC	0.247282	0.218843	0.201082	0.191057	0.181944	0.175353	0.169487
Osaka	0.219539	0.208809	0.202968	0.18527	0.17825	0.170116	0.163379
Oslo	0.026032	0.054354	0.054216	0.067081	0.061554	0.072444	0.088936
Paris	0.21139	0.196247	0.183985	0.167024	0.157864	0.154641	0.149752
Pittsburgh	0.210933	0.192719	0.175304	0.167939	0.159137	0.152064	0.155973
Rome	0.039065	0.060214	0.062663	0.053519	0.067955	0.055528	0.05157
San Diego	0.163662	0.163153	0.177928	0.17148	0.169878	0.164469	0.158944
Sao Paulo	0.008527	0.035169	0.023712	0.022118	0.017828	0.025445	0.044034
Seattle	0.143605	0.161323	0.160373	0.164739	0.164254	0.163048	0.155668
Seoul	0.014489	0.078107	0.151414	0.16744	0.17	0.170911	0.162534

Shanghai		0.016994	0.024511	0.031057	0.070589	0.116524	0.136233
Singapore	0.013952	0.098211	0.085038	0.121084	0.130182	0.14325	0.146306
Stockholm	0.131818	0.157729	0.134764	0.133142	0.136859	0.130761	0.115276
Stuttgart	0.186574	0.119548	0.167337	0.167113	0.156905	0.153275	0.150359
Sydney	0.058558	0.096364	0.081412	0.10034	0.116726	0.11966	0.11194
Taipei	0.032723	0.191199	0.159857	0.163704	0.164912	0.164446	0.16252
Tokyo	0.250205	0.17421	0.205817	0.193129	0.184137	0.176094	0.167544
Toronto	0.133521	0.102233	0.153437	0.149464	0.146797	0.15308	0.146652
Vancouver	0.061144	0.078529	0.116392	0.127782	0.132678	0.13579	0.141487
Vienna	0.050651	0.118078	0.072658	0.084329	0.081795	0.087816	0.083358
Zurich	0.150457	0.1343	0.133003	0.12877	0.121701	0.122195	0.127618

Table C.15 Eigenvector centralities of all our cites in the other electrical equipment network

