

International Downtown Association Vitality Index

Expanding the index into 2020 and beyond



Alan Wang (ahw9f@virginia.edu)
Leonel Siwe (yhu2bk@virginia.edu)
Qasim Mehdi (snc3uu@virginia.edu)
Treena Goswami (gcm8gw@virginia.edu)
Cesar Montalvo (cpm9w@virginia.edu)
Stephanie Shipp (sss5sc@virginia.edu)



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Introduction

The Vitality Index measures key characteristics that make a downtown vital, strong, and active. The UVA Bio-complexity Institute, Social and Decision Analytics Division was asked to scope and evaluate the feasibility of extending the International Downtown Association (IDA) Vitality Index into the year 2020, 1) calculate the metrics and the vitality index for years 2020 and 2021 for up to 50 downtown areas, and 2) acquire alternative data to calculate the indices.

IDA 2021 Tier classification categorizes downtowns into three categories: established, growing, and emerging. Established downtowns contain a significant portion of the city's residents, jobs, and assessed value. Growing downtowns are characterized by rapidly expanding populations and job counts. Emerging downtowns exhibit swift growth in either residents or jobs (though not both) or display signs of positive development. These tiers do not indicate the age of a district. They categorize downtowns that have reached similar stages of development maturity. Furthermore, these tiers are formulated through a separate methodology and do not align directly with the Vitality Index scoring. The classification into tiers is determined by various metrics, including density, jobs per square mile, residents per square mile, assessed value per square mile, significance to the city, percentage of citywide jobs, percentage of citywide residents, long-term growth, percent growth in jobs (2002–2017), and percent growth in population (2000–2017).

The team worked with IDA and produced a report and a CSV data file of the updated metrics to support the continuation and expansion of the vitality index into future years and additional areas. Table (1) summarizes these results by category. In addition to the three categories provided by the IDA - established, growing, and emerging, we have an additional category called "unclassified". This category corresponds to downtowns with no Tiers classification provided by IDA. In the following section of results, the categorized downtowns have been denoted by a specific color, allowing for easy identification and navigation - emerging (purple), growing (pink), established (yellow), and unclassified (gray).

Emerging Downtowns	Established Downtowns	Growing Downtowns	Unclassified
Albuquerque	Baltimore	Ann Arbor	Baton Rouge
Birmingham	Fort Lauderdale	Atlanta	Corpus Christi
Cleveland	Miami	Austin	Louisville
El Paso	Minneapolis	Boise	Milwaukee
Evansville	Pittsburgh	Charlotte	Nashville
Grand Rapids	Richmond	Dallas	New Haven
Greensboro	San Francisco	Durham	
Hollywood	Seattle	Huntsville	
Lancaster	Waikiki	Indianapolis	
Little Rock		Lexington	
Oklahoma City		Los Angeles	
San Antonio		Norfolk	
Spartanburg		Sacramento	
Tampa		Saint Paul	
Toledo		Santa Monica	
Tucson		Tempe	
Tulsa		West Palm Beach	

Table 1: Table overview of supporting measure of the vitality index and suggestions

Category	Variable	Data Source	Variable name from the data source	Years available	Aggregation Method used	Clarification	Notes
Economy	Job Growth	LEHD	C000	2010-2020	Sum of jobs at the downtown before computing job growth.	Should we maintain 2010 as the baseline for the growth? Why 2010 was the baseline?	We pulled historical data from 2010 to 2020 at the 2020 census geo-levels. We predict value in 2021 assuming the same rate of change from the past year.
	Job Density	LEHD	C000 and use shapefiles to compute the square footage.	2010-2020	Sum of jobs at the downtown before computing job density.		We pulled historical data from 2010 to 2020 at the 2020 census geo-levels. We predict value in 2021 assuming the same rate of change from the past year.
	Knowledge Jobs	LEHD	total jobs = C000 knowledge jobs = CNS09, CNS10, CNS11, CNS12, CNS13, CNS16	2010-2020	Sum of jobs at the downtown before computing the percentage of knowledge jobs.		We pulled historical data from 2010 to 2020 at the 2020 census geo-levels. We predict value in 2021 assuming the same rate of change from the past year.
	Educational Attainment Unemployment	ACS5 ACS5	B15003_001E to B15003_025E B23025_002E & B23025_005E	2010-2021 2010-2021			

Table 1 continued from previous page

Category	Variable	Data Source	Variable name from the data source	Years available	Aggregation Method used	Suggestions	Notes
Inclusion	Diversity Index	ESRI Business Analyst	ESRI diversity index	2010, 2020, 2023	Population weighted average	Can we use ACS5 and compute the diversity index to obtain a long-time series of this metric?	We downloaded ESRI diversity index at the 2020 census geo-levels for 2010, 2020, and 2023. For each downtown, the diversity index is computed as the population-weighted average of the diversity index at the 2020 census geo-levels included in the downtown.
	Housing and Transportation Cost	Center for Neighborhood Technology	ht_ami	2015, 2019, 2020	Simple mean	Vitality index dashboard says HT Cost "Source CNT 2017"? Contact CNT directly to access recent data?	We used population weights to aggregate across downtowns
	Middle-Income Households	ACS5	B19001_001E to B19001_017E	2010-2021			
	Home Price/Income Ratio	ACS5	Home price = "B25077_001E" Hhd income = hi = "B19013_001E" pop = "B01003_001E"	2010-2021	Simple mean		We used population weights to aggregate across downtowns
	% Children + Seniors	ACS5	B01001 pop = "B01003_001E"	2010-2020	Simple mean		

Table 1 continued from previous page

Category	Variable	Data Source	Variable name from the data source	Years available	Aggregation Method used	Suggestions	Notes
Vibrancy	Shop and Restaurant Density	ESRI Business Analyst	ESRI retail industry (SIC 52-59) business location point. Source: Axle data.	2023	Sum of all data points within a downtown divided by the downtown square footage.	We have the Axle historical data at UVA. Can we use the historical Axle data to build a time series of this metric.	We pulled data for the year 2023 and computed the metric.
	Population Growth	ACS5	B01003_001E	2010-2021	% change between 2010 to year in question		We checked against column K in the compendium
	Population Density	ACS5, 2020 Tiger files	B01003_001E, ALAND20	2010-2021	Population-weighted density (percentage of residents divided by district land area)		We checked against M1 column in compendium
	Walk Score	walkscore.com	Walk Score	2010-2023	Mean		We can use archived data to extract historical information closest to June 1st of the year in question
	% Sustainable Commute	ACS5	B08301_001E to B08301_018E	2010-2021	Mean		

1 Data Sources

1.1 American Community Survey (ACS)

The American Community Survey (ACS) 5-Year data for 2020 and 2021 provide comprehensive information on the U.S. population's social, economic, demographic, and housing characteristics. This U.S. Census Bureau's ongoing survey is crucial for communities to plan investments and services effectively. These estimates represent data collected over the entire 5-year period, not just specific points within that timeframe.

The ACS 5-Year data profiles include a broad geographical range, encompassing the nation, all states (including Washington D.C. and Puerto Rico), all metropolitan areas, congressional districts, counties, places, and tracts. This extensive coverage ensures a detailed and comprehensive understanding of various topics. ACS 5-Year data for 2020 and 2021 offer a valuable resource for understanding the multifaceted aspects of the U.S. population. However, the impact of the COVID-19 pandemic on the 2020 data collection should be considered when analyzing these findings.

For this report, we relied on the ACS 5-Year data to measure the following variables at tract and block group level: educational attainment, unemployment, middle-income households, home price/income ratio, percentage of children + seniors, population growth, population density, and percentage sustainable commute. For all these variables and those mentioned next, please refer to Table 1 for further details.

1.2 ESRI Business Analyst

To examine the metrics of inclusion and vibrancy, we employ ESRI Business Analyst, which is a Geographic Information System (GIS) tool for analyzing socioeconomic factors of communities. Using data on income distribution, access to amenities, and diversity provided by this tool, we calculate the level of inclusion in a community. Similarly, ESRI Business Analyst utilizes data on business activities, cultural facilities, and population trends for vibrancy assessment. The tool enables us to visualize and analyze community data, spanning aspects like income, amenities, and diversity, at specific local areas, such as tracts and block groups.

1.3 Walkscore.com

Walkscore.com provides data on the walkability, bikeability, and transit-friendliness of locations. The site calculates scores for these categories based on the proximity of amenities like grocery stores, parks, schools, restaurants, and public transit. A Walk Score measures how easy it is to live a car-lite lifestyle in a particular area, while a Bike Score evaluates cycling conditions. A Transit Score rates the effectiveness of public transit. We only collected walk scores from this website for the respective downtowns of interest.

1.4 Center for Neighborhood Technology

The relevant data sources from the Center for Neighborhood Technology (CNT) include the Housing and Transportation (H+T®) Affordability Index, used nationwide to promote sustainability and affordability in urban development. We used their datasets to measure housing and transportation costs.

1.5 Longitudinal Employer-Household Dynamics (LEHD)

The U.S. Census Bureau Longitudinal Employer-Household Dynamics program is a comprehensive resource for understanding the U.S. labor market. It is a quarterly database that links employer-employee data, covering over 95 percent of U.S. employment. This database is created by merging a variety of previously collected survey and administrative data about jobs, businesses, and workers. The LEHD program aims to provide detailed insights into the labor market and enhance the quality and scope of the economic and demographic data programs of the Census Bureau. By combining federal, state, and Census Bureau data on employers and employees under the Local

Employment Dynamics (LED) Partnership, the LEHD program exemplifies a cost-effective, accessible approach to labor market analysis, proving invaluable for policymakers, researchers, and the public alike.

We used historical employment information from the Longitudinal Employer-Household Dynamics (LEHD) at the census geo-levels defining downtown between 2010 and 2020. We use the LEHD8 (version 8), which provides employment information at the 2020 census geo-levels and focuses on all primary jobs (coded JT01) at the destination using the Workplace Area Characteristic (WAC). For each 2020 census geo-level, we extract the total number of jobs (coded C000), and the count of knowledge jobs defined as jobs from knowledge industries (see Downtown.org definition). Those industries include Information, Finance and Insurance, Real Estate and Rental and Leasing, Professional Scientific and Technical Services, Management of Companies and Enterprises, and finally, Health Care and Social Assistance. In addition, we also pull data from Educational Services, Public Administration, Accommodation and Food Services, and Retail Trade industries.

2 Results and Notes

This section presents descriptive results for up to 50 downtown areas. The observations are not tested for statistical significance.

2.1 Economy

Job Growth

- Job growth is computed as a percentage increase in primary jobs since 2010 at a downtown level.
- Figure (1) depicts the growth in primary jobs between 2010 and 2020 in downtown areas. Growing downtowns tend to experience a more rapid rate of job growth than emerging and established downtowns.

