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Can We Save The Downtown? Examining Pandemic Recovery Trajectories across 62 North American Cities

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Can We Save The Downtown? Examining Pandemic Recovery Trajectories across 62 North American Cities

Abstract

As cities emerge from the COVID-19 pandemic, the persistence of pandemic-era habits such as remote and hybrid work remained ingrained in urban activity patterns, presenting a threat to North American downtown districts as we know them. This paper examines the visitation trajectories of downtowns in 62 of the largest US and Canadian cities between 2020 and 2022 using location-based services data from mobile phones. Our analysis shows that downtowns with high concentrations of professional services, information, and finance fields, high density, long commute times, and colder winter temperatures continually struggle to maintain both raw visitation numbers and overall visitation proportions throughout the analysis period. In contrast, downtowns with higher concentrations of non-traditional industries like healthcare, education, arts & entertainment, and public administration recovered well, and in some cases exceeded their pre-pandemic visitation performance. We also found that the length of COVID-19 restrictions and pre-pandemic amount or characteristics of housing had lesser correlations with overall downtown recovery trajectories, suggesting the economic structure and environment had greater influence. We hope this analysis can inform city governments, downtown business associations, real estate developers, and communities on how to reinvent the North American downtown in order to remain the apexes of urban activity in the post-pandemic era.

1. Introduction

Throughout the urban history of North America, downtowns have overcome threats from industrial change, economic cycles, and widespread suburbanization to remain the apexes of commercial and cultural activity within cities. The image of the modern downtown is often characterized as a professional and knowledge district dominated by commercial office spaces which occupy, on average, 71% of all real estate (Kellerman, 1988; Loh and Kim, 2021). However, the lasting influences of the COVID-19 pandemic on the structure of urban activity, and particularly the persistence of working from home[1], uniquely threatens downtown districts, as the post-pandemic return to office severely lags the return to other in-person leisure activities (Kastle Systems 2022). Compounding the issue, studies show that working from home over COVID-19 increased the desirability of suburban living over urban living (Chan, 2022), and redistributed talent across many cities in North America (Berube 2022). The combination of these trends has led many to wonder: could this finally be the death of the downtown? Or, what do we need to do to save the downtown, and reinvent it yet again?

Although the dominant narrative of downtown districts has been one of the ‘doom loop’, the effects are characteristically different from financial and professional centers like New York and Chicago, to entertainment destinations like Las Vegas, to tech-focused cities like San Francisco.

[1] Working from home was first deployed as a widespread public health measure at the start of the COVID-19 Pandemic in March of 2020, but has remained a key feature of North American white-collar office jobs into 2022 and beyond.

In addition to economic differences, downtowns and cities also greatly differ in their demographics, environment, urban form, and governance during COVID-19. This paper seeks to investigate how these differences influence the various simultaneous recoveries of North American downtowns between 2020 and 2022, comparing the downtown districts of 62 of the largest cities in the United States and Canada. We measure and investigate these differences through fusing Location-Based Services (LBS) data from mobile phones with data on demographics, employment by industry, government COVID-19 policies, and the built urban environment. The primary research questions are:

- How do the activity recovery patterns of 62 downtown districts vary, amongst themselves and in relation to the rest of their cities?
- What variables, including industry concentration, socioeconomic factors, urban form, COVID-19 government policy, or the environment, explain the differential performance of downtown recovery?
- What are the characteristics of well-performing and poorly-performing downtown districts and urban regions over the COVID-19 recovery period?
- What are the possible policy actions which we can draw from well-performing downtowns to help poorly-performing downtowns adapt to the post COVID-19 era?

Our study found a variety of recovery trajectories across downtowns and cities, with the majority of downtowns struggling to recover to activity levels last seen during corresponding weeks in 2019, and recovering at lower rates relative to the areas within their municipal boundaries. A few downtowns, however, did experience activity at or above 2019 levels. These were characterized by a more diverse economic structure, avoiding overdependence on industries such as professional services, information, and finance, and instead comprising industries such as accommodation, healthcare, entertainment, and educational services. Downtowns with higher visitation recovery rates also tended to have warmer temperatures, shorter commute times, and a higher share of commuters via private automobiles. Our findings suggest that downtowns will benefit most from cultivating a more diverse set of economic sectors, and that longer commute times, cold winter temperatures, and high dependence on public transportation are characteristics that present continued challenges for downtowns in adapting to the post COVID-19 era.

This article begins with a brief discussion of how we understand patterns of downtown change, followed by sections on our data and methods and results. After exploring our findings in detail, we conclude with some implications for policy and future research.

2. Approaches to Understanding Downtown Change

A rapidly growing body of literature examines pandemic impacts in cities and/or pioneers new methods to leverage real-time big data sources such as the LBS data utilized in this paper. Section 2.1 reviews other studies documenting the impacts of COVID-19 to metropolitan structure and adaptation strategies of downtowns and cities, while Section 2.2 examines traditional methods used to track economic and social activity in downtown business districts, and compares them to our use of LBS data.

2.1 Impact of COVID-19 on Downtowns and Metropolitan Structure

Since the late 1800s, the term “downtown” has been used to refer to the Central Business District (CBD) of North American cities, where economies of agglomeration meant that the greatest volume of business and cultural activity occurred in close proximity (Fogelson, 2003). Characterized by an abundance of skyscrapers and historical landmarks, these districts endured waves of various economic shocks of differing degrees, but alternative drivers have helped revitalize downtowns time and again. For instance, industrial decentralization in the early 1900s threatened the vitality of downtowns as secondary industries moved out to the peripheries of cities, leaving tertiary service industries as their core (Fogelson, 2003). Another example comes from the 1970s, where urban out-migration and the development of ‘suburban downtowns’ threatened the primary downtowns in urban areas (Muller, 1997).

In contrast to these decades-long phenomena, COVID-19’s impact on downtowns was more sudden and uncertain in nature. The onset of the pandemic in 2020 prompted state, local and federal mitigation measures such as limitations on gathering sizes, school closing, workplace closing, and stay-at-home orders within weeks of the first detected virtual infections (Larsey et al., 2020). Key institutions such as schools and workplaces pivoted to entirely remote operations, aided by video conferencing technology which could replace face-to-face interactions. Brynjolfsson et al. (2020) documents that by April 2020, 50% of the US workforce was working remotely (including 15% who worked remotely before the pandemic), 10% had been furloughed or laid off, and just 40% (mostly essential workers) continued to commute to work. By region, the US Northeast and the West had a higher proportion of remote workers, while the Midwest and the South had higher proportions of workers who continued to work in-person (Brynjolfsson et al., 2020). As a result of pandemic-era working arrangements, Ramani & Bloom (2021) observed a “Donut Effect” emerge in major metropolitan areas over the course of the COVID-19 pandemic where up to 15% of the population and 14% of businesses left cities and CBDs respectively, either to relocate exurban subcenters or to operate completely remotely. This led to the fortification of polycentricity or urban sub-centering in metropolitan areas. Schmahmann et al. (2022) showed that in the New York City Metropolitan area, activity decreased in Manhattan but increased in suburbs and secondary cities such as Great Neck, NY and Newark, NJ. A study from The Seattle Times (Balk, 2021) shows that around 250,000 commutes (about one seventh of the total) over 20 minutes were lost by February 2021 compared to February 2020, while a smaller gain of 55,000 commutes under 20 minutes was observed. Ramani & Bloom (2021) also observe that most of those who relocated during the pandemic tended to be “affluent, young, and childless professionals”, and Petino et al. (2021) describes this demographic as the “untethered class”, who were able to leave cities when they were no longer required to work in-person.

