High-tech Business Location, Transportation Accessibility, and Implications for Sustainability: Evaluating the Differences between High-tech Specializations using Empirical Evidence from U.S. Booming Regions

Abstract:

Studies on the accessibility needs of high-tech firms often draw on agglomeration economies and creative class assumptions that emphasizes how transit and walkability encourage clustering, knowledge exchange and innovation. As a result, some argue that knowledge-led economic development aligns with sustainability planning, especially as high-tech industries become increasingly tied to smart city agendas. However, due to the new logistic revolution, global e-economy, rise of online workers and urban land values, it is likely that some tech industries prefer strong highway systems, potentially leading to higher GHG emissions. As such, the relationship between the knowledge economy and sustainability outcomes remains unclear. This study addresses these gaps by quantifying the geography of high-tech zones in North Texas and Northern California, measuring their specializations, and exploring their differences in terms of transportation infrastructures. Our results only partially support research suggesting high-tech industries prefer dense, walkable, transit-accessible places. For instance, we found large numbers of high-tech firms (e.g. IT and aerospace) are still attracted to peripheral, auto-centric spaces, which is at odds with sustainable transportation policies. Hence, policymakers may need to revisit their growth strategies to not only succeed in growing their knowledge economy, but also secure sustainability goals.

Keywords: High-Tech Zone, Transportation, Business Location, Sustainability

1. Introduction:

The shift from a commodity-based industrial economy to a knowledge-based economy has been accompanied by new urban forms and land use patterns. These changes raise important questions regarding the sustainability impacts of economic development policies. Although economic growth and sustainability outcomes are often theorized to be in tension (Campbell, 1996), ‘smart city’ policies integrate knowledge-based economic development, urban innovation, and sustainability agendas (Angelidou, 2015; Bibri, 2018; Dierwechter, 2014). Such policies leverage digital technologies to address urban environmental challenges, improve quality of life, while strengthening economic competitiveness (Adeoluwa et al., 2019; Ahvenniemi et al., 2017; Haarstad, 2016).

The presumed relationship between sustainable land uses and high-tech clusters is further strengthened by the literature on the geography of innovation. Despite early concerns regarding the ‘placelessness’ of economic activity made possible through information and communication technologies, a large body of empirical research has focused on how knowledge-based industries benefit from clustering in urban centers (Delgado et al., 2015; Koo, 2005; Porter, 2004). As some research suggests, knowledge-based industry clusters prefer dense, walkable, mixed-use, transit-accessible places to have access to markets and labor as well as support knowledge exchange. These place-based characteristics align well with sustainability strategies such as smart growth (Wlodarczak, 2012). However, these studies often do not address the specific needs of particular types of high-tech firms (Bakhshi et al., 2008; Granpayehvaghei et al., 2019; Hamidi et al., 2018; Hamidi and Zandiatashbar, 2018a, 2017b, 2017a; Zandiatashbar and Hamidi, 2018).

For example, industries impacted by the new logistic revolution are likely associated with different transportation preferences. Relying on a largely self-employed, part-time, and flexible workforce, IT industries are increasingly less place-based in the digital networking age (Audirac, 2005). The rise of the global economy, e-commerce and the need for fast processing and agile distribution of time-sensitive, high-tech production and goods extends the demand for road and air mobility (Aljohani and Thompson, 2016; Kasarda, 2000), potentially increasing GHG emissions (Lee and Erickson, 2017; Maggioni, 2002). For instance, the most high-tech booming U.S. region, the San Francisco Bay Area, also happens to have the fifth worst congestion in the world (Pishue, 2017). Moreover, in other regions, local experts have also expressed concerns about unmanageable congestion and long commute times as a result of high-tech economic growth (Dickson, 2018).

Further empirical analyses are needed on the transportation infrastructure preferences of high-tech firms while accounting for their specialized differences. Understanding these differences would lead to more evidence-based economic development and transportation policies that also meet sustainability goals. This study aims to address these gaps by quantifying the geography of high-tech zones in Texas and California, measuring their specializations, analyzing their differences in terms of transportation infrastructure. We selected North Texas' Dallas-Fort Worth (DFW) and Northern California's Bay Area regions since they are among the top five metro areas in terms of high-tech job growth between 2010 and 2015. In addition, the Bay Area and DFW hold more than 56% and 32% of their states' Information and Communication Technology (ICT) employees respectively (Muro and Liu, 2017).

To determine the location preferences of different high-tech industries with respect to transportation infrastructures, our methodology includes three analytical phases. First, we develop a geography of high-tech zones by employing spatial statistical techniques to identify the local spatial peaks of high-tech economic activity. Second, we develop a typology of high-tech zones based on zone-level industrial location quotients. Lastly, we present the results from four firm-level Analysis of Variance (ANOVA) models testing whether different types of high-tech firms have significantly different transportation infrastructure preferences. We use firm-level Walkscore and Transit Score, high-tech job accessibility within a 20-minute drive time, and network distance to primary hub international airports as measures of local, regional and (inter)national accessibility.

Our findings confirm that high-tech firms have significantly different transportation infrastructural preferences. While professional services (architecture/engineering) seek walkable and transit accessible zones, the IT sector prefers proximity to airports and road systems which likely stem from the specifications of these two industries. For example, the success of high-tech professional services depends on their ability to attract skilled workers who are drawn to transit and walking amenities. Moreover, dense and walkable CBDs also enhance frequent face-to-face encounters, tacit knowledge exchange, and physical access to the local market area, which are all associated with firm-level cost or productivity advantages (Hamidi and Zandiatashbar, 2018b; Zandiatashbar et al., 2019).

On the other hand, 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 (Kasarda, 2000). Our findings also confirm the formation of airport-adjacent industrial clusters in response to the global and e-commerce economy. Our findings in DFW and the Bay Area show the formation of airport adjacent high-tech corridors that include a cluster of airport-induced high-tech firms in ICT, aerospace and professional services along low density, fast moving, wide highways. As such, some high-tech zones are likely associated with negative environmental impacts. The findings therefore highlight the need for planners and policymakers to consider the potential impacts of certain high-tech specializations to better integrate knowledge-based economic development and sustainability strategies.

2. Literature Review

2.1. The Geography of Innovation

Innovation, underpinned by knowledge-based industry clusters, is thought to fuel economic development. As such, policymakers are keen to understand the location preferences and industrial dynamics related to high tech firms and workers. A dominant focus of knowledge economy research has been the importance of co-location. Starting with Marshall (1890), it has long been understood that clustering benefits firms through "external economies of scale", as a result of shared labor pools, specialized suppliers, and common infrastructure. This concept of industry clustering has been developed further by Porter in (2000). In his view, clusters are the "geographic concentrations of industries related by knowledge, skills, inputs, demand and/or other linkages." These inter-industry linkages result in three Marshallian sources of agglomeration externalities including input–output linkages, labor market pooling and knowledge spillovers which are all associated with cost or productivity advantages to firms (Marshall, 1890).

Further it is theorized that clustering is particularly beneficial for knowledge-based firms who rely on face-to-face contact, social networking, and tacit-knowledge exchange (Asheim et al., 2011). This research on the stickiness of places has been bolstered by creative class research, which suggests particular built environments such as density, walkability, mixed-uses and urban aesthetics both attract knowledge workers and increase innovation (Florida, 2002).

2.2. High-Tech Clusters and Sustainability

The research on clustering and the importance of the built environment suggests that there are synergies between knowledge-based economic development and sustainability planning (Wlodarczak, 2012). Further, the presumed relationship between high-tech industries and sustainability has strengthened in policy circles as a result of ‘smart city’ frameworks (Angelidou, 2015; Bibri, 2018). Smart city technologies are thought to spur collaborative, data-driven responses to urban environmental challenges, nudge people and organizations towards efficient and sustainable behavior, improve quality of life and increase economic competitiveness (Portney, 2003; Herrschel 2013). ‘Smartness’ also refers to the role collaboration, networking and learning play in developing innovation solutions to urban challenges (Herrschedl 2013).

Subsequently, urban policies integrating the development of tech-based knowledge clusters, land use policies, and sustainability agendas have gained prominence. Examples include innovation districts, urban laboratories, and knowledge hubs, which incorporate mixed-use zoning, transit accessibility and placemaking amenities (Asheim et al., 2011; Hamidi et al., 2018; Hamidi and Zandiatashbar, 2018a; Katz and Krueger, 2016; Yigitcanlar et al., 2008; Zandiatashbar and Hamidi, 2018). These developments may also include explicit commitments to developing low carbon technologies and reducing GHG emissions (Evans and Karvonen, 2014; Morisson, 2015).

