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Exploring the microgeography and typology of U.S. high-tech clusters

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ABSTRACT

Despite the principal role of high-tech clusters in local planning practice and research, their location and sectoral typology at the granular level have been rarely studied. This study explores the location of U.S. high-tech clusters at a micro-scale by employing firm-level data sets and spatial statistics and examines their sectoral typology using market concentration indices in 52 large U.S regions. The majority (80 %) of the 627 tech clusters we identify have multiple dominant tech industries or are specialized in professional services. Furthermore, while clusters form the major regional hubs for the high-tech economy, they are home to a very small share (7 %, on average) of regional population. U.S. regions also have widely diverse spatial patterns of high-tech clusters; although some regions have scattered clusters, the New York and Northern California high-tech booming regions have clusters concentrated in central business districts (CBDs). Last, U.S. high-tech clusters and the overall high-tech economy are strongly shaped by the location and performance of professional services, i.e., consulting, legal, computer, engineering, and architectural services.

1. Introduction

High tech industries generate more than 10 % of the US total employment and contribute to almost 20 % of the national GDP (Muro et al., 2015). Similarly, high-tech industries employment share in European Union (EU) has significantly increased in recent years. Eurostat 2020 goal is to increase the share of high-the industries in GDP by 3 %, bypassing other competitors such as Japan and the U.S (Europe 2020 indicators, 2010). High-tech industries are defined by high intensity research and development (R&D) input and product or production function and are classified based on their level of R&D intensity (Heckler, 2005). This study focuses on six sector categories with the highest degree of R&D intensity. These industries—characterized by a growing share of national employment, Gross Domestic Product (GDP), and innovation productivity—figure boldly in current economic development planning efforts (Aghion et al., 2015; Drucker & Kass, 2015; Katz & Krueger, 2016). These efforts are shaped based on the widely accepted theory that indicates high-tech industries tend to spatially cluster. Studies from the US (Knudsen et al., 2008), Canada (Shearmur, 2010) and other international comparative studies (Zandiatashbar and Hamidi, 2018) have confirmed the critical role of tech clustering in regional economic productivity and innovation capacity. Other American, European and Asian studies have emphasized the emergence of tech and creative clusters in areas with placemaking amenities such as walkability and public transit (e.i. Rao and Dai, 2017; Zandiatashbar et al., 2019; Zandiatashbar and Hamidi, 2021; Zandiatashbar and Kayanan, 2020). Accordingly, planners and policymakers increasingly search for tools to transition post-industrial economies into tech-based economies. Thus, the center of attention in recent years has been urban policies for integrating tech-based knowledge clusters using amenity-rich placemaking practices such as innovation districts, urban laboratories, and knowledge hubs (Hamidi & Zandiatashbar, 2019; Katz & Krueger, 2016; Yigitcanlar et al., 2008).

These strategies have sparked debate; several studies warn that knowledge-based urban development could lead to gentrification, displacement, and housing unaffordability (Atkinson & Easthope, 2009; Voith & Wachter, 2009). Empirical studies by Kemeny and Osman (2018) in the US and Lee and Clarke (2019) in Britain show that in a growing tech economy increased housing values couple with higher income for tech workers and, consequently, non-tech workers (i.e., non-tradable sectors). Research also points to other costs of high-tech urban clusters. These include health risks and environmental impacts from landfills, waste sites or hazardous manufacturing facilities (Chiu, 2011; Heppler, 2017; Yoshida, 1994).

To date there is little micro-scale empirical evidence on the costs and benefits of high-tech clusters, largely due to a lack of information on

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clusters' geographic boundaries and locations. At the international level, only a few case studies have focused on one or a small number of districts and cities (Alecke et al., 2006; Feser, 2004; Maggioni, 2002; Zandiatashbar et al., 2019). In addition, existing national studies are highly aggregated and mostly concentrate on metropolitan level policies and development practices (Katz & Bradley, 2013). No quantitative study identifies locations of high-tech clusters at the micro-level, that is, within U.S metropolitan areas using firm-level disaggregated data. Even less is known about the sectoral classifications of existing micro-level high-tech zones in the U.S. Tech cluster attributes such as sectoral type, size, and location could well have different impacts on quality-of-life outcomes. The minimal understanding of the micro-level location of existing high-tech clusters and their sectoral attributes has limited empirical study of the quality-of-life impacts these clusters have on surrounding communities, a critical requirement for evidence-based policymaking.

We address these gaps in planning research and practice in two ways: 1) by quantifying the boundary and location of high-tech zones; 2) by classifying these zones by tech sectors for the 52 largest metropolitan areas in the U.S. Through a series of spatial analyses done separately for each metro area, we identified 627 high-tech zones in these leading U.S. regions. On average, these zones encompass more than 60 % of high-tech jobs and half of large high-tech firms and headquarters. Notably, however, an average 7 % of any regional population lives in clusters that function as major high-tech job destinations. Furthermore, through sectoral typology analysis, we found that most high-tech zones have diverse tech sectors with a strong professional services presence while the biotech sector the bio-tech sector has a strong presence in a very small number of these zones. Given the growing interest among cities and economic development officials to develop tech clusters, planners and local governments should focus on the location of tech clusters (i.e., their existing capacities) in order to exert influence over how and where clusters grow, rather than reinventing the wheel by investing in dispersed areas with no clusters such as new suburban office parks. As firms and headquarters could be footloose and get motivated to move around the country seeking better incentives; local officials should recognize the clusters that exist in their own regions using the analytical methods and results of this paper for designing and implementing policies that can help clusters thrive as well as aligning with other policy objectives that support affordable housing, encourage public transit use, and promote equity.

Although there is a substantial empirical literature on geographic concentration of high-tech industries in different countries (e.g., Alecke et al. (2006) using county level employment data in Germany, De Beule & Van Beveren (2012) using regional data in Belgium, (Zandiatashbar et al. (2019) using province level data in China, or Feser et al. (2005) using county level data in the U.S.)), these efforts are mostly conducted at higher geographic level. For instance, thus, another major (international) contribution of this study is its novel approach and innovative methodology on how to quantify the location of high-tech clusters at the finest scale (firm level). This methodology offers a series of spatial analyses and data-driven methodology that are generalizable to other countries and global cities to identify the location of tech clusters and would help governments to make more informed decisions on how to maximize the innovation and tech capacity in their region while proactively considering the negative consequences of tech-based economic development.

2. Literature review

2.1. Firm clusters: concepts and measures

It is widely accepted that firms benefit from clustering through "external economies of scale" (Maggioni, 2002; Marshall, 1890; Porter, 1998). Some of the benefits include shared labor pools, specialized suppliers, and shared infrastructure. Furthermore, empirical work has confirmed that companies in clusters grow more robustly and innovate more rapidly than non-clustered companies and that clusters often tend to attract start-ups and result in spinoffs (Baptista & Swann, 1998; Chatman et al., 2016; Credit, 2018). These impacts show principally in the knowledge-based economy (Porter, 2000).

According to more recent studies, clustering is particularly important for knowledge-based industries reliant on face-to-face contact, social networking, and tacit-knowledge exchange (Asheim et al., 2011). The literature largely supports the notion that knowledge-based firms do cluster, that firms benefit from co-location, and that clusters are key to regional economic growth (Delgado et al., 2015; Koo, 2005; M. Porter, 2004). This line of research is also supported by creative class and creative city narratives, which point to the importance of particular place-based built environment qualities such as walkability, mixed land use, and urban aesthetics (Florida, 2014).

This combination of research on the geography of knowledge-based industry clusters and creative city schemes has led to knowledge-based urban development policies such as location incentives and placemaking strategies such as innovation districts (Hamidi & Zandiatashbar, 2019; Zandiatashbar, Hamidi, Foster, et al., 2019). These policies mainly advocate for certain infrastructures and types of urban developments in such clusters. The basic frameworks for such approaches are agglomeration economies and placemaking strategies that seek to address the location preferences of high-tech businesses and talented human capital (Zandiatashbar et al., 2019). For instance, transportation infrastructure is often integrated into policies, since walkability and access to public transit are known key characteristics of knowledge-led placemaking strategies (Esmaeilpoorarabi et al., 2018; Katz & Krueger, 2016).

While the existing literature largely supports the notion that knowledge-based firms cluster, (Delgado et al., 2015; Koo, 2005; Porter, 2004), there is little consensus on where these clusters occur. Scholars including Grodach et al. (2014) and Katz and Bradley (2013) assert that innovation districts are in dense, urban CBDs; other researchers identify different spatial clustering patterns based on firm size, geographic context, and specific industries and institutions (Currid & Connolly, 2008; Madanipour, 2013).