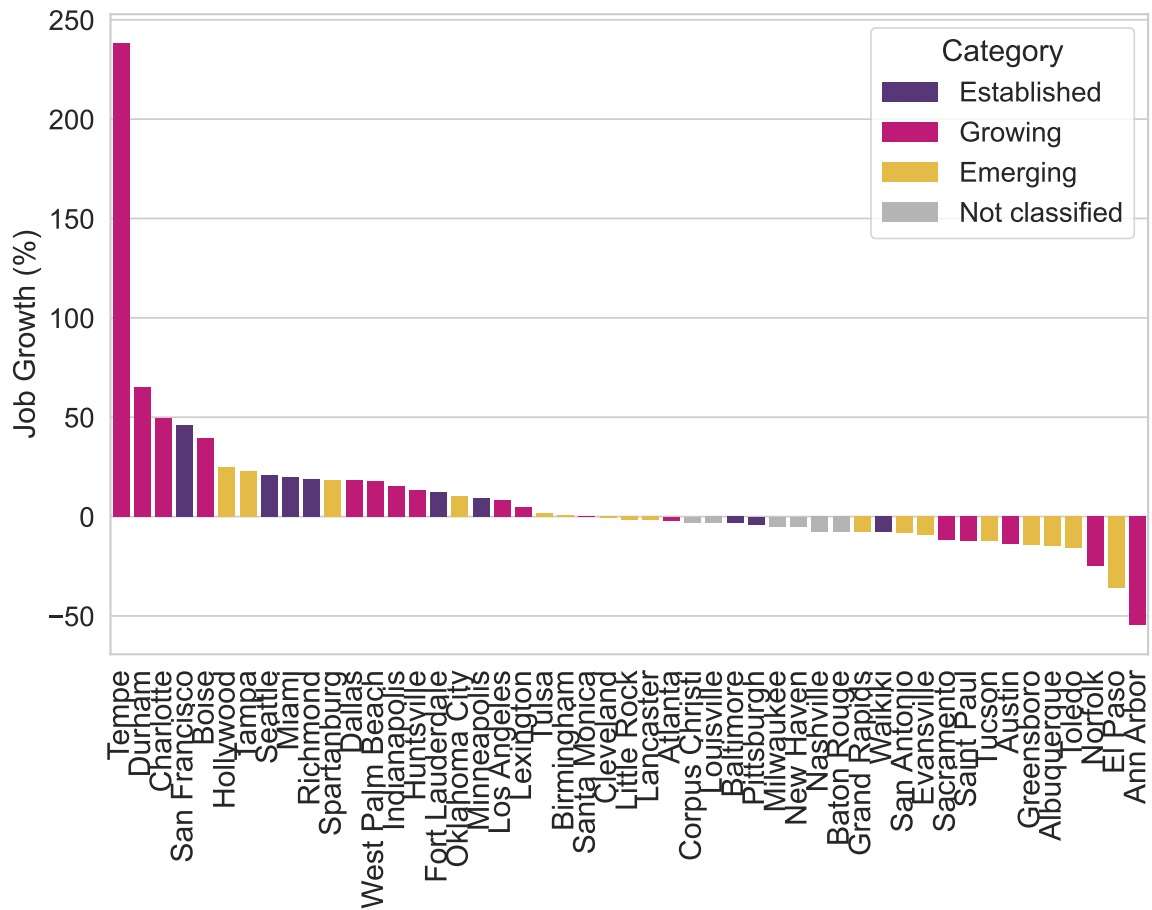


Fig. 1: Primary Job Growth in 2020 across Downtowns. (Source: LEHD).

Job Density

- Job density is computed as the number of primary jobs per square mile in a downtown.
- Figure (2) shows the number of primary jobs per square mile across downtowns, classified according to the 2021 Tier. Established and growing downtowns present higher job densities.

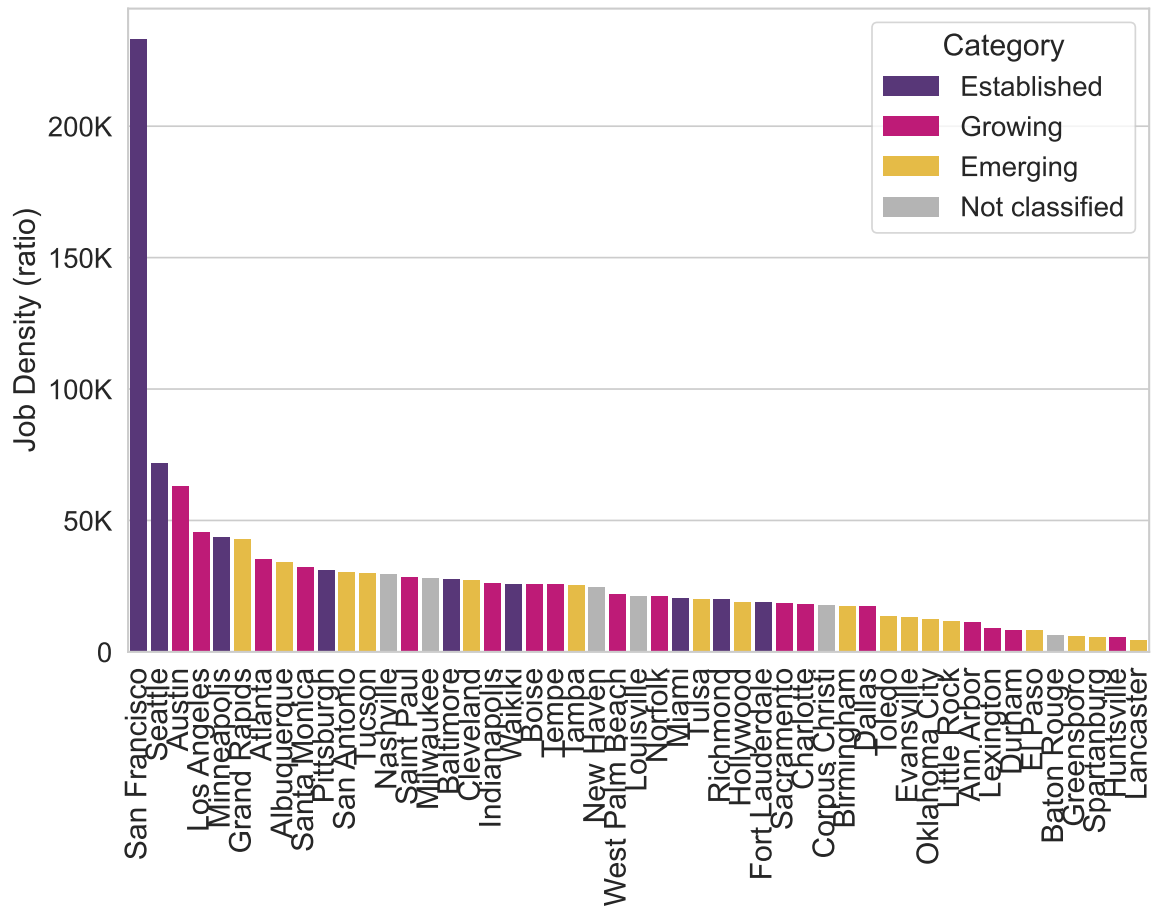


Fig. 2: Number of Primary Jobs by Square Miles across Downtowns in 2020. (Source: LEHD).

Knowledge Jobs

- We refer to knowledge Jobs as the percentage of jobs listed in knowledge industries at a downtown level.
- Figure (3) illustrates the distribution of knowledge jobs as a percentage across downtown areas, categorized according to the 2021 Tier classification. Notably, there continues to be a difference in the percentage of knowledge jobs between growing/established and emerging downtowns.

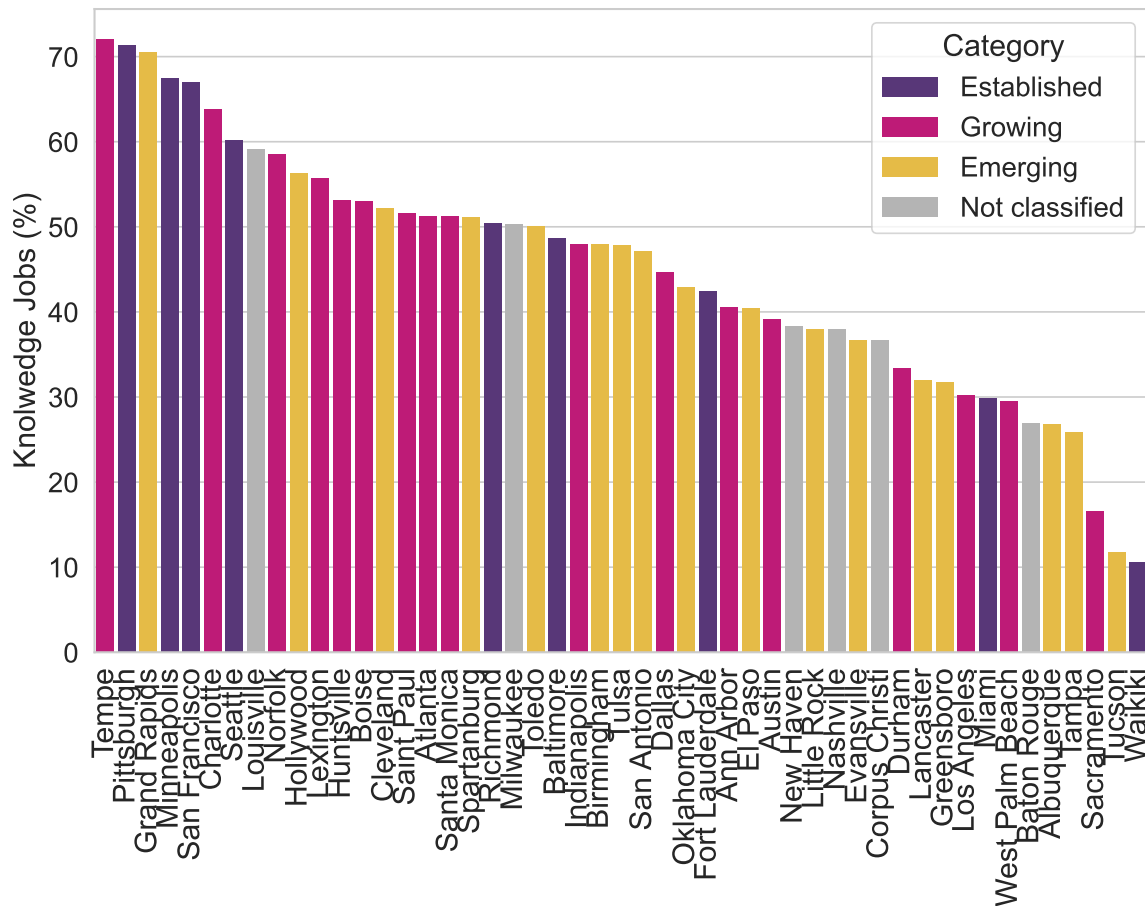


Fig. 3: Percentage of Knowledge Jobs across Downtowns in 2020. (Source: LEHD).

