The Annals of Regional Science (2019) 63:53–83
https://doi.org/10.1007/s00168-019-00920-3

ORIGINAL PAPER

The interaction between knowledge-intensive business services and urban economy

Seungil Yum[1]

Received: 13 February 2019 / Accepted: 17 June 2019 / Published online: 27 June 2019

Abstract
While the importance of knowledge-intensive business services (KIBS) has been rapidly growing in our knowledge-based era, most studies have analyzed KIBS in European countries. This study highlights the spatial patterns and economic impacts of KIBS in the US Metropolitan Statistical Areas (MSAs) by employing a new cluster quotient (CQ) index and Seemingly Unrelated Regression model. First, this study finds that Washington, DC, plays an important role in KIBS clusters and the CQ index would be a better index than the location quotient (LQ) index for measuring the magnitude of clusters given that LQ cannot consider the agglomeration of industries into its index. Second, this study highlights that KIBS and the GDP positively interact with each other. For example, the GDP shows an elasticity of 0.084 for KIBS, and KIBS exert an impact on the GDP with an elasticity of 0.515. The findings suggest that KIBS can be an economic driver for the US MSAs, and urban practitioners should develop policies for KIBS to promote regional economic growth.

JEL Classification B41 · O21 · R11 · R15 · R58

1 Introduction

Knowledge has become the major capital for national and regional competitiveness in the knowledge-based societies, and knowledge-intensive business services (KIBS) industries have become one of the main drivers in the modern economy. KIBS are considered one of the main characteristics of the knowledge economy over recent decades (Ciriaci and Palma 2016).

Macroeconomic research has identified KIBS as one of the fastest growing sectors in terms of adding value to the output of industries as well as job creation and trade value in the economy (see, e.g., Bain and Company 2012; BIZ 2010; Eurostat 2013; Fersht et al. 2011; Mieres et al. 2012; NSF 2012; Wirtz et al. 2015). For

✉ Seungil Yum
yumseungil@ufl.edu

[1] Design, Construction, and Planning, University of Florida, Gainesville, FL, USA

example, KIBS have been among the most dynamic segments of the service sector in European countries since the mid-1980s and are one of the most rapidly growing sectors of the EU economy (Strambach 2008). European Commission (2012) reports that there are approximately 18.8 million employees in KIBS in Europe, or 11% of overall employment. The employment in KIBS grew by an average 2.3% in the period between 2006 and 2011 compared to the growth of the overall economy by 1.5%.

Not only in the EU economy, but KIBS also contribute to innovation and economic development across different regional and national contexts (see, e.g., Freel 2016). A vast body of research suggests that KIBS play an important role in the innovation and economic development across the world (see, e.g., Andersson and Hellerstedt 2009; Czarnitzky and Spielkamp 2000; Hansen 1993; Marshall et al. 1987; Miles et al. 1995; Miles 2003; Muller and Zenker 2001). For example, Duranton and Puga (2004) illustrate that KIBS can be a main driver for urban agglomeration economies with labor market interactions. This is because KIBS are particularly representative of the knowledge-based economy, since knowledge constitutes both their main input and output, and they are both processors and producers of knowledge (see, e.g., Antonelli 1998; Gallouj 2002; Herstad and Ebersberger 2014).

While authors have recognized the importance of KIBS in our knowledge-based era and have studied the relationship between KIBS and economic development, most studies have examined the role of KIBS in European countries. For instance, Muller and Doloreux (2007) point out that 54 out of 68 articles (about 80%) are researched in Europe, and only four articles are studied in North America. In addition, the distribution of authors of the reviewed articles shows that KIBS research is mainly concentrated in the disciplines of economics (39%), management and business administration (38%) and, to a lesser extent, geography and regional planning (11%). In other words, while the role of KIBS has substantially increased in the modern economy, the spatial patterns and economic effects of KIBS in the USA remain largely unexamined, bringing the necessity of studies on KIBS in the context of the USA.

Therefore, this study highlights the spatial patterns and effects of KIBS on the urban economy at the US Metropolitan Statistical Areas (MSAs) in 2015 given that KIBS are located primarily in MSAs (see, e.g., Shearmur and Doloreux 2008). To the best of my knowledge, this article is the first study examining how KIBS are distributed across the US MSAs by each KIBS field and play an important role in economic development at the MSAs level based on empirical analysis by employing a cluster quotient (CQ) index and a simultaneous equations model. To be specific, this study proposes a new CQ to highlight the spatial patterns of KIBS clusters given that the traditional location quotient (LQ) index, which is often used to measure the magnitude of clusters in prior research, has a serious issue because it cannot reflect the agglomeration of industries, which is directly related to the definition of clusters (see the CQ part for the detailed explanation). Also, this study employs a Seemingly Unrelated Regression (SUR) model to estimate the mutual relationship between KIBS and the urban economy given that they interact with each other (see, e.g., Andersson and Hellerstedt 2009; Antonelli 1998; Bain and Company 2012; BIZ 2010; Gallouj 2002; González Mieres et al. 2012; Hansen 1993; Herstad and

Ebersberger 2014; Marshall et al. 1987; NSF 2012; Wirtz et al. 2015). To be specific, in order to estimate the effect of KIBS on the urban economy and vice versa, authors should develop a set of equations. While other regression models, such as Ordinary Least Square (OLS), may contain a number of linear equations, it is unrealistic to expect that the equation errors are not correlated. This is because a set of equations has contemporaneous cross-equation error correlation. For example, the error terms in each regression equation are correlated. In contrast, the SUR model allows scholars to reflect the error terms correlated into the model with unbiased estimators for the parameters by joint analysis of the set of regression equations unlike equation-by-equation analysis in other models. Therefore, the SUR model allows us to estimate the effect of KIBS on the urban economy or vice versa by gaining efficiency in estimation based on information combined on different equations (see the SUR part for the detailed explanation). The findings from the CQ index and SUR model would play an important role in understanding the spatial patterns and effects of KIBS in our knowledge-based societies and contribute to the KIBS literature. The data used in this article were collected from the US Census Bureau, Bureau of Economic Analysis, United States Patent and Trademark Office, and American FactFinder.

1.1 The characteristics of KIBS

Since the mid-1990s, many scholars have significantly paid attention to KIBS because KIBS are growing much faster than manufacturing and other service industries and play an important role in innovation systems and support economic development at regional and national levels (see, e.g., Aharoni and Nachum 2000; Javalgi and Grossman 2014; Muller and Zenker 2001; Peneder et al. 2003). According to Miles (2005), KIBS have some important characteristics as follows: (1) they rely heavily on professional knowledge: they either are themselves primary sources of information and knowledge, or use their knowledge to produce intermediary services for their clients' production; (2) they are of competitive importance and supplied primarily to business. Some of these are traditional professional services—others are new technology-based services. KIBS are highly innovative and facilitate innovation in other industrial sectors and thus contribute to economic growth. This is because they are very information technology-intensive industries and thus play a crucial role in the diffusion of knowledge and technology (see, e.g., Antonelli 1998; Herstad and Ebersberger 2015; Katsoulacos and Tsounis 2000; Miozzo and Grimshaw 2005). In this background, among a variety of industrial fields, KIBS can be one of the most growing industries in our contemporary societies. The industries themselves not only have strong potential for regional growth, but also exert a positive impact on other industries' productivity such as manufacturing or other service industries (see, e.g., Ciriaci et al. 2015; Corrocher and Cusmano 2014; Muller and Zenker 2001; Pina and Tether 2016; Shearmur and Doloreux 2008, 2019). For instance, Muller and Zenker (2001) reveal that KIBS show a considerable growth and innovation potential and promote economic development at both regional and national levels based on 1,144 KIBS between 1995 and 1997. Corrocher and

Cusmano (2014) exhibit that KIBS are key players in innovation systems and development based on a set of 220 European regions, particularly in advanced regions. Ciriaci et al. (2015) show that KIBS have a significant innovation impact on not only the knowledge based on fields but also the manufacturing fields by analyzing 18 manufacturing sectors in four European countries (France, Germany, Italy, and the UK) between the mid-1990 s and the mid-2000s. Shearmur and Doloreux (2008) demonstrate that the distribution of KIBS over geographic regions is connected with regional economic structure by analyzing 152 urban agglomerations and 230 rural areas in Canada between 1991 and 2001. Shearmur and Doloreux (2013) find evidence that KIBS are related to the geographic pattern of innovation based on a survey of 1122 KIBS firms in Quebec, Canada. Jacobs et al. (2013) show that the location of new entries of KIBS plays an important role in a regionalized service economy by analyzing the case in the Northwing of the Dutch Randstad. Meliciani and Savona (2014) show that the location of valued-added and knowledge-intensive activities fosters regional development in large metropolitan areas by analyzing across EU-27 regions over the period 1999–2003.

Given that there is no standard definition of KIBS, researchers have tried to define KIBS sectors and examine the role of KIBS (Tether and Hipp 2002). For example, Eurofound explains that KIBS are companies that provide inputs—based heavily on advanced technological or professional knowledge—to the business processes of other organizations. The KIBS sector includes a range of activities such as computer services, research and development (R&D) services, legal, accountancy and management services, architecture, engineering and technical services, advertising and market research, among others.[1] Hertog (2000) defines KIBS as firms that rely heavily on professional knowledge, i.e., knowledge or expertise connected to a specific discipline or functional domain to provide intermediate products and services that are knowledge based. Miles et al. (1995) explain KIBS as services that involve economic activities, which are intended to result in the creation, accumulation, or dissemination of knowledge. Toivonen (2006) suggests KIBS as expert companies that provide services to other companies and organizations. As prior research indicates, there is no single definition of KIBS (Wood 2002).

This study defines KIBS as industrial fields relying heavily on the high intensity of knowledge to produce products and services. KIBS include business services (e.g., accounting, finance, insurance, and legal), technical services [e.g., technology, telecommunications, and research and development (R&D)], and educational services. This study categorizes KIBS based on prior literature using North American Industry Classification System (NAICS) as follows: telecommunications, finance, insurance, legal, accounting, technology, R&D, and education (see Appendix Table 5).

[1] https://www.econstor.eu/obitstream/10419/29335/1/610017543.pdf.