The vast majority of the North American population was eligible to be vaccinated against COVID-19 in mid to late 2021, and a gradual lifting of public health restrictions that followed allowed for the resumption of in-person activity. During that time, Grant (2021) and Kastle Systems (2022), a building systems vendor with the ability to track foot traffic through their equipment, indicated that activity levels starting nearing those in 2019 for leisure purposes such as travel, dining, and sporting events, but returns to offices remained lower at 30 and 60 percent. Barrero et al. (2022) shows that employees in particular who could work remotely expressed a desire to continue doing so, and the future of work was anticipated to involve a greater degree of hybrid and remote work, as well as work from third places[2] and offsite locations, than previous anticipated before COVID-19. These policies and preferences varied substantially by industry, with information, finance, and professional services industries having the highest work from home rates, and hospitality, transportation, retail, and manufacturing industries having the lowest. Higher-paying jobs also tended to have greater degrees of flexibility (Holder, 2020; Cutter, 2020). A follow-up paper by Barrero et al. (2023) shows that the rate of working from home has remained relatively stagnant between 2022 and 2023, indicating some level or permanency to having around 30% of all paid days being performed at home.

Berube & Byerly-Duke (2022) observed that during the COVID-19 pandemic, the labor market has simultaneously improved and declined in various cities, but noted that the "superstar" metro areas such as New York, San Francisco, Boston, and Washington DC were on the slower end of recovery, while more affordable areas such as Atlanta, Dallas-Fort Worth, Raleigh-Durham, and Salt Lake City experienced a stronger labor market. Khan et al. (2021) notes that urban density and public transit were often erroneously associated with the spread of COVID-19, causing residents to flee denser urban areas at the onset of the pandemic. The aforementioned trends suggest that the decline in office traffic in downtown areas as well as its varying effects in different cities is likely to outlast the COVID-19 pandemic, and has led to calls to reinvent downtown districts as "Central Connectivity Districts" (Florida, 2022), or to convert hollowed offices to mixed-use and recreational districts (Loh & Kim, 2021). These calls are similar to downtown revitalization public-private partnerships launched in the late 1900s to counter the rapid suburbanization trend, which gave birth to new retail and entertainment complexes such as Faneuil Hall Marketplace in Boston and Inner Harbor in Baltimore (Sagalyn, 1989; Levine, 1987).

While many theories attempt to explain the differences in downtown activity recovery trajectories during and emerging out of the COVID-19 pandemic, no existing study to the authors knowledge explicitly compares activity across downtowns in standardized metrics and tests various variable associations to uncover the underlying factors which drive the differences in downtown recovery performance. This is the gap which this research aims to address, by creating a common benchmark to compare downtown activity recovery quantitatively from 2020 to 2022 vis-a-vis equivalent months in 2019, and investigating the associations between these patterns and many possible variables which are hypothesized to affect downtown recovery.

2.2 Measuring Economic and Social Activity

Traditional indicators that represent the vitality of downtowns and cities include retail spending, tax revenue (*State of Center City Philadelphia*, 2022), public transit ridership, parking occupancy (*The Chicago Loop Recovery*, 2022), pedestrian counts (Emmons, 1965), occupancy rates from offices, residences, and hotels (*Lower Manhattan Real Estate Overview Q2, 2022*), rental rates (*Economic Benchmark Report Downtown Salt Lake City*, 2022), new construction, net business openings (*Downtown Austin Retail, Live Music & Small Business COVID-19 Impact & Recovery Report*, 2021), employment numbers, and the unemployment rate (International Downtown Association, 2019). However, these conventional measures can be difficult to aggregate into a single, comparable metric to depict downtown activity entirely, since each proxy only accounts for a subset of the demand, derived demand, or supply of activity downtown. For example, measures of spending, revenue, or rent, only capture

[2] Third Places refer to work locations such as cafes, libraries, and public spaces which distinct from one's home and work locations.

commercial transactions and perceived property values downtown relative to the surrounding areas, excluding cultural or social aspects of downtowns. Additionally, the definition of downtown lacks uniformity across many of these studies and indicators, particularly because they are done on an individual city basis, which does not allow a national level comparison of downtown recovery. In unifying and comparing these metrics between cities, our study moves these indicators and resultant policy discussions to a continent-wide level.

LBS data, derived from anonymized mobile phone trajectories, is leveraged in this paper as a new way to measure activity levels in downtowns and cities with real-time granularity. Such data has recently been used across academic, public, and private applications to analyze travel patterns, business intelligence, and even social networks (Pan & Lai, 2019). Throughout the COVID-19 pandemic, researchers have utilized mobile phone data to quantify impacts of the pandemic on visits to businesses and urban amenities (Schmahmann et al., 2022; Sevtsuk et al., 2021), to understand the efficacy of movement control policies (Vinceti et al., 2020; Wu & Shimizu, 2022), to analyze travel preferences during the pandemic (Heiler et al., 2020), and to track migration patterns of remote workers (Schmahmann et al., 2022). LBS data can provide a more effective proxy to understand the total economic and social activity by aggregating visits to a comprehensive set of Places of Interest (POIs) within a defined downtown or city area from a representative sample of the US and Canadian populations. This allows the common measure of a “visit”, which occurs when an individual trajectory is detected to be at a stationary POI for more than 4 minutes, to be attributed to both commercial businesses and social amenities such as parks, community centers, and public services. In addition, the national database of SafeGraph data, which is a reliably representative sample of the US and Canadian populations (Li, 2023), can be used for cross-city comparisons. More information about LBS Data processing can be found in Section 3.2. In addition to quantifying and investigating reasons behind the differences in downtown recovery trajectories, this paper also contributes to the development of LBS-based methods to measure urban activity in real-time and at scale.

3. Data and Methods

The methods and analysis in this paper can be divided into two broad pipelines. The first is the creation of recovery trajectories based on LBS data and geospatial shapefiles, with the sorting of trajectories into clusters using DBA K-means time series clustering. The second pipeline is the acquisition of industry employment data, socio-economic data, COVID-19 related government policy data, and weather data as explanatory variables. These pipelines fuse when the explanatory variables are used to understand the reasons behind different recovery patterns in cities, identify patterns in uptrends, downtrends, or stagnation, and develop policy implications for downtowns and cities to thrive in a post-pandemic world. Figure 1 shows the data analysis and methods flowchart.