However, the relationship between high-tech economic development and sustainability may be more rhetorical than substantive (March and Ribera-Fumaz, 2016). Although high-tech innovation districts may locate in dense, urban areas (Grodach et al., 2014), Currid and Connolly (2008) identify three different spatial patterns including clustering in central business districts, dispersed regional clustering and specialist places. Madanipour (2013) has similarly identified a range of innovation clusters such live-work-play centers, technology parks and geographically distributed 'science cities'. This research suggests that high-tech clusters are more spatially diverse, and subsequently, may produce negative environmental impacts. However, this research is limited in that it does not explore how the particular types of high-tech clusters shape location preferences.

2.3. Theorizing High Tech Firms' Accessibility Needs

Industry specializations, logistical needs, customer and labor markets, as well as land utilization will influence firms' location preferences in regards to local, regional and (inter)national mobility infrastructures (Maggioni, 2002). For instance, high-tech firms could be categorized into two types in order to assess their regional and (inter)national accessibility needs. The first type includes service providers (i.e. engineering/architectural/drafting services, web-developer/software publishers, private Research and Development (R&D) labs) that produce immaterial commodities like professional and consultation services. These industries do not require production and distribution of goods or logistic mobility. The second type includes high-tech manufacturing industries (i.e. IT/semiconductors manufacturing, communication equipment, biopharmaceutical/biological products). Relying on e-commerce, just-in-time delivery, and time-sensitive distribution, these firms likely seek strong road and air mobility to satisfy their regional and (inter)national accessibility demands.

Specific labor needs could also lead to different local and regional accessibility preferences. For example, pharmaceutical research organizations or medical device firms, require a more homogenous, very specialized workforce (Mellander, 2009). Other high-tech firms, such as large 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 and Nicoll, 2012). While regional accessibility helps large high-tech manufacturing firms to have access to a wider labor market supporting their diverse occupational demands, the success of other firms often depends on their ability to attract and retain quality skilled workers.

In this regard, recent literature has emphasized the role of quality-of-life factors in location decisions by the creative class including walking and transit amenities (Zandiatashbar and Hamidi, 2018). In addition to walkability, commuting by transit is also the lifestyle of millennials and university graduates who are relatively more car-free (Hamidi and Zandiatashbar, 2018). Millennials own 12% fewer cars than previous generations, are less likely to be licensed drivers, and live in denser places, which have on average twice the level of transit access to jobs as compared to older generations (Klein and Smart, 2017). While the demand for a highly specialized workforce justify the need for walking and transit amenities, there exist several types of high-tech firms which do not necessarily benefit from place-based amenities for their workforce recruitment. As these firms (i.e. IT, communication technologies) have footloose economic activities and flexible production systems, they prefer a more part-time and flexible workforce. This workforce often joins organizational teams remotely using online spaces, which makes these new economic activities increasingly personalized rather than place-based (Audirac, 2005).

High-tech firms' different customer markets could also lead to different transportation preferences for local, regional and (inter)national accessibilities. Financial consultants, legal services or headquarters of IT or aerospace companies resonate with Sassen's (1991) concept of global cities in which nations are firmly connected and draw on a global market of customers. As a result, air mobility and online interactions are becoming increasingly important modes of transaction and transportation. Airports on the other hand are also 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, co-working spaces) or on the landside (i.e. hotels, offices, conference and exhibition centers) to serve these needs (Kasarda, 2000). However, local accessibility might matter more for some high-tech industries (i.e. facilities support services, computer services, engineering and architectural services, and placement services) as service to the local customer base is important. Accordingly, per Christaller's central place theory, these industries are considered a high-order service category, which unlike low or medium order services, need to concentrate in walkable and transit accessible Central Business Districts (CBDs) in order to have access to a wider customer market area (Zandiatashbar and Hamidi, 2018).

Lastly, high-tech firms' land uses may be different due to land costs as these have been a critical factor in business location decision and transportation preferences per classical location theory (Maggioni, 2002). High-tech industries that involve manufacturing (i.e. IT manufacturing, semiconductor manufacturing, control instrument manufacturing, aerospace products/manufacturing, and navigational equipment production) require larger land areas for their production processes, and technical or R&D activities. Thus, these businesses are drawn to the peripheries, or the newly developed employment sub-centers in edge cities in order to minimize land cost. Accessibility to these locations therefore require roadway systems (Maggioni, 2002), which have implications about sustainable urban development strategies and outcomes.

3. Methods:

3.1. Sample & Study Area:

In this study, we analyzed high-tech firms in four Metropolitan Statistical Areas (MSAs) in Texas and California. We selected San Francisco-Oakland-Hayward (SFO), San Jose-Sunnyvale-Santa Clara (SJSC), and Santa Cruz-Watsonville (SCW) metropolitan areas which compose the economic territory of the Bay Area in Northern California. We also included Dallas-Fort Worth-Arlington (DFW) metropolitan area in North Texas. Generally, a metropolitan area is a region that consists of a densely populated urban core and less-populated territories that are economically and socially linked. With respect to the high-tech economy, Texas and California hold almost 25% of U.S. high-tech employment and are the top two states in the national share of IT and pharmaceutical employment (Feser et al., 2005). In addition, our selected regions are home to high concentrations of high-tech activity. According to Brookings, excluding SCW MSA, our sample regions are among the U.S. top-five metro areas in terms of 2010-2015 high-tech job growth (Muro and Liu, 2017). Furthermore, the Bay area holds more than 56% and DFW holds more than 32% of their states' ITC employees, respectively. This evidence confirms that our sample regions stand out in high-tech economic growth both statewide and nationally. Despite these regions being largely auto-oriented (Ewing, 2008; Ewing and Hamidi, 2017), their built environments were developed during the rise of the knowledge economy. Analysis of these regions would, therefore, shed lights on which high-tech zones are more prominent in these areas and how they are associated with proximity to different transportation infrastructures.

In this study, we included 32,279 high-tech firms and 8,363 census block groups in the study area. The Bureau of Labor Statistics (BLS) classifies high-tech firms in three levels based on R&D intensity:

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

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

Level III: 2-2.9 times greater than average employment share in STEM fields

The BLS also adjusts this classification based on R&D output. About 10 out of 14 sectors in level I produce R&D outputs while only 4 out of 11 sectors in level II. No sector in level III produces R&D outputs (Heckler, 2005). For this analysis, we applied the BLS level I definition of high-tech firms.

3.2. Data and Variables:

Table 1 shows the list of variables and data sources used in our analysis. Firm level data is drawn from the ESRI Business Dataset (2016), which is based on Infogroup data covering 100% of firm counts in the U.S. From this data source, we extracted the BLS high-tech level I firms in our study area. We obtained metropolitan area and census block group shape files for 2016 using Topologically Integrated Geographic Encoding and Referencing (TIGER) in ESRI shape file format. Using these shape files and Arc GIS, we aggregated our business data to the block group level as our unit of measurement. We also used 2016 census block group population and land area in order to control for the size of a block group. In addition, we used the CBDs in ESRI shape file format obtained from Hamidi (2015), which identifies the location of CBDs (MSA's hotspot block groups in terms of employment density) using spatial statistic techniques (Local Moran's I). Finally, we used the Walkscore API package in R and collected Walkscores and Transit Scores for the firms within the specialized high-tech zones.

TABLE 1: Data and Variables Used in the Study

Name	*Description*	*Source*	*Mean (s.d.)*
HT_Emp	BLS level I high-tech employment	EBD (2016)	55.85(523.601)
HT_Den	BLS level I high-tech employment density in block group (/sqmile)	EBD & ACS (2016)	137.37(1000.105)
HT_Pop	BLS level I high-tech employment per capita in block group	EBD & ACS (2016)	44.75(437.64)
HT	*HT_EMP, HT_Den, HT_POP* combined using factor analysis	EBD & ACS (2016)	0.00(1)
Walkscore	Firm's Walkscore obtained from Walkscore Inc.	Walkscore Inc. (2018)	58.55 (29.1)
Transit Scores	Firm's Transit Score obtained from Walkscore Inc.	Walkscore Inc. (2018)	56.11 (30.34)
Airport Scores	Reversed and normalized measure of firm's network distance to the nearest primary hub international airport	EBA Street Route & FAA (2018)	64.86 (19.69)
Auto Score	Normalized number of amenities accessible via 20-minute driving from a high-tech firm.	EBA Street Route & US Inforgroup (2016)	61.57 (22.13)

EBD = ESRI Business Dataset
ACS = American Community Survey
EBA = ESRI Business Analyst
LEHD = Longitudinal Employer-Household Dynamics
FAA= Federal Aviation Administration
s.d.=Standard Deviation

3.3. Analytical Methods:

Our methodology for identifying the location of specialized high-tech zones and analyzing high-tech firms has three main phases: (1) identifying high-tech zone candidates; (2) developing a specialization typology; and (3) analyzing the difference between high-tech specializations in terms of transportation infrastructure measures.