Unemployment Rate

- Figure (4) shows the percentage of unemployment across downtown, classified according to the 2021 Tier. Many of the top growing and emerging downtown areas appear to have higher unemployment rates, perhaps because people are changing jobs as opportunities surface.

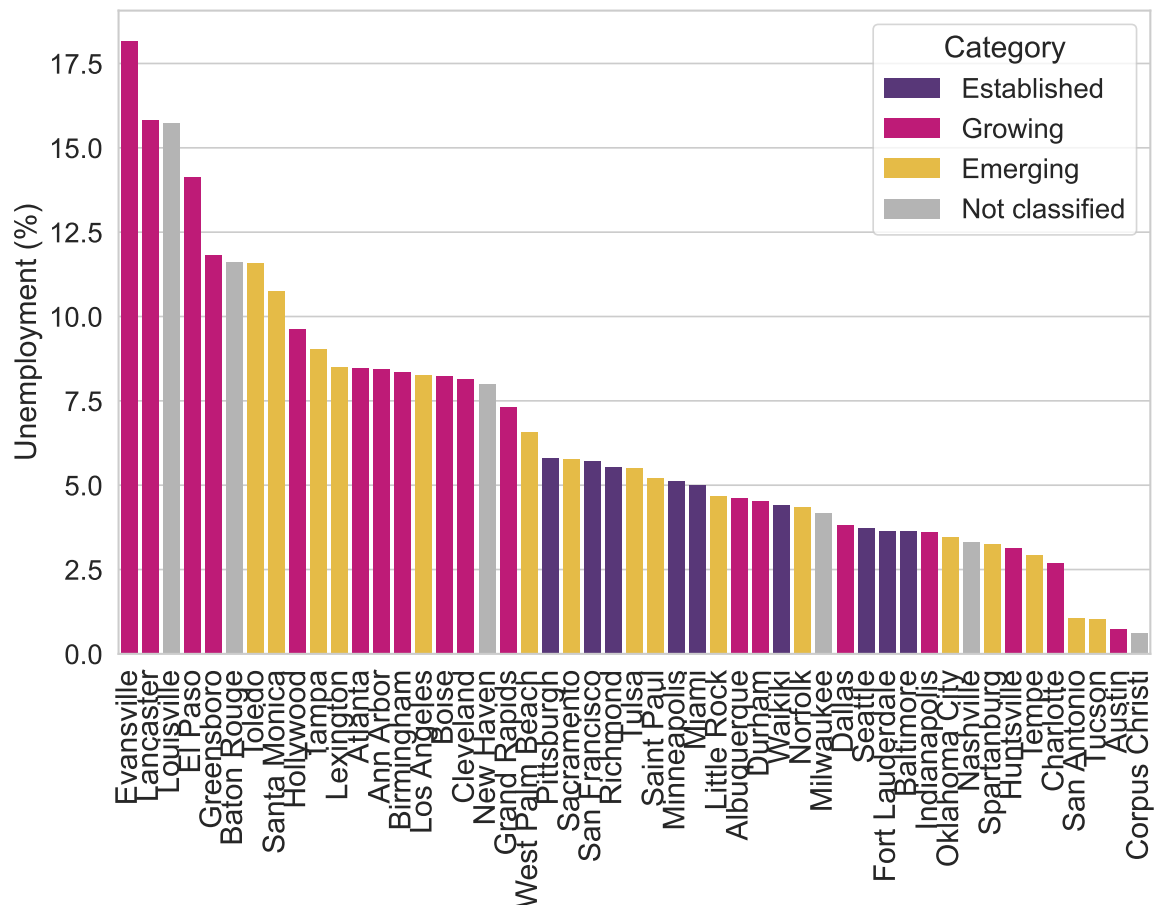


Fig. 4: Unemployment Rate across Downtowns in 2020 (source: ACS5).

Education Attainment

- Figure (5) shows the percentage of the population with education attainment less than high school, classified according to the 2021 Tier. Growing and emerging downtowns are more likely to have a higher percentage of the population with less than a high school degree.

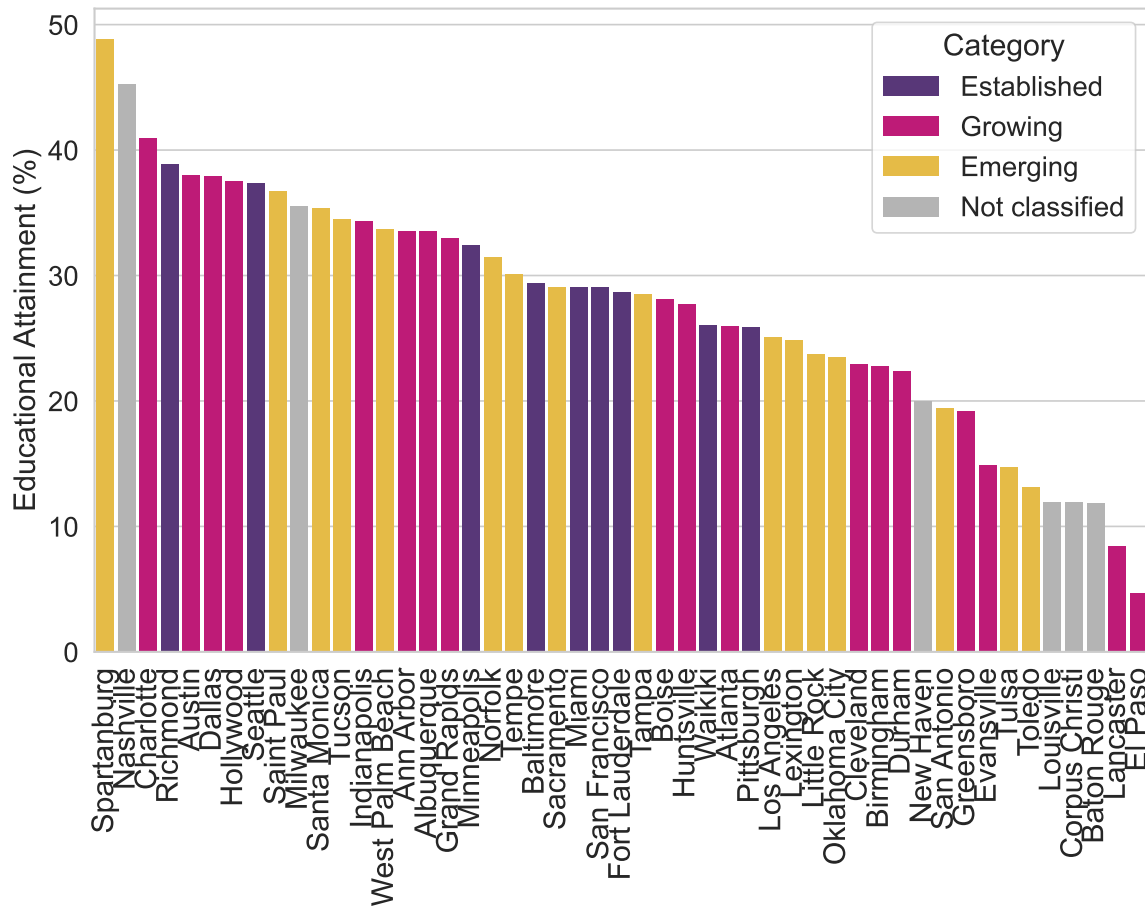


Fig. 5: Education Attainment Rate across Downtowns in 2020 (bachelor's degree or higher) (source: ACS5).

2.2 Inclusion

Residential diversity

- We pulled data on the diversity index from ESRI at the 2020 census geo-levels. The data were available for the decennial census years 2010 and 2020 and for 2023. The diversity index measures the probability that two randomly selected individuals in a downtown area have different racial backgrounds. The probability is scaled to range from 0 to 100, where 0 refers to non-diversity. The diversity index at the downtown level is a population-weighted average of the diversity index at the 2020 census geo-levels designing the downtown.
- Figure (6) illustrates the diversity index across downtowns, classified according to the 2021 Tier. Some emerging downtown areas exhibit greater racial diversity than growing or established downtowns.

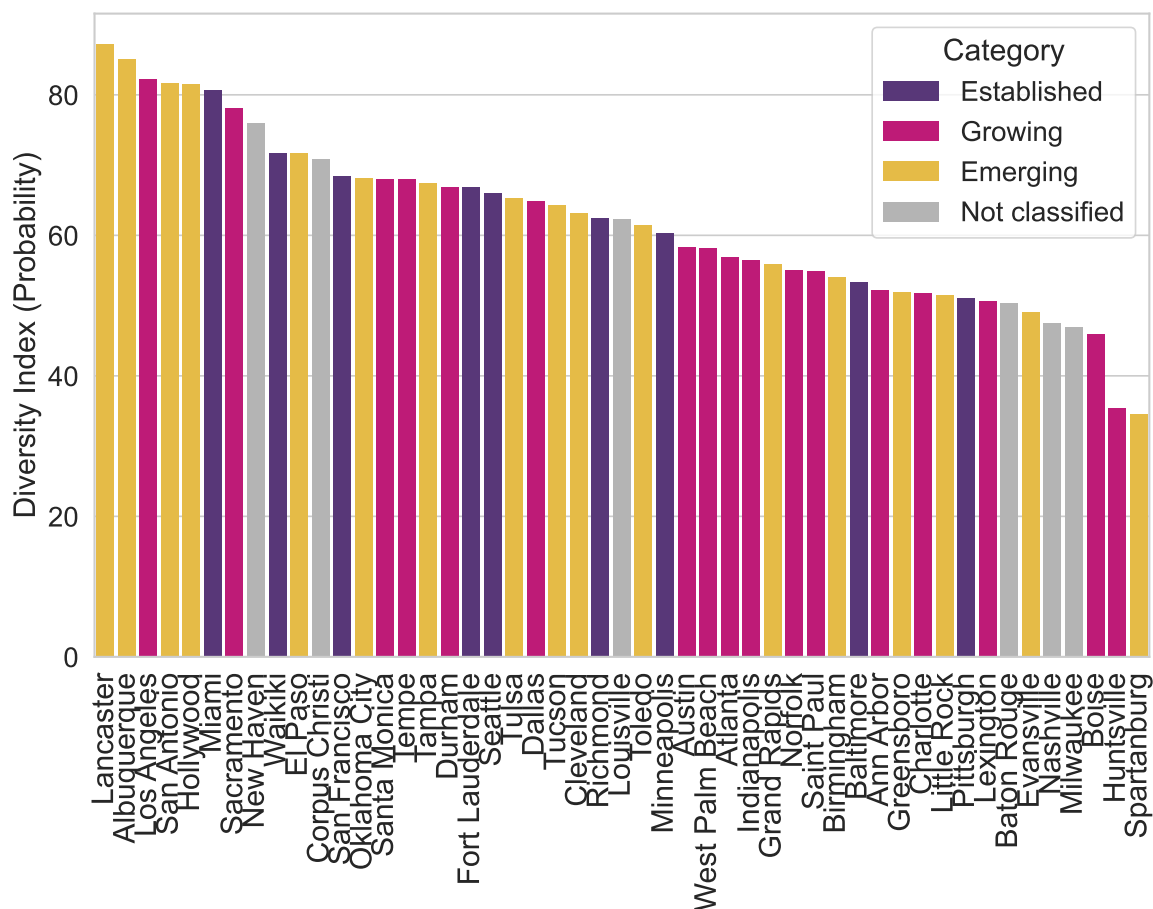


Fig. 6: Diversity Index across Downtowns in 2020 (source: ERSI 2020-2023).