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
Atlanta	313.2	806.8	29.4	110	130.8	176.8	223.75
Auckland	249.8	516.2	1.4	3.6	6.4	10	14.75
Austin	221	275.6	12.6	20.8	41.8	61.2	165.5
Bangalore	135.8	240.8				1.4	7.5
Barcelona	122.8	234.4	5.8	10.6	16	17.8	17.5
Basel	88.4	175	7.6	7	7.2	11.2	15
Bay Area	79.2	168.4	176.2	328	559.4	798.8	908.75
Beijing	60.6	114.6		0.6	3.6	3	6.5
Berlin	58	108.8	6.6	8.4	15.2	24.4	37.25
Birmingham	56.8	106.2	41.8	40.6	73.6	61.8	69.75
Boston	46.6	80.8	196.4	351	620.4	842.2	991.5
Brussels	32.2	60.6	2.4	3.2	11	6.4	13.5
Buenos Aires	31.2	58.6	0.6	4.2	4.8	3.8	5.5
Chicago	28.8	49.6	261	317.8	581.2	735.6	826.5
Copenhagen	28.8	42.8	2.4	6.8	10.2	14	32.25
Dallas	23.6	42.8	44.6	113.2	232.2	236	322
Delhi	22.2	41.2	0	0.2	0	0.6	2.5
Dublin	18	39.2	0.6	3.8	4.2	5.2	12.25
Dusseldorf	17.4	38.6	89.2	96.4	130.4	122.6	130.5
Eindhoven	17.2	32.4	11	10.8	14.6	20	25.25
Frankfurt	17	31.2	14.8	8.2	15.6	13.4	21
Glasgow	16.8	24.6	0.8	4.2	1.8	3.4	4.75
Grenoble	13.8	20.2	11.4	24.8	38.4	38.4	34.25
Guangzhou	7.4	18	0.6	0.2	1	1.6	11
Hamburg	7	16.2	18.2	20.2	32.8	69.6	73
Helsinki	6.4	12.4	4.6	2.4	11.2	14	15
Hong Kong	6.4	10.4	2	5.8	11.8	18.4	35.5
Houston	5.4	10.2	79	148.2	222.6	160.8	289.75
LA	5	10	442.4	697.2	869.6	1328.6	1762.5
London	3.6	10	79.4	90.6	110.4	96	147.75
Lyon	3.4	7.6	19	19	23.6	20	33
Madrid	3.2	7.4	1.2	3.6	6	13.8	17
Manchester	3	6	4.4	9.8	10.2	10.4	11.5
Mexico City	2	5.8	1.2	2	3.4	5.2	3.75
Miami	2	5.6	61.6	112.6	182	206.2	299.5
Milan	1.8	5.2	31.6	30.8	43.8	35.8	67.25
Montreal	1.8	5.2	17.8	37.6	61	76.2	101.5
Moscow	1.6	4.8	3	7.8	11	13	25.75
Mumbai	1.6	4.8	0.2	0.6	4.8	2.8	2.5
Munich	1.6	4.6	45.8	62	91.2	83.2	87.25
Nagoya	1.4	3.6	450	598.6	954.2	1153.2	1209.75
NYC	1.4	3.2	361.4	592.6	1052	1037.8	1382.75
Osaka	1.4	3	337.8	470.2	773.2	916	822.5
Oslo	1.4	3	7.4	9	14.4	18	28.25
Paris	1.4	2.8	102.6	145.4	211.2	182.6	219.75
Pittsburgh	1.2	2.6	67	91	114.6	147.2	220
Rome	0.8	2.6	6.4	9.8	8.6	9	13.25
San Diego	0.8	2.6	80.2	136.6	221.4	280	399.75
Sao Paulo	0.8	2.6	2.4	2.8	6	2.4	4.5
Seattle	0.6	1.6	141.4	204.8	319.4	415	680.25
Seoul	0.4	1.6	4.8	27.6	70	123.2	204.5

Shanghai	0.4	1.4	1.4	0.2	1.2	2.8	10.5
Singapore	0.4	1.2	3.2	1.6	3.6	12.6	15.25
Stockholm	0.4	1.2	19	21.6	36	46.8	50
Stuttgart	0.2	0.8	291.8	390.8	637.2	559.4	519.25
Sydney	0	0.6	6.6	14.8	25.8	31.4	34
Taipei	0	0.2	21.2	54	145.6	169.6	279.25
Tokyo		0	1233	1471.8	2280.8	2900.2	3322.5
Toronto		0	47	79	153	203.2	246.5
Vancouver			13.6	33.2	62.2	74.6	100
Vienna			52.8	21.2	34.6	23.6	38.5
Zurich			14.4	24.4	37.8	30.6	45.75