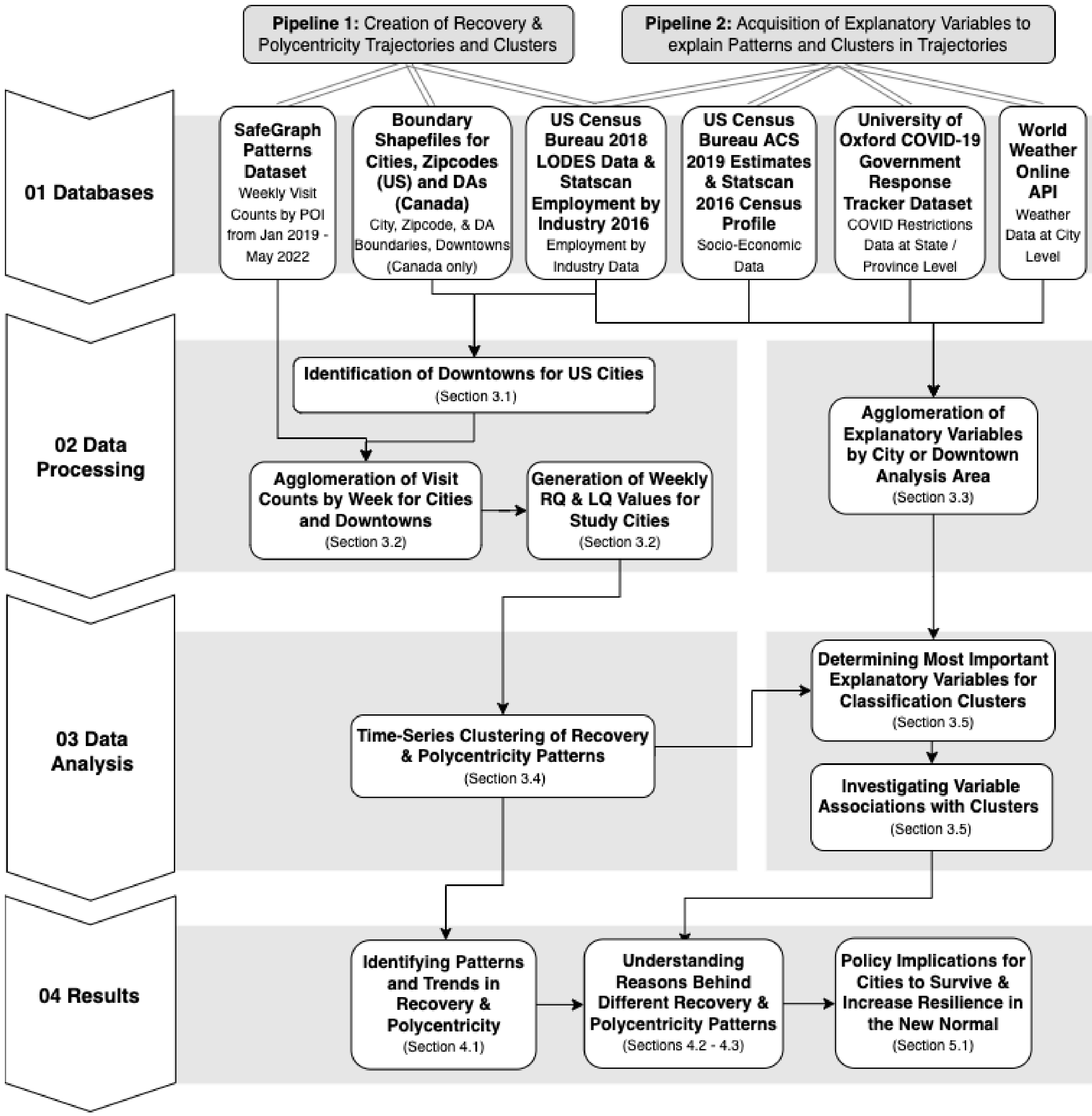

Figure 1: Data Analysis Flowchart

Section 3.1 will focus on how the relevant cities were selected for this paper and how the downtown neighborhoods were defined. Section 3.2 will detail the methods used to calculate Recovery Quotients (RQs) and Location Quotients (LQs) to quantify activity levels in cities over our study timeframe. Section 3.3 will detail the explanatory variables used and their levels of aggregation. Section 3.4 will detail how the time series of RQs and LQs were clustered into patterns over time, and Section 3.5 will detail how models and analysis linked the most defining explanatory variables to clusters and analyzed the reasons behind their RQ and LQ patterns.

3.1 Selection of Cities and Defining Downtowns

This study encompasses cities in the United States (US) and Canada with a population of more than 350,000, or were the primary city of a metropolitan area with a population over 2,000,000 as at the 2019 American Community Survey (ACS) or the 2016 Canadian Census[3], totaling 75 cities. Of these, we excluded nine cities where the employment density of its city center zip codes did not exceed at least 500 jobs per square mile, from which we determined that they did not have their own economically significant downtown area[4]. We also had to exclude four cities due to data inconsistencies over parts of the period of study[5]. This left our study with 62 cities which have been grouped into six regions, as detailed in Table 1.

Table 1: Cities in Scope of Study

US Northeast	US Midwest	US Southeast	US Southwest	US Pacific	Canada
Baltimore, MD	Chicago, IL	Atlanta, GA	Albuquerque, NM	Bakersfield, CA	Calgary, AB
Boston, MA	Cincinnati, OH	Charlotte, NC	Austin, TX	Fresno, CA	Edmonton, AB
New York, NY	Cleveland, OH	Jacksonville, FL	Colorado Springs, CO	Honolulu, HI	Halifax, NS
Philadelphia, PA	Columbus, OH	Memphis, TN	Denver, CO	Los Angeles, CA	London, ON
Washington DC	Detroit, MI	Miami, FL	El Paso, TX	Oakland, CA	Ottawa, ON
	Indianapolis, IN	Nashville, TN	Fort Worth, TX	Portland, OR	Quebec, QC
	Kansas City, MO	New Orleans, LA	Houston, TX	Sacramento, CA	Toronto, ON
	Louisville, KY	Raleigh, NC	Las Vegas, NV	San Diego, CA	Vancouver, BC
	Milwaukee, WI	Tampa, FL	Phoenix, AZ	San Francisco, CA	Winnipeg, MB
	Minneapolis, MN		Salt Lake City, UT	San Jose, CA	
	Omaha, NE		San Antonio, TX	Seattle, WA	
	Pittsburgh, PA		Tucson, AZ		
	St. Louis, MO		Tulsa, OK		
	Wichita, KS				

Downtown areas in this study consisted of the areas within each city with the highest kernel density estimates (KDE) of employment density. In Canada, we use the downtown boundaries defined by Sergerie et al. (2021) at the Dissemination Area (DA) level. In the United States, we replicated Sergerie et al's method using employment densities at the zip code level. Figure 2 shows nine downtown neighborhoods - three defined by Statistics Canada (Toronto, Vancouver, and Montreal), and six defined by our method (New York, Chicago, Los Angeles, San Francisco, Denver, and Austin), while Appendix A contains the definition of all the downtown neighborhoods for our study cities.

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[3] The 2020 American Community Survey and the 2021 Canadian Census were not available at the time of research.

[4] These were Mesa, AZ, Long Beach, CA, Aurora, CO, Arlington, TX, Virginia Beach, VA, Surrey, BC, Brampton, ON, Mississauga, ON, and Laval, QC