These studies are largely theoretical and rely on limited observations. Very few empirical attempts to identify knowledge-based firm clusters are highly aggregated or employ measures of sectoral concentration (e.g., Gini coefficient, Ellison and Glaeser, or Location Quotient) for counties or regions (Feser et al., 2005; Koo, 2005; Kopczewska, 2018). A widely noted weakness of such measures is their "aspatial" property: they treat space as discrete units and, hence, do not account for the spatial clustering patterns of high-tech industries (Alecke et al., 2006). Existing literature offers little or no micro-scale empirical analyses that can identify high-tech clusters using spatial techniques and exploring sectoral and development types.

The need for identifying the geographic concentration of high-tech businesses is more plausible both in academic and policy developments areas as these clusters play a fundamental role in forming the regional innovation systems, production systems, and urban and economic development, given the rise of knowledge-based economy (Asheim et al., 2011; Porter, 2000; Scott & Storper, 2003). The present study addresses this gap in the literature by identifying the local high-tech zones in the U.S. large regions using spatial statistical technique and developing a sectoral typology for them at the most disaggregated level using a firm-level micro dataset. However, while the methodology used in this research uses data from the U.S., it is applicable to cases across the world.

2.2. High-tech clusters, sectoral typology and quality of life outcomes

The basic frameworks for innovation-based economic development policies are agglomeration economies and placemaking strategies that seek to address the high-tech businesses and talented human capital's location preferences (Zandiatashbar, 2019). The principle pillar of these placemaking strategies is the local place-based characteristics that satisfy life quality of skillful millennials such as their car-free life style, and strong desire for urban social life, mixed-use, compact neighborhoods, transit quality, and walkable proximity to restaurants, retail, and cultural and educational institutions (Credit, 2018; Shearmur, 2012; Zandiatashbar & Hamidi, 2018). For instance, transportation infrastructure is often integrated in these policies as walkability and access to public transit are known as key characteristics of knowledge-led placemaking strategies (Katz & Krueger, 2016; Yigitcanlar et al., 2016; Zandiatashbar, Hamidi, Foster, et al., 2019). Such place-based amenity richness brings a great potential for housing price inflations and the lack of affordable housing (Voith & Wachter, 2009). These trends over time could lead to gentrification and displacement and unaffordability for majority of the residents (Morisson & Bevilacqua, 2018). In addition, the loss of low wage jobs is more likely to occur in the case of high-tech industries that deal more with high-advanced technologies on a daily basis (Rifkin, 1996). From the viewpoint of local residents of a newly emerged high-tech zone, local policy makers, in order to harness the regional high-tech economy, rely on attracting outsider educated high-skilled workforce. This inflow migration of High-Skilled Professionals would fill the second class while higher portion of original residents might stay in the first class (Frydman and Papanikolaou, 2018). The tangible example is Austin's creative city-region, where its high-technology sector grew in the late 1990s. Many in the city have identified an increasing income gap between the creative professionals and the city's poor, many of whom are African American and Latino; 13.1 % of the city's population was living in poverty compared with the U.S. average of 12.7 %. Furthermore, the average wage in the high-technology sector increased by $26,500 during the 1990s. The average rise in wages for all industries, including high-tech, was only $18,000 — a growth in line with the U.S. average (Comunian, 2011; McCann, 2007).

However, the high-tech sectorial differences could make this conclusion questionable. Firstly, the industrial differences between high-tech firms could lead to different labor needs. For instance, pharmaceutical research organizations or medical device firms, require a more homogenous, very specialized workforce who are drawn to high amenity urban areas (Mellander, 2009). Other high-tech firms, such as large advanced manufacturing businesses, employ a range of occupations (i.e. accountants, software engineers, traditional manufacturing jobs, health-care assistants, and service jobs) as opposed to a highly specialized workforce (Kimelberg & Nicoll, 2012; Zandiatashbar et al., 2019). Second, research points to the potential environmental impacts of industrial clusters on real-estate values (Hite et al., 2001; Kaufman & Cloutier, 2006). Industrial clusters' health risks, landfills, waste sites or hazardous manufacturing facilities could cause negative externalities which could also be transformed economically into negative effects on residential property values (De Vor & De Groot, 2011; Farber, 1998). Nevertheless, the degree to which these dis-amenities exist in high-tech clusters could depend on the sectoral classification. Environmental scientists and advocates are widely concerned with the impact and leakage of water, gas, and the industrial waste and garbage of some high-tech advanced manufacturing industries such as semiconductors to the adjacent residential areas (Chiu, 2011; Pellow & Park, 2002; Yoshida, 1994).

Despite the importance of accounting for tech sectorial differences in studying the quality-of-life impacts of high-tech clusters, literature shows very few empirical attempts on quantitative measures of tech sectoral typology (e.g. Gini coefficient, Ellison and Glaeser, or Location Quotient). The majority of existing studies in different countries across the world are aggregated at the country or regional levels (Feser et al., 2005; Koo, 2005; Kopczewska, 2018). Our review of literature offers little or no empirical analyses at the micro-scale that identify high-tech clusters using spatial techniques and explore their sectoral and development types.

2.3. Necessary knowledge for place-based economic development planning: micro-level location of high-tech clusters

Cities' interest in plans and policies that stimulate high-tech economies continues to grow since tech industries are commonly described as drivers of regional development with a fundamental role in forming regional innovation systems, production systems, and urban and economic development (Asheim et al., 2011; Porter, 2000; Scott & Storper, 2003). While high-tech businesses stimulate growth by hosting high wage jobs, according to Kemeny and Osman (2018) and Lee and Clarke (2019) these high-tech jobs also generate knock-on effects throughout the local economies that host them by spurring growth in non-high-tech jobs and wages (i.e., non-tradable activities) as well, although the effect is small, especially so when increased housing costs are considered. With these effects in mind, policymakers and economic developers across the world continually search for local economic development practices that can spur transition from post-industrial economies to knowledge economies. This has led to growth in place-based polices aimed at concentrating high-tech firms in cities (Esmaeilpoorarabi et al., 2018; Zandiatashbar & Kayanan, 2020).

A wide-ranging body of research on the role of place in increasing city attractiveness and value often draws connections between the City Beautiful Movement (Hall, 2004), urban renewal (Page & Ross, 2017), tactical urbanism (Lydon & Garcia, 2015), and placemaking practices (Fincher et al., 2016). Despite differences in their names and constitution—for instance, a university park captures research spillovers; an innovation district may or may not have a university presence; a creative district may target both creative and tech workers—these approaches share a focus: place and location (Drucker et al., 2019; Hamidi & Zandiatashbar, 2019). These features have become key to local economic development strategies and master plans that target developments in designated areas to attract high-tech clusters. This is a rapidly growing trend in cities across the globe and often leads to new developments on post-industrial sites, such as the Seaport Innovation District in the South Boston Waterfront (Drucker et al., 2019) or 22@BCN in Barcelona's Poblenou neighborhood (Charnock & Ribera-Fumaz, 2011). These sites depend heavily on design and placemaking strategies to create an entrepreneurial ecosystem attractive to high-tech firms and individuals closely associated with startup activities and the technology sector (Acs et al., 2002; Rossi & Di Bella, 2017).

The basic frameworks for these policies and developments are agglomeration economies and placemaking strategies that seek to address the location preferences of high-tech businesses and talented human capital (Hamidi & Zandiatashbar, 2019). The principle pillar of these placemaking strategies is the set of local, place-based characteristics that satisfy skillful millennial quality-of-life features such as car-free lifestyle and strong desires for urban social life, mixed-use, compact neighborhoods, transit quality, and walkable proximity of restaurants, retail, cultural, and educational institutions (Credit, 2018; Shearmur, 2012; Zandiatashbar & Hamidi, 2018). This line of research is also supported by the creative class and creative city narratives, which point to the importance of particular place-based built environmental qualities such as walkability, mixed land use, and urban aesthetics (Florida, 2002). For instance, these policies often integrate transportation infrastructure, since walkability and access to public transit are known to be key characteristics of knowledge-led placemaking strategies (Katz & Krueger, 2016; Yigitcanlar et al., 2016; Zandiatashbar, Hamidi, Foster, et al., 2019). In many cases, investment in local high-tech economy and in new, high quality residential construction occur in tandem to promote knowledge "clusters" (Voith & Wachter, 2009). As noted above, place-based amenity-richness brings potential for housing price inflation (Voith & Wachter, 2009) and for health and environmental impacts (Chiu, 2011; Heppler, 2017; Yoshida, 1994). These effects, however, may vary based on sectoral differences.