Table C.16 Outdegree strength of all patents in the transport network

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
Atlanta	17.2	25.8	82.8	183	234	376.2	315.25
Auckland	0.2	1.8	3.4	4.2	12.6	7.8	2.5
Austin	4.8	6.4	22	37.8	57.8	336.4	278.75
Bangalore						8.6	47.5
Barcelona	3	8.2	3.4	6.4	1.6	12	8.75
Basel	1.4	3.4	2.8	7.6	3	1.6	25
Bay Area	44.6	119.2	184.8	314.4	605.6	976	1191.25
Beijing		0.6		4.2	4.2	5.4	32.75
Berlin	0.8	2	2.6	10.4	29	35.4	43.25
Birmingham	15.6	27.4	29.6	24	51.6	31.4	29.75
Boston	55.8	119.6	266.6	454	939	1089.8	1322
Brussels	2	1.6	4.2	7.8	9.6	6.4	11
Buenos Aires	0	0.2	7	1	8.8	5.6	9
Chicago	83.8	152.6	228.4	350.2	695.4	676.6	792.5
Copenhagen	1	1	1.4	9.2	5.6	5.4	18
Dallas	24.6	32.6	84.2	182	368	335.4	413.75
Delhi			0.2	0	0.8	5.8	1.75
Dublin	0	0.2	0.6	7.4	2.6	2.2	4.25
Dusseldorf	31.8	41.2	72.2	69	73.8	67	119.25
Eindhoven	3.4	5	2.6	5.6	8.8	14.8	40.5
Frankfurt	2.8	8	12.4	0.4	26.6	11.6	26.5
Glasgow	0.6	1	0	0	1.2	1.4	22.75
Grenoble	1.4	13.2	10.6	27.2	40.2	29.4	40.25
Guangzhou			0.2	0	16.4	19	40
Hamburg	3.6	15.6	10.6	19.6	32.4	46.8	178.75
Helsinki	3.2	3.4	6	5.4	16.6	12.2	1.75
Hong Kong	1	0.6	4.2	9	21.6	26.8	74.5
Houston	19.8	58	76	179.8	213.8	143.4	200.25
LA	87.4	195	489.8	833.4	926.2	1269.6	1790.25
London	37.8	53.8	53.2	51.4	107.8	81.6	106
Lyon	8.8	10	10.8	9.2	14	14.8	27.75
Madrid	0.2	2.8	2.4	11.8	8.6	19.8	53
Manchester	3	2.8	1	4.8	15.6	8.2	9
Mexico City	1	3.2	0.4	0.4	1	0.8	11.25
Miami	13.6	45.2	66.2	106.2	160.6	153.2	326.5
Milan	12.6	19	15.2	19.6	38.6	24	54.25
Montreal	5.2	10	17.4	17.6	56.2	67	129.5
Moscow	2	0.4	3	14.4	27.4	3.4	5.5
Mumbai	0.2	0	0	3.4	5.2	2.2	0.25
Munich	15.6	33	20.8	37.2	79	59.6	104.25
Nagoya	315	400.8	332.2	625.4	749.8	1130.8	1110
NYC	103.8	225.4	326.6	528.2	845.2	746	936.25
Osaka	86	258.2	440	309.2	613.4	758.2	524.5
Oslo	2.2	1.6	6.6	8.8	20.2	17	39.75
Paris	59.2	73.6	83.6	74.2	97.4	122.6	224.25
Pittsburgh	33	29.8	87.2	101.6	126.8	87.2	189.25
Rome	2.4	3.6	9.2	3.2	6.8	2.6	2.75
San Diego	22.8	61	105.6	145.2	292	257.6	512.5
Sao Paulo	0	2.2	1.4	3.4	1.8	1.6	8
Seattle	41.4	92.2	132.8	250.4	321.6	751.2	795
Seoul	1	5.2	19.8	79.4	136.4	236.6	551.5

Shanghai		4.6	2.4	0	2	16	33.75
Singapore	0.4	1	8.4	8.4	10.4	14.6	27
Stockholm	6	3	10.6	21.6	20.4	16.8	40.5
Stuttgart	203.2	222.8	361.4	467.4	740.4	355	447
Sydney	1.8	8	8.6	16.8	47.4	75.8	100.5
Taipei	2.4	13.2	45.8	48.4	140.6	131.8	155.5
Tokyo	338	945.6	1073.6	1223.8	1968.8	2317	2301.75
Toronto	9.8	24.4	62	117.6	208.8	505.4	423.5
Vancouver	5.8	19.4	23.2	42.4	64.8	131.2	310.75
Vienna	28.2	45	46	11	26.6	20.4	30
Zurich	3.2	23.8	8	10.2	15.6	12.8	45.25