[5] These were Orlando, FL, Oklahoma City, OK, Dallas, TX, and Hamilton, ON

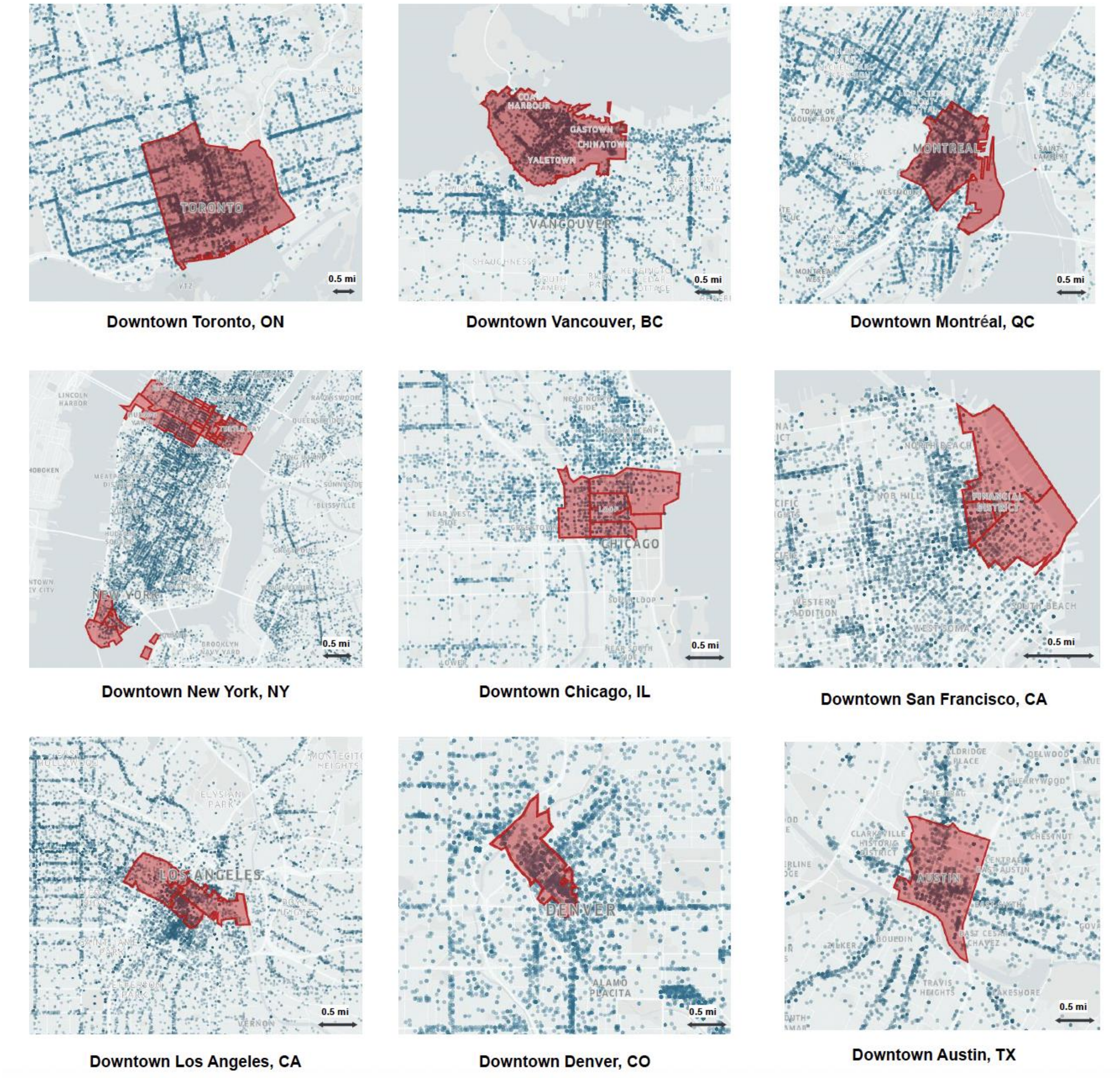


Figure 2: POIs and Downtown Definitions in 9 North American Cities

3.2 Quantifying Activity and Recovery

Activity levels between January 2019 and May 2022 within downtown neighborhoods and entire cities were calculated using data from SafeGraph, Inc.'s Patterns dataset. SafeGraph reports visits to POIs across the US and Canada, which could include but are not limited to businesses, offices, shops, restaurants, parks, community facilities, and stadiums. This diversity in POIs captures the overall economic and social activity levels in cities and downtowns more broadly than existing methods, which often target one particular user group or demographic (e.g., office occupants).

SafeGraph, Inc.'s Patterns is viewed as one of the most frequently utilized sources of mobility data in academic research including the urban sciences discipline (Li, 2023). Raw visit counts in the dataset were obtained by pinging the locations of 18,000,000 smartphones throughout North America through apps which access LBS, accounting for a sample of around 5% of all devices. Li et al. (2023) shows that the number of sampled devices in the SafeGraph dataset was strongly correlated with census population, indicating representativeness and the sample rate largely stayed uniform across regions, and that there was no systematic bias between sampling rate and population size. While minor biases involving gender, age, and moderate-income were identified, these concerns were observed to be minimal, and contrary to popular belief that using smartphones creates a negative bias towards low-income individuals, populations of aged 65 and over or lower socioeconomic status were actually slightly overrepresented in SafeGraph's data, owing to the high penetration rates of mobile devices amongst these groups today.

SafeGraph determines visits to POIs via an algorithm that detects clusters of stops within POI geofences based on proximity, duration of stay, and characteristics of the POI such as opening hours or industry. The raw number of visits detected at each POI was then normalized by the total visits observed in the entire SafeGraph database to account for differences in the entire sample size over time, resulting in a metric defined as "normalized visits by total visits." Figure 2 shows subsets of the POI location database along with the downtown definitions of six selected cities.

The "study period" defined as the time period between March 2020 and May 2022, while the "comparison period" relies on data between January to December 2019. During this time, our study aggregated the normalized visit counts into Downtown and City total counts for each city in the scope of study. In the US, visit counts were aggregated by the zipcode using the geocoded address of each POI, with downtowns based on the definitions in Appendix B, and cities based on the geometric union of each city's municipal boundary and overlapping zipcodes. In Canada, visit counts were aggregated by the Dissemination Area (DA) field encoded into the SafeGraph POI database, with downtowns based on methods defined in Seregie et al. (2021), and cities based on the geometric union of city boundaries with overlapping DAs. The aggregated normalized visits count can hence be expressed as:

Total Visits = $\Sigma\nu(i)$ for i = POIs Analysis Area

where ν = Normalized Visits by Total Visits at Individual POI

In order to quantify the activity levels of cities in the study period relative to pre-pandemic levels, two primary metrics were used: the Recovery Quotient (RQ) and the Location Quotient (LQ). These were adapted from previous work by Schmahmann et al. (2022). The RQ, which measures raw recovery levels in a particular analysis area at a particular time, is defined as:

$$RQ_{Analysis\ Area} = \frac{Total\ Visits\ over\ Analysis\ Week}{Total\ Visits\ over\ Comparison\ Week} \quad (1)$$

RQ values less than 1 indicate there is less activity during the analysis week than the corresponding week in 2019, while RQ values greater than 1 indicate there is more activity during the analysis week than the corresponding week in 2019.

The LQ value measures the proportion of total city visits inside the downtown area compared to all activity within the municipal boundary of each city. This metric represents the extent to which activity patterns returned to other areas within the city compared to the downtown. This proportion can be expressed as:

$$\text{Proportion of Visits, } \eta = \frac{\Sigma v(i) \ for \ \ i{=}POIs \in Downtown}{\Sigma v(i) \ for \ \ i{=}POIs \in City} \quad (2)$$

where Downtown ⊂ City and v = Normalized Visits by Total Visits at Individual POI

Thus, the LQ can be expressed as:

$$\text{LQ} = \frac{\eta \text{ over Analysis Week}}{\eta \text{ over Comparison Week}} \quad (3)$$

LQ values less than 1 indicate that the downtown area had a lower proportion of total activity in the city during the analysis week compared to the corresponding week in 2019, while LQ values greater than 1 indicate that the downtown area had a greater proportion of activity during the analysis week than the corresponding week in 2019.

Mathematically, the LQ also represents the relative recovery rate of the downtown region compared to the city, such that:

$$\text{LQ} = \frac{\text{RQ}_{\text{Downtown}}}{\text{RQ}_{\text{City}}} \quad (4)$$

RQ values for Downtowns, Cities, and LQ values for cities were calculated on a weekly basis with available SafeGraph patterns data and presented on a time-series scale. Figure 3 shows the time series of RQ and LQ values for 9 selected cities in the US and Canada, while Appendix B contains time series data for all cities in the scope of study.