In phase 1, we use local spatial statistics to identify the location of significant clustering of high-tech employment. In phase 2, we use the classification from the U.S. Cluster Mapping Project (Delgado et al., 2015) and location quotients to identify specialized high-tech zones and develop a typology for them. In phase 3, we use descriptive statistics and Analysis of Variance (ANOVA) to evaluate the difference between high-tech firms residing in the specialized zones.

3.3.1. Phase 1: Identifying High-Tech Zone Candidates:

According to BLS, a high-tech firm demonstrates a high level of R&D intensity in both inputs (employee, supplies, process) and outputs (products) (Heckler, 2005). As discussed before, in this analysis, we included 14 industries that are considered BLS high-tech level I. The high level of R&D in these industries is due to their high share of STEM educated employment and R&D products (i.e. pharmaceutical products, scientific R&D services, navigational, measuring, electromedical, or control instruments, etc.). Although BLS level I includes a small fraction of high-tech industries compared to other lists, it accurately accounts for R&D in both input and output. Table 2 presents further details for these industries.

To identify high-tech zone candidates, we applied a spatial modeling technique. Recent studies have applied spatial modeling techniques such as spatial statistics to identify the level of clustering of economic activities in various geographies across the country. These techniques have been used more to detect the monocentric or polycentric spatial structures of the regions, changes in the location of CBDs or to locate employment sub-centers (Hajrasouliha and Hamidi, 2017; Hamidi, 2015). While the use of spatial statistics in location analysis of high-tech clusters is limited, Feser and his colleagues (2005) used Getis-ord Gi* statistics to identify the clusters of U.S. counties that encompass strong economic activities. In addition to Getis-ord

Gi*, Koo (2005) used the local Moran's I statistics to examine the geographical patterns of knowledge-based clusters in U.S. counties using employment and patents. Local Moran's I identifies cases of positive (HH, LL) and negative (HL, LH) spatial autocorrelation, while the Getis-Ord Gi* identifies cases with positive autocorrelation with a more straightforward definition and readily interpretable output (Getis and Ord, 1992). As we were interested in all clusters of positive values, we chose local Getis- Ord Gi* statistics.

Our methodology addresses three major shortcomings that exist in previous studies analyzing the geography of high-tech clusters. First, the criteria used for identifying high-tech industries failed to control for the R&D intensity of the output, or they are inconsistent across the studies. For instance, some studies only included ten sectors (Wu et al., 2016), while others included more than 100 industries (Feser et al., 2005). Second, previous high-tech cluster analyses that used spatial statistics, could not remove the sources of heterogeneity, which stem from their methodological approaches. For instance, in our analysis, since San Francisco and San Jose have a substantive share of high-tech employees in the nation, the local spatial peaks in Dallas could be dismissed. To address this shortcoming, we ran our analysis on a one-by-one basis for all MSAs in the study area. Lastly, the unit of analysis in such studies is not finer than county level boundaries, which limits detecting local specialized high-tech clusters. Studying the impacts of firms on their surrounding urban developments and locational attributes require identifying specialized clusters at a finer geography. We address this shortcoming by using a firm-level dataset.

In terms of the variables used for spatial statistics analysis of high-tech (and other types of) employment clusters or sub-centers, studies have employed different approaches. Total employment, residual of regressed high-tech employment on total employment, patent numbers, high-tech plant counts, employment density, and employment-to-population ratio measures are among the widely used variables (Fallah et al., 2013; Feser et al., 2005; Hajrasouliha and Hamidi, 2017). Employment density or employment-to-population ratio control for the size of a unit (compared to the number of total jobs); however, they come with shortcomings. There exist cases that the block group's land area, while included in the census' land area, is not developable. These cases are often around specific ecological reserves. We encountered such examples in our analysis particularly on the southeast side of the Bay area in Northern California. An employment-to-population ratio could be used as a substitute; however, outliers would still exist as low-populated block groups with small numbers of high-tech employment would result in high ratios. To overcome these challenges, we used factor analysis and defined a new value, *HT*, which is an index, composed of the number of high-tech employees, high-tech employment density and high-tech employment-to-population ratio. We used factor analysis to estimate *HT, which* includes factor loadings of 0.916 for employment, 0.700 for employment density, and 0.903 employment-to-population ratio. The factor analysis also provided three index options. The first option has an eigenvalue of 2.146, which includes 71.53% of variance. The second option has an eigenvalue of 0.662, which explains 22.1% of variance, and the third option has an eigenvalue of 0.192, which explains only 6.4% of variance. Hence, we selected the first option for our *HT*.

Using the *HT* factor for every census block group, we estimated the local Getis-Ord Gi* for each MSA in the study area separately. This analysis compares the sum *HT* value of a block group's neighbors (local sum) to the overall sum *HT* value of an MSA. When the local sum is higher than the total sum, and that difference is too large to be the result of random chance, there would be a statistically high chance that this group of block groups is a hotspot. Ultimately, we identified a cluster of neighboring block groups with high *HT* values (hotspot) as a high-tech zone candidate.

The Getis-Ord Gi* is defined as:

$$G_i^* = \frac{\sum_j^n \quad w_{ij} x_j}{\sum_j \quad x_j} \tag{1}$$

Where:
The numerator is the sum of all values in the neighborhood of i.

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

Gi* is the percentage of the total sum found in the neighborhood of i

We also used the False Discover Rate (FDR) adjustment to control for the presence of “overlapping subsets” in the analysis. This overlapping is caused because the data used to produce a local statistic at block group *i* is also used to produce the statistics for nearby block groups. The FDR procedure controls for the expected proportion of incorrectly rejected null hypotheses or “false discoveries.” We used the ‘spden’ and ‘psych’ packages in R for estimating the Getis-Ord Gi* and factor analysis estimating the *HT*.

As the result of hotspot analysis, we found 30 high-tech zones. Figure 1 illustrates the location of high-tech zones in DFW and the Bay Area. All the zones are labeled with ID numbers, which we will refer to in presenting the results.

In DFW, as shown in figure 2, we found the highest G-values (strongest high-tech cluster) in zone 4, which is the city of Plano’s newly developed *The Grand at Legacy West High-Tech Urban Village.* This multiuse district was initially planned to be North Texas’ IT, data, software, and telecommunication core (Audirac, 2002;

Taylor and Singleton, 1996). Ongoing developments in this district including Plano's financial incentives (i.e. tax abatements, economic development grants, tax increment finance) have attracted several high-tech corporations and their workforces (Brass, 2016). In the Bay area, the strongest high-tech cluster is found in zone 3 in the city of Fremont. This cluster includes a corridor of high-tech firms that extend along Interstate 880 including the Tesla factory, Western Digital Corp, and Life Scan Inc. The major difference between these two high-tech clusters is that in Plano, IT and telecommunication are the major industries, while in Fremont the high-tech corridor includes these two industries as well as pharmaceutical industries.