Housing and Transportation Cost

- Figure (7) shows the Housing and Transportation Cost that provides information on place affordability, achieved by dividing housing and transportation expenses by income in the downtown. Seven of the top ten downtown areas with high housing and transportation costs are in the growing tier. This implies that the rapidly expanding population and job counts in these areas might impact the availability of affordable housing and transportation in the future.

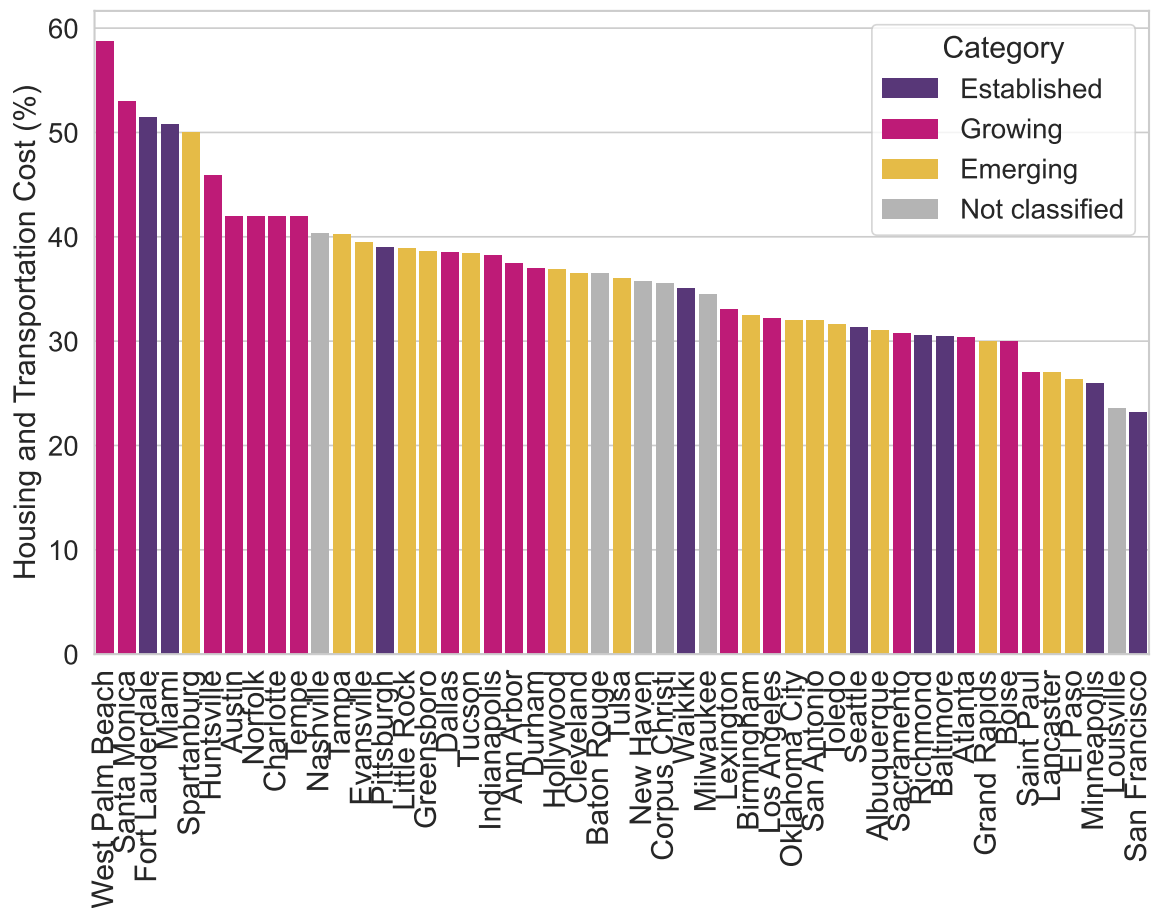


Fig. 7: Housing and Transportation Cost across Downtowns in 2020 (source: Center for Neighborhood Technology (CNT)).

Middle Income Households

- Figure (8) shows the percentage of middle-income households across downtowns. Half of the top ten downtown areas with a large share of middle-income households are growing downtowns.

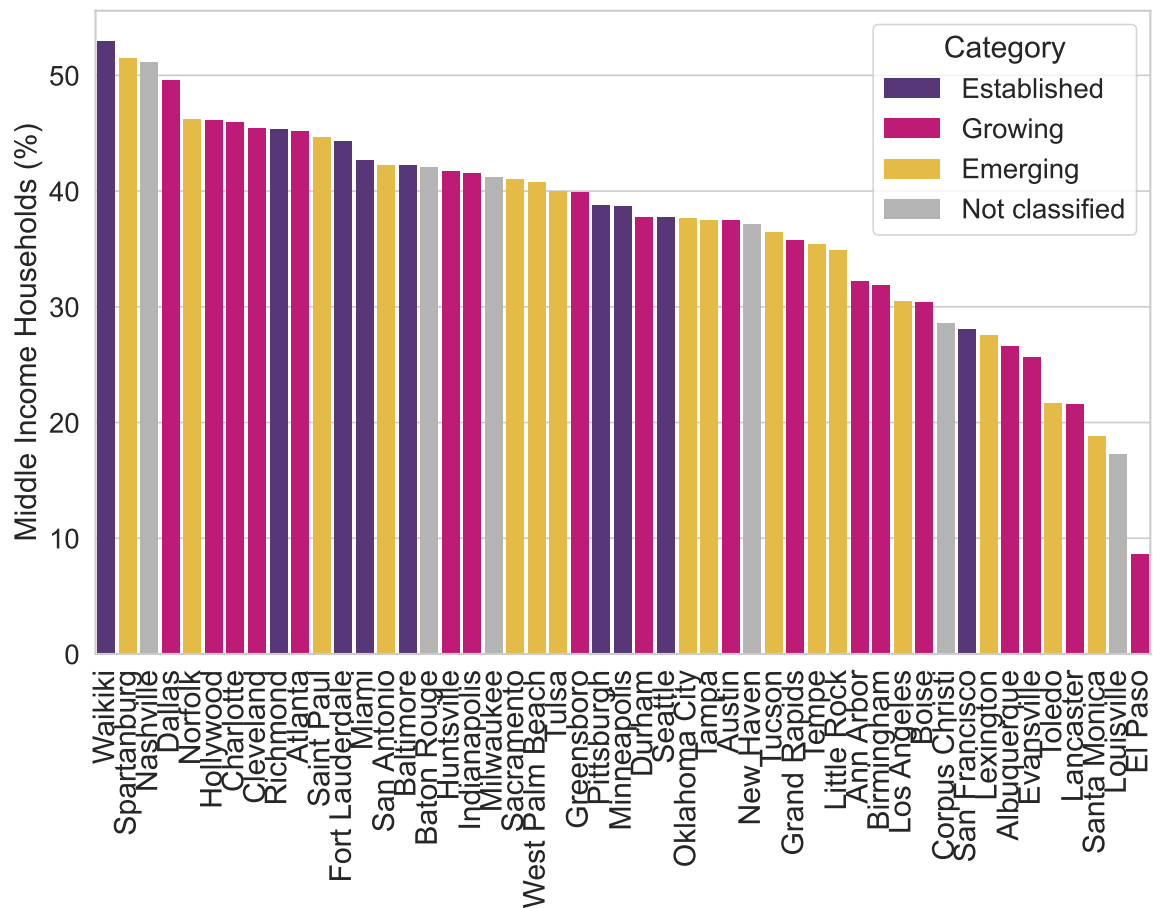


Fig. 8: Middle Income Household Percentage across Downtowns in 2020 (source: ACS5).

Home Price/ Income Ratio

- Figure (9) represents the ratio of home price and household income for the downtowns under study.

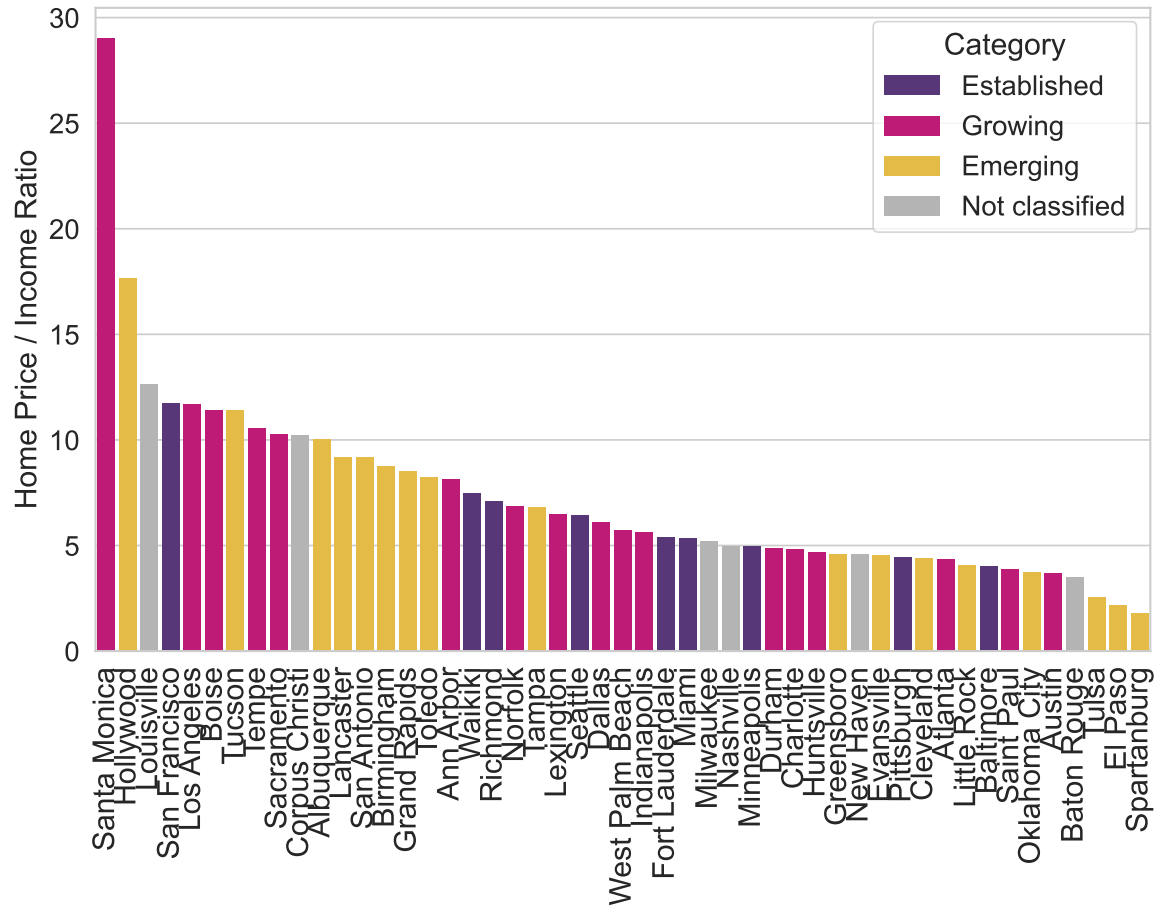


Fig. 9: Home Price/Income Ratio across Downtowns in 2020 (source: ACS 5-Year 2020).