1.2 The geographic distribution of knowledge economy in the USA

In order to understand the spatial patterns of KIBS in the context of knowledge economy, it is worth exploring the geographic distribution of knowledge economy in the USA. While scholars have barely highlighted KIBS in the context of US MSAs based on empirical analysis, there are many articles on the knowledge economy at the US states level, such as regional innovation systems, innovative clusters, and innovation ecosystems (see, e.g., Acs et al. 2002; Almeida and Kogut 1999; Amin and Cohendet 1999; Audretsch and Feldman 1996; Baptista and Swann 1998; Baptista 2000; Cooke and Morgan 1999; Feldman and Florida 1994; Gertler 2003; Leamer and Storper 2014; Levy and Murnane 2005; Lundvall et al. 2002; Maskell 2001; Nelson 1993; Sonn and Storper 2008). Varga et al. (2005) highlight that whereas there are no significant results for Midwest, Northeast, and the West, there is a significantly negative result of the South region for regional innovation systems by running pooled time series cross-sectional regressions based on 429 observations. Porter (2001) shows that the highest per capita patent-producing region (Boise City, ID) produces almost nine times the number patterns per person of the median region, and the top 10 patenting regions account for 51% of the nation's patents. Porter et al. (2001) demonstrate that California plays an important role in patenting activity as the information technology cluster and California and New Jersey are the major centers in pharmaceutical/biotechnology clusters.

Many other authors also show that the knowledge economy is largely concentrated in some regions in the USA based on empirical analysis. For instance, Feldman and Florida (1994) show that the geographic distribution of innovations is heavily concentrated in some states; 11 states, such as New York, California, New Jersey, and Massachusetts, consist of 81 percent of the 4200 innovations. Audretsch and Feldman (1996) exhibit that the distribution of knowledge economy is heavily concentrated in California, followed by New York, New Jersey, and Massachusetts. In contrast, Midwestern states, such as North Dakota, South Dakota, Montana, and Wyoming, demonstrate underdeveloped knowledge economy. Acs et al. (2002) find that 10 states are innovative clusters given that 80% of the total US activity is for innovation and 70% for patents, respectively: California, New Jersey, New York, Pennsylvania, Illinois, Ohio, Texas, Michigan, Massachusetts, and Connecticut.

The empirical evidence shows that the knowledge economy is highly clustered in some regions. It can apply to the distribution of KIBS given that they are based on the knowledge economy. In this background, this study explores the geographic distribution of KIBS across the US MSAs by employing a new CQ index in the next section.

1.3 The differences between a traditional LQ and a new CQ

Clusters are defined as geographic concentrations of interconnected businesses, suppliers, and associated institutions in a particular field (Porter 1990). To be specific, a cluster can be explained as a group of interconnected industries gather together in a specific region to share their ideas, produce products, increase the productivity with other companies, and interact with other industries. Therefore, the agglomeration of industries plays an important role in developing clusters.

However, most prior studies have employed a location quotient (LQ) index to highlight industrial clusters in regions, which cannot consider the agglomeration of industries (see, e.g., Austrian 2000; Billings and Johnson 2012; Carroll et al. 2008; Fallick et al. 2006; Fernhaber et al. 2008; O'Donoghue and Gleave 2004; Woodward and Guimarães 2009; Zook 2000). For example, Henderson and Ono (2008) highlight location patterns of manufacturing by analyzing County Business Patterns based on the LQ. The LQ index is calculated as follows:

$$LQ_{ij} = \frac{\frac{e_{ij}}{e_j}}{\frac{E_i}{E}} \tag{1}$$

where $LQij$ = location quotient, i = industries, e = employment, j = MSAs, and E = employment in all MSAs.

As we can see the equation above, while LQ may be a valuable way of quantifying the number of workers or the size of industries in the region, it has a serious problem to measure the magnitude of clusters. This is because it relies only on the number of workers. In contrast, a new CQ proposed by this article considers both the number of industries and workers as follows:

$$CQ_{ij} = \frac{\left(IQ_{ij} + EQ_{ij}\right)}{2} = \frac{1}{2}\left(\frac{\frac{i_{ij}}{i_j}}{\frac{I_i}{I}} + \frac{\frac{e_{ij}}{e_j}}{\frac{E_i}{E}}\right) \tag{2}$$

where $CQij$ = cluster quotient, $IQij$ = Industry Quotient, $EQij$ = Employment Quotient, i = industries, e = employment, j = MSAs, I = industries in all MSAs, and E = employment in all MSAs. In the index, a CQ greater than 1 indicates that the region has a greater share of the cluster than the case in the reference area. If a CQ is equal to 1, then the region has the same share of the cluster as it does in the reference area.

Equation 2 indicates that the CQ index is a better method than the LQ index given that the CQ enhances conceptual and methodological strength by considering the agglomeration of industries that is the definition of clusters. In order to highlight the flows of LQ, let us assume that there are two regions: the former region has one firm hiring 1000 workers, and the latter region has 100 firms hiring 1000 workers. The LQ calculates their cluster value as the same even though it does not make any sense for the same value given that one firm cannot make the cluster effect and is not the same with 100 firms for the cluster. In contrast, the CQ calculates the different number of firms between one and 100, reflecting the number of firms in the region into its index. The CQ index also includes the number of workers given that it shows the size and economic impact of the industries in the region. For instance, it is easy to understand that 10 firms hiring 10,000 workers have a more cluster effect than

Table 1 Top 20 MSAs of IQ, EQ, and CQ

	IQ	EQ	CQ
1	Boulder, CO (1.52)	California, MD (1.95)	Washington, DC (1.64)
2	Washington, DC (1.43)	Washington, DC (1.86)	California, MD (1.56)
3	Denver, CO (1.31)	Huntsville, AL (1.69)	Boulder, CO (1.50)
4	San Jose, CA (1.31)	Boston, MA (1.54)	Huntsville, AL (1.43)
5	Austin, TX (1.29)	Des Moines, IA (1.50)	Boston, MA (1.31)
6	Trenton, NJ (1.27)	Boulder, CO (1.47)	Des Moines, IA (1.29)
7	San Francisco, CA (1.25)	Baltimore, MD (1.38)	Denver, CO (1.28)
8	Cheyenne, WY (1.23)	Albany, NY (1.36)	San Francisco, CA (1.28)
9	San Diego, CA (1.21)	New York, NY (1.33)	Trenton, NJ (1.27)
10	Colorado Springs, CO (1.21)	Philadelphia, PA (1.33)	Baltimore, MD (1.26)
11	Tallahassee, FL (1.20)	San Francisco, CA (1.32)	Austin, TX (1.24)
12	Atlanta, GA (1.20)	Lynchburg, VA (1.31)	San Jose CA (1.22)
13	Miami, FL (1.18)	New Haven, CT (1.28)	Bridgeport, CT (1.21)
14	California, MD (1.17)	Trenton, NJ (1.27)	Philadelphia, PA (1.18)
15	Salt Lake City, UT (1.17)	Denver, CO (1.26)	Colorado Springs, CO (1.18)
16	Huntsville, AL (1.17)	Bridgeport, CT (1.26)	Tampa, FL (1.18)
17	Raleigh, NC (1.17)	Hartford, CT (1.24)	Raleigh, NC (1.18)
18	Durham, NC (1.17)	Tampa, FL (1.20)	Atlanta, GA (1.17)
19	Bridgeport, CT (1.16)	Austin, TX (1.18)	Albany, NY (1.17)
20	Provo, UT (1.16)	Omaha, NE (1.18)	Salt Lake City, UT (1.15)

The values of EQ and LQ are the same given that they are calculated by the same equation

10 firms hiring 10 workers. Therefore, the CQ index considers both the number of industries and workers into its value.

One may be still curious about the differences in LQ and CQ, the flaws of LQ, and results of measuring clusters by LQ and CQ. This study empirically provides them by analyzing the spatial patterns of KIBS clusters drew by the indices based on all US MSAs in 2015. First, Table 1 demonstrates that the spatial patterns of KIBS clusters calculated by the LQ and CQ are quite different. None of the MSAs between LQ and CQ have the same ranking within top 20th (see the EQ value given that LQ and EQ are calculated by the same equation). To be specific, California, MD, which placed first in LQ, ranked second in CQ. In contrast, Washington, DC, took first place in CQ even though it ranked second in LQ. It is reasonable to interpret that Washington, DC, has a more developed cluster than California, MD, given that the agglomeration of industries (IQ) of Washington, DC, ranked second, even though that of California, MD, ranked 14th. Not only that five out of top 20 MSAs in CQ, such as San Jose, CA; Colorado Springs, CO; Raleigh, NC; Atlanta, GA; and Salt Lake City, UT, are excluded in the LQ even though they have the high agglomeration of industries. The findings show that some important KIBS clusters cannot be measured by the LQ index. In other words, the LQ index overestimates, underestimates, and misses some important clusters, and scholars may totally misunderstand the magnitude of clusters when they apply the LQ to measure the degree of clusters given that the LQ does not reflect the agglomeration of industries that is the definition of clusters. The results empirically exhibit the differences between LQ and CQ, show the flaws of LQ, and support that the CQ index would be a better index over the LQ index. Therefore, this study highlights the spatial patterns of KIBS clusters across all US MSAs in 2015 based on the new CQ index in the next section.

1.4 The spatial patterns of KIBS clusters

Scholars have showed that KIBS cluster in large MSAs owing to benefits of the agglomeration, such as input sharing, a specialized labor force, and knowledge spillovers (see, e.g., Jacobs et al. 2013; Keeble and Nachum 2002; Muller and Doloreux 2009; Shearmur and Alvergne 2002; Shearmur and Doloreux 2008). This study shows the spatial patterns of Industry Quotient (IQ), Employment Quotient (EQ), and cluster quotient (CQ) across US MSAs in 2015. Table 1 indicates that high IQ MSAs and high EQ MSAs show different spatial patterns across US MSAs. For instance, Boulder, CO, ranked first in IQ, whereas it ranked sixth in EQ. California, MD, which ranked first in EQ, placed 14th in IQ. The biggest difference between IQ and EQ is that high IQ MSAs are more concentrated in the West and South region, whereas high EQ MSAs are more clustered in the Midwest and Northeast region, meaning that industry-centered regions and worker-centered regions are differentiated across the US MSAs (see Figs. 1, 2). This result also highlights that the LQ (LQ is calculated by the same methodology with the EQ) cannot reflect the developed IQ MSAs in the West and South region, causing a serious problem as a cluster index. For instance, 11 out of top 20 MSAs in IQ, such as San Jose, CA, Cheyenne, WY, and San Diego, CA, are ruled out in EQ.