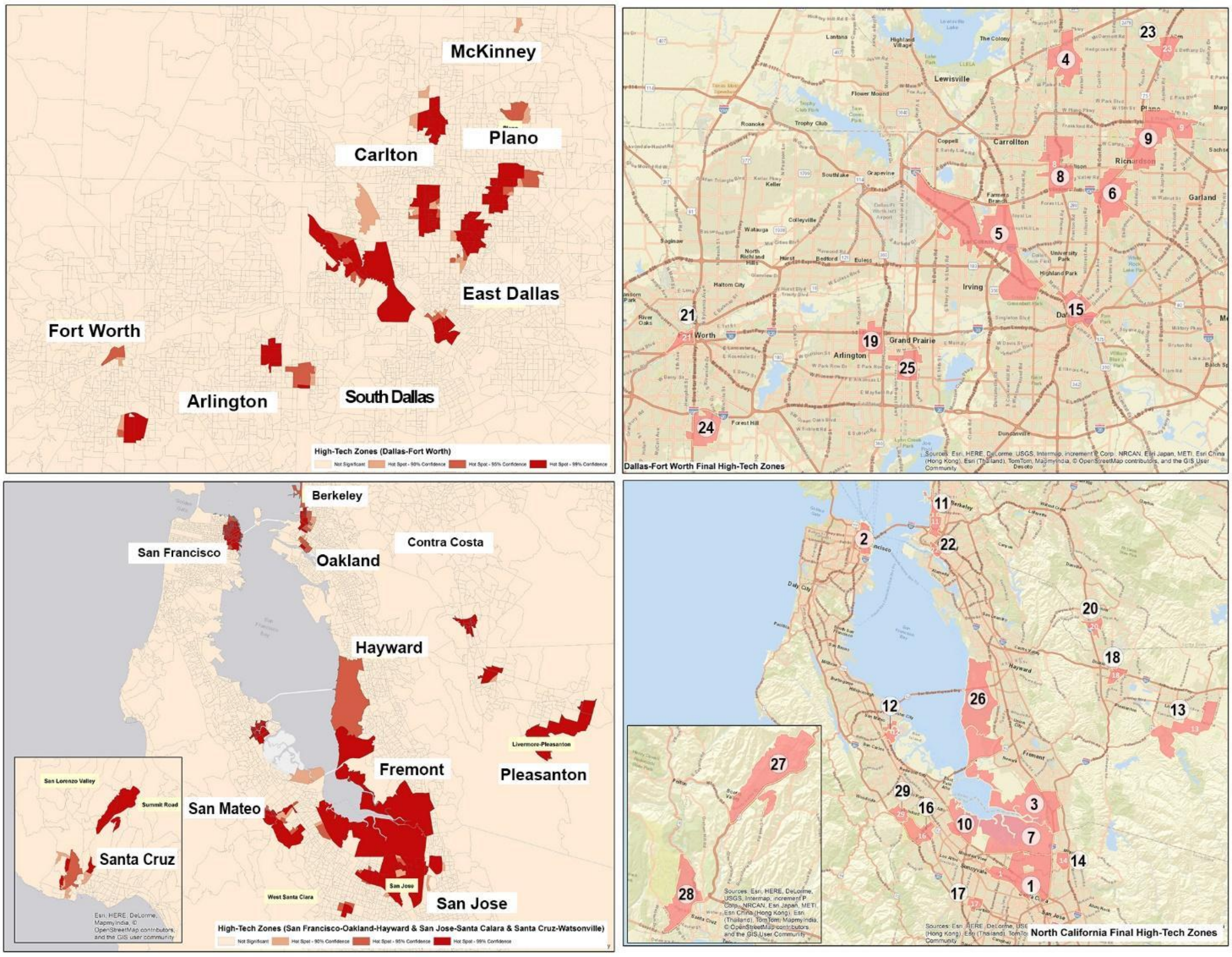

FIGURE 1: Results of hotspot analysis

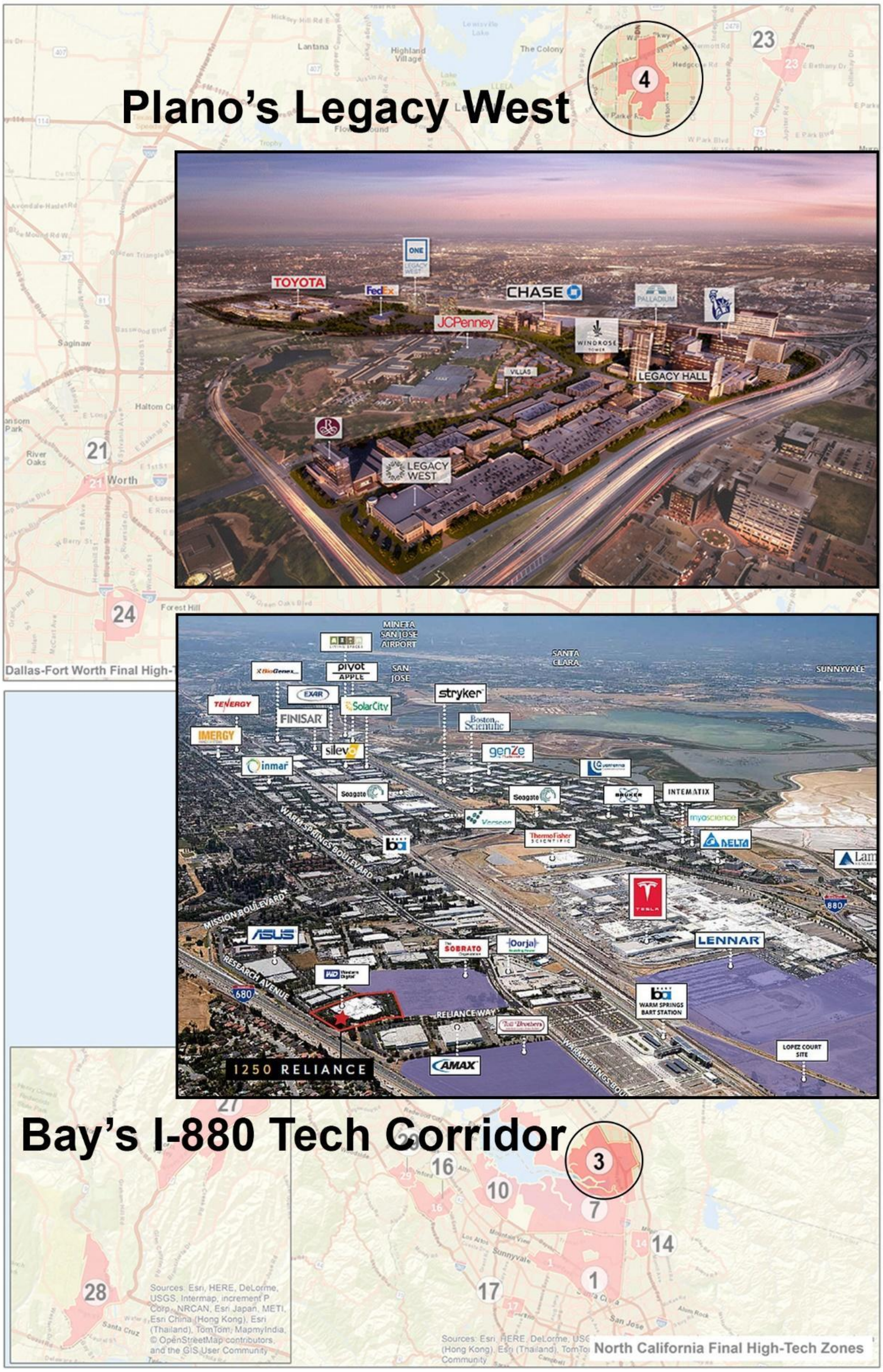

FIGURE 2: Areas with highest G-values (Brass, 2016; "Miramar Capital," n.d.)

3.3.2. Phase 2: Specialization Typology and Profile of the Zones:

After identifying the high-tech zone candidates, we classify the 14 BLS high-tech level I sectors into six categories. Each category includes the sectors that have the strongest inter-industry linkages based on co-location patterns, input-output links, and similarities in labor occupations. We use the same methodology as the U.S. Cluster Mapping project which used six-digit NAICS codes to classify 778 industries in manufacturing and services into 51 sector categories (TABLE 2).

TABLE 2: high-tech specializations and number of zones we found for each category (Delgado et al., 2010; Heckler, 2005).
Specialization
1) Information Technology and Analytical Instruments
This cluster consists of information technology and analytical products such as computers, software, audio visual equipment, laboratory instruments, and medical apparatus as well as standard and precision electronics used by these products (e.g. circuit boards and semiconductor devices). *Industries included:* 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 cluster manufacture aircraft, space vehicles, guided missiles, and related parts. This cluster also contains firms that manufacture the necessary search and navigation equipment used by these products. *Industries:* NAICS 3364: Aerospace products/manufacturing, NAICS 334511: Navigational equipment
3) Bio-pharmaceutical
Establishments in this cluster 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) Services
Firms in this cluster provide services primarily designed to support other businesses such as consulting, legal services, facilities support services, computer services, engineering and architectural services, and placement services. This includes corporate headquarters. *Industries:* NAICS 5182 & 5415: Data Processing, system design and computer services, NAICS 5413: Engineering Services, Architectural and Drafting Services
5) Communications Equipment and Services
This cluster involves goods and services used for communications such as cable, wireless, and satellite services, as well as telephone, broadcasting, and wireless communications equipment. *Industries:* NAICS 3342: Communications equipment manufacturing, NAICS 5179: Other telecommunications
6) Education and Knowledge Creation
This cluster includes research and development institutions in biotechnology, physical sciences, engineering, life sciences, and social sciences. *Industries:* NAICS 5417: Research Organization

We measure the specialization of high-tech zones by computing the location quotients (LQ) for each of the six categories. LQs have been widely used to study the specializations of high-tech MSAs or counties (Cortright and Mayer, 2001; Fallah et al., 2013). We define specialized zones as areas with an LQ greater than 1.5 for at least one category in Table 2. The cut off value of 1.5 indicates that the high-tech share of a zone's employment is 1.5 times greater than the state's share of high-tech employment. This cut off value is borrowed from similar studies (Cortright and Mayer, 2001). Accordingly, we dropped one high-tech zone candidate with an LQ of 1.19 for R&D, 0.99 for services and 0 for the other sectors, which led to our final set of 29 specialized high-tech zones in both regions.