Table C.17 Indegree strength of all patents in the transport network

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
Atlanta	0.1254	0.124853	0.158141	0.169767	0.171798	0.175764	0.166332
Auckland	0.002246	0.017315	0.028578	0.029764	0.059963	0.052825	0.044652
Austin	0.042897	0.074715	0.102597	0.110089	0.119635	0.135399	0.139622
Bangalore						0.014398	0.096678
Barcelona	0.037984	0.054531	0.046288	0.066075	0.050251	0.074973	0.056834
Basel	0.014384	0.055145	0.051863	0.039348	0.038886	0.044437	0.074994
Bay Area	0.22838	0.217192	0.200303	0.203813	0.194466	0.203848	0.194054
Beijing		0.005917		0.021681	0.030879	0.041027	0.076414
Berlin	0.035898	0.050097	0.0454	0.063087	0.090677	0.094138	0.099878
Birmingham	0.166595	0.12277	0.140365	0.131324	0.129008	0.123451	0.10873
Boston	0.223235	0.213268	0.211058	0.207502	0.206124	0.208403	0.193365
Brussels	0.020494	0.032126	0.036055	0.038856	0.060319	0.055493	0.066176
Buenos Aires	0.004328	0.009283	0.033463	0.027548	0.049133	0.026209	0.041991
Chicago	0.22619	0.223959	0.21454	0.2044	0.194833	0.187891	0.184037
Copenhagen	0.03116	0.028313	0.028008	0.052605	0.061894	0.057726	0.071877
Dallas	0.164878	0.157619	0.174599	0.181391	0.186333	0.172893	0.170892
Delhi			0.001888	0.001506	0.005177	0.016644	0.015615
Dublin	0.007768	0.001984	0.009871	0.026988	0.031788	0.026886	0.037195
Dusseldorf	0.174825	0.186605	0.186537	0.161251	0.155858	0.153686	0.148315
Eindhoven	0.040309	0.046651	0.04892	0.060762	0.059435	0.080315	0.091995
Frankfurt	0.023789	0.061252	0.066897	0.038748	0.079376	0.04875	0.061426
Glasgow	0.003678	0.015643	0.005283	0.022137	0.01556	0.026192	0.041083
Grenoble	0.018554	0.065314	0.077091	0.103295	0.101144	0.102707	0.096811
Guangzhou			0.0058	0.001416	0.030949	0.061689	0.08254
Hamburg	0.069408	0.107823	0.105322	0.098401	0.114463	0.117277	0.134594
Helsinki	0.018511	0.045193	0.043935	0.041494	0.072731	0.074674	0.05201
Hong Kong	0.020901	0.024221	0.035387	0.066963	0.073215	0.096886	0.106858
Houston	0.152602	0.181138	0.170278	0.181001	0.170878	0.170615	0.15667
LA	0.267312	0.241419	0.235798	0.221109	0.203524	0.213061	0.200388
London	0.192967	0.187536	0.172508	0.153142	0.166222	0.14827	0.153918
Lyon	0.092574	0.103253	0.090867	0.090627	0.085853	0.091981	0.102348
Madrid	0.008506	0.02826	0.024238	0.05986	0.043969	0.052345	0.07656
Manchester	0.031804	0.061015	0.032962	0.062238	0.070359	0.052085	0.063855
Mexico City	0.035236	0.029771	0.008862	0.016871	0.024429	0.022619	0.036593
Miami	0.135194	0.168938	0.181015	0.177177	0.164593	0.166124	0.168352
Milan	0.116796	0.129805	0.112349	0.121748	0.12806	0.094803	0.126441
Montreal	0.075207	0.108249	0.118308	0.110715	0.134597	0.140912	0.12491
Moscow	0.023155	0.023781	0.035139	0.071206	0.062971	0.056724	0.060892
Mumbai	0.006687	0.001831	0.001888	0.014873	0.021467	0.016841	0.010815
Munich	0.144313	0.15098	0.138618	0.14101	0.147814	0.13993	0.143622
Nagoya	0.226047	0.221959	0.211903	0.202954	0.187759	0.191221	0.182102
NYC	0.27314	0.247348	0.232027	0.219983	0.211882	0.20903	0.195712
Osaka	0.240309	0.204011	0.220558	0.205273	0.19424	0.195496	0.180278
Oslo	0.039312	0.032267	0.056709	0.056524	0.074737	0.087681	0.086741
Paris	0.219316	0.200213	0.184267	0.183539	0.175022	0.167424	0.165658
Pittsburgh	0.181741	0.151313	0.171837	0.153728	0.160746	0.151305	0.152896
Rome	0.033923	0.041288	0.054695	0.054615	0.049832	0.040723	0.051311
San Diego	0.171878	0.185166	0.186086	0.19176	0.187288	0.173108	0.174994
Sao Paulo	0.017447	0.032254	0.019853	0.030433	0.025709	0.019087	0.046472
Seattle	0.181619	0.211475	0.203486	0.198116	0.188275	0.188087	0.181122
Seoul	0.008593	0.049547	0.078787	0.135522	0.140274	0.168008	0.168672