When looking into the CQ index, Washington, DC, ranked first with a value of 1.64, followed by California, MD (1.56), Boulder, CO (1.50), Huntsville, AL (1.43), and Boston, MA (1.31). CQ has high values in the Northeast region, especially nearby Washington, DC. Also, MSAs in Colorado, such as Boulder (1.50), Denver

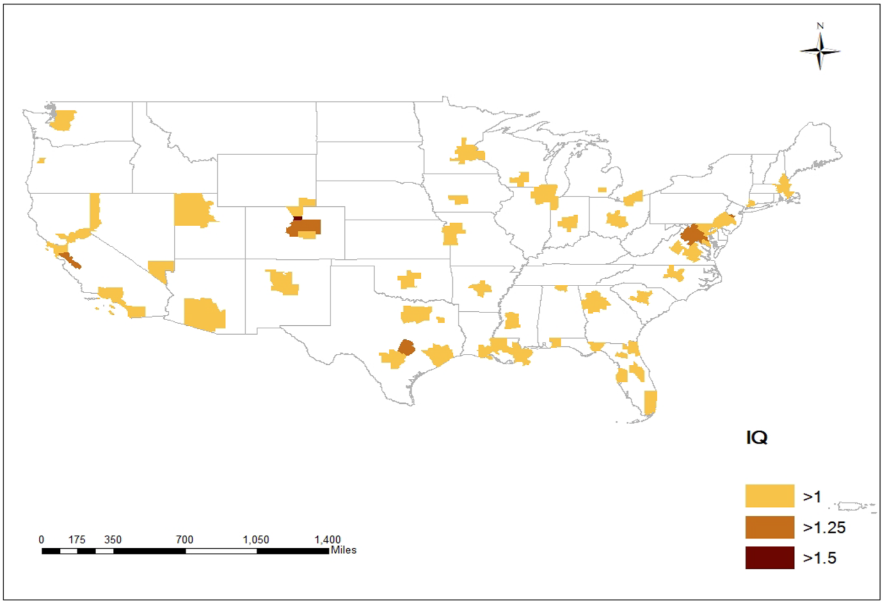

Fig. 1 Value of Industry Quotient across US MSAs in 2015

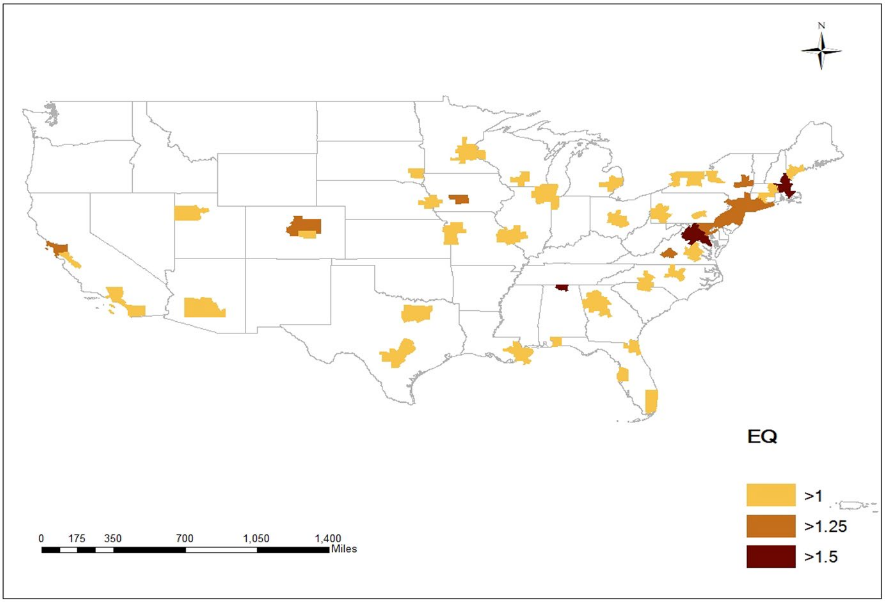

Fig. 2 Value of Employment Quotient across US MSAs in 2015

Table 2 Top 20 MSAs by KIBS fields

	Telecommunications	Finance	Insurance	Legal	Accounting	Technology	R&D	Education
1	Denver, CO (2.17)	Owensboro, KY (1.82)	Des Moines, IA (3.10)	Tallahassee, FL (1.94)	Los Angeles, CA (2.12)	California, MD (4.31)	Boulder, CO (6.99)	Lynchburg, VA (2.57)
2	Anchorage, AK (1.93)	Bridgeport, CT (1.80)	Macon, GA (2.98)	Miami, FL (1.94)	Elizabethtown, KY (1.49)	Washington, DC (2.93)	Durham, NC (6.90)	New Haven, CT (2.46)
3	Cedar Rapids, IA (1.84)	Sioux Falls, SD (1.73)	Hartford, CT (2.64)	Charleston, WV (1.88)	Warner Robins, GA (1.39)	Huntsville, AL (2.71)	Huntsville, AL (5.07)	Springfield, MA (2.16)
4	Fond du Lac, WI (1.84)	Des Moines, IA (1.70)	Madison, WI (2.04)	New Orleans, LA (1.71)	Bay City, MI (1.32)	Boulder, CO (2.39)	Trenton, NJ (4.12)	Boston, MA (1.89)
5	La Crosse, WI (1.81)	Charlotte, NC (1.56)	Harrisburg, PA (1.99)	Washington, DC (1.50)	Dalton, GA (1.31)	San Jose CA (2.04)	San Jose CA (3.55)	Rochester, NY (1.86)
6	Wilmington, NC (1.80)	Omaha, NE (1.50)	Columbia, MO (1.92)	Cheyenne, WY (1.47)	Modesto, CA (1.30)	Austin, TX (1.78)	Ann Arbor, MI (3.30)	Worcester, MA (1.60)
7	Missoula, MT (1.78)	Cleveland, TN (1.47)	Pocatello, ID (1.90)	Tampa, FL (1.40)	Salt Lake City, UT (1.27)	Baltimore, MD (1.70)	California, MD (3.10)	Syracuse, NY (1.59)
8	Cheyenne, WY (1.76)	Dallas, TX (1.40)	Lakeland, FL (1.76)	Jackson, MS (1.38)	Oklahoma City, OK (1.19)	Sierra Vista, AZ (1.63)	Washington, DC (3.05)	Albany, NY (1.57)
9	El Paso, TX (1.74)	Pensacola, FL (1.39)	Omaha, NE (1.75)	Monroe, LA (1.35)	Jacksonville, NC (1.19)	San Francisco, CA (1.61)	San Diego, CA (2.83)	Philadelphia, PA (1.52)
10	Manchester, NH (1.72)	Salt Lake City, UT (1.38)	Lansing, MI (1.75)	New York, NY (1.33)	Tampa, FL (1.18)	Raleigh, NC (1.55)	Boston, MA (2.73)	Providence, RI (1.47)
11	Blacksburg, VA (1.71)	Jacksonville, FL (1.36)	Louisville, KY (1.74)	Albuquerque, NM (1.32)	Miami, FL (1.18)	Colorado Springs, CO (1.54)	San Francisco, CA (2.69)	New Orleans, LA (1.44)
12	Tulsa, OK (1.68)	Birmingham, AL (1.35)	Columbus, OH (1.64)	Columbia, SC (1.31)	Augusta, GA (1.17)	Trenton, NJ (1.52)	Ithaca, NY (2.57)	Baltimore, MD (1.42)

Table 2 (continued)

	Telecommunications	Finance	Insurance	Legal	Accounting	Technology	R&D	Education
13	Charleston, WV (1.67)	Lawton, OK (1.33)	Tampa, FL (1.60)	Lafayette, LA (1.29)	Atlanta, GA (1.17)	Denver, CO (1.51)	Albany, NY (2.28)	Prescott, AZ (1.42)
14	Lubbock, TX (1.67)	Pocatello, ID (1.29)	Sioux Falls, SD (1.60)	Oklahoma City, OK (1.29)	Florence, SC (1.16)	Atlanta, GA (1.40)	Corvallis, OR (2.26)	Pittsburgh, PA (1.42)
15	Jackson, MS (1.64)	Phoenix, AZ (1.27)	Cleveland, OH (1.57)	Philadelphia, PA (1.28)	Richmond, VA (1.16)	San Diego, CA (1.37)	Raleigh, NC (2.07)	Washington, DC (1.38)
16	Kansas City, MO (1.59)	Columbus, OH (1.26)	Appleton, WI (1.52)	Wheeling, WV (1.28)	Bakersfield, CA (1.15)	Anchorage, AK (1.34)	Madison, WI (2.06)	Burlington, VT (1.38)
17	Atlanta, GA (1.57)	New York, NY (1.25)	Jackson, MS (1.50)	Missoula, MT (1.26)	New York, NY (1.14)	Ann Arbor, MI (1.33)	Charlottesville, VA (1.87)	New York, NY (1.37)
18	Parkersburg, WV (1.57)	Cedar Rapids, IA (1.25)	Little Rock, AR (1.49)	Santa Fe, NM (1.25)	Pensacola, FL (1.14)	Houston, TX (1.29)	Bridgeport, CT (1.84)	Dubuque, IA (1.35)
19	Saginaw, MI (1.55)	Texarkana, TX (1.24)	Lincoln, NE (1.49)	Birmingham, AL (1.24)	Wichita, KS (1.14)	Provo, UT (1.28)	Ames, IA (1.83)	Santa Fe, NM (1.33)
20	Colorado Springs, CO (1.52)	San Antonio, TX (1.21)	San Antonio, TX (1.46)	Alexandria, LA (1.23)	Kansas City, MO (1.13)	Palm Bay, FL (1.28)	Blacksburg, VA (1.82)	Erie, PA (1.33)

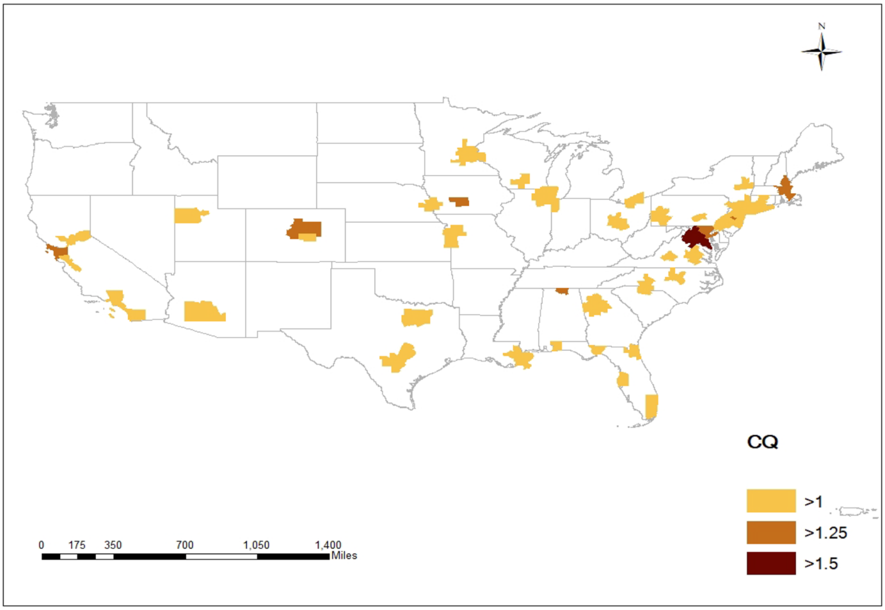

Fig. 3 Value of cluster quotient across US MSAs in 2015

(1.28), and Colorado Springs (1.18), and MSAs in California, such as San Francisco (1.28) and San Jose (1.22), show a high CQ value (see Table 2; Figs. 3, 4).