The zones could specialize in multiple categories if they have LQs of greater than 1.5. Figure 3 is a linear chart of location quotients for these 29 zones. The chart reflects strong within group differences of six LQs for these 29 zones. In other words, in each zone, one or a few specializations have significantly higher LQs, which were then selected as specialization types. Table 3 presents the number of zones we found specialized in each category. As illustrated in Figure 4, among our 29 specialized zones, eight zones have mixed specializations and 21 are single type. Four single type zones are CBDs and specialize in the services category. IT was found to be the most frequent and dominant specialization across our specialized high-tech zones.

FIGURE 3: Linear Chart; Location Quotients in High-Tech Zones

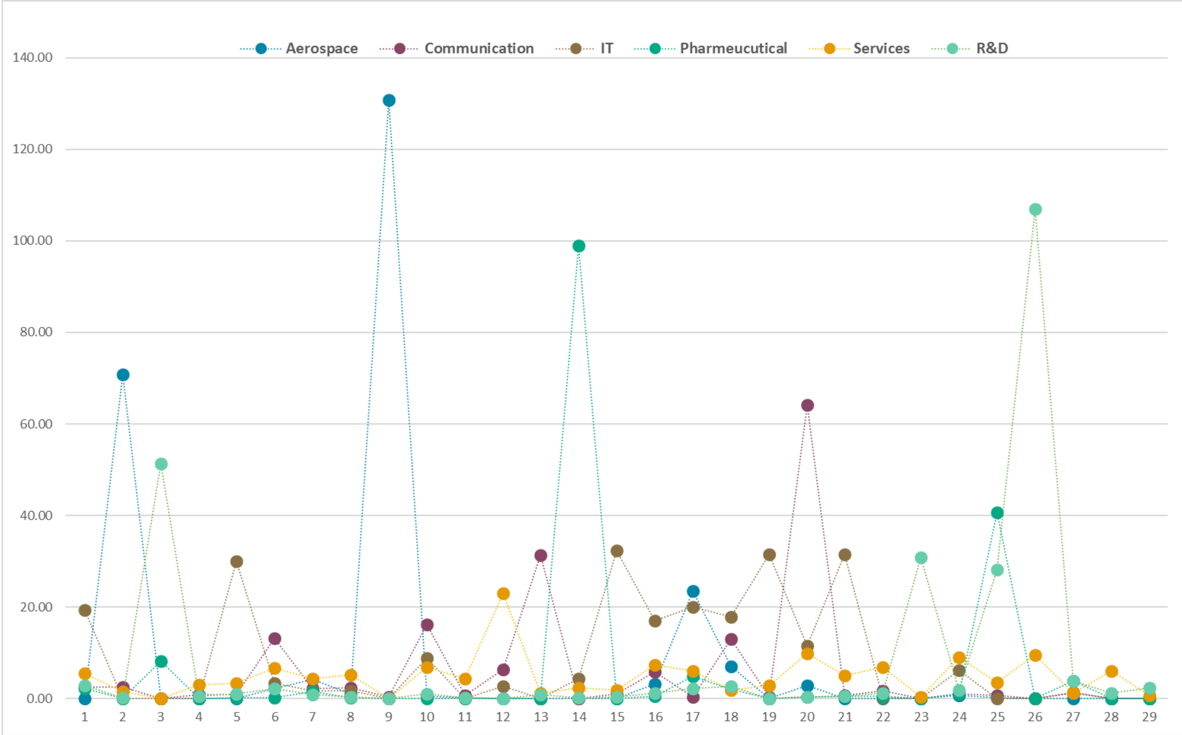

TABLE 3: Frequency of Zone Types

	Frequency	Percent	Cumulative Percent
Aerospace	2	6.9	6.9
Aerospace, IT	1	3.4	10.3
Communication	2	6.9	17.2
Communication, IT	1	3.4	20.7
Communication, IT, Services	1	3.4	24.1
IT	6	20.7	44.8
IT, Aerospace, Services	1	3.4	48.3
IT, Communication	1	3.4	51.7
Pharmaceutical	1	3.4	55.2
Pharmaceutical, R&D	1	3.4	58.6
R&D	4	13.8	72.4
R&D, Pharmaceutical	1	3.4	75.9
Services	6	20.7	96.6
Services, IT	1	3.4	100.0
Total	29	100.0	

Moreover, we found in general, IT, aerospace, services, and communication zone types locate either in proximity to major highway systems, in urban cores, or nearby other transportation infrastructures such as railroads or airports. As shown in

Figure 4, most IT zones are located along interstates or major highway networks. For instance, zone 6 is the Telecom Corridor, a technology business center that has been a booming area of Dallas's economy since the late 1990s. As shown in Figure 4, this zone is extending along highway U.S. 75 (North Central Expressway) following zones 9 and 23. Other high-tech zones in DFW (zones 4, 5 and 8) follow the same pattern along President George Bush Turnpike.

In line with the logistics demands in the global and e-commerce economy, we found two airport adjacent high-tech zones (zones 1 & 5). Both zones have the same type which is a mixed specialization of IT, aerospace, communication and services. In DFW, this zone is a corridor that includes a cluster of airport-induced high-tech firms extending from DFW international airport to Dallas Love Field airport. In Northern California, this zone is adjacent to the Mineta San Jose International Airport. While the Bay area has three major airports, Mineta San Jose and San Francisco International Airports have been the major destinations for business trips. The majority of business trips to Silicon Valley fly to Mineta airport since it is located within the San Jose CBD with less crowded terminals (Witlox et al., 2007). On the other hand, we found five specialized zones in education, knowledge creation and bio-pharmaceutical including zone 11 with proximity to U.C. Berkeley, zone 29 in Palo Alto adjacent to Stanford University, and zone 13, which is home to The Sandia National Laboratories, one of three national nuclear security administration R&D labs in the Bay area. We also found Alcon Eye R&D and manufacturing headquarters and Tarrant County College - South Campus, as possible anchors for a similar zone (zone 24) in DFW. We found these zones in proximity to educational, medical or research anchors that were not necessarily a private business or corporation.