Percentage of Children and Seniors

- Figure (10) shows the percentage of children (under 18) and seniors (over 65) in the studied downtowns. This dependency measure estimates the number of people who need support by those who work. This measure assumes that children under 18 and seniors over age 65 do not work. Five of the top ten downtowns with high dependency ratios are emerging downtowns.

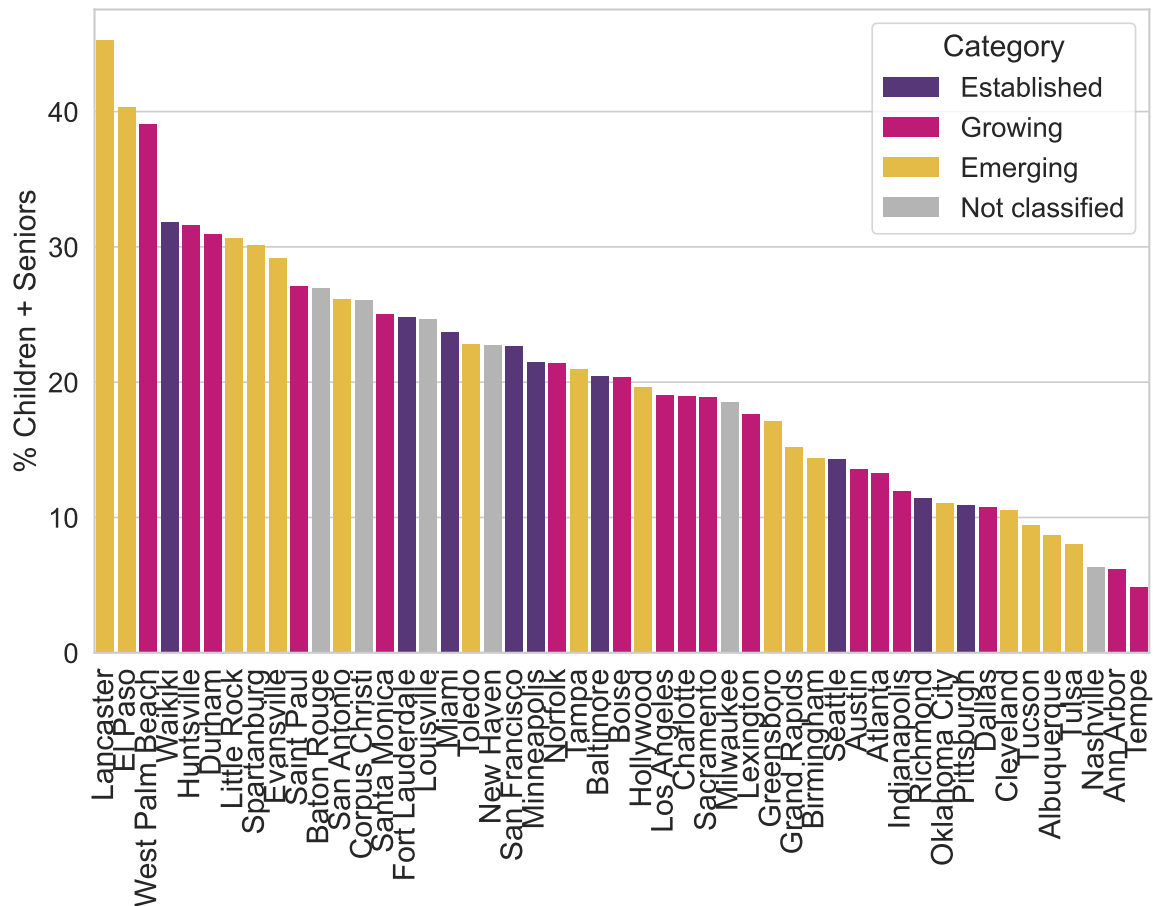


Fig. 10: Percentage of Children and Seniors across Downtowns in 2020 (source: ACS 5-Year 2020).

2.3 Vibrancy

Retail and Restaurant Density

- We pulled retail shops and restaurants point location from ESRI and counted the number of retail shops and restaurants at the 2020 census geo-levels defining downtowns. The ESRI data were only available for 2023 and built from Axle data. Retail and restaurant shops correspond to all businesses in industries with an SIC code 52-59. The retail and shop density is computed as the number of shops and restaurants per square mile in a downtown area.
- Figure (11) displays the density of retail shops and restaurants per square mile across downtown areas, categorized according to the 2021 Tier. Established downtowns exhibit a higher concentration of retail shops and restaurants per square mile than growing or emerging downtowns. Similar to the findings from 2019, Union Square in San Francisco stands out as the downtown area with the highest density of retail and restaurant establishments per square mile.

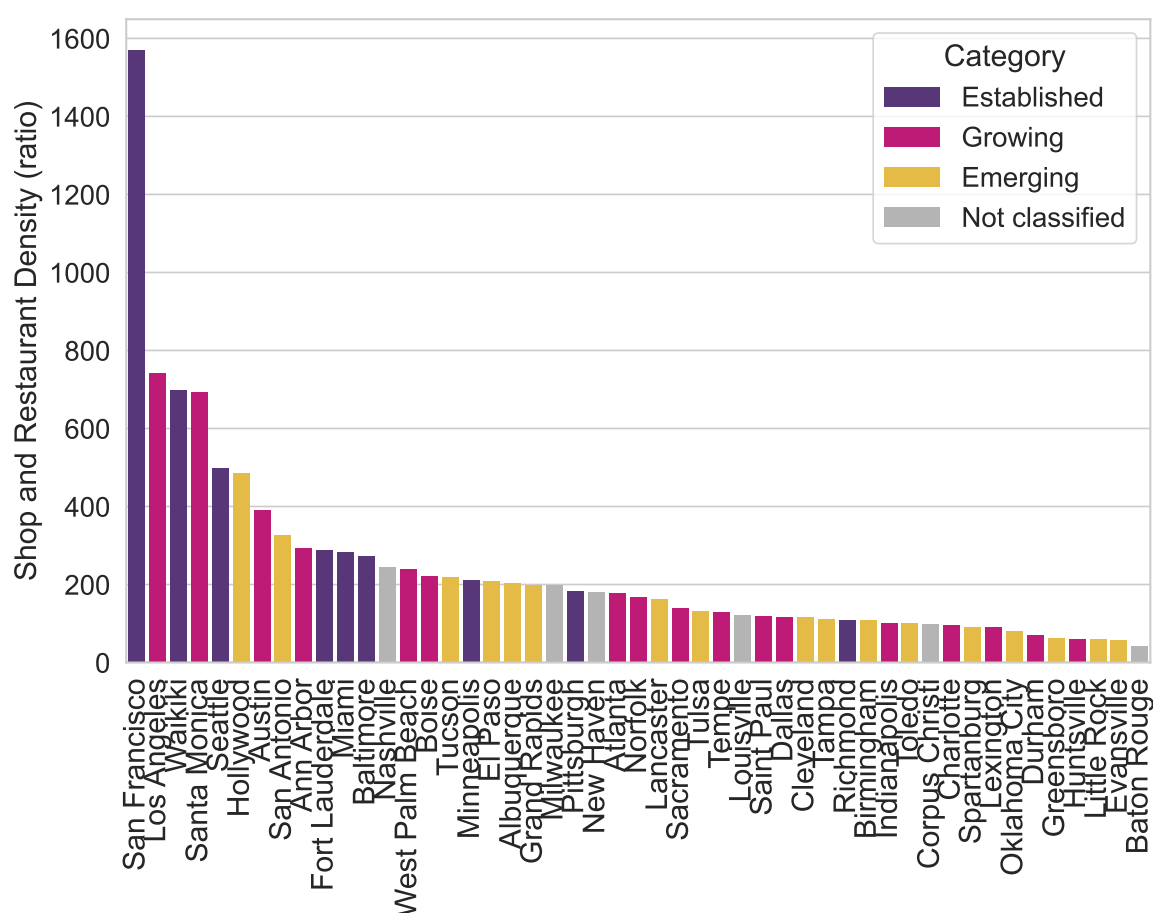


Fig. 11: Retail and Restaurant Density across Downtowns in 2020. (Source: ERSI 2023).

Population density

- To calculate the population density, we used the extracted geoids to retrieve the land area variable from the 2020 TIGER files and summed the population and land mass separately (after converting square meters of ALAND20 to square miles). We then took the summed population, divided it by 6,321 based on the CityLab benchmark¹, then divided it by the converted land mass to get Figure (12).