This study advances some implications for urban planners and governments based on the results of CQ. First, this study empirically shows that LQ and CQ illustrate different spatial patterns of clusters across US MSAs, and the LQ index can underestimate, overestimate, and exclude important clusters, meaning that urban planners and policy practitioners should reconsider the results of clusters, which are based on the LQ index, in the prior papers. The CQ index allows them to measure the magnitude of clusters more accurately by reflecting both the agglomeration of industries and workers. Second, this article practically highlights that the spatial patterns of IQ and EQ are different across US MSAs, meaning that urban planners and governments need to develop different policies based on their purpose. For example, high IQ MSAs have a large number of firms, meaning that the regions may have many start-up companies and a variety of industrial environments in the industry field. In this case, governments can aim to develop cluster effects and industrial networks to promote the industry field. In contrast, high EQ MSAs have a great number of workers, implying that the regions have significant job effects and major companies. In this background, governments can develop strategies based on the industry field to increase employment creation and economic development. Third, the CQ index can be utilized in any industry field as well as the KIBS field in this study because of generality. Governments and policymakers can readily compute the magnitude of clusters for other industries when they have the information on the industry's share of regional employment and firms with its share of national employment and firms.

Fig. 4 Value of cluster quotient by each field across US MSAs (Telecommunications, finance, insurance, legal, accounting, technology, R&D, and education)

1.5 The effect of KIBS on economic development

This study employs a Seemingly Unrelated Regression model (SUR) to reflect the interaction between KIBS and the urban economy in the real world. SUR, proposed by Arnold Zellner (1962), is a generalization of a linear regression model that consists of some regression equations and has been widely adopted by many authors (Carlson 1978; Kakwani 1967; Kmenta and Gilbert 1968; Moon and Perron 2008; Srivastava and Dwivedi 1979; Srivastava and Giles 1987; Wilde et al. 1999). The SUR model comprises some individual relationships from the fact that their disturbances are correlated (Hyungsik and Perron 2006). The correlation among the equation disturbances could come from industries and the urban economy given that they interact with each other. The SUR model provides a natural application for explaining the relationship between industries and the urban economy in different cities, metropolitan areas, states, and countries because the diverse entities tend to be associated with other entities. The SUR model shows the variation in not just one dependent variable, but that of a set of dependent variables (Zellner 2006). In other words, in the SUR model, each equation has its own dependent variable and different sets of exogenous independent variables. Each equation has a valid linear regression on its own and can be estimated, respectively, which is why the model is called Seemingly Unrelated (Greene 2012). Scholars have employed the SUR model for two reasons. The former is to gain efficiency in calculation by gathering information from different equations. The latter is to impose and/or check restrictions that involve parameters (Fiebig 2001; Srivastava and Giles 1987; Zellner 1962). The SUR model allows us to solve the problem of the error terms correlated between KIBS and the urban economy. It is a better model than the OLS model when the error terms are correlated because the OLS model brings a biased result, but the SUR model can consider feedback loops in the equations. For example, Zellner (1962) highlights that SUR is efficient over separate equation by equation when the correlation between disturbances is high and independent variables are uncorrelated in two-stage approach. He shows that definite gains are obtained for all samples when $|\rho| > 0.3$ where ρ is the contemporaneous correlation for the disturbances in the equations. Yahya et al. (2008) show that SUR estimators are consistently more efficient than the OLS in all cases considered in their simulation studies, especially when the predictors have Gaussian distribution. He shows that definite gains are obtained when $|\rho| > 0.333$. Alaba et al. (2010) also insist that the standard errors of the SUR estimator are consistently lower than the OLS estimator. Thus, the SUR performs better than OLS when the errors are correlated between the equations. Many scholars have proved that SUR is the better model than OLS when $|\rho| \geq 0.3$ and for at least sample size of 23 for cross-sectional data (see, e.g., Kmenta and Gilbert 1968; Kunitomo 1977; Mehta and Swamy 1976; Telser 1964; Zellner 1962). This study compares the results between OLS and SUR to verify the relationship between KIBS and the urban economy. The basic SUR model consists of multiple regression equations as follows:

$$ym = Xm\beta m + \varepsilon m \tag{3}$$

The equation can be written in matrix form:

$$\begin{bmatrix} y_1 \\ \cdot \\ \cdot \\ y_m \end{bmatrix} = \begin{bmatrix} x_1 & & \\ & \ddots & \\ & & x_m \end{bmatrix} \begin{bmatrix} \beta_1 \\ \cdot \\ \cdot \\ \beta_m \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \cdot \\ \cdot \\ \varepsilon_m \end{bmatrix} = X\beta + \varepsilon \tag{4}$$

$$\in = \left[\varepsilon_1', \varepsilon_2', \dots \varepsilon_m'\right]' E[\varepsilon] = 0 \tag{5}$$

$$E = \left[\varepsilon\varepsilon'\right] = V = \begin{bmatrix} \sigma_{11}I & \cdots & \sigma_{1m}I \\ \vdots & \ddots & \vdots \\ \sigma_{m1}I & \cdots & \sigma_{mm}I \end{bmatrix} \tag{6}$$

When there are M regression equations, the expected value of disturbance terms is zero like Eq. 5, but the value of covariance across disturbance terms is not zero like Eq. 6. In the SUR model, Cov(εi, εj) = σij; then, variance covariance matrix of ε can be easily shown as follows:

$$\Omega = \begin{bmatrix} \sigma_{11} & \cdots & \sigma_{1m} \\ \vdots & \ddots & \vdots \\ \sigma_{m1} & \cdots & \sigma_{mm} \end{bmatrix} \tag{7}$$

The covariance matrix of the stacked error terms can be equal to:

$$V = \sum \otimes In \tag{8}$$

where In is the N-dimensional identity matrix and $\otimes$ denotes the matrix Kronecker product. This study highlights the relationship between KIBS as well as KIBS clusters and the urban economy, and the SUR model in this study consists of two equations as follows:

KIBS_{2015} (or CQ_{2015}) = f (the GDP_{2012}, population, the specialization of knowledge-based industries, the diversity of knowledge-based industries, education achievement (the proportion of the bachelor's degree above), regional innovation systems (patents), Internet Information Technology (IIT) (NAICS: 519130)).

The GDP_{2015} = f (KIBS_{2012} (or CQ_{2012}), labor stock (the number of workers), capital stock (real personal income), an industrial environment (the number of all industries), demographic variables (the proportion of whites, blacks, Asians, and foreigners), education achievement).

This study sets a time lag (3 years) between KIBS (or CQ) and the GDP to solve the simultaneity problem. This method helps the author correctly calculate the causal link between KIBS and the urban economy. In this study, the first equation demonstrates the effect of the GDP on KIBS (or CQ). The number of KIBS (or the CQ value) is the dependent variable, and this study adds seven explanatory variables: first, a population in the region can be one of the important factors for the number of KIBS (or CQ) given that a larger population of the region can have a bigger market for the industries, and KIBS prefer to locate in the region. For instance, Shearmur and Doloreux (2008) highlight that KIBS increase their presence in larger cities because the labor market, synergies, and spillover effects. Andersson and Hellerstedt (2009) show that 78 percent of KIBS start-ups are stimulated by the simultaneous presence of a large market. Shearmur (2010) reveals that KIBS locate in places where many clients and markets can be found. This is because development of new products is also based on interpretations of market trends (Isaksen 2004). Shearmur and Doloreux (2019) find that KIBS are clustered in metropolitan areas to increase the likelihood of having recourse to KIBS intermediation services for the innovation activity.

Next, the specialization[2] and the diversity[3] of knowledge-based industries (KBI)[4] (see Appendix Table 6) are included as explanatory variables because the diffusion and the growth of KIBS are deeply affected by the parallel diffusion and implementation of the new knowledge and information (Antonelli 1998). The core competence common to all KIBS is the integration of various forms of knowledge given that they rely highly on knowledge to produce their products (Consoli and Elche-Hortelano 2010). KIBS rely on qualified professionals, which are experts in specific technical disciplines or functional domains, and supply information, knowledge or other knowledge-based services (Scarso and Bolisani 2010). In the KIBS sectors, competitive success comes directly from continuous technological innovations, where a single organization cannot successfully innovate in isolation; therefore, KIBS should be dependent on external relationships and networks in order to complement its knowledge domains and then develop better and faster innovations (Martín-de Castro 2015). KIBS have been found in the knowledge-based regions, because of their role as a driver of the development of the knowledge-based economy (Smedlund and Toivonen 2007). In this sense, KBI can play an important role in the industrial environment for KIBS.

Human capital can be one of the important factors for the location of KIBS since human capital has been increasingly emphasized in industrial development (Cover et al. 2011; Glaeser and Shapiro 2003; Jones 2014; Langdon et al. 2011; Shapiro 2006; Simon and Nardinelli 2002). KIBS rely heavily on the knowledge, creativity, and innovative ideas of their knowledge workers (see, e.g., Bessant 2003; Kheng et al. 2013). KIBS should hire well-educated workers with management organization, information systems, legal affairs, market research, technical testing, and much more (Tomlinson and Miles 1999). Knowledge workers contribute to promoting the specialization and diversification of knowledge products for KIBS (Strambach 2010). For instance, Yeoh and Mahmood (2013) find that knowledge workers play an important role in the development of KIBS based on 310 questionnaires. In

[2] The specialization index = Max j (Sij/Sj) Sij denotes the share of industry j in city i, and Sj is the share of industry j in national employment [see Duranton and Puga (2004) for the specialization and diversity index].

[3] The diversity index $= 1/\sum_j |Sij - Sj|$.

[4] Knowledge-based industries have been classified by various ways in the previous studies. This study classifies the sectors based on European Commission (2012), Industry Canada and the Business Development Bank of Canada (1996), NSF (2012), and OECD (2006).

this sense, education achievement can be used to analyze spatial patterns of KIBS (Growe 2016).

This study assumes that regional innovation systems hold a specific position for KIBS since they act as an external knowledge source and contribute to KIBS and KIBS are highly related to internal innovations and economic performance and growth (Muller and Zenker 2001). For instance, Strambach (2001) highlights that KIBS should establish themselves in the innovative regions to ensure their survival with new products. Innovative networks in the regions play an important role in KIBS as carriers of knowledge and intermediates for their products (Hipp 1999). In this background, regional innovation systems can be the great attraction for KIBS. This article uses the number of patents in regions as a proxy variable of the regional innovation systems. According to the existing literature, patents are a commonly used measure of the innovative intensity of firms and industries (Acs et al. 2002; Ahuja 2000; Bottazzi and Peri 2003; Fritsch and Slavtchev 2011; Jaffe 1989; Singh 2008; Stuart 2000; Whittington et al. 2009).