There may be variation from firms in different high-tech sectors seeking different types of urban developments and locations across a region (Zandiatashbar & Hamidi, 2021). Although high-tech innovation districts may locate in dense, urban areas, Currid and Connolly (2008) identify three different spatial patterns. These are clustering in central business districts, dispersed regional clustering, and specialist places. Madanipour (2013) has similarly identified a range of innovation clusters, such as live-work-play centers, technology parks, and geographically distributed 'science cities.' This line of research suggests that high-tech clusters are spatially diverse and may thus produce different negative environmental impacts. The research is limited, however, in that it does not explore sectoral differences between high-tech clusters, differences that could shape varied location preferences due to different logistical needs, customer and labor markets, and land utilization (Zandiatashbar et al., 2019). High-tech industrial differences could lead to different labor needs. For instance, pharmaceutical research organizations or medical device firms require a relatively homogenous, very specialized workforce drawn to high-amenity urban areas (Mellander, 2009). In contrast, large, advanced manufacturing businesses employ a range of occupations (i.e., accountants, software engineers, traditional manufacturing jobs, health-care assistants, and service jobs) rather than a highly specialized workforce (Kimelberg & Nicoll, 2012; Zandiatashbar et al., 2019).

High-tech sectors also vary in terms of accessibility or logistical needs. For instance, service providers (i.e., engineering/architectural/drafting services, web-developer/software publishers, private R&D labs) that produce immaterial commodities like professional and consultation services do not require production and distribution of goods or logistic mobility. However, high-tech manufacturing industries (i.e., IT/semiconductors, communication equipment, biopharmaceutical/biological products) reliant on e-commerce, just-in-time delivery, and time-sensitive distribution likely seek strong road and air mobility to satisfy their regional and (inter)national accessibility demands.

Finally, high-tech firm footprints may differ due to land costs, a critical factor in business location decisions and transportation preferences per classical location theory (Maggioni, 2002). High-tech industries that involve manufacturing (i.e., IT, semiconductors, control instruments, aerospace products, and navigational equipment) often require large land areas for production processes and technical or R&D activities. Thus, these businesses are drawn to the peripheries or recently developed employment sub-centers in edge cities in order to minimize land cost; such locations require roadway systems (Maggioni, 2002).

As efforts to plan toward knowledge economies and high-tech clusters increase in cities across the world, it becomes ever more critical to understand and quantify the positive and negative externalities of high-tech clusters on local communities. The first step for data-driven analyses is twofold: identifying the locations of existing high-tech firm clusters and exploring their sectoral differences at the most granular level. The fact that many new developments for attracting tech firm clusters are young challenges our ability to derive concrete evidence of negative consequences or sectoral differences—e.g., rise in polarized division of labor, housing unaffordability, income inequality, or congestion (Berkes & Gaetani, 2019; McCann, 2007; Zandiatashbar et al., 2019)—of tech clusters through associated policy solutions (Peck, 2005; Scott, 2006).

The present study addresses this need by identifying local high-tech zones in the largest U.S. regions using spatial statistical techniques and then developing a sectoral typology for them at the most disaggregated level using a firm-level micro data set.

3. Research process and methods

One of the major contributions of this research is to design and present a generalizable methodology with the step-by-step details that other researchers simply could use for areas around the world. To be specific, this study employs a 5-step research design to identify locations and sectoral types of high-tech clusters in the 52 largest regions of the U.S. at the finest level. Fig. 1 illustrates the framework and our methodological pathway. The first three steps identify the location of high-tech clusters by employing tessellation sampling and region-by-region hot-spot analysis. The last two steps identify the sectoral specializations of each cluster using Herfindahl-Hirschman (HH) Index, Location Quotient (LQ), and cluster analysis. The following sections provide details on the analytical method and results from each step. The combination of using hexagon mesh and spatial statistics with firm level data, and different indices to identify the sectoral typology in the sequence presented in Fig. 1, supports generalizability of this method.

To identify the location of high-tech clusters and their sectoral typology, this study covers high-tech firms in the 52 largest regions of the U.S., each with more than one million in population. According to the ESRI Business Analyst Database (EBAD) 2016 data set, nearly 71 % of U.S. high-tech firms are in these regions. Additionally, the selection of large MSAs accounts for the characteristics associated with region size such as land value, land availability, labor and customer markets, all of which could affect firm location behavior (Anas et al., 1998; McDonald, 1989). Furthermore, our spatial analysis focuses only on the urbanized portions of the MSAs since only 7 % of high-tech firms scatter in rural areas with no clustering patterns. We use the Census Bureau's urban-rural classification to remove rural areas from the analysis. Per the Bureau's urban-rural classification, an urban area comprises a densely settled core of census blocks that meet minimum population density requirements, along with adjacent territories containing non-residential urban land uses as well as territory with low population density that links outlying densely settled territory to the densely settled core. An urban area must encompass at least 2500 people, at least 1500 of whom reside outside institutional group quarters (Zandiatashbar, 2019).

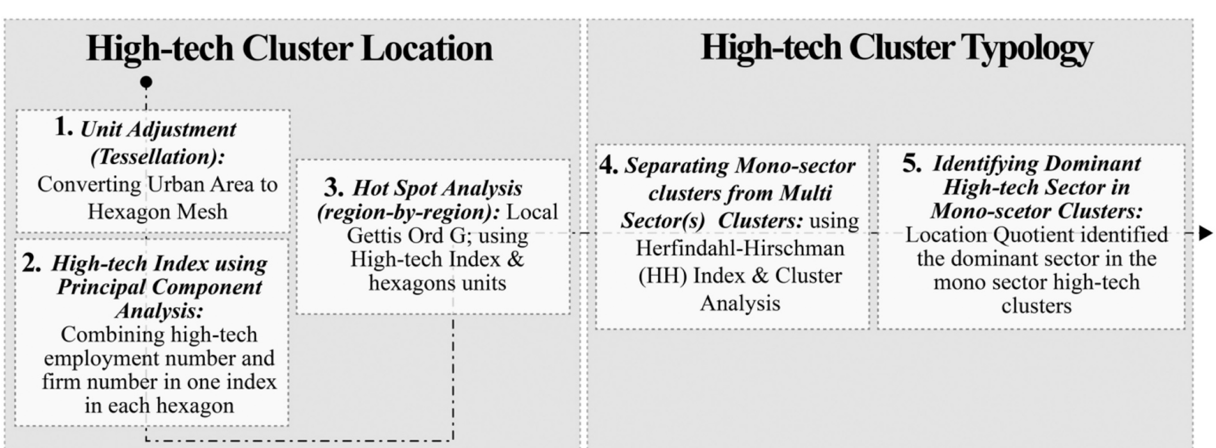

Fig. 1. Research process and methods summary.

Ultimately, the study area included 314,303 high-tech firms in six sectors with the highest R&D intensity to qualify as high-tech. Our classification of high-tech industries comes from U.S. Bureau of Labor Statistics (BLS) methodology, which classifies three levels of high-tech firms based on R&D intensity (Heckler, 2005):

Level I: 5 times greater than average employment share in the STEM fields

Level II: 3 to 4.9 times greater than average employment share in the STEM fields

Level III: 2 to 2.9 times greater than average employment share in the STEM fields.

For this analysis, we applied the BLS level I definition of high-tech firms to control for R&D capacity. Table 1 presents these industry sectors. Coupling this definition with a micro-level firm data set, we were able to detect the most disaggregated high-tech zones using the process that will be explained in the next sections.

This study uses the address-level firm data set from EBAD, which includes the 6-digit NAICS for identifying high-tech industry sectors. By using the BLS definition of high-tech industries, an address-level data set of firms, and one-by-one regional analysis, we address several methodological shortcomings in previous studies. First, earlier studies for identifying high-tech industries only loosely considered the level of industries' R&D intensity, which led to inconsistency across studies. As result, numbers for high-tech industries ranged from ten sectors to more than 100 sectors (Feser et al., 2005). Second, these studies did not use any unit of analysis finer than county level, which makes it impossible to study local specialized high-tech clusters. In order to identify how firm clusters could have impact on their immediate communities, it is necessary to identify the specialized clusters at a finer level.

Table 1
High-tech specializations.