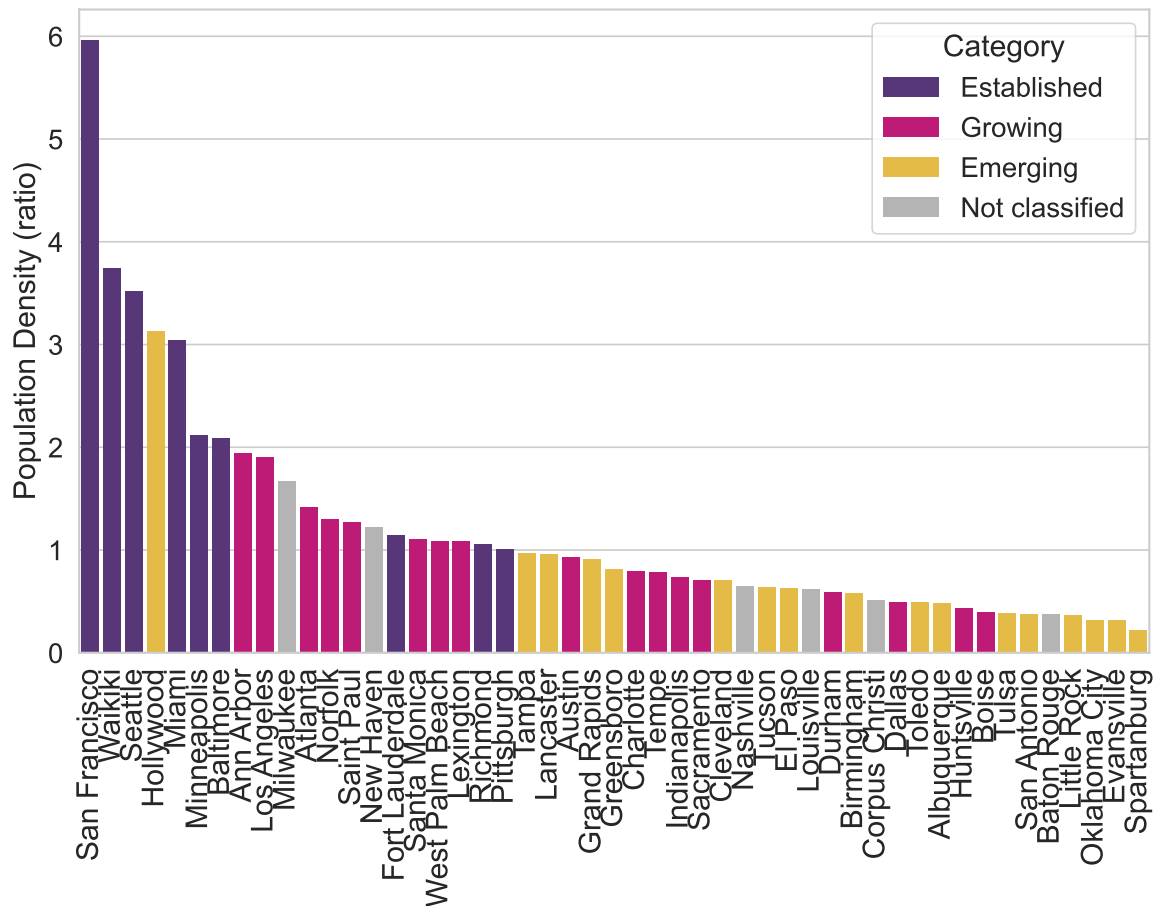


Fig. 12: 2020 Population Density across Downtowns (source: ACS5).

¹ <https://www.bloomberg.com/news/articles/2012-10-15/america-s-truly-densest-metro-areas>

Sustainable commute

- Figure (13) shows the percentage of the population that sustainably commutes (carpool, public transportation, bike, and walk), classified according to the 2021 Tier.

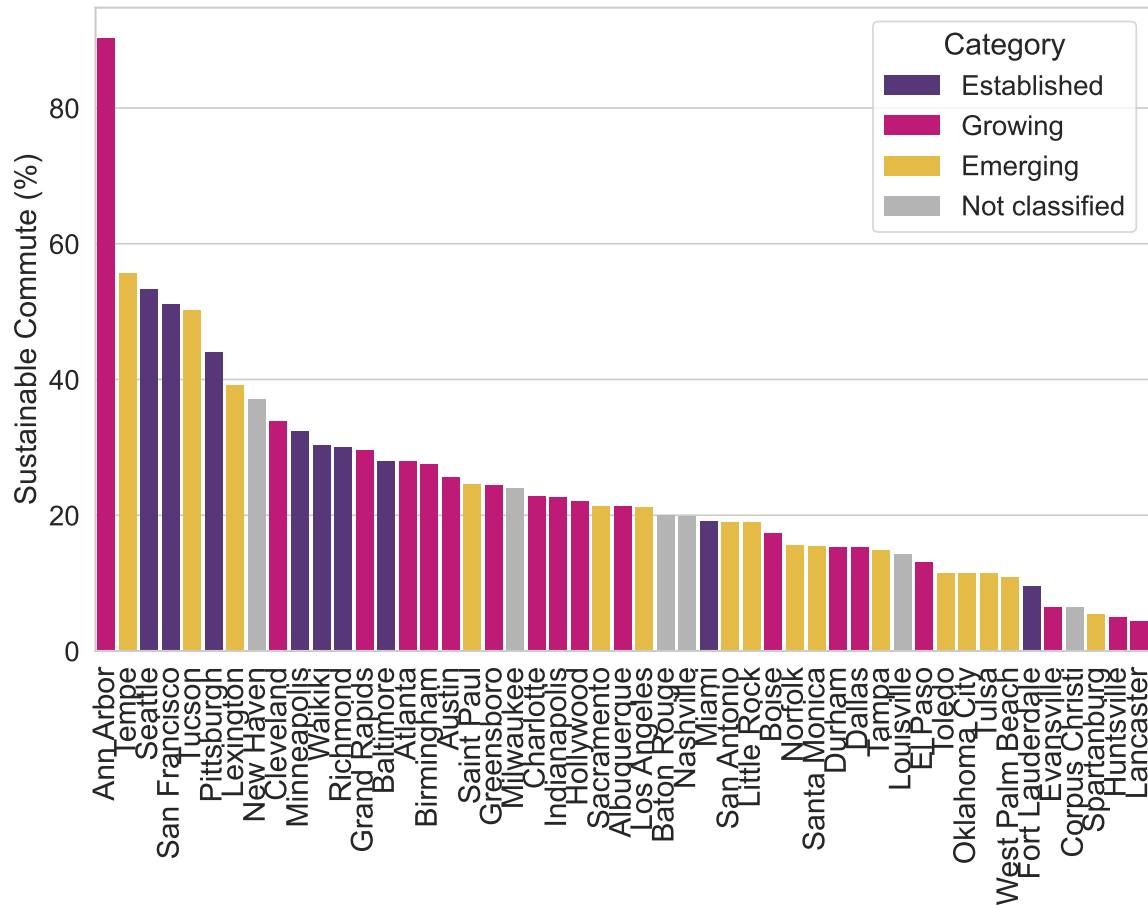


Fig. 13: Sustainable Commute Percentage across Downtowns in 2020 (source: ACS5).

Population growth

- To calculate the change in population, we acquired the corresponding geoids that are a mixture of tracts and block groups and summed it for each year to get Figure (14).

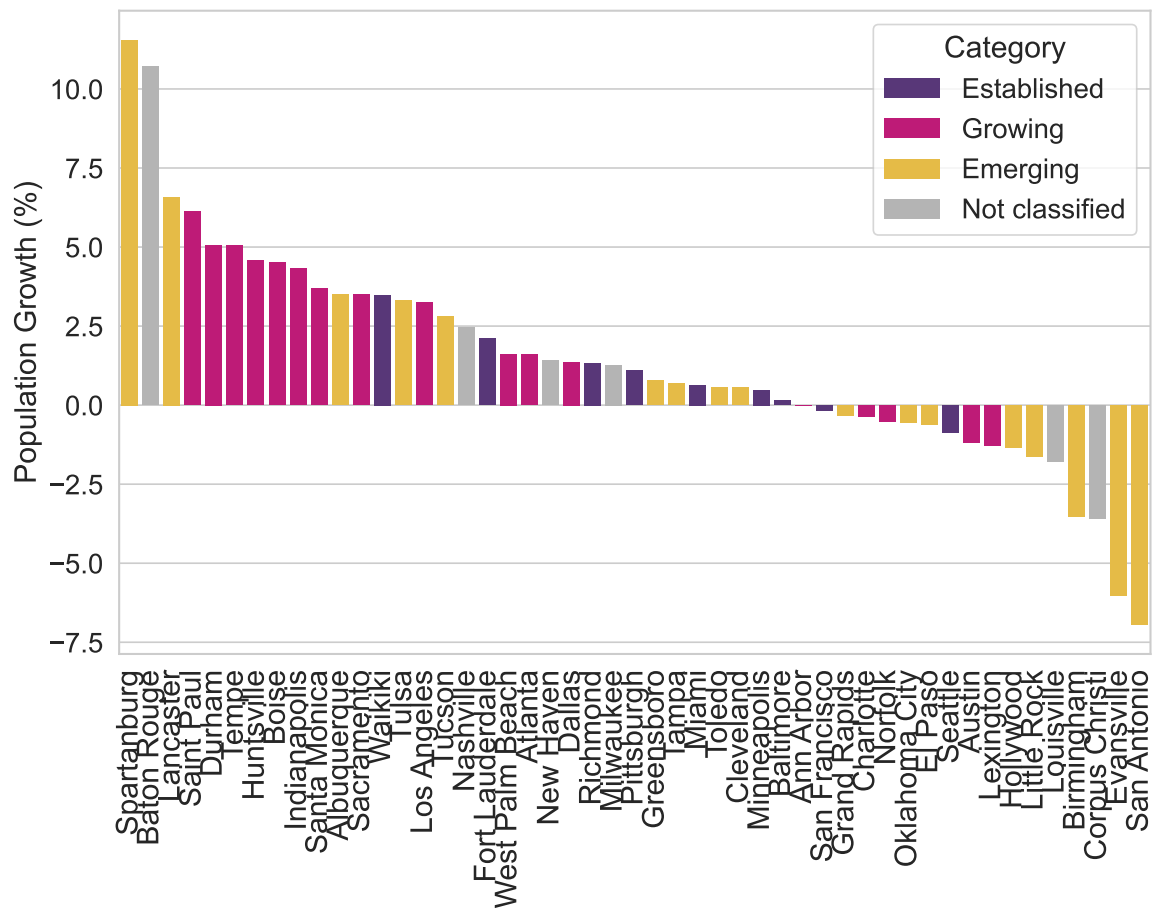


Fig. 14: Difference in 2021 Population Compared to 2020 Population across Downtowns (source: ACS5).

Walkability score

- We retrieved the walk score by scraping an online website using the web archives (further documented in Section 3.2). We retrieved scores for 43 of the 49 total downtowns in this study.
- Established downtowns are more likely to have high walkability scores.