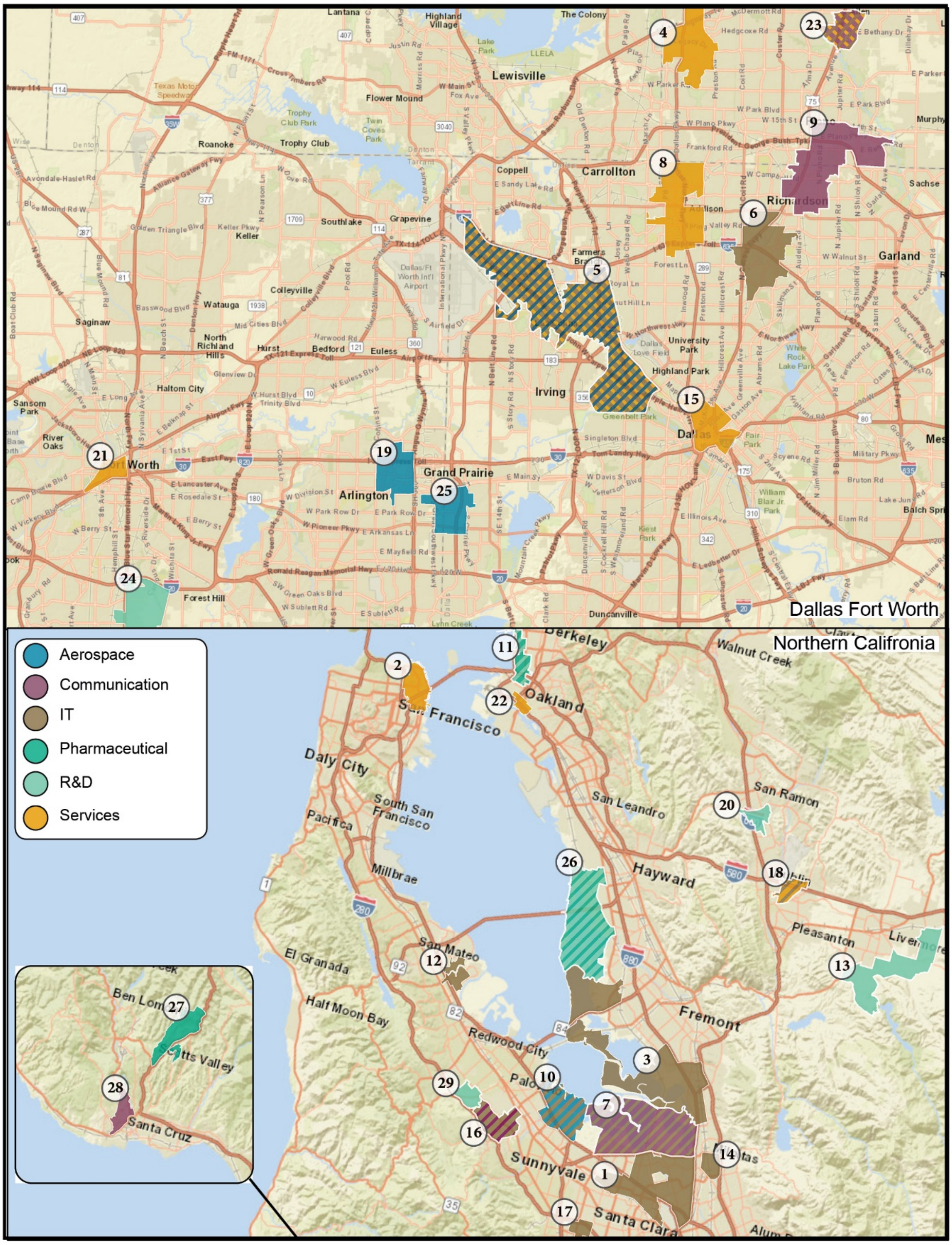

FIGURE 4: High-tech Zone Typology

461

3.3.3. Phase 3: Mobility Preferences of High-Tech Firms in the Specialized Zones:

In phase 3, we focused on the specialization of high-tech firms in the zones to assess differences in locational preferences with respect to transportation infrastructure. We employed ANOVA, which is an analytical method used to test statistical differences between two or more groups, suitable for our hypothesis. Using SPSS 23, we ran four firm-level ANOVA models with the results presented in Table 4. Our data for the ANOVA models showed an unequal variance between the groups so we adjusted the P-values using Bonferroni test. In these models, we used six high-tech specializations as our factor variables. Our dependent variables are the following four indicators of transportation infrastructure.

First, we used Walkscore and Transit Score indicating local accessibility. Developed by Walkscore Inc[1]., these scores measure walkability and transit accessibility for any address point in several countries. For each address, Walkscore uses walking routes to measure proximity to amenities which are weighted differently and discounted as the distance to them increases up to one and a half miles, where they are assumed to be no longer accessible on foot. Transit Score also measures public transit quality. This measure uses data released by public transit agencies through General Transit Feed Specification (GTFS) including stops and routes for available modes of public transportation (i.e. local, express, and rapid bus routes, commuter rail, light rail, streetcar, and subway systems). Using this data, Transit Score calculates the value of all nearby routes for an address. This value equals to the frequency per week multiplied by the transit type weight (heavy/light rail is

[1] https://www.walkscore.com/methodology.shtml

weighted 2X, ferry/cable and street car/other are 1.5X, and bus is 1X) multiplied by a distance penalty which uses the distance to the nearest stop on a route (Walkscore Inc., 2014). Second, we developed a regional auto-accessibility score. This score measures proximity to a range of businesses and amenities within a 20-minute driving distance of a given high-tech firm. Literature points to these businesses and amenities as the most frequent trip destinations of individuals (i.e. food stores, social/religious services, educational services, public health services, etc.) (Hamidi et al., 2017). For this variable, we used the Network Analysis and street routes in ArcGIS. Lastly, we developed a score indicating (inter)national accessibility based on the street route distance to the nearest international primary hub airport using Arc GIS-based network analysis. According to Federal Aviation Administration's Airports Category, primary hub airports have more than 10,000 passenger boardings each year and therefore are used by one or more airlines to concentrate passenger traffic and flight operations ("Airport Categories – Airports," 2018). Our network analysis, based on street routes, considers high-tech firms as the origin of a trip and the nearest airport as the destination. The distance measure was reversed to match the measurement of the other three variables. Furthermore, all of our scores were normalized to a range between 0 (lowest accessibility) to 100 (highest accessibility).

3.4. Results:

The results of our ANOVA show that our four accessibility scores are significantly different between the six high-tech specializations[2].

Figure 5 presents the means of our four scores indicating firms' preferences for transportation, grouped by their high-tech specializations. Professional services high-tech specialization has an average Walkscore higher than all other high-tech firms. The average Walkscore for these firms is 62.25. Walkscore Inc. interprets places with a Walkscore below 50 as a "car dependent area" (Brewster et al., 2009). Therefore and according to this interpretation, only services and communication industries are located in somewhat walkable areas. All other sectors are located, on average, in car dependent areas. Transit score follows similar patterns between the high-tech specializations. Additionally, IT and aerospace firms have on average very low Walk and Transit Scores.

On the other hand, IT and aerospace specializations have a higher average airport-access score when compared to all other specializations. The average airport-access scores for these two industries are also higher than the average score for all high-tech firms. In the other words, when compared to all other high-tech firms, these firms are on average closer to major airports in the region. Lastly, the two sectors that collectively have low averages in all these scores are pharmaceutical and R&D firms.

[2] Although these results confirm significant differences between specializations for each score, these scores could be collectively exclusive. Therefore, these four types of accessibility scores are not directly comparable to one another.

FIGURE 5: Average Scores of Specializations per Mode

526

TABLE 4: ANOVA Results

		Walkscore	Transit Score	Auto-access Score	Airport Prox. Score
(I)	(J)	Mean Diff. (I-J)	Mean Diff. (I-J)	Mean Diff. (I-J)	Mean Diff. (I-J)
IT	Aerospace	4.509	3.115	-0.2482	4.324
	Bio-pharmaceutical	-7.227	1.891	**24.681***	**20.165***
	Services	-28.171*	-22.843*	**-6.314***	**12.625***
	Communication	-17.063*	-14.196*	-7.797*	**15.388***
	R&D	-10.945*	2.988	**17.473***	**21.620***
Aerospace	IT	-4.509	-3.115	0.248	-4.324
	Bio-pharmaceutical	-11.736	-1.225	**24.929***	**15.841***
	Services	-32.680*	-25.958*	-6.066	8.301
	Communication	-21.572*	-17.311*	-7.548*	**11.064***
	R&D	-15.454*	-0.128	**17.721***	**17.296***
Pharmaceutical	IT	7.227	-1.891	-24.681*	**-20.165***
	Aerospace	11.736	1.225	-24.929*	**-15.841***
	Services	-20.944*	-24.733*	-30.994*	-7.541
	Communication	-9.836	-16.087	-32.478*	-4.778
	R&D	-3.718	1.097	-7.208	1.454
Services	IT	**28.171***	**22.843***	**6.314***	-12.625*
	Aerospace	**32.680***	**25.958***	6.065	-8.301
	Bio-pharmaceutical	**20.944***	**24.733***	**30.994***	7.541
	Communication	**11.109***	**8.647***	-1.483	2.7631
	R&D	**17.226***	**25.830***	**23.787***	**8.995***
Communication	IT	**17.063***	**14.196***	**7.797***	-15.388*
	Aerospace	**21.572***	**17.311***	**7.548***	-11.064*
	Bio-pharmaceutical	9.836	16.087	**32.478***	4.778
	Services	-11.109*	-8.647*	1.483	-2.763
	R&D	6.117	**17.184***	**25.270***	**6.232***
R&D	IT	**10.945***	-2.988	-17.473*	-21.620*
	Aerospace	**15.454***	0.128	-17.721*	-17.296*
	Bio-pharmaceutical	3.718	-1.097	7.208	-1.454
	Services	-17.226*	-25.830*	-23.787*	-8.995*
	Communication	-6.117	-17.184*	-25.270*	-6.232*

*. The mean difference is significant at the 0.05 level.
Bold: Significantly higher value than other sectors
ht: High-Tech Specializations

The results of our ANOVA models have low P-values (<0.000) and high F-values (69.28 to 171.70). These measures indicate that there are significantly different locational attributes between high-tech specializations with respect to our four accessibility scores. Table 4 presents the results of the four ANOVA analyses of specialized firms. Each column presents results for each ANOVA and the numbers in

Table 4 are bold whenever they have a significantly higher mean value than their paired specializations. For instance, business services have significantly higher means for Walkscore and transit score compared to all other sectors. On the other hand, the mean values of airport proximity score are significantly higher for IT than the other five specializations. The mean value of airport proximity score for aerospace firms is also significantly higher than others, except for IT firms.