Specializations, categorized by inter-industry linkages based on co-location patterns, input-output links, and similarities in labor occupation (Delgado et al., 2016; Heckler, 2005)
1) Information technology and analytical instruments (i.e., IT manufacturing) This category consists of information technology and analytical products such as computers, software, audiovisual equipment, laboratory instruments, and medical apparatus as well as the standard and precision electronics used by these products (for example, circuit boards and semiconductor devices). *Industries*: NAICS 5112: Software Publishers, NAICS 3341: Computer & Peripheral Equipment Manufacturing, NAICS 3344: Semiconductor Manufacturing, NAICS 3345: Measuring, Electromedical, and Control Instrument Manufacturing
2) Aerospace (devices) Establishments in this category manufacture aircraft, space vehicles, guided missiles, and related parts. This cluster also contains firms that manufacture the search and navigation equipment these products require. *Industries*: NAICS 3364: Aerospace Products/manufacturing, NAICS 334511: Navigational Equipment
3) Biopharmaceutical (i.e., bio tech) Establishments in this category produce complex chemical and biological substances used in medications, vaccines, diagnostic tests, and similar medical applications. *Industries*: NAICS 3254: Biopharmaceutical Products, Biological Products, Diagnostic Substances
4) (Professional) Services Firms in this category include services primarily designed to support other businesses. This includes corporate headquarters, professional services such as consulting, legal services, facilities support services, computer services, engineering and architectural services, and placement services. *Industries*: NAICS 5182 & 5415: Data Processing, System Design and Computer Services, NAICS 5413: Engineering Services, Architectural and Drafting Services
5) Communications equipment and services (i.e., communication tech) This category involves goods and services used for communication. This includes cable, wireless, and satellite services, as well as telephone, broadcasting, and wireless communication equipment. *Industries*: NAICS 3342: Communications Equipment Manufacturing, NAICS 5179: Other Telecommunications
6) Education and knowledge creation (i.e., R&D) This category includes research and development institutions in biotechnology, physical sciences, engineering, life sciences, and social sciences. *Industries*: NAICS 5417: Research Organization

We ran the spatial statistical analysis for each Metropolitan Statistical Area (MSA) separately to account for sources of heterogeneity. We employed Getis-Ord Gi* to identify high-tech hotspots. Getis-Ord Gi* is a spatial statistics technique widely used to study the location of CBDs and employment sub-centers (Hamidi, 2015). It detects whether neighboring geographical units have similar values (e.g., neighborhood population, median income or property values); in other words, it measures spatial associations. If a geographic unit and its neighboring units exhibit a significantly high value for a variable of interest, the entire neighborhood is detected as a high-tech cluster candidate. In this study, the variable of interest is a composite index (Htech) that accounts for the number of high-tech employees and the number of high-tech firms obtained through Principal Component Analysis (PCA). Different specializations demand different employment sizes and number of firms is widely cited as an indicator of urbanization externalities which occur as a result of agglomerative forces (Jacobs, 2016). The index derived from PCA has an eigenvalue of 1.41, which explains 70.75 % of variance.

For the spatial analysis, we first divided the urbanized portion of each region into hexagon cells as the unit of analysis in order to overcome the inconsistency issues of census boundaries (Fig. 2). Each cell has an area of 0.3 mile^2, which equals the average land area of U.S. urban census block groups (see Fig. 2). Census-defined geographic units such as census block groups and census tracts vary widely in terms of size and land area, which creates a limitation for contiguity-based spatial analysis (Feser et al., 2005). Our firm-level data set and tessellation sampling (hexagon cells) remedy these issues (see Fig. 2 below).

Using the Htech index as our variable of interest and hexagon cells as the unit of analysis, we conducted the local Getis-Ord Gi* with queen neighboring weighting (in queen neighboring, units are neighbors when they have common borders or corners) for each of the 52 MSAs in our sample. This analysis compares the sum Htech value of a cell's neighbors (local sum) to the overall Htech value for the MSA. Cell groups with statistically significant differences are considered hotspot candidates (Formula (1), below).

Formula 1: The Getis-Ord Gi*

$$G_i^* = \frac{\sum_i^n \sum_j^n w_{ij} x_i x_j}{\sum_i^n \sum_j^n x_i x_j} \qquad (1)$$

where:

The numerator is the sum of all values in the neighborhood of i including W_{ij} which is the spatial weight between neighborhoods i and j.

The denominator is the sum of all values in the study area.

Gi* is the indicator of clustering between neighborhoods i & j.

Ultimately, we identified clusters of hexagon cells with significantly higher Htech values as high-tech cluster candidates. To obtain the census-equivalent boundary for each cluster, we converted each hexagon cluster into a cluster of census blocks.

4. Results and discussion

Overall, we identified 627 high-tech clusters in 52 large U.S regions. Among the 52 regions, our hotspot analysis shows that only one region—the Richmond MSA—does not have a high-tech cluster. In terms of spatial distribution, the majority of tech clusters are located in CBDs or in urban fringes with expansion along interstate highways.

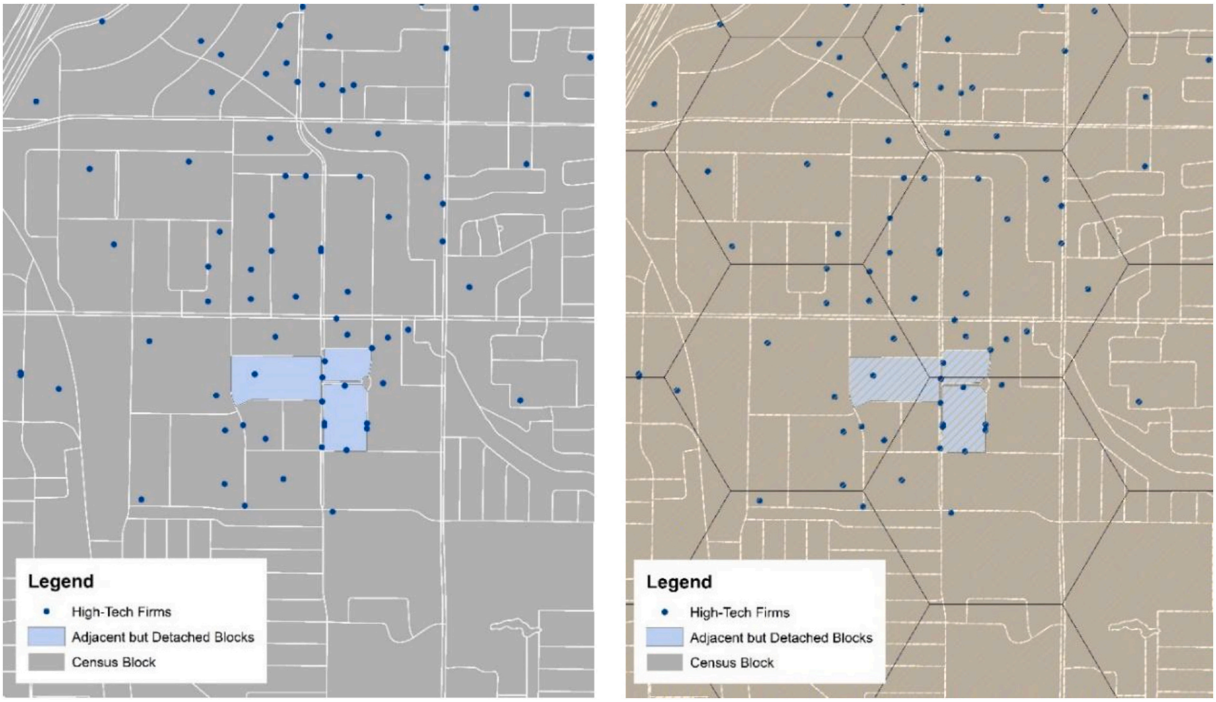

Fig. 2. Unit size inequality of census boundaries and application of tessellation.

Table 2
Cluster analysis result and descriptive statistics.

High-Tech Group (HT-G)	# of clusters	Number of zones		MSA's HT emp share (%)		MSA's HT Firm share (%)		US's HT emp share (%)	
		Avg.	s.d.	Avg.	s.d.	Avg.	s.d.	Avg.	s.d.
HLHN[a]	12	21.08	7.30	64.39	7.13	39.58	5.66	3.67	1.75
HLLN[b]	20	10.30	3.89	61.99	4.18	42.15	6.10	0.72	0.27
LLHN[c]	19	8.84	4.25	49.96	6.76	26.65	6.98	2.19	2.17

[a] HLHN: high local clustering and high national presence.
[b] HLLN: high local clustering and low national presence.
[c] LLHN: low local clustering and high national presence.