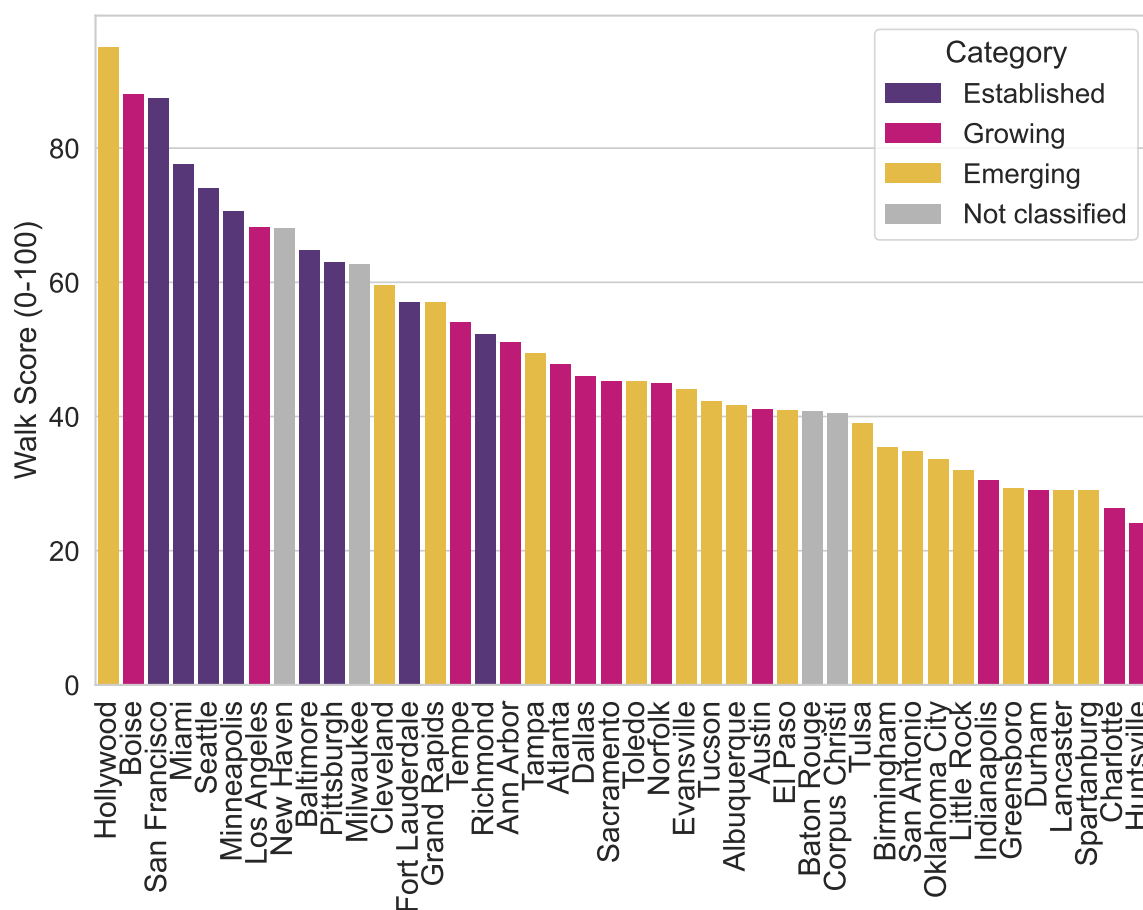


Fig. 15: Walk Score across Downtowns in 2020. (Source: Walkscore.com).

2.4 Vitality Index

- The downtown vitality index is computed using a two-step process. First, we combine the previous metrics into three different dimensions following the methodology proposed by IDA, 2019. All those metrics were grouped by topics (Economic, Inclusion, and Vibrancy) and then normalized to the US average. Sections 2.1; 2.2, and 2.3 show the metrics grouped by topics. To normalize the metrics, we use the 2019 US average values.² Each metric is normalized in such a way that the value ranges from 0 to 100, where 50 represents the US national average. Finally, the score of each topic is computed as the average normalized metrics included in the topic.
- Figure (16) shows three different dimensions of the vitality index (Economic, Inclusion, and Vibrancy) across all downtowns. On average, most of the downtowns are performing in at least one dimension, especially economically. A few downtowns underperformed in both Inclusion and Vibrancy compared to the US average. Those included Austin, Baton Rouge, Charlotte, El Paso, Greensboro, Huntsville, Little Rock, Oklahoma City, Spartanburg and Tusla.

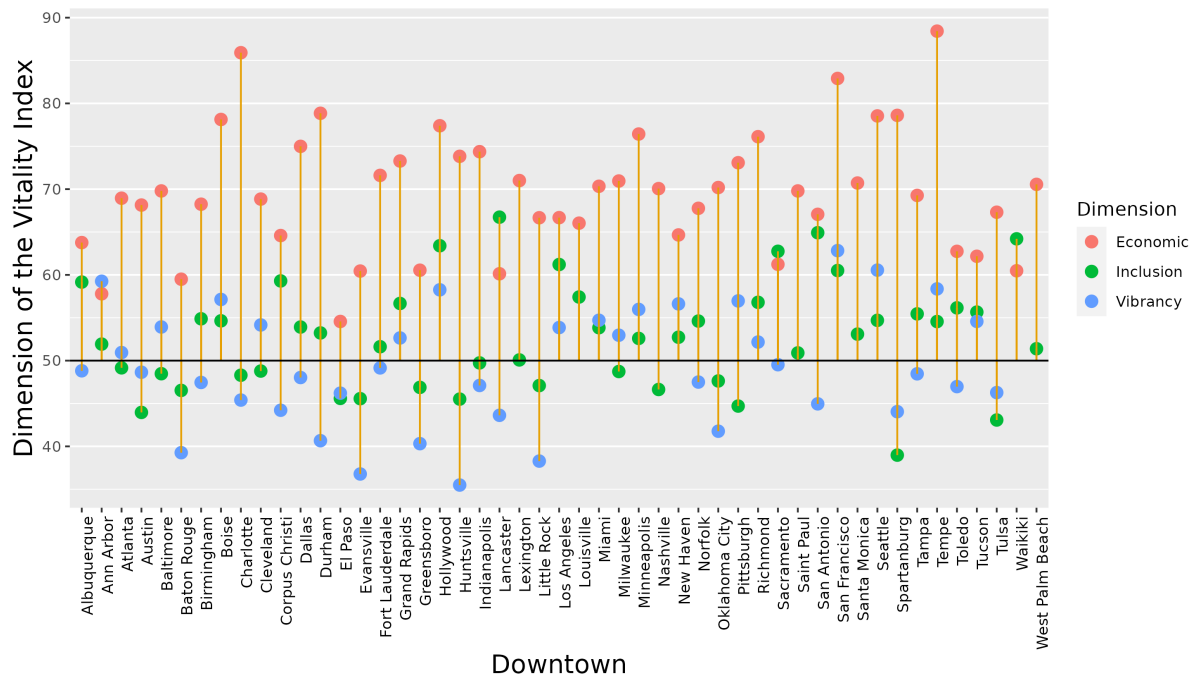


Fig. 16: The Dimension of the Vitality Index.

- The vitality index is measured as the average score of the three score dimensions (Economic, Inclusion, and Vibrancy).

$$Vitality = \frac{Economic + Inclusion + Vibrancy}{3} \quad (1)$$

- Figure (17) shows the vitality index across all downtowns. On average, most of the downtowns are performing well compared to the US average vitality score of 50.³ Only a few downtowns are underperforming, including Baton Rouge, El Paso, Evansville, and Greensboro, based on a vitality score lower than 50. The good performance observed in some downtowns are driven by their economic performance. Hollywood, San Francisco, and Tempe

² These values were provided by Downtown.org for the 2019 vitality index. Using the 2019 US average values affects each score value but not the rank of each downtown.

³ The US average vitality score is 50 because it is the average of the US values across the three dimensions (Economic, Inclusion, Vibrancy) normalized to 50.

are the most vital downtowns, with a vitality score higher than 65. These high vitality scores highlight the fact that these three downtowns are vibrant, inclusive, and have high economic activity.⁴

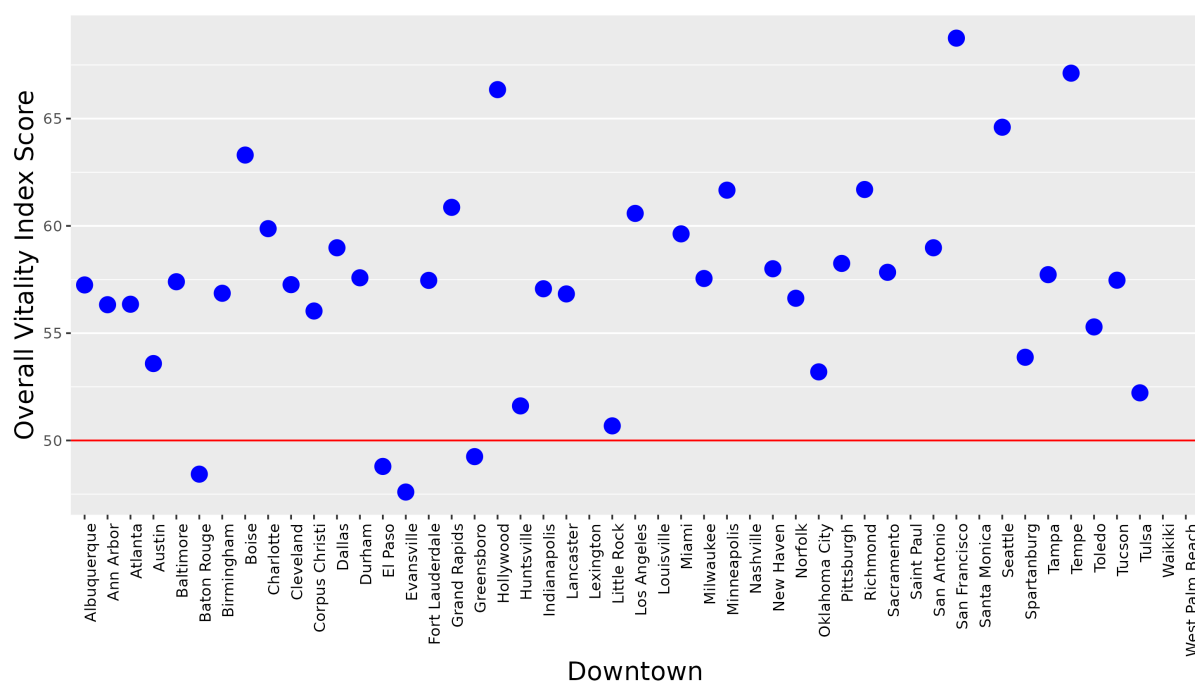


Fig. 17: The Vitality Index.

⁴ We did not find walk scores for Waikiki and West Palm Beach. Therefore they were excluded from our calculations of the Vitality Index.

3 Suggested Future Work

3.1 Standardize definition of downtown

The conceptualization of “downtown” lacks a standardized definition, exhibiting notable heterogeneity across diverse contexts. The absence of an official definition by entities such as the US Census Bureau or the Department of Housing and Urban Development further accentuates this lack of clarity in the definition of downtown. Several efforts, however, tried to narrow this gap. Katz and Lang, 2004 acknowledged a degree of commonality in downtowns, positing them as places for maximum rent for commercial office space, typically representing the area’s business district. Sohmer, 1999 attempted to consolidate criteria from various experts without a definitive delineation of downtown due to the absence of a universally applicable template.