Next, information technology is intimately connected to development of KIBS (Antonelli 2000). It contributes to growth and competitiveness of KIBS (Hipp 2000). Not only localized knowledge, but also information inputs and high-quality information infrastructure are explanations for the spatial concentration of KIBS (Simmie and Strambach 2006). Information technology has fundamentally promoted the opportunities to effectively combine internal and external knowledge for KIBS (Smedlund and Toivonen 2007). Information technology is an important determinant of specialization in KIBS (Meliciani and Savona 2014). Therefore, information technology can be one of the important factors for the locations of KIBS (Zieba 2013). This study especially highlights the role of Internet Information Technology (IIT) given that many KIBS products, such as online games, software, programs, rely highly on the Internet environments.

In the second equation, the GDP is the dependent variable as a proxy variable for the urban economy because it represents the productivity of economic activities. This study employs the Cobb–Douglas function to estimate the productivity of KIBS (or CQ). The Cobb–Douglas function has been widely employed for large-scale studies (such as MSAs, states, and countries), which estimates between the effect of input and the change of output consistent with this study (see, e.g., Balistreri et al. 2003; Blundell and Bond 2000; ECFIN 2006; Garcia-Mila et al. 1993; Stern 2000). For example, Garcia-Mila et al. (1993) analyze the effect of public capital at the state level in the USA, using a panel data set from 1970 to 1983. Stern (2000) explores the causal relationship of the GDP and energy use in the USA in the post-war period by employing four different Cobb–Douglas models. Balistreri et al. (2003) support the Cobb–Douglas function in the context of the USA by analyzing 28 industries that cover the entire economy in the USA. Blundell and Bond (2000) analyze 509 R&D-performing US manufacturing companies in 8 years based on the Cobb–Douglas function. ECFIN (2006) employs the Cobb–Douglas function to calculate potential growth and output gaps estimates for EU member states and the USA.

Lastly, this study sets some control variables, which can affect the productivity of the regions, such as an industrial environment (the number of all industries),

Table 3 Relationship between KIBS (CQ) and the GDP in OLS and SUR

	KIBS		CQ	
	OLS (Model 1)	SUR (Model 2)	OLS (Model 3)	SUR (Model 4)
Equation 1				
INTERCEPT	−4.740	−4.659	−14.223***	−14.203***
GDP	0.054***	0.084***	0.019*	0.024**
POP	0.896***	0.871***	−0.482***	−0.486***
SPE	0.104***	0.100***	0.087***	0.087***
DIV	−0.249	−0.267	7.676***	7.670***
EDU	0.017***	0.016***	0.014***	0.014***
RIS	−0.015	−0.015	−0.031***	−0.032***
IIT	0.110***	0.108***	0.045***	0.045***
Equation 2				
INTERCEPT	−1.859	0.505	−3.999***	−3.759***
KIBS/CQ	0.262	0.515***	0.139	0.216
ALL IN	0.075**	0.069**	0.080**	0.079**
LABOR	0.036	0.039	0.031	0.031
CAPITAL	0.583***	0.334*	0.831***	0.819***
WHITE	−0.014*	−0.013**	−0.015*	−0.014*
BLACK	−0.013*	−0.012	−0.014*	−0.013*
ASIAN	−0.039*	−0.038**	−0.041**	−0.040**
FOREIGNER	0	0	0	0
EDU	0.011**	0.007	0.013*	0.012**

All variables are transferred into log values except percentage variables

Variables: the GDP, the population, specialization, diversity, education, regional innovation systems, IIT, KIBS/CQ, all industries, labor stock, capital stock, white people, black people, Asian people, foreigners, and education

Adj-R^2: model 1 (0.98/0.75), model 3 (0.78/0.75). Weighted-R^2: model 2 (0.96), model 4 (0.77)

***<0.01; **<0.05; *<0.1

population composition (the proportion of whites, blacks, Asians, and foreign-born people), and educational achievement (the number of people who have bachelor's degree above). For example, industries have been one of the main drivers for economic growth (see, e.g., Florida 2003; Hall 2000; Scott 2004), population composition is associated with the regional income (see, e.g., Bailey 1959; Price-Spratlen and Guest 2002; Reardon and Bischoff 2011), and human capital is one of the important resources for economic growth in our knowledge-based era (see, e.g., Benhabib and Spiegel 1994; Florida 2014; Gennaioli et al. 2012).

This study explores the differences in results between OLS and SUR by suggesting four models (see Table 3). When comparing each model, there are notable differences in the significance or the coefficient value for KIBS, CQ, and the GDP. For example, the GDP shows an elasticity of 0.054 in OLS (significant at the 0.01 level) and 0.084 in SUR (significant at the 0.01 level), and KIBS exert an impact on the

GDP with an elasticity of 0.262 in OLS (insignificant) and 0.515 in SUR (significant at the 0.01 level). This result highlights that the error terms are correlated, meaning that the SUR model would be a better model to estimate the effect of KIBS on the urban economy because the OLS model brings a biased result in this situation.

To be specific, in Eq. 1 of model 2, all explanatory variables except the diversity of KBI and regional innovation systems have a positive effect on the GDP at the 0.01 level, and the elasticity of each variable is as follows: population (0.871) > IIT (0.108) > specialization of KBI (0.100) > the GDP (0.084) > education achievement (0.016). This result shows that the population is the most important variable for bringing KIBS in the model, and it is reasonable given that the population is highly related to the worker's pool and the markets. Also, the result shows that governments should develop KIBS by considering knowledge-based environments, such as IIT and the specialization of KBI, as well as human capital.

In Eq. 2, the biggest difference between model 1 and model 2 is that KIBS is insignificant for the GDP in OLS, whereas it is positively related to the GDP at the 0.01 level in SUR. In contrast, the capital stock has a positive impact on the GDP at the 0.01 level in OLS, while the effect and significance of capital stock decrease for the GDP in SUR. This may be because the OLS model cannot consider the relationship between KIBS and the GDP, and the error terms correlated affect the results of equations. In other words, the OLS model may cause a serious problem, that is, KIBS are insignificant for the GDP even though they are positively related to the GDP. Moreover, KIBS have the highest elasticity (0.515) for the GDP among all explanatory variables in the SUR model. In particular, they are positively associated with the GDP when all industries (0.069) are controlled, implying that the higher proportion of KIBS can also contribute to economic development.

In model 3 and model 4, OLS and SUR show different results for the relationship between CQ and the GDP. For instance, the GDP is positively associated with CQ with an elasticity of 0.019 in OLS (significant at the 0.1 level) and 0.024 in SUR (significant at the 0.05 level), and the effect of CQ on the GDP is 0.139 in OLS (insignificant) and 0.216 in SUR (insignificant). To be specific, in Eq. 1 of model 4, the GDP, the diversity and specialization of KBI, education achievement, and IIT exert a positive impact on CQ, and the diversity of KBI shows the highest elasticity for CQ. This result shows that development strategies based on the diversity of KBI would be better than the specialization of that for increasing the magnitude of KIBS clusters. In Eq. 2 of model 4, the capital stock shows the highest elasticity for the GDP (0.819), ahead of all industries (0.079), and education achievement (0.012).

Next, this study further highlights the relationships between KIBS and the GDP by each field (see Table 4). All KIBS fields except insurance and R&D interact with the GDP. Insurance industries are positively affected by the GDP, whereas it does not exert an impact on the GDP in the model. R&D industries are not associated with the GDP in the model. This may be because R&D industries have some unique characteristics compared to other KIBS. For example, R&D industries are the only industrial field, which is not affected by the GDP and positively affected by the innovation variable. This is reasonable given that innovation environments and research funding play an important role in R&D industries and the GDP may not be an important location factor for R&D. One more notable characteristic in R&D

Table 4 Relationship between KIBS and the GDP by each field in SUR

	TEL	FIN	INS	LEG
Equation 1				
INTERCEPT	−3.023	−0.794	−6.345	−9.436
GDP	0.075***	0.072***	0.067***	0.116***
POP	1.142***	1.128***	0.893***	0.865***
SPE	0.094***	0.094***	0.108***	0.109***
DIV	−3.370	−3.458	−0.294	0.860
EDU	0.008***	0.007***	0.005*	0.013***
RIS	−0.012	−0.030**	−0.003	−0.08***
IIT	0.037*	0.064***	0.066***	0.100***
Equation 2				
INTERCEPT	−0.282	−1.003	−2.537	−0.90
KIBS	0.349***	0.342**	0.170	0.304***
ALL IN	0.072**	0.073**	0.076**	0.074**
LABOR	0.039	0.036	0.034	0.036
CAPITAL	0.512***	0.526***	0.682***	0.541***
WHITE	−0.014*	−0.015*	−0.015*	−0.014*
BLACK	−0.013*	−0.014*	−0.013*	−0.014*
ASIAN	−0.040***	−0.040***	−0.041***	0.038**
FOREIGNER	0.002	0	0	0
EDU	0.013***	0.014***	0.014***	0.013***
	ACC	TECH	R&D	EDU
Equation 1				
INTERCEPT	−6.343	−18.423***	−33.073***	−11.983**
GDP	0.074***	0.125***	0.009	0.071***
POP	0.916***	0.230	−0.286	0.639**
SPE	0.063***	0.129***	0.083**	0.048***
DIV	−0.562	7.415*	14.676**	2.623
EDU	0.005**	0.030***	0.060***	0.024***
RIS	−0.017	0.016	0.068**	0.024
IIT	0.100***	0.174***	0.147***	0.104***
Equation 2				
INTERCEPT	−1.132	−0.672	−4.430***	−0.281
KIBS	0.288**	0.296***	0	0.328***
ALL IN	0.073**	0.072**	0.079**	0.073**
LABOR	0.036	0.036	0.031	0.036
CAPITAL	0.565***	0.531***	0.853***	0.525***
WHITE	−0.014*	−0.013*	−0.015*	−0.014*
BLACK	−0.013*	−0.012	−0.014*	−0.012*
ASIAN	0.040**	−0.038*	0.042***	−0.041***
FOREIGNER	0	0	0	0
EDU	0.014***	0.004	0.015**	0.007

All variables are transferred into log values except percentage variables

Weighted-R^2: TEL (0.93), FIN (0.94), INS (0.91), and LEG (0.91)

Table 4 (continued)

Weighted-R^2: ACC (0.94), TECH (0.93), R&D (0.85), and EDU (0.94)
Telecommunications, finance, insurance, and legal
Accounting, technology, R&D, and education
***< 0.01; **< 0.05; *< 0.1

is that R&D (and technology) are not associated with the population and positively related to the diversity of KBI.

On the other hand, the specialization of KBI, education achievement, and IIT play a positive role in all KIBS fields, meaning that governments design policies based on those factors regardless of the industrial fields and should develop those factors to grow KIBS.