4.1. Locations of the U.S. high-tech clusters

Table 2 provides a full description of the regions covered in our study. It includes a grouping of regions estimated through a hierarchical clustering (hc) algorithm to classify regions based on four components: number of clusters in the region, share of the region's high-tech economic activities in those clusters (share of employees and firm number), and the region's high-tech employment as a percentage of national high-tech employment. We standardized these values for cluster analysis through four hc methods among which three suggested three groups. We validated the optimal group number using Calinski index which confirmed that three would be the best number of groups. The grouping is designed to maximize similarity between regions in a group based on the degree of tech job clustering in each region while accounting for the region's high-tech employment strength within the nation. Table 2 presents the result of this analysis and descriptive statistics.

Our first group has relatively higher values for all four measures, representing a strong local clustering of zones and strong national presence in the high tech economy. Hence, we label this group high local clustering and high national presence (HLHN). The second group, while having strong local clustering of the high-tech activities, does not hold a strong share of national high-tech employees; hence we identify this group as having high local clustering and low national presence (HLLN). Our last group has a slightly lower number of zones than HLLN with a smaller share of the region's high-tech activities in these clusters, however, has two times stronger presence in the nation on average; therefore, we identify this group as having low local clustering and high national presence (LLHN). Our HLHN category includes 12 regions with notable regions such as Los Angeles Metro Area, CA, Boston Metro Area, MA-NH, Washington Metro Area, DC, Dallas-Fort Worth Metro Area, TX, San Diego Metro Area, CA, San Jose Santa Clara, CA. Most of these regions are among the top growth tech hubs in the nation according to Atkinson et al. (2019). However, our classification shows a range of other regions across the nation with great potential, such as Dallas-Fort Worth Metro and Houston Metro Areas, TX; Philadelphia Metro Area, PA; Phoenix Metro Area, AZ; Minneapolis Metro Area, MN; Detroit Metro Area, MI; and Chicago Metro Area, IL. We used this grouping to classify the regions into the three classes shown in Table 3.

Most of the HLHN regions are also among the leaders in the number of zones. For instance, we found that the Los Angeles, CA metro area has the highest number with 33 tech clusters followed by the Atlanta, Washington DC, Boston, and Detroit metro areas while the Oklahoma City metro area has only two high-tech zones. Regions with relatively higher numbers of clusters typically show a fragmented economic and urban spatial structure (Gordon et al., 1986). In the case of Los Angeles, our results align with previous studies that found this region has a highly polycentric economic spatial structure with the majority of its economic activities located in employment subcenters (Giuliano et al., 2012;

Table 3
Regions ranked by cluster score, color-coded by quantile classification.

HT-G	Name	# of clusters	Region's HT Emp share (%)	Region's HT Firms share (%)	Region's HT big Firms share (%)	Region's HT HQ share (%)	Region's pop share (%)
HLHN	Los Angeles Metro Area, CA	33	54.94	36.17	49.99	56.75	7.55
	Boston Metro Area, MA-NH	28	57.45	33.49	43.03	61.72	13.67
	Atlanta Metro Area, GA	28	69.22	44.83	67.6	84.47	10.91
	Washington Metro Area, DC	27	67.02	43.64	57.89	72.84	10.36
	Detroit Metro Area, MI	24	61.13	36.59	55.13	67.21	6.17
	Miami Metro Area, FL	20	50.02	35.98	46.03	54.84	7.72
	Minneapolis Metro Area, MN-WI	20	63.76	34.38	53.72	55.38	6.99
	Dallas-Fort Worth Metro Area, TX	19	67.48	41.61	57.82	78.1	6.5
	Houston Metro Area, TX	18	70.62	44.56	56.54	68.75	8.11
	Phoenix Metro Area, AZ	16	66.72	30.54	42.77	40.74	13.67
	San Diego Metro Area, CA	13	71.61	45.8	67.56	85.22	7.94
	San Jose Santa Clara, CA	7	72.66	47.38	61.78	72.86	8.73
HLLN	Riverside Metro Area, CA	21	61.19	44.07	64.21	81.25	8.74
	Pittsburgh, PA	16	55.7	36.28	50.27	64.29	9.93
	Tampa Metro Area, FL	14	60.35	38.81	54	80	7.26
	Charlotte Metro Area, NC-SC	12	57.74	42.27	64.1	38.71	7.55
	Memphis, TN-MS-AR	12	58.73	49.96	64.24	100	11.91
	Milwaukee Metro Area, WI	12	57.58	35.3	52.5	68.97	7.71
	Kansas City, MO-KS	11	66.82	40.36	56.15	70.97	7.24
	Nashville Metro Area, TN	11	67.45	52.9	71.93	76.92	7.56
	Orlando Metro Area, FL	11	64.59	41.79	57.56	58.33	7.56
	Columbus, OH	10	55.63	44.08	59.89	87.5	8.2
	Virginia Beach Metro Area, VA-NC	10	65.89	38.33	55.55	54.55	7.96
	Jacksonville, FL	9	68.25	33.48	49.12	93.75	6.92
	Louisville/Jefferson County, KY-IN	9	61.85	49.1	68.16	66.67	8.7
	Rochester, NY	9	62.27	43.86	58.59	63.64	10.81
	San Antonio Metro Area, TX	9	67.81	45.14	60.49	66.67	8.44
	Birmingham Metro Area, AL	8	64.81	51.68	64.09	55.56	9.92
	Indianapolis Metro Area, IN	8	64.67	33.46	50.91	65	3.16
	Las Vegas Metro Area, NV	6	56.08	48.05	57.94	69.7	10.1
	New Orleans Metro Area, LA	5	61.84	40.47	57.31	88.89	10.89
	Buffalo Metro Area, NY	3	60.51	33.65	45.88	45	6.8
LLHN	Philadelphia Metro Area, PA	18	48.78	23.37	35.26	42.74	5.54
	Cleveland Metro Area, OH	15	52.34	29.31	42.75	30	5.71
	Baltimore Metro Area, MD	14	50.81	30.75	42.38	32.35	7.69
	Chicago Metro Area, IL-IN-WI	14	49.23	28.65	51.13	46.79	7.55
	New York Metro Area, NY-NJ-PA	13	35.56	25.12	42.46	43.76	3.91
	St. Louis, MO-IL	11	49.5	23.92	34.5	71.05	3.26
	Cincinnati, OH-KY-IN	9	58.55	31.3	44.73	72	4.54
	San Francisco Metro Area, CA	9	56.8	32.43	48.78	37.32	7.4
	Grand Rapids Metro Area, MI	8	47.24	34.3	50.72	50	9.01
	Denver Metro Area, CO	7	46.77	33.68	51.98	59.74	5.4
	Portland Metro Area, OR-WA	7	55.18	34.57	54.9	62.16	5.74
	Providence Metro Area, RI-MA	7	42.41	19.68	26.1	23.08	5.81
	Sacramento Metro Area, CA	7	51	25.8	38.58	42.86	4.18
	Salt Lake City, UT	7	37.16	29.94	36.76	38.89	4.78
	Austin Metro Area, TX	6	51.6	32.35	42.16	50	4.72
	Oxnard Metro Area, CA	6	58.2	26.37	45.53	26.67	5.73
	Hartford Metro Area, CT	4	43.65	10.71	20.1	19.05	2.89
	Seattle Metro Area, WA	4	58.84	23.12	40.11	56.58	3.96
	Oklahoma City, OK	2	55.55	11.07	17.64	57.14	1.23

Gordon & Richardson, 1996). On the other hand, we found that several high-tech regions have high-tech firms and employees concentrated in one or few clusters. These include the Rochester, San Francisco, and San Jose metro areas. In these examples, CBDs are the magnets for high-tech economic activities.

High-tech clusters hold a substantially high share of high-tech jobs. Overall, our high-tech clusters have more than 3,196,000 high-tech employees, averaging about 58 % of regional high-tech jobs. In addition, nearly 60 % of a region's high-tech headquarters and 51 % of large high-tech establishments are in the clusters that anchor high-tech employees. On average, more than 50 % of regional high-tech jobs, large firms, and headquarters are in these zones while only 7 % of the regional population lives there. This contrast is stronger in suburban high-tech zones, which could raise concern about increased job-population imbalance in these zones.