More research is needed to complete an integral definition of downtowns under various geographical realities. For example, Van Leuven, 2022 recommendations advocate a methodological approach for defining downtown business districts. This methodology involves systematically delineating a relative density map of businesses, grouping dense cells, excluding zero-density cells, and identifying contiguous areas boasting the highest densities. Furthermore, using floating catchment areas can also become a pertinent method, introducing a buffer mechanism over a defined area of interest. A comprehensive framework and methodology for defining downtowns calls for relevant future research.

3.2 Alternative data sources, automatons, and dashboards

- Variables such as the *Diversity Index*, *Shop and Restaurant Density* might consider alternative methods of calculation. Extracting data closer to the source supports future efforts to set up scalable automation for a “virtual sensor” to routinely sample and update the index.
- For example, extracting information from the Wayback machine API enables us to retrieve data anywhere between 2010 and 2023. The following Python script demonstrates an example query and results:

```
1 import requests
2 import pandas
3 import pandas as pd
4
5 api = 'http://archive.org/wayback/available?url={url}&timestamp={timestamp}'
6 timestamp = '20190601' #YYYYmmdd, check for middle of the year
7 r = requests.get(api.format(url=url, timestamp = timestamp))
8 r.json()
9 '''
10 {
11     'url': 'https://www.walkscore.com/cities-and-neighborhoods/',
12     'archived_snapshots': {'closest': {'status': '200',
13     'available': True,
14     'http://web.archive.org/web/20190611165353/https://www.walkscore.com/cities-and-neighborhoods/',
15     'timestamp': '20190611165353'}},
16 }
17 '''
18 table = pd.read_html(r.json()['archived_snapshots']['closest']['url'])[0]
19 '''
20 City State Walk Score Transit Score Bike Score Population
21 0 New York NY 89.2 84.3 67.7 8175133
22 1 Los Angeles CA 67.4 52.6 55.1 3792621
23 2 Chicago IL 77.8 65.3 71.5 2695598
24 3 Houston TX 48.7 36.9 47.9 2099451
25 4 Philadelphia PA 79.0 66.8 65.6 1526006
26 ... ..
27 138 Adelaide AU-SA 53.6 -- -- 1103979
28 139 Perth AU-WA 50.2 -- -- 1627576
29 140 Canberra AU-ACT 39.9 -- -- 355596
30 141 rows 6 columns
31 '''
```

Listing 1: Walkscore.com downtown historical data can be expediently extracted.

- Figure 18 demonstrates a sample of longitudinal walk scores for three downtowns.

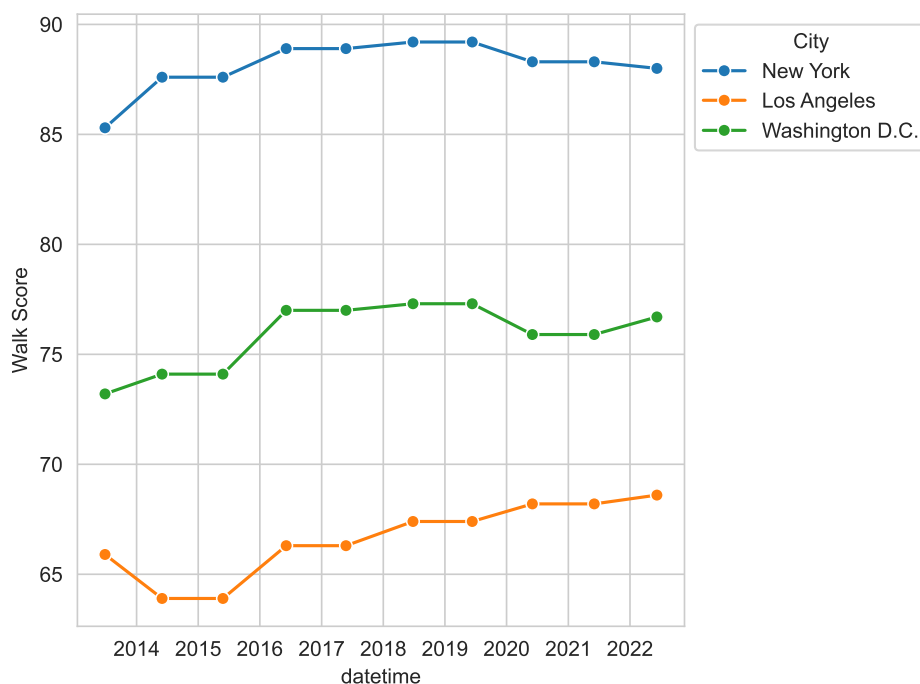


Fig. 18: Changes in walk score between 2010 to 2023 for New York, Los Angeles, and Washington D.C. showcasing a sustainable method to accessing most historical walk score data over time. (Source: Walkscore.com)

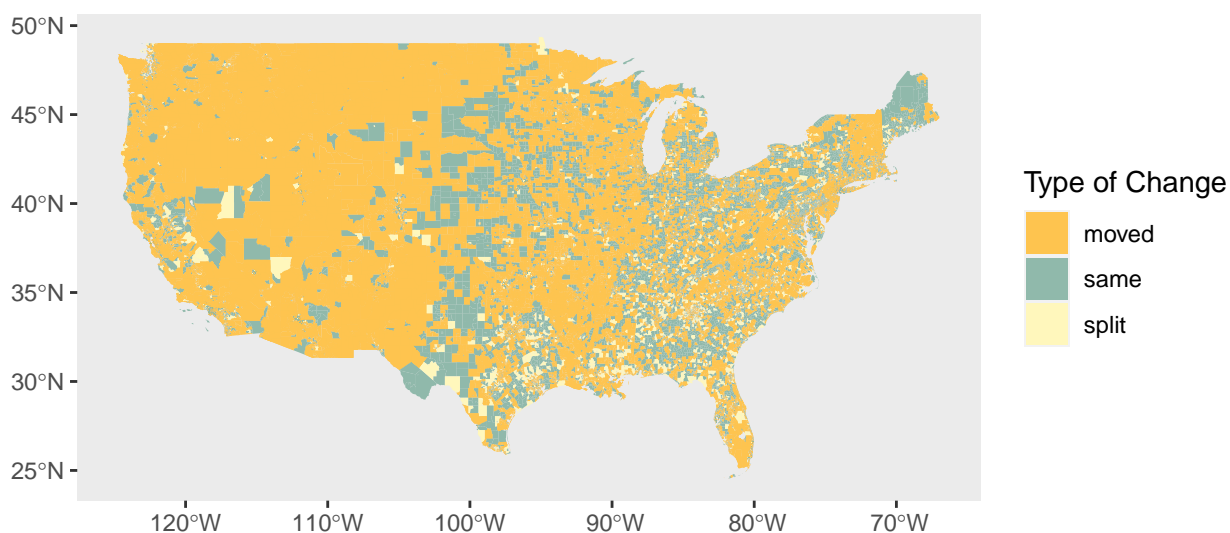


Fig. 19: The majority of sub-county geography boundaries in the US between 2010 and 2020 have either moved or split. For example, a census tract boundary can change (moved) or be split into multiple distinct tracts (split) based on population movements within the area. For example, “... there are thousands of cases where a single 1990 census tract corresponds to multiple 2010 tracts. This is especially common in fast-growing areas on the outskirts of cities” (Source: [NHGIS Geographic Crosswalks](#))

3.3 Other activities

- Calculating crosswalks between 2010 and 2020 geoids. The majority of sub-county geographies shift every ten years. Figure 19 demonstrates the quantity and categories of these shifts. Accurately calculating crosswalks enables pre-2020 data sources to be imputed for post-2020 shapes, providing additional robustness for potentially hard-to-replicate data sources. For historical views of certain indices, it remains to be decided how far into history it is worth imputing data and for what variables (e.g., imputing pre-2015 Housing and Transportation Cost).
- Updated Benchmarks. Additional work can be done to streamline the calculation of the benchmarks. For example, using the U.S. average for shop and restaurant density or just the average of the collection of the downtowns under study.
- Classifying downtowns into one of three categories given the predictors. Depending on how the ground truth of these classifications is drawn, future work can be done to train a machine learning classifier to automatically classify downtowns based on the studied metrics.

Recommendations

- The IDA index is a very useful index to understand the vitality of communities that are the center of economic and social activity. There exists an opportunity to enhance the efficacy of the downtown vitality metric by instituting a tracking mechanism over time. This would facilitate a longitudinal assessment, enabling the monitoring of fluctuations in key variables.
- Automation of the IDA index is proposed by establishing a centralized repository, facilitating real-time updates and automated data input to estimators using open-source code. This mechanization streamlines the assessment process, ensuring accuracy and efficiency.
- We recommend developing an interactive dashboard with information on the IDA vitality index and its elements. This interface should not only offer dynamic insights but also provide downloadable options for further analysis.
- We recommend working on a more universal definition of downtown and publishing this definition in a peer-reviewed journal. This document can serve as a citable reference for both local governments and the academic community.
- We also suggest establishing a collaborative research group between the IDA office and the UVA Biocomplexity Institute. This partnership aims to allocate necessary resources for the research, and potential financial support could be sought through grant applications to entities such as the NSF or HUD.
- We recommend the identification of Potential Funding Sources. Four prospective funding avenues are delineated for consideration.
 - FY 2023 Choice Neighborhoods Implementation Grants. [Link](#)
 - EPSCoR Collaborations for Optimizing Research Ecosystems Research Infrastructure Improvement Program (E-CORE RII). [Link](#)
 - Strengthening American Infrastructure (SAI). [Link](#)
 - FY2023 and FY2024 Authority to Accept Unsolicited Proposals for Research Partnerships. [Link](#)

References

- IDA. (2019). *Ida vitality index* (tech. rep.). International Downtown Association.
- Katz, B., & Lang, R. E. (2004). *Redefining urban and suburban america: Evidence from census 2000*. Brookings Institution Press.
- Sohmer, R. (1999). Downtown housing as an urban redevelopment tool: Hype or hope? *Housing Policy Debate*, 10(2), 477–505.
- Van Leuven, A. J. (2022). A method for defining downtown business district boundaries in pre-automobile towns and cities. *Cityscape*, 24(1), 369–382.

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About SDAD

The Social and Decision Analytics Division ([SDAD](#)) is a leading Division in the Biocomplexity Institute ([BI](#)) at the University of Virginia. The Biocomplexity Institute is at the forefront of a scientific evolution, applying a deeply contextual approach to answering some of the most pressing challenges to human health and well-being within our changing environment. SDAD was created in the fall of 2013 to extend the Biocomplexity Institute's capabilities in social informatics, policy analytics, and program evaluation. The researchers at SDAD form a multidisciplinary team, with expertise in statistics, policy and program evaluation, economics, political science, psychology, computational social science, and data governance and information architecture. SDAD's mission is to embrace today's data revolution, developing evidence-based research and quantitative methods to inform policy decision-making and evaluation.