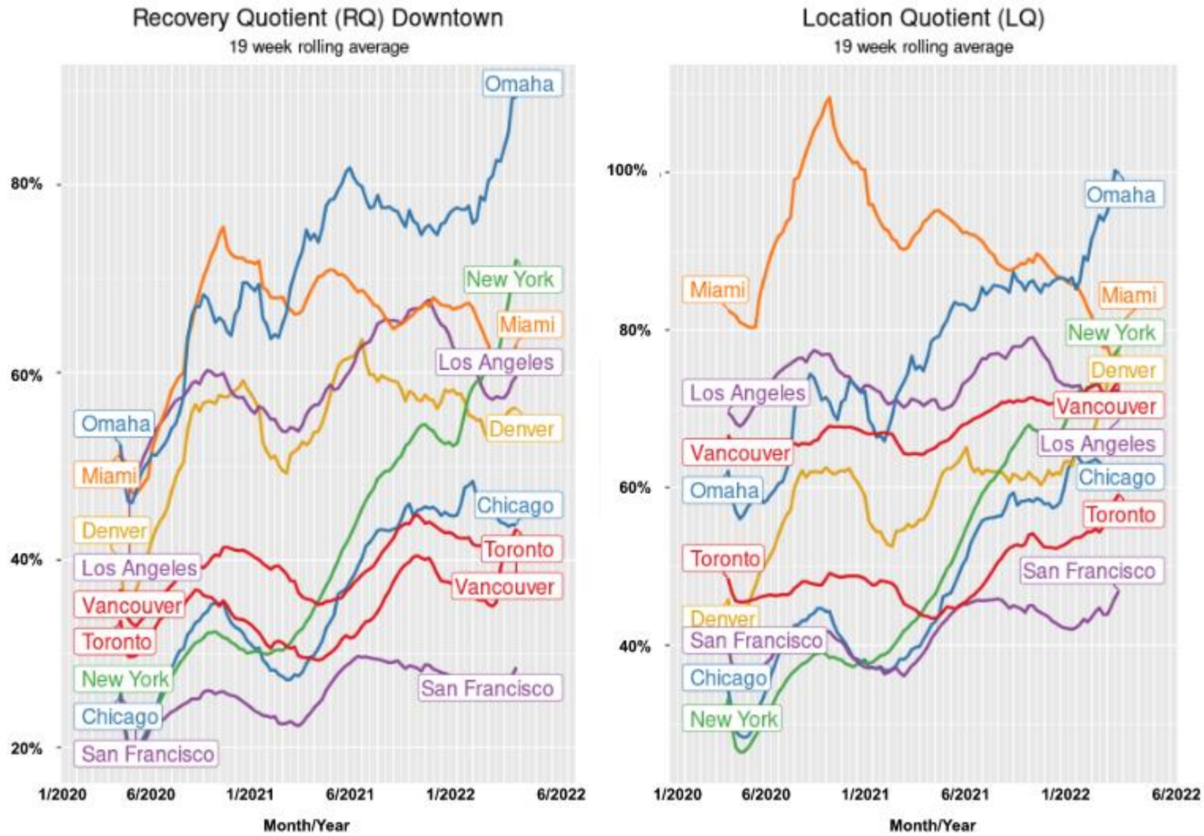


Figure 3: Downtown RQ and LQ Time Series in 9 Selected North American Cities

In Figure 3, we can see that recovery were both on a general uptrend for the cities presented. However, the differences in RQ and LQ allow for interesting comparisons. For example, Toronto and Vancouver have similarly low Downtown RQ values, however Toronto has a lower LQ value than Vancouver. This indicates that Toronto's proportion of downtown activity in comparison to the entire city is lower than Vancouver's, indicating that Toronto has more activity in non-downtown areas than Vancouver in 2022, while both downtowns still see a lower proportion of total visits in their respective cities compared to 2019. By using Equation (4), this also indicates that Vancouver as a city is recovering at a slower rate than Toronto.

3.3 Clustering Activity Recovery Trajectories

Dynamic Time Warping Barycenter Averaging (DBA) K-Means Clustering, developed by Petitjean et al. (2011), was used to classify common underlying patterns in RQ and LQ trajectories. DBA K-means clustering is a widely used method to reduce the dimensionality and noise of large datasets to interpretable clusters with common characteristics. In DBA K-Means, Dynamic Time Warping (DTW) was used as a similarity measure, while the DTW Barycenter Averaging (DBA) algorithm clusters trajectories by optimizing the distance between each time series and *n* k-medoids (where *n* is the number of clusters). The DTW similarity measure was calculated using mean-variance scaling as a preprocessing step. This was implemented using the Python library tslearn by Tavenard et al. (2020).

Using DBA K-means as a clustering approach has advantages over averaging RQs as euclidean distances, since it uses a nonparametric approach to identify the nuances of recovery patterns over time. This is especially beneficial since downtown activity varied in non-uniform ways during our study period, but several cities exhibited similar non-linear trajectory patterns. Li et al. (2019) used this method to infer usage patterns across different bike-sharing stations in Chicago from a large dataset over a 3 month period, while Teichgraber & Brandt (2019) used DBA K-means to cluster energy use patterns to determine optimal energy system operations, concluding that the dynamic time warping process produced the most effective time series clusters, over alternative Euclidean distance and shape-based distance measures. Figure 4 is an example of how DTW computes the temporal similarity in cities trajectory. Cities with more similar recovery patterns will have mostly straight and shorter lines. Meanwhile, cities with less similar recovery patterns will display extensive warping.

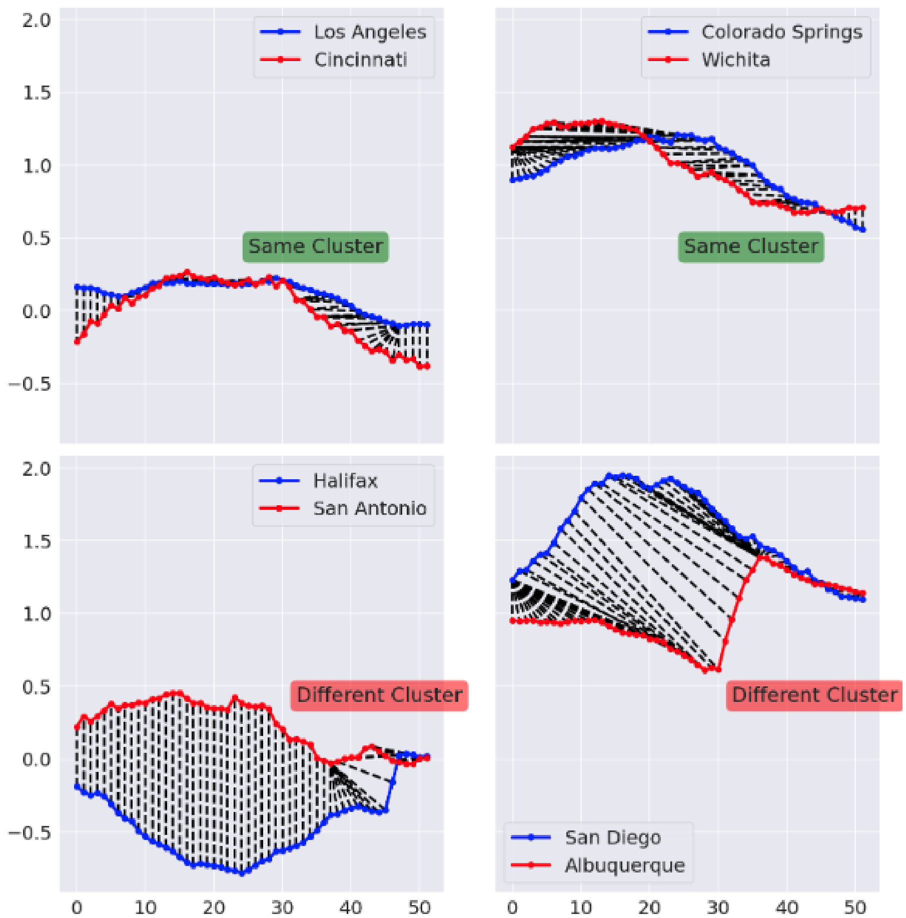


Figure 4: Dynamic Time Warping (DTW) Analysis on 4 City Pairs

DBA K-Means produced 4 to 5 usable clusters of all cities' Downtown RQ and LQ trajectories. Clustering for Downtown Recovery Quotients was done over two 1-year periods: Period 1 from June 2020 through May 2021, when the lack of vaccinations and COVID-19 restrictions dominated people's daily lifestyles; and Period 2 June 2021 through May 2022, when mass vaccinations were available and society gradually tried to resume daily activities. Using two separate periods increased the interpretability of clusters amongst different causal conditions for Downtown RQs, but was not necessary for LQs since they varied less over time. The results of these trajectories are detailed in Section 4.1.

3.4 Explanatory Variables

In addition to weekly LQ and RQ values, characteristics of each city were analyzed to determine associations with downtown recovery patterns. These variables were from four main groups: downtown employment by industry, socio-economic information, COVID-19 public health restrictions, and the prevailing weather conditions.

Downtown employment by industry variables were sourced from the LEHD Origin-Destination Employment Statistics (LODES) Workforce Area Characteristic tables (US Census Bureau, 2019) and the Employment by industry, annual table (Statistics Canada, 2016). The volume of jobs in each industry per the North American Industry Classification System (NAICS) were aggregated over the downtown area, and the percentage of each industry was reported as its concentration. The nature of each industry not only indicates different degrees of work-from-home capabilities throughout and after the COVID-19 pandemic, but also the degree to which downtowns are office-oriented or service-oriented. Employment density divides the total number of jobs by the land area of the downtown definition. An employment entropy index, which was also used by Schmahmann et al. (2022), captures the diversity of businesses within each downtown region. It is defined as:

$$\text{Entropy} = -\Sigma p_i \log(p_i) \text{ for i = all industries} \quad (5)$$

where $\boldsymbol{i}$ indicates each industry of employment and $\boldsymbol{p_i}$ indicates the proportion of total jobs within each industry $\boldsymbol{i}$.