Shanghai		0.048248	0.018879	0.001632	0.011073	0.044244	0.080124
Singapore	0.010217	0.012032	0.037117	0.040752	0.048712	0.055386	0.075972
Stockholm	0.089783	0.057158	0.101748	0.117893	0.10969	0.115863	0.118925
Stuttgart	0.233262	0.208282	0.20213	0.193816	0.193804	0.187634	0.178504
Sydney	0.051495	0.071159	0.072571	0.102737	0.12054	0.117539	0.104792
Taipei	0.050478	0.081677	0.144774	0.148858	0.162614	0.164878	0.168023
Tokyo	0.258678	0.254404	0.237891	0.22293	0.213806	0.211301	0.198552
Toronto	0.155469	0.120872	0.162155	0.174638	0.164795	0.173557	0.164391
Vancouver	0.08697	0.118428	0.113276	0.130527	0.138618	0.145957	0.146692
Vienna	0.074729	0.115643	0.088757	0.085444	0.0821	0.069821	0.092536
Zurich	0.093736	0.118068	0.10171	0.099619	0.104913	0.105527	0.109036

Table C.18 Eigenvector centralities of all cities in the transport network

	1981	1985	1990	1995	2000	2005	2010	2014
Auckland	6	16	12	23	97	165	301	1505
Bangalore			1	16	19	400	1653	4629
Barcelona	1	15	25	69	223	275	336	836
Basel	85	86	136	81	137	150	423	835
Beijing			14	54	67	242	2405	2718
Berlin	38	66	90	146	376	463	1057	854
Birmingham	40	44	105	153	208	148	466	647
Brussels	18	21	31	42	144	239	377	320
Buenos Aires	2	6	9	33	70	94	99	229
Copenhagen	24	60	90	132	374	529	1574	2617
Delhi		1	3	4	37	203	402	795
Dublin	0	8	42	33	210	416	763	2767
Dusseldorf	267	346	535	599	786	806	944	1790
Eindhoven	64	142	338	299	497	663	1923	2617
Frankfurt	33	79	61	51	97	116	255	1121
Glasgow	16	32	32	57	112	95	197	930
Grenoble	35	71	136	208	539	914	1373	1467
Guangzhou				5	9	191	1659	3039
Hamburg	31	60	107	135	162	174	660	726
Helsinki	29	48	79	149	568	888	1950	2289
Hong Kong	31	18	72	190	465	836	1344	2171
London	264	430	858	888	1731	2679	5525	8108
Lyon	36	82	123	136	209	215	364	427
Madrid	5	15	22	17	83	110	536	380
Manchester	28	63	88	95	157	164	229	425
Mexico City	4	12	8	5	34	49	143	168
Milan	100	100	337	222	483	427	591	1515
Montreal	75	122	240	393	1201	1439	3222	7117
Moscow	29	23	43	107	330	230	470	1385
Mumbai	2	0	0	2	32	44	65	230
Munich	179	253	300	301	996	1153	2574	4508
Nagoya	173	498	896	1135	2110	2194	2882	2954
Osaka	413	1166	2760	4067	5034	5648	7138	8464
Oslo	18	31	41	121	196	322	807	1043
Paris	449	755	1104	1405	1998	2014	3473	6220
Rome	14	42	60	32	76	135	426	545
Sao Paulo	1	9	13	34	31	49	109	395
Seoul	11	13	218	983	4478	6095	15893	18192
Shanghai	1		14	15	29	225	1371	3132
Singapore	4	3	18	81	608	1933	2638	3637
Stockholm	77	165	177	605	1282	1062	988	1957
Stuttgart	190	310	442	500	969	1391	1808	2922
Sydney	29	63	120	264	1235	1738	6048	14943
Taipei	13	54	331	789	2622	3621	6016	7647
Tokyo	1925	4525	9079	13265	23364	27444	38500	37617
Toronto	93	276	596	960	2181	2771	6886	9320
Vancouver	24	49	217	465	1207	1509	3988	6336
Vienna	31	41	67	111	139	175	396	565
Zurich	77	156	214	255	419	650	954	1741