Our finding that clusters hold a notable share of high-tech employees and high-tech large establishments or headquarters confirms the long-standing theory that the high-tech economy tends to cluster and that clusters are mostly home to stronger high-tech firms in terms of both employment numbers and headquarter status. For instance, all high-tech headquarters in the Memphis TN metro area are in the clusters.

4.2. Sectoral typology of U.S. high-tech clusters

The second part of this research was developing a sectoral typology to apply to each high-tech cluster. We used the well-known measure of industrial diversity, the Herfindahl-Hirschman (HH) Index. It is widely used in the literature as the absolute measure of sectoral concentration or diversity (Kopczewska, 2018). First, we divided clusters into mono, where there is one dominant sector, or multi, where there are multiple important sectors. The HH index ranges from 0 to 1, with 0 indicating even distribution of employment across tech sectors and 1 indicating extreme concentration employment in a single sector or few sectors (Kopczewska, 2018) (See Formula (2) for HH calculation.)

Formula 2: Herfindahl-Hirschman (HH) Index

$$HH = \sum\nolimits_{i=1\dots6}^{I} \left(\frac{A_{ic}}{A_c}\right)^2 \quad (2)$$

A_{ic} = Number of Employees and Firms in High-tech Category *i* According to the Table 1

Ac = Total number of High-tech Employees/Firms

We found 263 out of 627 high-tech clusters to be mono-specialized. In the next step, we identified the specializations of these clusters, using Location Quotient (LQ), the local measure of concentration for each cluster. (See Formula (3) for LQ calculation.)

Formula 3: Location Quotient

$$LQ = \frac{\frac{e_i}{e_t}}{\frac{E_i}{E_t}} \quad (3)$$

e_i = Zone's Number of Employees in High-tech Category *i* (see Table 1)

e_t = Zone's total employment

E_i = Region's Number of Employees in High-tech Category *i* (see Table 1)

E_t = Region's total employment.

LQ value greater than 1 indicates the concentration of an industrial category in the cluster; LQ value greater than 1.25 indicates that the industry sector is a potential exporter. LQ value less than 1 indicates underrepresentation of an industrial sector in the cluster (Kopczewska, 2018). We computed the LQ measures for the 263 mono-specialized clusters.

Table 4 shows the distribution of high-tech clusters according to specializations as well as size, employment, and residential profiles. We found that 58 % of all clusters are diverse and nearly 42 % are monopolized by one or few high-tech sectors. Additionally, when compared to mono-specialized clusters, diverse clusters have on average 1.3 times the population and almost 1.5 the workforce.

Table 4 results indicate that high-tech clusters in large metro areas tend to be diverse. However, we also found 15 metro areas with more mono-clusters than diverse clusters. These include some notable regions such as Seattle WA, St. Louis MO, Las Vegas NV, Chicago IL, New Orleans LA, Portland OR, and most markedly, the Detroit and Dallas-Fort Worth metro areas. Fig. 3 presents the sectoral typology attributes of high-tech zones for all regions included in our study.

Our findings also show that the U.S. high-tech economy is highly dependent on professional services. As noted above, this category includes firms that support other tech industries such as consulting, legal, facilities support, computer, engineering and architectural, and placement services (Delgado et al., 2015). A notable attribute of professional services tech clusters is overall population size, employee population, and a racial diversity index above the average value for all tech clusters. The Atlanta, Detroit, and Chicago regions are relatively outstanding for the high share of professional services among their tech clusters. They thus suggest opportunities for case studies to further investigate the social attributes of these high population, employment, and racial diversity clusters, as well as the impact strong service tech clusters may have on the overall economy of their regions and states.

Large manufacturing high-tech industries such as aerospace have notably fewer mono-specialized clusters in large U.S regions. More than 85 % of employment in this sector is currently in six regions: Seattle WA, Los Angeles CA, Dallas-Fort Worth TX, Hartford CT, Boston MA and Cincinnati OH. Niosi and Zhegu (2010) propose that aircraft industry growth may follow the anchor tenant model. The anchor tenant is often a large high-tech firm, research university, or public laboratory that produces knowledge externalities that can lead to spinning off new companies and attracting additional ones. These dynamics could help to explain the growth of aerospace high-tech clusters in these six regions.

The services category accounts for almost 49 % of mono-specialized clusters and 20 % of all clusters. In contrast, biotech clusters represent the lowest number of mono-specialized clusters (3 % of all clusters, 6 % of mono-clusters). Among all clusters, however, biotech clusters have a notably bigger population size and share of educated residents. On average, more than half of biotech cluster residents have university-level

Table 4
High-tech cluster typology in the top 52 U.S. Metropolitan areas.

	Freq.	% of all	% of mono	Avg. Pop.[a]	Avg. Emp.[b]	Avg. Median Inc.[a]	Avg. Edu. Pop[a]	Avg. Simp.[c]
Mono-clusters	***263***	***42 %***		***16,709***	***32,685***	***$69k***	***40.12 %***	***0.44***
IT manufacturing	*26*	*4 %*	*10 %*	*9967*	*17,394*	*$75k*	*37.02 %*	*0.39*
Aerospace	*19*	*3 %*	*7 %*	*7894*	*12,337*	*$48k*	*19.94 %*	*0.36*
Bio tech	*17*	*3 %*	*6 %*	*17,584*	*42,846*	*$65k*	*51.96 %*	*0.42*
Professional services	*128*	*20 %*	*49 %*	*21,276*	*40,545*	*$72k*	*42.72 %*	*0.47*
Communication tech	*24*	*4 %*	*9 %*	*12,782*	*26,176*	*$61k*	*36.80 %*	*0.46*
R&D	*25*	*4 %*	*10 %*	*11,217*	*25,628*	*$60k*	*42.38 %*	*0.43*
Multi tech	***364***	***58 %***		***21,909***	***47,292***	***$72k***	***39.38 %***	***0.47***
Total	**627**	**100 %**		**19,728**	**41,165**	**$71k**	**39.67 %**	**0.46**

n = Number of residents of particular category per cluster (White, Black, Native American, Asian, Pacific Islander, Hispanic and 'some other race'). N = Total number of residents per cluster. The index varies from 0 to 1, with higher values indicating greater diversity.
Bold values are general categories and italic values are subcategoies

[a] Calculated using 2015 American Community Survey 5-Year Estimate.

[b] Calculated using BAD 2015.

[c] Calculated using the Simpson (1949) method for measuring diversity. Simpson's Index of Diversity = $1 - \sum_k \frac{n^2}{N}$.

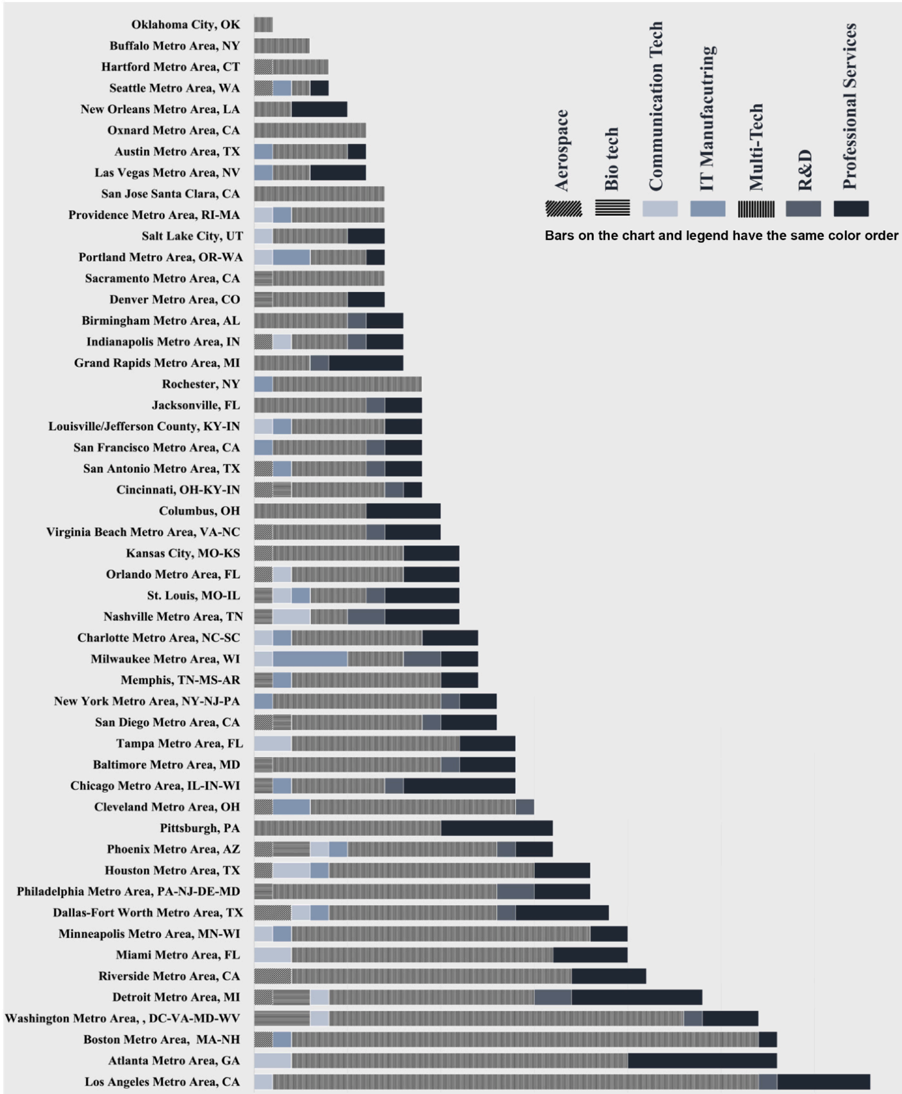

Fig. 3. Top 52 U.S. regional high-tech cluster profiles.