Socio-economic variables were sourced from the ACS 5-Year Estimates Detailed Tables (United States Census Bureau, 2019), Canadian Census of Population (Statistics Canada, 2016), and helped to identify the demographics and housing stock characteristics of downtown areas or cities. Variables for RQ Downtown analysis were aggregated (or averaged) across downtown definitions, while variables for LQ analysis were aggregated across the entire city definition. The relative education levels, rent, renter vs owner tenure, income, and age help determine the relative flexibility of the city’s population in the age of remote working. The characteristics of housing stock can be compared at the downtown level to gauge the performance of cities with strong residential cores downtown to cities without, as well as the type and age of housing stock. Each downtown and city’s population and housing density was calculated by dividing the total population or housing stock by the land area of the downtown or city definition.

Government restrictions and closure-related policies were sourced from the Oxford University Covid-19 Government Response Tracker (OxCGRT) developed by Hale et al. (2021), which collects and ranks policy responses at a state/provincial level across 180 countries on a daily interval. The relevant variables which could have impacts on economic activity patterns were closures (school closures, workplace closures); restrictions on movement and activities (stay at home orders, canceling large events, and restrictions on gatherings); income support for workers unemployed as a result of COVID-19; and masking mandates. Closures and restrictions on movement directly impacted travel and visitation patterns across cities by restricting travel to essential purposes only, while income support and masking mandates indirectly influenced activity patterns based on the ability to spend and the ease of visiting places, respectively. The severity of restrictions was a static variable created by summing the number of days a particular restriction or policy was in place over the study period. For the purpose of this study, given the populous nature of cities, we assume that the most stringent policy from states/provinces are applied to cities, and equate the strictest state/province-level policy to the city policy. This means that cities which exist in the same state or province will have identical variables for restrictions. The same variables are applied to city and downtown analyses.

Lastly, average seasonal weather conditions for each season came from the World Weather Online API (Weather API, n.d.). For the purposes of this study, winter was approximated to December, January, and February; spring from March through May, summer from June through August, and fall from September through November. Weather conditions had an influence on activity during the earlier stages of the pandemic as public health mitigation measures such as outdoor dining and outdoor events for social distancing were more workable in warmer climates. In later stages of the pandemic, newfound habits of working from home or relying on the on-demand delivery economy may have influenced activity during adverse weather conditions. The same variables are applied to city and downtown analyses.

Table 2 lists all 50 explanatory variables, all of which are numerical.

Table 2: Explanatory Variables

Variable Category & Name
Downtown Employment Variables *(Source: US Census Bureau LODES Data & Statistics Canada Employment by Industry Data)* Percentage of Jobs in Agriculture, Forestry, Fishing, and Hunting (NAICS 11) Percentage of Jobs in Mining, Quarrying, Oil, and Gas (NAICS 21) Percentage of Jobs in Utilities (NAICS 22) Percentage of Jobs in Construction (NAICS 23) Percentage of Jobs in Manufacturing (NAICS 31 - 33) Percentage of Jobs in Wholesale Trade (NAICS 41 - 42) Percentage of Jobs in Retail Trade (NAICS 44 - 45) Percentage of Jobs in Transportation & Warehousing (NAICS 48 - 49) Percentage of Jobs in Information (NAICS 51) Percentage of Jobs in Finance & Insurance (NAICS 42) Percentage of Jobs in Real Estate (NAICS 53) Percentage of Jobs in Professional, Scientific, and Technical Fields (NAICS 54) Percentage of Jobs in Management of Companies and Enterprises (NAICS 55) Percentage of Jobs in Administrative Support & Waste Management (NAICS 56) Percentage of Jobs in Educational Services (NAICS 61) Percentage of Jobs in Healthcare & Social Assistance (NAICS 62) Percentage of Jobs in Arts, Entertainment & Recreation (NAICS 71) Percentage of Jobs in Accommodation & Food Services (NAICS 72) Percentage of Jobs in Public Administration (NAICS 91) Employment Density Downtown (Calculated - jobs per square meter) Employment Entropy Downtown (Calculated - see equation 5)
Downtown Housing Socio-Economic Variables *(Source: US Census Bureau ACS 2019 & Statistics Canada Census 2016)* Population* Population Density (Calculated - people per square meter)* Number of Housing Units Housing Density (Calculated - housing units per square meter) Median Age (years) Median Household Income (USD, 2019 inflation adjusted)^

Median Rent (USD, 2019 inflation adjusted)^ Percentage of Housing Units in Single-Family Homes* Percentage of Housing Units in Multi-Family Homes Percentage of Vacant Housing Units Percentage of Residents with a Bachelor's Degree or Higher Median Year of Structure Built of Housing Units Median Number of Rooms per Housing Unit
City-Wide Commute Variables *(Source: US Census Bureau ACS 2019 & Statistics Canada Census 2016)* Average Commute Time Percentage of Commuters who use Private Automobiles* Percentage of Commuters who use Public Transportation Percentage of Commuters who use Bicycle Percentage of Commuters who Walk
City-Wide COVID-19 Restriction Variables *(Source: Oxford University COVID-19 Government Response Tracker)* Number of days schools were closed Number of days workplaces were closed Number of days large public events were canceled Number of days all private gatherings were not allowed Number of days stay-at-home requirements were imposed Number of days mask/facial covering mandates were imposed Number of days income support was disbursed
City-Wide Weather Variables *(Source: World Weather Online API)* Average Winter Temperature in Degrees Fahrenheit Average Spring Temperature in Degrees Fahrenheit* Average Summer Temperature in Degrees Fahrenheit Average Fall Temperature in Degrees Fahrenheit*

**Variables with an asterisk were found to be multicollinear or strongly correlated with a coefficient above 0.9, and were removed from classification model inputs in Section 4.2.*
^Canadian income and rent variables were adjusted for Canada nation-wide inflation rates from 2016 to 2019, and then converted to US dollars using the conversion rate on January 1, 2019.

3.5 Investigating Associations between Clusters and Explanatory Variables

To determine the most defining explanatory variables behind each set of 5 DBA K-Means clusters, a Random Forest Classifier (RFC) (Pedregosa et al., 2011) predicted the cluster of each city given all 48 explanatory variables from Section 3.3 as features. An RFC analysis was performed over more classical methods of linear regression due to the large amount of explanatory variables, owing to competing theories of the determinants of downtown activity variation during the study period. The hyperparameters of the RFC were selected using a randomized search cross-validation (Pedregosa et al., 2011). The variables with the highest feature importance from the RFC, as well as some specific key variables, were then analyzed to identify key characteristics for each cluster, which informed more specific analyses. In this regard, the RFC was used as a 'screening tool' to identify significant relationships for further study. The results of the RFC variables can be found in Section 4.2, while the more specific analyses of variable associations can be found in Sections 4.3 to 4.6.

4. Results

Downtown activity patterns and recovery trajectories were analyzed for all selected cities based on the methods in Section 3. Section 4.1 shows the patterns and clusters in recovery trajectories, while Section 4.2 examines the most important explanatory variables that distinguish each cluster computationally through random forest classification. Sections 4.3 to 4.6 explore the associations of clusters with employment by industry, socioeconomic characteristics, environment and urban form, commute, and COVID-19 restrictions.

4.1 Clusters of Downtown Recovery

Analysis of Downtown RQ values yielded 5 highly interpretable clusters over two periods, while analysis of LQ values yielded 4 highly interpretable clusters over a single period. This difference in cluster interpretability can be attributed to the changing course of many downtowns between Period 1 of the pandemic, where most in-person activity was restricted, and Period 2, where selective in-person activity resumed following widespread vaccinations. LQ values, on the other hand, were not seen to change course over the two study periods, and relevant clusters could be identified based on the entire 2-year trajectory.