Also, this study finds that the GDP and each KIBS field differently interact with each other. In other words, they show different elasticities by their fields. The elasticities of the GDP for each KIBS field (at the 0.01 level) are as follows: technology (0.125) > legal (0.116) > telecommunications (0.075) > accounting (0.074) > finance (0.072) > education (0.071) > insurance (0.067). Those of KIBS for the GDP (at the 0.05 and 0.01 level) are as follows: telecommunications (0.349) > finance (0.342) > education (0.328) > legal (0.304) > technology (0.296) > accounting (0.288). The results show that the relationships are differentiated by industrial fields and governments and urban planners should develop urban planning by looking at the different characteristics of each KIBS field. For instance, governments and urban practitioners should promote innovation environments and give weight to the diversity of knowledge environments to attract R&D industries. They should take full advantage of telecommunication industries as a first driver for economic development given that it shows the highest elasticity for the GDP.

1.6 The local impact of KIBS: a case study of Washington, DC

In order to specifically highlight how KIBS exert a positive impact on economic development and suggest more urban planning implications, this study provides a case study of Washington, DC, which ranks first in the CQ index. Figure 5 demonstrates that IQ, EQ, and CQ in Washington, DC, are largely differentiated by fields and the values of those vary across the fields. For instance, Washington, DC, has the highest IQ value in the R&D field, while the MSA has the highest EQ value in the technology field. This result suggests that governments should design a different urban planning based on their purpose. For example, governments should focus more on the R&D field, which ranks first in IQ, when they try to advance industrial networks among films to create cluster effects, whereas they would rather concentrate their efforts on the technology field, which has the highest EQ, if they aim to cause job creation effects.

The figure also highlights that even though Washington, DC, ranks first in the CQ index, some industry fields in the MSA are underdeveloped than the national industry fields. For example, IQ, EQ, and CQ in technology and R&D fields are higher than two, whereas they in finance and insurance fields are lower than one. This result shows that governments should look into the industry fields in detail and develop strategies based on their strength and weakness of industrial fields.

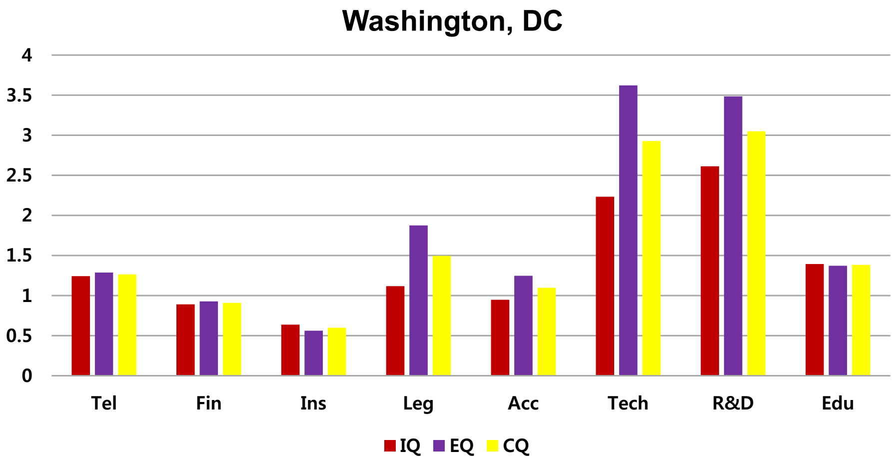

Fig. 5 Value of IQ, EQ, and CQ by each field in Washington, DC (telecommunications, finance, insurance, legal, accounting, technology, R&D, and education)

Next, this study shows how KIBS exert a positive local impact on Washington, DC, based on further empirical evidence. Indeed, many authors and articles have highlighted that Washington, DC, has evolved into a leading-edge knowledge economy and KIBS, especially technology and R&D, play an important role in regional growth consistent with the findings of this article. For example, according to the Office of the Deputy Mayor for Planning and Economic Development, Washington, DC, ranks first for women in technology and places third in technology. Washington, DC, is not only one of the best tech ecosystems in the USA; it is one of the most inclusive (https://dmped.dc.gov/page/technology-and-innovation). Also, according to EMSI data (https://www.economicmodeling.com/data/), the largest industry in Washington, DC, is professional, scientific, and technical services. The knowledge-based sector accounts for more than half a million jobs, consisting of a full 15 percent of the metro's workforce. The region has added nearly 17,000 new professional services jobs since 2009. Florida (2013) supports that Washington, DC, has in fact developed a diversified tech and knowledge economy. He highlights that the MSA is home to nearly 110, 000 private educational service jobs, which grew at a 13 percent rate, nearly 100,000 finance and insurance jobs, which grew 3 percent and 76,000 information jobs (https://www.citylab.com/life/2013/10/truth-about-dcs-growing-knowledge-based-economy/7317/). In sum, the economy of Washington, DC, has become a highly developed economy driven by KIBS. This case study provides a more nuanced look into the positive impact of KIBS for local economy.

2 Conclusions

KIBS play an important role in the economy and make a pivotal contribution to regional innovation (see, e.g., Corrocher et al. 2009; Corrocher and Cusmano 2014; Pinto et al. 2015). The distribution and quality of KIBS have important effects on the economic system in terms of innovative capacity and economic development because they are highly innovative and also facilitate innovations in other economic sectors (Antonelli 1998; Hipp and Grupp 2005). KIBS play a pivotal role in knowledge transfer structure and are thus a pivotal factor for economic development. Therefore, it is worth exploring their role in our knowledge-based economy in depth (Gotsch and Hipp 2012).

In this background, this study highlights the spatial patterns of KIBS clusters by employing a new CQ index. This article finds that Washington, DC, plays an important role in KIBS clusters in the USA, followed by California, MD, Boulder, CO, Huntsville, AL, and Boston, MA. This study also finds that the CQ index would be a better index than the LQ index for measuring the magnitude of clusters given that LQ cannot consider the agglomeration of industries into its index. For instance, the LQ index cannot find some high IQ MSAs that are located in the West and South region. This can be a serious problem for finding clusters given that the agglomeration of industries is directly related to the definition of clusters. In contrast, the CQ index could consider both the agglomeration of industries and workers and be utilized for finding other industries' clusters.

Next, this study employs four econometric models to reflect the interaction between KIBS and the urban economy. The study both runs OLS models and SUR models to compare their results and finds that there are notable differences in the significance or the coefficient value for KIBS, CQ, and the GDP. For example, the GDP shows an elasticity of 0.054 in OLS (significant at the 0.01 level) and 0.084 in SUR (significant at the 0.01 level), and KIBS exert an impact on the GDP with an elasticity of 0.262 in OLS (insignificant) and 0.515 in SUR (significant at the 0.01 level).

By exploring econometric models, the study finds that KIBS and the GDP positively interact with each other, and the SUR model would be a better model than the OLS model given that the OLS model underestimates or insignificantly estimates the relationship between them because of the error terms correlated. The results of this study suggest that the number and proportion of KIBS can be an economic driver for the US MSAs, and urban practitioners should develop policies for KIBS to promote regional economic growth. Also, this study finds that the GDP and each KIBS field differently interact with each other. In other words, they show different elasticities by their fields. The results show that the relationships between the GDP and KIBS are differentiated by industrial fields and governments and urban planners should develop urban planning by looking at the different characteristics of each KIBS field.

The findings in this article also allow governments and urban planners to find KIBS clusters, analyze strength and weakness of KIBS in their region, and establish policies for economic development based on KIBS. For example, they can invest their specialized KIBS field by analyzing the CQ index, compare their KIBS industry structure with other MSAs by looking into the magnitude of KIBS clusters in each field, and develop strategies based on the results of empirical models across US MSAs. This study would contribute to the KIBS literature by proposing a new cluster quotient index, which can consider both the agglomeration of industries and workers, and employing a SUR model, which can reflect the mutual relationship between KIBS and the urban economy.

As this study and previous papers indicate, KIBS can be regarded as an engine for the economic growth and would play an essential role in translating the potential of new technology into business results and improved economies (see, e.g., Corrocher et al. 2009; Corrocher and Cusmano 2014; Gallouj et al. 2015; Gotsch and Hipp 2012). Developing strategies for utilizing KIBS would be one of the best ways forward to the successful future of countries.

Appendix

See Tables 5 and 6.

Table 5 Classification of KIBS (NAICS code)

Sector	Code	Sector	Code	Sector	Code	Sector	Code
Telecommunication	517110	Insurance	524113	Technology (continued)	541360	Education (continued)	611511
	517210		524114		541370		611512
	517410		524126		541380		611513
	517911		524127		541410		611519
	517919		524128		541420		611610
Finance	521110		524130		541430		611620
	522110		524210		541490		611630
	522120		524291		541511		611691
	522130		524292		541512		611692
	522190		524298		541513		611699
	522220		525110		541519		611710
	522291		525120		541611		
	522292		525190		541612		
	522293		525910		541613		
	522294		525920		541614		
	522298		525990		541618		
	522310	Legal	541110		541620		
	522320		541120		541690		
	522390		541191	R&D	541711		
	523110		541199		541712		
	523120	Accounting	541211		541720		
	523130		541213		541910		
	523140		541214		813212		
	523210		541219	Education	611110		
	523910	Technology	541310		611210		
	523920		541320		611310		
	523930		541330		611410		
	523991		541340		611420		
	523999		541350		611430		

Table 6 Knowledge-based industries

	NAICS		NAICS		NAICS		NAICS
Utilities	221111	Manufacturing	333922	Finance and insurance	521110	Professional, scientific, and technical services	541214
	221112		333923		522110		541219
	221113		333924		522120		541310
	221118		333991		522130		541320
	221121		333992		522190		541330
	221122		333993		522210		541340
Manufacturing	324110		333994		522220		541350
	324121		333995		522291		541360
	324199		333996		522292		541370
	325110		333997		522293		541380
	325120		333999		522294		541410
	325130		334111		522298		541420
	325180		334112		522310		541430
	325193		334118		522320		541490
	325194		334210		522390		541511
	325199		334220		523110		541512
	325211		334290		523120		541513
	325212		334310		523130		541519
	325314		334412		523140		541611
	325314		334413		523210		541612
	325320		334416		523910		541613
	325411		334417		523920		541614
	325412		334418		523930		541618
	325413		334419		523991		541620
	325414		334511		523999		541690

Table 6 (continued)

	NAICS		NAICS		NAICS		NAICS
	325520		334512		524113		541711
	325910		335311		524114		541712
	325920		335312		524126		541720
	325991		335313		524127		541910
	325998		335921		524128	Educational services	611110
	332991		335929		524130		611210
	333111		336320		524210		611310
	333112		336411		524291		611410
	333120		336412		524292		611420
	333131		336413		524298		611430
	333132		336414		525110		611511
	333314		336415		525120		611512
	333316		336419		525190		611513
	333318	Transportation and warehousing	486110		525910		611519
	333413		486210		525920		611610
	333414		486910		525990		611620
	333611		486990	Professional, scientific, and technical services	541110		611630
	333618	Information	517110		541120		611691
	333911		517210		541191		611692
	333912		517410		541199		611699
	333913		517911		541211		611710
	333921		517919		541213		