Communication and R&D also have significantly higher Walkscore and Transit Score means when paired with IT and aerospace. Furthermore, the specialized firms in the communication category have significantly higher means of auto-access score when paired with with all other high-tech specializations.

4. Discussion and Conclusions:

To ensure cities remain resilient in the face of climate change and economic uncertainty, planners and policymakers are increasingly interested in policy initiatives that strengthen regional economies as well as improve urban sustainability. Emerging smart-sustainable city initiatives suggest that the knowledge economy, especially high-tech industries, are key to developing innovative solutions to urban environmental challenges. Further, agglomeration economies and creative class literatures suggest that these industries thrive in places that are dense, walkable and transit-accessible. These features support more sustainable land use patterns and behaviors. As a result, policymakers and planners often employ location incentives and placemaking to promote innovation districts, knowledge hubs, and other examples of place-based high-tech clustering to meet both economic and sustainability goals (Katz and Krueger, 2016; Pancholi et al., 2015; Yigitcanlar et al., 2008).

Although these examples suggest there may be synergies between the high tech industries and sustainability interests, empirical evidence is limited. Indeed, preferences for walkability and transit access likely only apply to a subset of high-tech industries. A large number of high-tech firms may prefer and therefore continue to produce more auto-centric developments on the urban fringe (Maggioni, 2002). As policymakers continue to pursue knowledge-based economic development strategies, it is important to identify transportation preferences in order to understand the role these industries play in promoting certain spatial forms and their implications for sustainability outcomes.

Our empirical results support theoretical work indicating that different types of high-tech firms have varied preferences for specific transportation infrastructures. For instance, we found that business services have significantly higher means for Walkscore and Transit Score compared to all other sectors. Business services industries include computer/system services and engineering and architecture firms, which primarily provide services to other businesses, facilities or unrelated companies (Maggioni, 2002). Consequently, they are highly reliant on a specialized workforce to deliver high-order services, and therefore concentrate in walkable, transit accessible CBDs to cover a wider market area (Zandiatashbar and Hamidi, 2018). Furthermore, they provide services or immaterial commodities, which unlike traditional manufacturers, do not need cheaper, larger or more peripheral land areas for their manufacturing facilities (Maggioni, 2002). These firms also draw upon the externalities of frequent face-to-face encounters and tacit knowledge exchange that stem from their proximity in dense and walkable CBDs.

On the other hand, our results confirm that IT sectors have significantly higher mean values for airport proximity when compared to all other high-tech specializations. Meanwhile these industries have a relatively low average Walkscore of 34, which suggests they prefer car-dependent areas according to Walkscore Inc's interpretation. Unlike business services, IT employees mostly exchange codified knowledge. Studies indicate that online digital interactions could be a substitute for face-to-face encounters for exchanging codified knowledge (Audirac, 2002; Relph, 1976). Moreover, these firms manufacture, process and distribute goods which need production facilities usually in auto-accessible peripheries (Audirac, 2005). In addition, their involvement in e-commerce deepens their demand for fast road and air mobility (Kasarda, 2000).

In addition to IT sectors, we found that the mean value of airport proximity score for aerospace firms is also significantly higher than all other sectors. The proximity to airport addresses their need for air mobility, airport facilities and services (i.e. runways, control tower, hangers) (Haug, 1991).

These findings suggest that more critical attention is required for understanding the relationship between knowledge-based firms and their preferences for transportation infrastructure. The dominant narrative regarding the spatiality of knowledge-based clusters suggests that these industries prefer dense, walkable, mixed use, transit accessible urban environments. Our research supports this theory, however only partially. Our findings suggest that large numbers of high-tech firms are still attracted to peripheral, auto-centric spaces, which are at odds with sustainable transportation policies.

This study has a few limitations. First, both DFW and Northern California regions are largely auto-oriented. It is possible that the high auto and airport accessibility scores are the result of land use decision-making, transportation cultures, and zoning laws favoring car dependency in these regions. More studies are needed to investigate these relationships in regions with more diverse land use and development patterns. Secondly, while this study offers an innovative approach in identifying the location of high-tech zones, it is not within the scope of this paper to investigate which factors actually determine high-tech firm location decisions. More evidence is needed to link the locational preference of high tech firms, inside and outside the high-tech zones, to other factors widely supported by the literature such as access to talent, diversity and inclusion (Granpayehvaghei et al., 2019; Hamidi et al., 2018; Hamidi and Zandiatashbar, 2018b, 2017a, 2017b; Zandiatashbar et al., 2019; Zandiatashbar and Hamidi, 2018). Furthermore, while our sectorial classifications come from one of the most widely cited studies done by Harvard's economist Michael Porter, it is possible that the changes in the classification leads to the changes in the ANOVA findings.

Finally, while our findings confirm that not all high tech industries follow the same pattern with regard to proximity to transportation infrastructures, we did not study the reasons behind these sectorial differences. More empirical research is needed to tackle the transportation preferences of different high tech industries. This research calls for deeper analyses of high tech firm location preferences and how economic development, land use and transportation policies could incentivize more sustainable outcomes.

Despite the long-standing debates regarding urban form and sustainability as well as emerging policies suggesting knowledge-led economic development is compatible with sustainability agendas, these findings demonstrate that many high-tech zones may be problematic in terms of their environmental impacts. As the result of these findings, policymakers may need to attend to the specializations present in their regional economy and balance growth strategies to not only succeed in growing their knowledge economy, but also ensure they are meeting sustainability goals.

References:

Adeoluwa, A., Cabral, P., Gomes, P., Casteleyn, S., 2019. The Lisbon ranking for smart sustainable cities in Europe. Sustain. Cities Soc. 44, 475–487. https://doi.org/10.1016/j.scs.2018.10.009

Ahvenniemi, H., Huovila, A., Pinto-Seppä, I., Airaksinen, M., 2017. What are the differences between sustainable and smart cities? Cities 60, 234–245. https://doi.org/10.1016/j.cities.2016.09.009

Airport Categories – Airports [WWW Document], 2018. URL https://www.faa.gov/airports/planning_capacity/passenger_allcargo_stats/categories/ (accessed 5.6.19).

Aljohani, K., Thompson, R.G., 2016. Impacts of logistics sprawl on the urban environment and logistics: Taxonomy and review of literature. J. Transp. Geogr. 57, 255–263.

Angelidou, M., 2015. Smart cities: A conjuncture of four forces. Cities, Current Research on Cities (CRoC) 47, 95–106. https://doi.org/10.1016/j.cities.2015.05.004

Asheim, B., Smith, H.L., Oughton, C., 2011. Regional Innovation Systems: Theory, Empirics and Policy. Reg. Stud. 45, 875.

Audirac, I., 2005. Information technology and urban form: challenges to smart growth. Int. Reg. Sci. Rev. 28, 119–145.

Audirac, I., 2002. Information technology and urban form. J. Plan. Lit. 17, 212–226.

Bakhshi, H., McVittie, E., Simmie, J., 2008. Creating Innovation: Do the creative industries support innovation in the wider economy? Nesta London.

Bibri, S.E., 2018. A foundational framework for smart sustainable city development: Theoretical, disciplinary, and discursive dimensions and their synergies. Sustain. Cities Soc. 38, 758–794. https://doi.org/10.1016/j.scs.2017.12.032

Brass, K., 2016. Dense, Walkable Urbanism Drawing Corporate Offices to Plano, Texas - Urban Land Magazine [WWW Document]. URL https://urbanland.uli.org/development-business/legacy-west-whats-drawing-corporate-headquarters-plano-texas/ (accessed 9.2.18).

Brewster, M., Hurtado, D., Olson, S., Yen, J., 2009. Walkscore. com: A new methodology to explore associations between neighborhood resources, race, and health. APHA Poster Present. Retrieved Electron. Httpsapha Confex Comrecordingapha137ampdffree4db77adf5df9fff0d3caf5cafe28f496paper2050821 Pdf.

Campbell, S., 1996. Green cities, growing cities, just cities?: Urban planning and the contradictions of sustainable development. J. Am. Plann. Assoc. 62, 296–312.

Cortright, J., Mayer, H., 2001. High tech specialization: a comparison of high technology centers. Brookings Institution, Center on Urban and Metropolitan Policy Washington, DC.