In Period 1, two RQ clusters (Clusters R1.1 and R1.5) which were well above and below average emerged where the cluster k-medoid was consistently 1 standard deviation above or below the mean recovery. Two other clusters (Clusters R1.2 and R1.4) were slightly below and above the average, where the k-medoid was consistently between 0 and 1 standard deviations above or below the mean recovery. Finally, Cluster R1.3 emerged as a stagnant cluster which started at average recovery levels (higher than R1.4 and R1.5) but failed to improve over time, declining below average at the end of the period. In Period 2, all clusters displayed a general uptrend, but a cluster of exceptional performers (Cluster R2.1) with RQs around 2 standard deviations above the mean emerged. Cluster R2.1 cities were the only cities which were observed to recover around 2019 activity levels, and in some cases, exceed them. Figure 5 shows these DBA K-Means Clusters while Figure 6 shows a directed graph displaying the mapping of each city between Period 1 and Period 2 clusters. The directed graph shows that many of the stagnant (Cluster R1.3) cities ended up in Cluster 2.5, well below the average of other cities. It also shows that Cluster 1.2, the above-average cluster, contained a mixture of cities which performed exceptionally well, above-average, and closer to average (indicating stagnation) in Period 2.

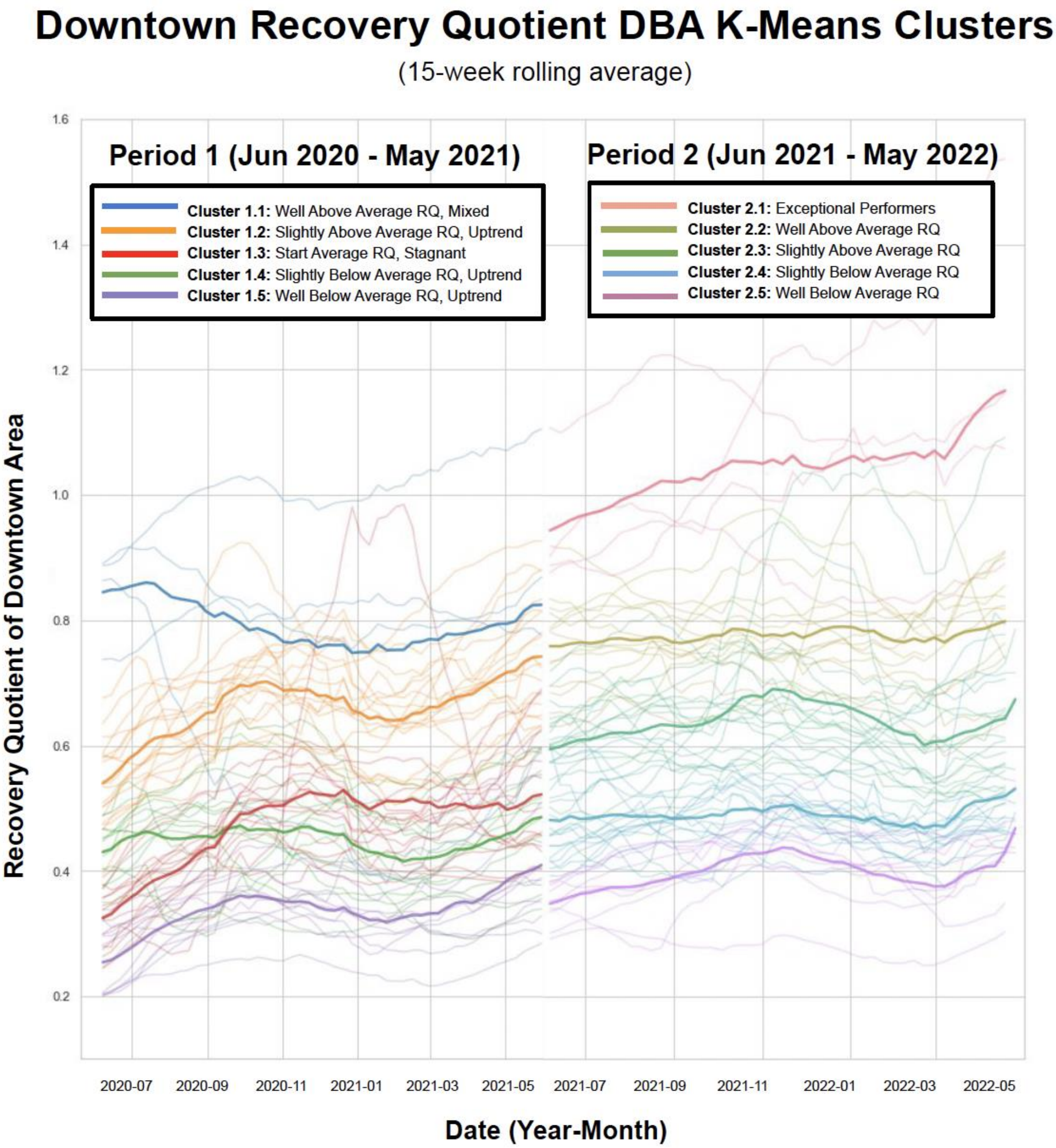


Figure 5: DBA K-Means Clusters for Downtown Recovery Quotients

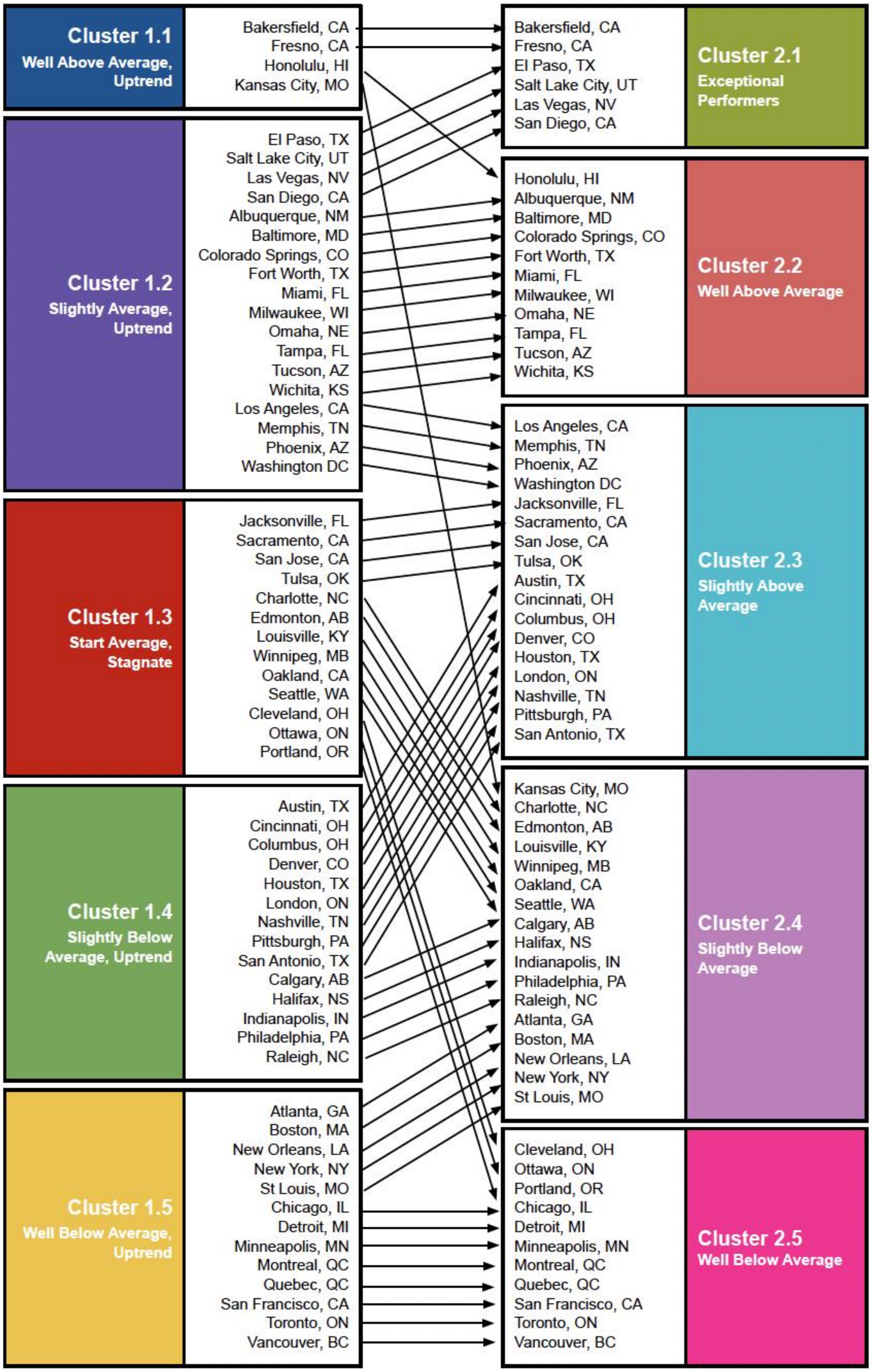


Figure 6: Directed Graph for Downtown Recovery Clusters

The relative stagnation of LQ trajectories compared to RQ trajectories indicates that while downtown areas saw progressive increases in activity in general, the proportion of activity in downtown districts compared to the rest of their respective cities was more constant throughout the entire study period. Four clusters emerged from the analysis of these trajectories, with two clusters (Clusters L1 and L4) of LQs at above and below average levels. The median of Cluster L1 sees a slight improvement throughout the study period, while the median of Cluster L4 sees a decline during the first year of the study period and an uptrend during the second year of the study period. Clusters L2 and L3 both comprised cities which started at average LQs; however, cities in Cluster L2 saw a discernible improvement in LQ between the start and the end of the study period, while Cluster L3's LQs stagnated at average levels, to the point where they matched some lower Cluster L4 LQs by the end of the study period. We also observe that the downtowns of Cluster 