Table C.19 Outdegree of all cities in the US network

	1981	1985	1990	1995	2000	2005	2010	2014
Auckland	2	7	18	46	66	103	320	757
Bangalore			1	1	34	96	484	1477
Barcelona	1	6	23	61	108	98	339	590
Basel	64	128	206	281	813	388	881	1239
Beijing			4	12	44	99	665	1979
Berlin	34	57	128	217	476	533	1231	1879
Birmingham	36	86	116	175	288	390	605	899
Brussels	25	51	65	82	164	268	588	836
Buenos Aires	5	5	20	50	183	175	463	772
Copenhagen	26	51	94	158	380	643	2317	3637
Delhi		0	0	7	8	36	210	449
Dublin	1	9	10	34	107	189	868	1744
Dusseldorf	176	393	627	1080	1669	1480	3048	4231
Eindhoven	102	174	319	555	1041	1135	2744	3541
Frankfurt	8	36	61	85	152	176	297	565
Glasgow	13	18	44	30	140	153	377	572
Grenoble	32	64	116	327	875	916	1702	2810
Guangzhou				1	1	28	114	946
Hamburg	27	63	104	183	348	425	976	1443
Helsinki	20	20	60	139	425	1091	3072	5986
Hong Kong	6	10	41	91	265	497	1313	2041
London	357	582	988	1617	3093	3434	9137	13270
Lyon	28	94	145	184	414	385	926	1587
Madrid	9	9	21	30	77	125	379	659
Manchester	46	83	106	139	336	319	667	1037
Mexico City	14	9	27	30	44	36	96	179
Milan	84	143	230	429	843	867	1556	2042
Montreal	64	117	262	482	1025	1537	3574	6196
Moscow	36	63	64	179	247	469	945	1662
Mumbai	0	4	12	7	21	26	60	156
Munich	109	254	452	588	1123	1177	2787	3807
Nagoya	118	258	669	1324	2832	3467	6351	10238
Osaka	435	800	2035	4599	9743	10940	21792	33441
Oslo	11	27	41	86	230	268	758	1250
Paris	408	863	1430	2001	3927	4165	8690	12146
Rome	21	22	57	95	199	189	492	901
Sao Paulo	3	6	19	31	51	40	155	275
Seoul	3	7	44	277	2142	4639	10790	20781
Shanghai	0		3	10	17	37	196	774
Singapore	0	4	17	41	283	788	1837	3480
Stockholm	70	138	333	485	1162	1616	3502	5832
Stuttgart	84	229	502	722	1370	1806	3743	5694
Sydney	18	32	95	224	622	846	2705	5327
Taipei	5	9	124	528	1846	2837	6494	10700
Tokyo	1500	3386	7953	17072	39155	45763	88517	125041
Toronto	88	157	467	836	2332	2871	7355	10958
Vancouver	37	49	109	274	839	1378	3132	5798
Vienna	22	39	81	158	290	268	647	1204
Zurich	72	145	324	457	825	909	1777	2675

Table C.20 Indegree strength of all cities in the US network