References

Acs ZJ, Anselin L, Varga A (2002) Patents and innovation counts as measures of regional production of new knowledge. Res Policy 31(7):1069–1085

Aharoni Y, Nachum L (2000) Globalization of services: some implications for theory and practice. Routledge, London

Ahuja G (2000) Collaboration networks, structural holes, and innovation: a longitudinal study. Adm Sci Q 45:425–455

Alaba OO, Olubusoye EO, Ojo SO (2010) Efficiency of seemingly unrelated regression estimator over the ordinary least squares. Eur J Sci Res 39(1):153–160

Almeida P, Kogut B (1999) Localization of knowledge and the mobility of engineers in regional networks. Manag Sci 45(7):905–917

Amin A, Cohendet P (1999) Learning and adaptation in decentralised business networks. Environ Plan D: Soc Space 17(1):87–104

Andersson M, Hellerstedt K (2009) Location attributes and start-ups in knowledge-intensive business services. Ind Innov 16(1):103–121

Antonelli C (1998) Localized technological change, new information technology and the knowledge-based economy: the European evidence. J Evol Econ 8(2):177–198

Antonelli C (2000) New information technology and localized technological change in the knowledge-based economy. Serv Knowl-Based Econ 170–191

Audretsch DB, Feldman MP (1996) R&D spillovers and the geography of innovation and production. Am Econ Rev 86(3):630–640

Austrian Z (2000) Cluster case studies: the marriage of quantitative and qualitative information for action. Econ Dev Q 14(1):97–110

Bailey MJ (1959) Note on the economics of residential zoning and urban renewal. Land Econ 35(3):288–292

Bain & Company (2012) A world awash in money. Capitol Trends Through 2020, New York

Balistreri EJ, McDaniel CA, Wong EV (2003) An estimation of US industry-level capital–labor substitution elasticities: support for Cobb–Douglas. N Am J Econ Finance 14(3):343–356

Baptista R (2000) Do innovations diffuse faster within geographical clusters? Int J Ind Organ 18(3):515–535

Baptista R, Swann P (1998) Do firms in clusters innovate more? Res Policy 27(5):525–540

Benhabib J, Spiegel MM (1994) The role of human capital in economic development evidence from aggregate cross-country data. J Monet Econ 34(2):143–173

Bessant J (2003) Challenges in innovation management. In: Shavinina LV (ed) The international handbook on innovation. Elsevier, Oxford, pp 761–774

Billings SB, Johnson EB (2012) The location quotient as an estimator of industrial concentration. Reg Sci Urban Econ 42(4):642–647

BIZ (2010) Professional and business services: a 2020 vision for growth. London

Blundell R, Bond S (2000) GMM estimation with persistent panel data: an application to production functions. Econom Rev 19(3):321–340

Bottazzi L, Peri G (2003) Innovation and spillovers in regions: evidence from European patent data. Eur Econ Rev 47(4):687–710

Carlson RL (1978) Seemingly unrelated regression and the demand for automobiles of different sizes, 1965–1975: a disaggregate approach. J Bus 51(2):243–262

Carroll MC, Reid N, Smith BW (2008) Location quotients versus spatial autocorrelation in identifying potential cluster regions. Ann Reg Sci 42(2):449–463

Ciriaci D, Palma D (2016) Structural change and blurred sectoral boundaries: assessing the extent to which knowledge-intensive business services satisfy manufacturing final demand in Western countries. Econ Syst Res 28(1):55–77

Ciriaci D, Montresor S, Palma D (2015) Do KIBS make manufacturing more innovative? An empirical investigation of four European countries. Technol Forecast Soc Change 95:135–151

Consoli D, Elche-Hortelano D (2010) Variety in the knowledge base of knowledge intensive business services. Res Policy 39(10):1303–1310

Cooke P, Morgan K (1999) The associational economy: firms, regions, and innovation. OUP Catalogue

Corrocher N, Cusmano L (2014) The 'KIBS engine' of regional innovation systems: empirical evidence from European regions. Reg Stud 48(7):1212–1226

Corrocher N, Cusmano L, Morrison A (2009) Modes of innovation in knowledge-intensive business services evidence from Lombardy. J Evol Econ 19(2):173–196
Cover B, Jones JI, Watson A (2011) Science, technology, engineering, and mathematics (STEM) occupations: a visual essay. Mon Labor Rev 134(5):3–15
Czarnitzky D, Spielkamp A (2000) Business services in Germany: bridges for innovation. Serv Ind J 23:1–30
Duranton G, Puga D (2004) Micro-foundations of urban agglomeration economies. In: Handbook of regional and urban economics. Elsevier, Amsterdam
ECFIN D (2006) The production function approach to calculating potential growth and output gaps estimates for EU Member States and the US
European Commission (2012) Knowledge-intensive (business) services in Europe. https://ec.europa.eu/research/innovationunion/pdf/knowledge_intensive_business_services_in_europe_2011.pdf
Eurostat (2013) Business services statistics – NACE Rev. 1.1, Data from January 2009, 26 http://epp.eurostat.ec.europa.eu/statistics_explained/index.php/Business_services_statistics_-_NACE_Rev._1.1
Fallick B, Fleischman CA, Rebitzer JB (2006) Job-hopping in Silicon Valley: some evidence concerning the microfoundations of a high-technology cluster. Rev Econ Stat 88(3):472–481
Feldman MP, Florida R (1994) The geographic sources of innovation: technological infrastructure and product innovation in the United States. Ann Assoc Am Geogr 84(2):210–229
Fernhaber SA, Gilbert BA, McDougall PP (2008) International entrepreneurship and geographic location: an empirical examination of new venture internationalization. J Int Bus Stud 39(2):267–290
Fersht P, Filippone T, Aird C, Sappenfield D (2011) The evolution of global business services: enhancing the benefits of shared services and outsourcing, July, HfS Research
Fiebig DG (2001) Seemingly unrelated regression: a companion to theoretical econometrics, 101–121
Florida R (2013) Entrepreneurship, creativity, and regional economic growth. The emergence of entrepreneurship policy: governance, start-ups, and growth in the US knowledge economy, pp 39–58
Florida R (2014) The creative class and economic development. Econ Dev Q 28(3):196–205
Freel M (2016) Knowledge-intensive business services: geography and innovation. Routledge, London
Fritsch M, Slavtchev V (2011) Determinants of the efficiency of regional innovation systems. Reg Stud 45(7):905–918
Gallouj F (2002) Knowledge-intensive business services: processing knowledge and producing innovation. In: Productivity, innovation and knowledge in services: new economic and socio-economic approaches, p 256
Gallouj F, Weber KM, Stare M, Rubalcaba L (2015) The futures of the service economy in Europe: a foresight analysis. Technol Forecast Soc Change 94:80–96
Garcia-Mila T, McGuire TJ, Porter RH (1993) The effect of public capital in state-level production functions reconsidered. Economics working paper 36
Gennaioli N, La Porta R, Lopez-de-Silanes F, Shleifer A (2012) Human capital and regional development. Q J Econ 128(1):105–164
Gertler MS (2003) Tacit knowledge and the economic geography of context, or the undefinable tacitness of being (there). J Econ Geogr 3(1):75–99
Glaeser EL, Shapiro JM (2003) Urban growth in the 1990s: Is city living back? J Reg Sci 43(1):139–165
Gotsch M, Hipp C (2012) Measurement of innovation activities in the knowledge-intensive services industry: a trademark approach. Serv Ind J 32(13):2167–2184
Greene WH (2012) Econometric analysis, 7th edn. Pearson Prentice-Hall, Upper Saddle River
Growe A (2016) Where do KIBS workers work in Germany? Shifting patterns of KIBS employment in metropoles, regiopoles and industrialised hinterlands. Erdkunde, pp 201–215
Hall P (2000) Creative cities and economic development. Urban Stud 37(4):639–649
Hansen N (1993) Producer services, productivity and urban income. Rev Reg Stud 3:255–264
Henderson JV, Ono Y (2008) Where do manufacturing firms locate their headquarters? J Urban Econ 63(2):431–450
Herstad S, Ebersberger B (2014) Urban agglomerations, knowledge intensive services and innovation activity: establishing the core connections. Entrep Reg Dev 26(03–04):211–233
Herstad SJ, Ebersberger B (2015) On the link between urban location and the involvement of knowledge-intensive business services firms in collaboration networks. Reg Stud 49(7):1160–1175
Hertog PD (2000) Knowledge-intensive business services as co-producers of innovation. Int J Innov Manag 4(4):491–528
Hipp C (1999) Knowledge-intensive business services in the new mode of knowledge production. AI & Soc 13(1–2):88–106

Hipp C (2000) Information flows and knowledge creation in knowledge-intensive business services: scheme for a conceptualization. In: Innovation systems in the service economy. Springer, Boston, pp 149–167

Hipp C, Grupp H (2005) Innovation in the service sector: the demand for servicespecific innovation measurement concepts and typologies. Res Policy 34:517–535

Hyungsik RM, Perron B (2006) Seemingly unrelated regressions. Department of Economics University of Southern California & Departement de sciences economiques, CIREQ, and CIRANO Université de Montréal

Industry Canada and the Business Development Bank of Canada. (1996). Knowledge-based Industries (KBI). http://www23.statcan.gc.ca/imdb-bmdi/document/2514_D2_T9_V1-eng.pdf

Isaksen A (2004) Knowledge-based clusters and urban location: the clustering of software consultancy in Oslo. Urban Stud 41(5–6):1157–1174

Jacobs W, Koster HR, van Oort F (2013) Co-agglomeration of knowledge-intensive business services and multinational enterprises. J Econ Geogr 14(2):443–475

Jaffe AB (1989) Real effects of academic research. Am Econ Rev 79:957–970

Javalgi RRG, Grossman DA (2014) Firm resources and host-country factors impacting internationalization of knowledge-intensive service firms. Thunderbird Int Bus Rev 56(3):285–300

Jones JI (2014) An overview of employment and wages in science, technology, engineering and math (STEM) groups. Bureau of Labor Statistics, Washington

Kakwani NC (1967) The unbiasedness of Zellner's seemingly unrelated regression equations estimators. J Am Stat Assoc 62(317):141–142

Katsoulacos Y, Tsounis N (2000) Knowledge-intensive business services and productivity growth: the Greek evidence. In: Boden M, Miles I (eds) Services and the knowledge-based economy. Continuun, London, pp 192–208