Currid, E., Connolly, J., 2008. Patterns of knowledge: the geography of advanced services and the case of art and culture. Ann. Assoc. Am. Geogr. 98, 414–434.

Delgado, M., Porter, M.E., Stern, S., 2015. Defining clusters of related industries. J. Econ. Geogr. 16, 1–38.

Dickson, G., 2018. Will Dallas-Fort Worth's rapid growth turn it into the next Los Angeles? [WWW Document]. Star-Telegr. URL http://www.star-telegram.com/news/business/growth/article212129739.html (accessed 6.5.18).

Dierwechter, Y., 2014. The spaces that smart growth makes: sustainability, segregation, and residential change across Greater Seattle. Urban Geogr. 35, 691–714. https://doi.org/10.1080/02723638.2014.916905

Evans, J., Karvonen, A., 2014. 'Give me a laboratory and I will lower your carbon footprint!'—Urban laboratories and the governance of low-carbon futures. Int. J. Urban Reg. Res. 38, 413–430.

Ewing, R., 2008. Highway-induced development: research results for metropolitan areas. Transp. Res. Rec. J. Transp. Res. Board 101–109.

Ewing, R., Hamidi, S., 2017. Costs of Sprawl. Taylor & Francis.

Fallah, B., Partridge, M.D., Rickman, D.S., 2013. Geography and high-tech employment growth in US counties. J. Econ. Geogr. 14, 683–720.
Feser, E., Sweeney, S., Renski, H., 2005. A descriptive analysis of discrete US industrial complexes. J. Reg. Sci. 45, 395–419.
Florida, R., 2002. The rise of the creative class. Wash. Mon. 34, 15–25.
Getis, A., Ord, J.K., 1992. The analysis of spatial association by use of distance statistics. Geogr. Anal. 24, 189–206.
Granpayehvaghei, T., Bonakdar, A., Zandiatashbar, A., Hamidi, S., 2019. The Quest for Creative Industries: A Multilevel National Study of the Impacts of Urban Form on the Geography of Creative Industries. Transp. Res. Rec. 0361198119843470.
Grodach, C., Foster, N., Murdoch III, J., 2014. Gentrification and the artistic dividend: The role of the arts in neighborhood change. J. Am. Plann. Assoc. 80, 21–35.
Haarstad, H., 2016. Who Is Driving the 'Smart City' Agenda? Assessing Smartness as a Governance Strategy for Cities in Europe, in: Jones, A., Ström, P., Hermelin, B., Rusten, G. (Eds.), Services and the Green Economy. Palgrave Macmillan UK, London, pp. 199–218. https://doi.org/10.1057/978-1-137-52710-3_9
Hajrasouliha, A.H., Hamidi, S., 2017. The typology of the American metropolis: monocentricity, polycentricity, or generalized dispersion? Urban Geogr. 38, 420–444.
Hamidi, S., 2015. Measuring metropolitan form: Remaking urban form for sustainability. The University of Utah.
Hamidi, S., Moazzeni, S., Jahan, J., Sardari, R., Weinreich, D., 2017. Does Location Matter? Performance Analysis of the Affordable Housing Programs in Dallas Fort Wayne Metropolis.
Hamidi, S., Zandiatashbar, A., 2018a. Does urban form matter for innovation productivity? A national multi-level study of the association between neighbourhood innovation capacity and urban sprawl. Urban Stud. 0042098018767002.
Hamidi, S., Zandiatashbar, A., 2018b. Does urban form matter for innovation productivity? A national multi-level study of the association between neighbourhood innovation capacity and urban sprawl: Urban Stud. https://doi.org/10.1177/0042098018767002
Hamidi, S., Zandiatashbar, A., 2017a. The Forgotten Dimension: National Investigation of the Relationship Between Urban Sprawl, Transportation Accessibility, and Regional Innovative Capacity.
Hamidi, S., Zandiatashbar, A., 2017b. Does Built Environment Matter for Innovation? A Quantitative Study of the Physical Assets of Innovation Districts in the United States.
Hamidi, S., Zandiatashbar, A., Bonakdar, A., 2018. The relationship between regional compactness and regional innovation capacity (RIC): Empirical evidence from a national study. Technol. Forecast. Soc. Change.
Haug, P., 1991. The location decisions and operations of high technology organizations in Washington State. Reg. Stud. 25, 525–541.
Heckler, D.E., 2005. High-technology employment: a NAICS-based update. Mon. Lab Rev 128, 57.
Kasarda, J.D., 2000. New logistics technologies and infrastructure for the digitized economy, in: 4th International Conference on Technology Policy and Innovation. Citeseer, pp. 28–31.
Katz, L.F., Krueger, A.B., 2016. The rise and nature of alternative work arrangements in the United States, 1995-2015. National Bureau of Economic Research.
Kimelberg, S.M., Nicoll, L.A., 2012. Business location decisions in the medical device industry: evidence from Massachusetts. Econ. Dev. Q. 26, 34–49.
Klein, N.J., Smart, M.J., 2017. Millennials and car ownership: Less money, fewer cars. Transp. Policy 53, 20–29.
Koo, J., 2005. Knowledge-based industry clusters: Evidenced by geographical patterns of patents in manufacturing. Urban Stud. 42, 1487–1505.
Lee, C.M., Erickson, P., 2017. How does local economic development in cities affect global GHG emissions? Sustain. Cities Soc. 35, 626–636. https://doi.org/10.1016/j.scs.2017.08.027

Madanipour, A., 2013. Knowledge economy and the city: Spaces of knowledge. Routledge.
Maggioni, M., 2002. The location of high-tech firms and the development of innovative industrial cluster: A survey of the literature. Progetto Ric. Interesse Naz. Work. Pap. AT2 1, 2002.
March, H., Ribera-Fumaz, R., 2016. Smart contradictions: The politics of making Barcelona a Self-sufficient city. Eur. Urban Reg. Stud. 23, 816–830. https://doi.org/10.1177/0969776414554488
Marshall, A., 1890. Principles of economics. Macmillan, London.
Mellander, C., 2009. Creative and knowledge industries: an occupational distribution approach. Econ. Dev. Q. 23, 294–305.
Miramar Capital [WWW Document], n.d. . Miramar Cap. URL https://www.miramarcapital.com/fremont-ca/ (accessed 9.2.18).
Morisson, A., 2015. Innovation districts: a toolkit for urban leaders. CreateSpace Independent Publishing Platform.
Muro, M., Liu, S., 2017. Tech in metros: The strong are getting stronger. Wash. DC Brook. Inst. Accessed March 9, 2017.
Pancholi, S., Yigitcanlar, T., Guaralda, M., 2015. Place making facilitators of knowledge and innovation spaces: insights from European best practices. Int. J. Knowl.-Based Dev. 6, 215–240.
Pishue, B., 2017. US Traffic Hot Spots: Measuring the Impact of Congestion in the United States.
Porter, M., 2004. Cluster mapping project–Institute for Strategy and Competitiveness, Harvard University.
Porter, M.E., 2000. Location, competition, and economic development: Local clusters in a global economy. Econ. Dev. Q. 14, 15–34.
Relph, E., 1976. Place and placelessness. Pion.
Sassen, S., 1991. Global city. Princeton University Press Princeton, NJ.
Taylor, S.T., Singleton, B.N., 1996. ITS: Communications technology case study, Plano, Texas. ITE J. 66.
Walk Score Inc., 2014. Walk score methodology. Accessed April 24.
Witlox, F., Derudder, B., Devriendt, L., 2007. A Spatial Analysis of Multiple Airport Cities, in: 11th World Conference on Transport ResearchWorld Conference on Transport Research Society.
Wlodarczak, D., 2012. Smart Growth and Urban Economic Development: Connecting Economic Development and Land-Use Planning Using the Example of High-Tech Firms. Environ. Plan. A 44, 1255–1269. https://doi.org/10.1068/a44450
Wu, J., Nager, A., Chuzhin, J., 2016. High-Tech Nation: How Technological Innovation Shapes America’s 435 Congressional Districts. Information Technology and Innovation Foundation.
Yigitcanlar, T., O’connor, K., Westerman, C., 2008. The making of knowledge cities: Melbourne’s knowledge-based urban development experience. Cities 25, 63–72.
Zandiatashbar, A., Hamidi, S., 2018. Impacts of transit and walking amenities on robust local knowledge economy. Cities.
Zandiatashbar, A., Hamidi, S., Foster, N., Park, K., 2019. The Missing Link between Place and Productivity? The Impact of Transit-Oriented Development on the Knowledge and Creative Economy. J. Plan. Educ. Res. 0739456X19826271. https://doi.org/10.1177/0739456X19826271