educations. The Washington DC metro area, with largest number of biotech clusters, is also where we earlier found that an above-average percentage of residents live in the high-tech clusters. As presented in Fig. 4, random examples of regions from the three categories in Table 3, these bio-tech clusters in D.C. tend to locate on the north side of the region along the major freeway system. This finding suggests that DC metro area biotech clusters could be a relatively strong study area for analyzing the characteristics of thriving "work-plus-live" places.

IT clusters, mostly located on the periphery, have the lowest average populations and workforce. However, almost all IT clusters are far from the CBDs, in some regions, they are in more developed suburban areas (e.g., Richardson TX or Belmont CA). On the other hand, CBDs generally overlap high-tech cluster boundaries. For instance, all the six regions; from HHLN, HLLN and LLHN groups, presented in Fig. 4 as illustrative examples have CBD clusters, however the major point that could distinguish the CBD tech clusters from each other is their typologies. The CBD high-tech clusters are typically diverse or specialized in professional services; however, there are some notable exceptions. The CBD high-tech clusters in Nashville TN (Fig. 4) and Salt Lake City UT are specialized in communications; Cincinnati OH, Denver CO, and St. Louis MO are home to biotech clusters; and R&D clusters predominate in Milwaukee WI, Grand Rapids MI, and Birmingham AL.

The other common notable location factor is proximity of clusters to major airports, those with more than a million passengers per year. Similar to the CBD case, all the six regions presented as illustrative examples in Fig. 4 have at least one major airport in a cluster, however these could be more in other examples, like Washington D.C., and Los Angeles, CA. Regardless of their group classes presented in Table 3, high-tech clusters are proximate to major airports in most of the regions in our study. As to sectors, airports typically attract multi-tech clusters. One notable airport cluster is in the San Jose CA region (i.e., Silicon Valley), one of the regions that were found to be in the HLHN group. Its tech clustering score ranks second, which means that the tech clusters are home to most high-tech activities: more than 70 % of San Jose area high-tech jobs are in the clusters and the size of the airport-adjacent cluster is quite notable. This multi-tech cluster expands from Mineta International Airport to the CBD.

These findings are in line with previous studies that emphasize IT industries' need for fast distribution of products (Zandiatashbar et al., 2019; Zandiatashbar & Hamidi, 2021) as well as response to the global and e-commerce economy. According to Kasarda (2000) some high-tech industries like IT industries' need for fast distribution of products, just-in-time delivery and use of online interactions for exchanging codified knowledge could justify their desire for proximity to air and road infrastructure. In other words, in many megaregions, airports are expanding their functionality beyond air mobility by adding a variety of

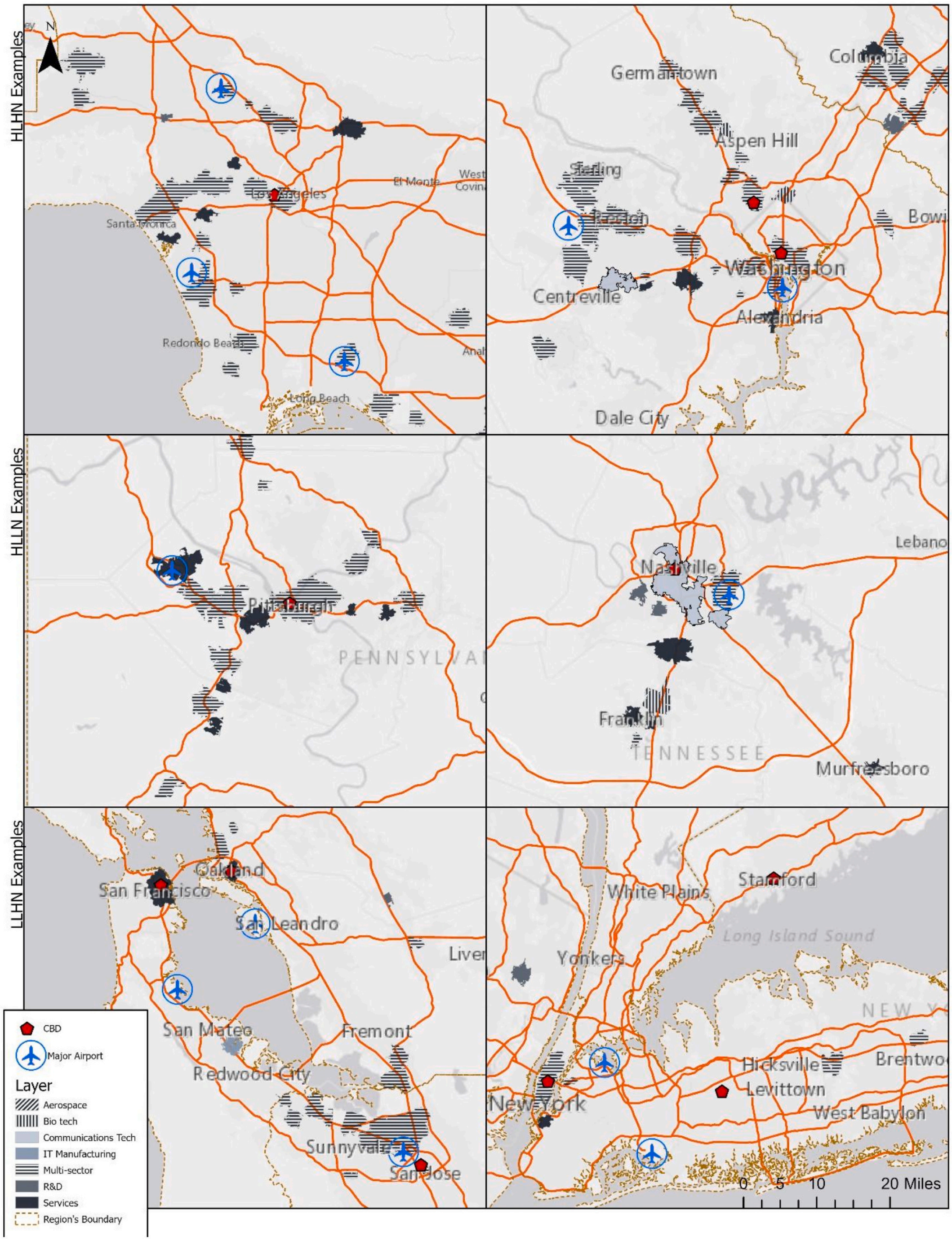

Fig. 4. Six region examples from the three high-tech groups.

business and commercial functions into passenger terminals (i.e. magazine shops, restaurants, boutiques, VIP rooms, coworking spaces) or on the landside (i.e. hotels, offices, conference and exhibition centers) to serve these needs (Kasarda, 2000). The book "Aerotropolis: The Way We'll Live Next" argues that large, well-connected airports can serve as nuclei for many urban functions that in prior eras would have clustered around seaports, rail terminals, CBDs, and freeway interchanges.

5. Conclusions and policy implications

Cities are keen to stimulate economic growth through promoting high-tech clusters. In general, they concentrate on amenity-rich urban developments, which can be associated with inflated property values, unaffordability, and ultimately displacement (Florida, 2017; Morisson & Bevilacqua, 2018; Stehlin, 2016). Silicon Valley is a good example of the major ripple effect of a robust high-tech economy. Housing unaffordability causes jobs-residents imbalance, increasing employee's wasted time in work commute traffic congestion, which results in an estimated \$2.7 billion in lost productivity (*2019 Silicon Valley Index*, 2019).