Keeble D, Nachum L (2002) Why do business service firms cluster? Small consultancies, clustering and decentralization in London and southern England. Trans Inst Br Geogr 27(1):67–90

Kheng YK, Mahmood R, Beris SJH (2013) A conceptual review of innovative work behavior in knowledge intensive business services among knowledge workers in Malaysia. Int J Bus Humanit Technol 3(2):91–99

Kmenta J, Gilbert RF (1968) Small sample properties of alternative estimators of seemingly unrelated regressions. J Am Stat Assoc 63(324):1180–1200

Kunitomo N (1977) A note on the efficiency of Zellner's estimator for the case of two seemingly unrelated regression equations. Econ Stud Q (Tokyo. 1950) 28(1):73–77

Langdon D, Mckittrick G, Beede D, Khan B, Doms M (2011) Stem: good jobs and now and for the future. US Department of Commerce 03(11), 1–10

Leamer EE, Storper M (2014) The economic geography of the internet age. In: Location of International business activities. Palgrave Macmillan, London, pp 63–93

Levy F, Murnane RJ (2005) The new division of labor: how computers are creating the next job market. Princeton University Press, Princeton

Lundvall BÅ, Johnson B, Andersen ES, Dalum B (2002) National systems of production, innovation and competence building. Res Policy 31(2):213–231

Marshall J-N, Damesick P, Wood O (1987) Understanding the location and role of producer services in the United Kingdom. Environ Plan A 19:575–595

Martín-de Castro G (2015) Knowledge management and innovation in knowledge-based and high-tech industrial markets: the role of openness and absorptive capacity. Ind Mark Manag 47:143–146

Maskell P (2001) Knowledge creation and diffusion in geographic clusters. Int J Innov Manag 5(02):213–237

Mehta JS, Swamy PAVB (1976) Further evidence on the relative efficiencies of Zellner's seemingly unrelated regressions estimator. J Am Stat Assoc 71(355):634–639

Meliciani V, Savona M (2014) The determinants of regional specialisation in business services: agglomeration economies, vertical linkages and innovation. J Econ Geogr 15(2):387–416

Mieres CG, Sánchez JAL, Vijande MLS (2012) Internal marketing, innovation and performance in business services firms: the role of organizational unlearning. Int J Manag 29(4):403–429

Miles I (2003) Services and the knowledge-based economy. In: Service innovation, organizational responses to technological opportunities and market imperatives. London, pp 81–112

Miles I (2005) Knowledge intensive business services: prospects and policies. Foresight 7(6):39–63

Miles I, Kastrinos N, Flanagan K, Bilderbeek R, Hertog P, Huntink W, Bouman M (1995) Knowledge-intensive business services: their role as users, carriers and sources of innovation [Report]. EC DG

XIII Sprint EIMS Programme, Luxembourg. Retrieved from https://research.mbs.ac.uk/INNOVATION/Portals/0/docs/KIBSEIMS1995shortreport.pdf
Miozzo M, Grimshaw D (2005) Modularity and innovation in knowledge-intensive business services: IT outsourcing in Germany and the UK. Res Policy 34(9):1419–1439
Moon HR, Perron B (2008) Seemingly unrelated regressions. The New Palgrave Dictionary of Economics. SN Durlauf and LE Blume
Muller E, Doloreux D (2007) The key dimensions of knowledge-intensive business services (KIBS) analysis: a decade of evolution (No. U1/2007). Arbeitspapiere Unternehmen und Region
Muller E, Doloreux D (2009) What we should know about knowledge-intensive business services. Technol Soc 31(1):64–72
Muller E, Zenker A (2001) Business services as actors of knowledge transformation: the role of KIBS in regional and national innovation systems. Res Policy 30(9):1501–1516
Nelson RR (1993) National innovation systems: a comparative analysis. Oxford University Press on Demand
NSF (2012) Science and Engineering Indicators 2012: Chapter 6. Industry, Technology, and the Global Marketplace, National Science Foundation, Arlington, VA
O'Donoghue D, Gleave B (2004) A note on methods for measuring industrial agglomeration. Reg Stud 38(4):419–427
OECD (2006) Innovation and knowledge-intensive service activities. http://www.keepeek.com/Digital-Asset-Management/oecd/science-and-technology/innovation-and-knowledge-intensive-serviceactivities_9789264022744-en#page3
Peneder M, Kaniovski S, Dachs B (2003) What follows tertiarisation? Structural change and the role of knowledge-based services. Serv Ind J 23(2):47–66
Pina K, Tether BS (2016) Towards understanding variety in knowledge intensive business services by distinguishing their knowledge bases. Res Policy 45(2):401–413
Pinto H, Fernandez-Esquinas M, Uyarra E (2015) Universities and knowledge-intensive business services (KIBS) as sources of knowledge for innovative firms in peripheral regions. Reg Stud 49(11):1873–1891
Porter M, Van Opstal D, US C (2001) Strengths, vulnerabilities and long term priorities
Porter ME (1990) The competitive advantage of nations. The Free Press, New York
Porter ME (2001) Clusters of innovation: regional foundations of US competitiveness. Council on competitiveness
Price-Spratlen T, Guest AM (2002) Race and population change: a longitudinal look at Cleveland neighborhoods. Sociol Forum 17(1):105–136
Reardon SF, Bischoff K (2011) Income inequality and income segregation. Am J Sociol 116(4):1092–1153
Scarso E, Bolisani E (2010) Knowledge-based strategies for knowledge intensive business services: a multiple case-study of computer service companies. Electron J Knowl Manag 8(1):1–10
Scott AJ (2004) Cultural-products industries and urban economic development: prospects for growth and market contestation in global context. Urban Aff Rev 39(4):461–490
Shapiro JM (2006) Smart cities: quality of life, productivity, and the growth effects of human capital. Rev Econ Stat 88(2):324–335
Shearmur R (2010) Scale, distance and embeddedness: knowledge-intensive business services location and growth in Canada. In: Knowledge-intensive business services: geography and innovation, pp 43–74
Shearmur R, Alvergne C (2002) Intrametropolitan patterns of high-order business service location: a comparative study of seventeen sectors in Ile-de-France. Urban Stud 39(7):1143–1163
Shearmur R, Doloreux D (2008) Urban hierarchy or local buzz? High-order producer service and (or) knowledge-intensive business service location in Canada, 1991–2001. Prof Geogr 60(3):333–355
Shearmur R, Doloreux D (2013) Place, space and distance: towards a geography of knowledge-intensive business services innovation. In: When is regional "Beautiful"? Routledge: London, pp 85–108
Shearmur R, Doloreux D (2019) KIBS as both innovators and knowledge intermediaries in the innovation process: intermediation as a contingent role. Pap Reg Sci 98(1):191–209
Simmie J, Strambach S (2006) The contribution of KIBS to innovation in cities: an evolutionary and institutional perspective. J Knowl Manag 10(5):26–40
Simon CJ, Nardinelli C (2002) Human capital and the rise of American cities, 1900–1990. Reg Sci Urban Econ 32(1):59–96

Singh J (2008) Distributed R&D, cross-regional knowledge integration and quality of innovative output. Res Policy 37(1):77–96
Smedlund A, Toivonen M (2007) The role of KIBS in the IC development of regional clusters. J Intellect Cap 8(1):159–170
Sonn JW, Storper M (2008) The increasing importance of geographical proximity in knowledge production: an analysis of US patent citations, 1975–1997. Environ Plan A 40(5):1020–1039
Srivastava VK, Dwivedi TD (1979) Estimation of seemingly unrelated regression equations: a brief survey. J Econom 10(1):15–32
Srivastava VK, Giles DE (1987) Seemingly unrelated regression equations models: estimation and inference. CRC Press, London
Stern DI (2000) A multivariate cointegration analysis of the role of energy in the US macroeconomy. Energy Econ 22(2):267–283
Strambach, S. (2001). Innovation processes and the role of knowledge-intensive business services (KIBS). In: Innovation networks, pp 53–68
Strambach S (2008) Knowledge-intensive business services (KIBS) as drivers of multilevel knowledge dynamics. Int J Serv Technol Manag 10(2–4):152–174
Strambach S (2010) Knowledge commodification and new patterns of specialisation: professionals and experts in knowledge-intensive business services (KIBS) (No. 04.10). In: Working papers on innovation and space
Stuart TE (2000) Interorganizational alliances and the performance of firms: a study of growth and innovation rates in a high-technology industry. Strateg Manag J 21:791–811
Telser LG (1964) Iterative estimation of a set of linear regression equations. J Am Stat Assoc 59(307):845–862
Tether BS, Hipp C (2002) Knowledge intensive, technical and other services: patterns of competitiveness and innovation compared. Technol Anal Strateg Manag 14(2):163–182
Toivonen M (2006) Future prospects of knowledge-intensive business services (KIBS) and implications to regional economies. ICFAI J Knowl Manag 4:3
Tomlinson M, Miles I (1999) The career trajectories of knowledge workers. In: Mobilising human resources for innovation: proceedings from the OECD workshop on science and technology labour markets, vol 17, 152–167
Varga A, Anselin L, Acs Z (2005) Regional Innovation in the US over space and time. Spillovers and Innovations, pp 93–104
Whittington KB, Smith JO, Powell WW (2009) Networks, propinquity, and innovation in knowledge-intensive industries. Adm Sci Q 54:90–122
Wilde PE, McNamara PE, Ranney CK (1999) The effect of income and food programs on dietary quality: a seemingly unrelated regression analysis with error components. Am J Agric Econ 81(4):959–971
Wirtz J, Tuzovic S, Ehret M (2015) Global business services: increasing specialization and integration of the world economy as drivers of economic growth. J Serv Manag 26(4):565–587
Wood P (2002) Knowledge-intensive services and urban innovativeness. Urban Stud 39:993–1002
Woodward D, Guimarães P (2009) Targeting regional economic development. Routledge
Yahya WB, Adebayo SB, Jolayemi ET, Oyejola BA, Sanni OOM (2008) Effects of non-orthogonality on the efficiency of seemingly unrelated regression (SUR) models. InterStat J 003:1–29
Yeoh KK, Mahmood R (2013) The relationship between pro-innovation organizational climate, leader-member exchange and innovative work behavior: a study among the knowledge workers of the knowledge intensive business services in Malaysia. Bus Manag Dyn 2(8):15–30
Zellner A (1962) An efficient method of estimating seemingly unrelated regression equations and tests of aggregation bias. J Am Stat Assoc 57:500–509
Zellner A (2006) Seemingly unrelated regressions. University of Chicago
Zieba M (2013) Knowledge-intensive business services (KIBS) and their role in the knowledge-based economy (No. 7/2013 (7)). GUT FME Working Paper Series A
Zook MA (2000) The web of production: the economic geography of commercial Internet content production in the United States. Environ Plan A 32(3):411–426