Local economic and planning efforts oriented to high-tech with little knowledge about the micro-level geography of existing high-tech economies can follow a path to unforeseen, multiple ripple effects. At present, practitioners, scholars, policy makers, and advocates confront a dearth of empirical studies that specifically locate high-tech clusters and their sectoral typology in a way that could support assessing high-tech cluster impacts on surrounding communities. This study has aimed to answer the need by quantifying spatial characteristics and sectoral types of high-tech clusters in the largest U.S. regions. The five-step methodology we use, however, is applicable to different countries.

Our findings show that the spatial patterns of high-tech clusters vary across regions, confirming that location and sectoral typology can provide critical knowledge for shaping local policies. The U.S. high-tech economy relies strongly on professional services. Seventy percent of all U.S. high-tech employees work in professional services, which is a more deeply knowledge-based sector than manufacturing industries, for instance. While more than a fifth of the U.S. tech clusters are specialized in professional services, this sector also holds a notable share of employment in the multi-tech clusters that compose more than 60 % of the 627 clusters we found in the largest U.S. regions.

Regions also vary in tech clustering degree (i.e., concentration of high-tech economic activities). The top five regions for clustering degree are the Los Angeles, Washington DC, New York, Boston and Atlanta metro areas. However, a strong clustering score (i.e., more clusters) could indicate strong spatial dispersion of economic activities, particularly since tech clusters are the major job destinations in these regions. Relatively low population size of clusters could be at odds with smart growth policies. For instance, California's Los Angeles and Riverside metro areas or the Miami metro area in Florida are susceptible to ripple effects of housing unaffordability, congestion, and socioeconomic division (Zandiatashbar & Kayanan, 2020). A growth control plan needs to apply knowledge about the location of existing clusters as well as their capacity for growth. In other words, evidence-based economic development strategies can help to affect a shift from new high-tech cluster development toward a more robust understanding and use of the full capacity of the existing ones. The fact that property value increases tend to occur in tandem with cluster growth could be a serious barrier for new entrant high-tech firms. Such firms will instead be drawn to new, emerging clusters in more affordable areas on the regional peripheries (Menzel & Fornahl, 2009).

The growing interest of cities and economic development officials in tech clusters are leading rising efforts in targeting areas with little capacity for tech clusters. The success of such efforts could be ambiguous due to multiple exogenous factors such as the location of universities; accidents of history (e.g., where company CEOs grew up; or even the prior existence of a strong counterculture scene in the 1960s (according to an expert peer reviewer of this article)). However, the major capacity in a region to exert influence over how and where clusters grow requires a deep understanding of the existing landscape of tech industries in the region. This is one the main contributions of this paper and the location of high-tech clusters identified in this paper could inform local economic development plans in order to remove barriers to the growth of a cluster getting underway. For instance, the use of transportation or land use policy levers can motivate firms to locate within such clusters rather than investing in dispersed areas with no clusters (i.e., suburban office parks).

Furthermore, the findings of this study would inform economic diversification programs in order to motivate tech firms different but relevant sectors to locate in certain clusters to form multi-sector tech clusters. Examples of such programs could be industrial zoning or other mechanisms to protect critically important employers that underpin certain clusters. Accordingly, such mechanisms should have been in place to avoid major employers leaving long standing clusters in advance; for instance, to underpin Boeing in Seattle which has been home to Boeing headquarter since 1916 until its departure in 2001 (Rast & Carlson, 2006) or to avoid the ripple effects of competition in Dublin Ireland between Digital Hub and Grand Canal Dock which left the Dock's high-end construction unoccupied during the 2007–2012 period of economic uncertainty (Kayanan, 2022). Hence, knowing the location of tech clusters and their anchors is necessary for the success of planning and policy for the growth of tech clusters (Zandiatashbar & Hamidi, 2022).

In other words, as firms and headquarters tend to prioritize location and relocation to areas with better incentives; planners, economic development, and city officials should be proactive, and recognize the clusters that exist in their regions using the analytical methods and results of this paper for designing and implementing policies that can help clusters thrive as well as aligning with other policy objectives that support affordable housing, encouraging public transit use, and promote equity

In addition, promoting affordability should be a major focus of policies that target high-tech clusters. Using micro-level cluster geography to see and evaluate varying dynamics between housing affordability and different tech cluster types can sharpen that focus. Future studies should assess different vectors of the dynamic between housing value and tech clusters, including variation across different sectoral cluster typologies with respect to housing values, housing value variance, and housing value change over time. Local government success in offering affordability while supporting a high-tech economy largely relies on regional or state level support. In Silicon Valley, the failure of local affordable housing actions and ever-growing unaffordability led by high-tech traces to lack of coordination between the state and localities (Downs, 2005). Understanding high-tech cluster location and sectoral types at the micro-level is key in facilitating better coordination.

Additionally, an emphasis on existing clusters could help in allocating some corporate relocation tax incentives to community stabilization and affordable housing programs. While the goal of such incentives is to form clusters by attracting tech firms, existing clusters already possess a relatively high number of firms. The Payment-In-Lieu-of-Taxes (PILOT) program is an example of such a strategy adopted in Tennessee for Chattanooga's downtown. PILOT was typically offered to lure corporations such as Amazon, Coca-Cola, and Volkswagen, among others (Brogdon, 2015). In 2014, the City Council reallocated PILOT resources to support affordable housing, offering a 10- to 14-year tax break to developers committing to renting 20 % of their units to those who earn less than 80 % of the area median income (Smith & Smith, 2014). City Council revisited the program in 2016 and increased the share of affordable units to 50 %, which appears to reflect developers' willingness to qualify for these tax breaks (Leach, 2016). In fact, PILOT reallocation was actually a tactic supporting affordable housing prior to development of the downtown Chattanooga innovation district (Morisson & Bevilacqua, 2018).

In sum, there are multiple contributions this research makes including; first a generalizable new methodology for measuring the boundary and quantifying the types of high-tech zones at the micro level, which could be generalized to other cities, second, the minimal understanding of the micro-level location of existing high-tech clusters and their sectoral attributes has limited empirical study of the quality-of-life impacts these clusters have on surrounding communities, a critical requirement for evidence-based policymaking, third, our findings confirmed previous studies that emphasize IT industries' need for fast distribution of products as well as response to the global and e-commerce economy which justifies their desire for proximity to air and road infrastructure, in many megaregions, and lastly our findings show that airports are expanding their functionality beyond air mobility by adding a variety of business and commercial functions into passenger terminals (i.e. magazine shops, restaurants, boutiques, VIP rooms, coworking spaces) or on the landside (i.e. hotels, offices, conference and exhibition centers) to serve these bringing attention to the theoretical argument Kasarda (2000) made on airport in his book "Aerotropolis: The Way We'll Live Next", where it is argued that large, well-connected airports can serve as nuclei for many urban functions that in prior eras would have clustered around seaports, rail terminals, CBDs, and freeway interchanges.

Cities and regions, largely in favor of growth in high-tech clusters, are drawn to apply place-based economic development strategies such as innovation districts in order to promote the high-tech economy. Since rising housing value is one of several associated negative externalities that need to be addressed (Florida, 2017; Stehlin, 2016), this study suggests untapped synergies between sectoral typology of high-tech clusters and housing value. By integrating knowledge about tech cluster sectoral type and location with a smart growth agenda, planners and policy makers may be better equipped to find ways to associate high-tech cluster growth with a framework for battling the associated ripple effects, such as a polarized division of labor, income inequality, and housing unaffordability (Zandiatashbar & Kayanan, 2020).

CRediT authorship contribution statement

The authors confirm contribution to the paper as follows: study conception and design: AZ, SH; literature review, data collection: AZ; analysis and modeling: AZ; interpretation of results: AZ; draft manuscript preparation: AZ, SH; Both authors reviewed the results and approved the final version of the manuscript

Declaration of competing interest

- o All authors have participated in (a) conception and design, or analysis and interpretation of the data; (b) drafting the article or revising it critically for important intellectual content; and (c) approval of the final version.
- o This manuscript has not been submitted to, nor is under review at, another journal or other publishing venue.
- o The authors have no affiliation with any organization with a direct or indirect financial interest in the subject matter discussed in the manuscript.
- o The following authors have affiliations with organizations with direct or indirect financial interest in the subject matter discussed in the manuscript.

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