1 cities were the closest to maintaining the same proportion of total city visits compared to 2019, and a select few cities exceeded that proportion. Cities in Clusters 2 through 4 are struggling to maintain the same proportion of city visits in downtown areas; however Clusters 2 and 4 are showing noticeable uptrends in that regard between April 2020 and May 2022, while Cluster 3 does not. Figure 7 shows these DBA K-Means Clusters and Table 3 shows the cities in each of these clusters.

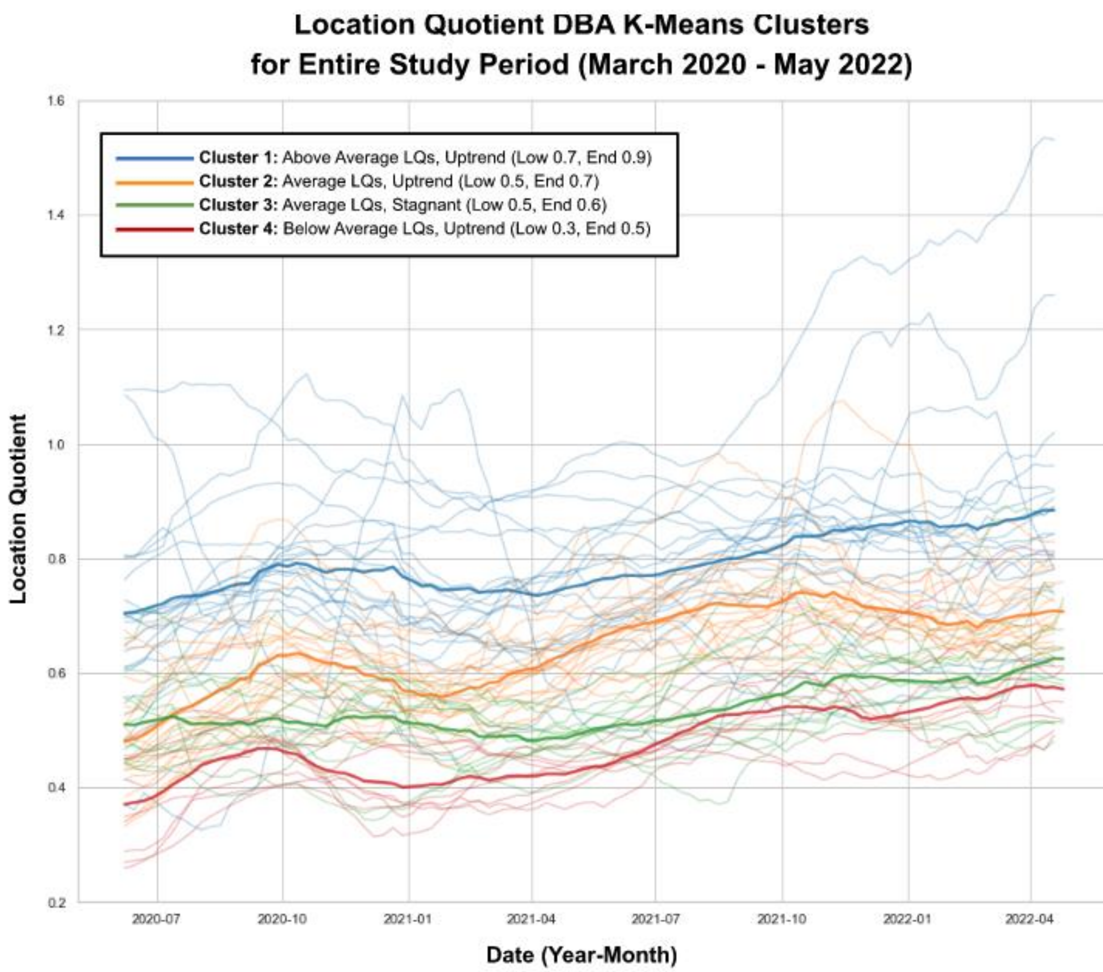


Figure 7: DBA K-Means Clusters for Location Quotients

Table 3: Cities in Location Quotient Clusters

Cluster 1	Cluster 2	Cluster 3	Cluster 4
Albuquerque, NM Bakersfield, CA Baltimore, MD El Paso, TX Fresno, CA Honolulu, HI Kansas City, MO Las Vegas, NV Los Angeles, CA Memphis, TN Miami, FL Milwaukee, WI Oakland, CA Omaha, NE Phoenix, AZ Salt Lake City, UT San Diego, CA Tampa, FL Wichita, KS	Austin, TX Boston, MA Colorado Springs, CO Columbus, OH Cincinnati, OH Denver, CO Fort Worth, TX Houston, TX Nashville, TN New Orleans, LA Philadelphia, PA Pittsburgh, PA Raleigh, NC San Antonio, TX San Jose, CA Seattle, WA St Louis, MO Tucson, AZ Vancouver, BC Washington DC	Calgary, AB Charlotte, NC Edmonton, AB Halifax, NS Indianapolis, IN Jacksonville, FL London, ON Louisville, KY Montreal, QC Ottawa, ON Portland, OR Quebec, QC Sacramento, CA Toronto, ON Tulsa, OK Winnipeg, MB	Chicago, IL Detroit, MI Minneapolis, MN New York, NY San Francisco, CA

4.2 Most Important Explanatory Variables Defining Clusters

Table 4 shows the feature importance results of the random forest classifier (RFC), displayed as a percentage of total variance. While the variable importance in the RFC does not include the direction of the variables' influence, these are uncovered in more specific studies in Sections 4.3 and 4.6.

Table 4: Importance of Variables from Random Forest Classifier

Downtown RQ (P1)		Downtown RQ (P2)		Downtown LQ	
% Jobs in Information	6.44%	% Jobs in Prof, Sci, Tech	5.27%	Median Household Income	5.63%
% Jobs in Prof, Sci, Tech	5.00%	% Multi-Family Housing	4.67%	Winter Average Temperature	4.98%
% of Multi-Family Housing	4.89%	Summer Average Temperature	4.34%	% Jobs in Prof, Sci, Tech	4.57%
% Jobs in Construction	4.76%	% Commute Bicycle	4.03%	% Residents Bachelor +	4.39%
% Commute Public Transit	3.91%	% Commute Public Transit	3.93%	% Jobs in Information	4.34%
% Commute Walk	3.70%	% Commute Walking	3.61%	Employment Density	4.21%
% Renter-Occupied Units	3.29%	% Jobs in Information	3.52%	Average Commute Time	4.00%
Employment Entropy	3.03%	Days of Income Support	3.30%	Median Rent Downtown	3.76%
% Jobs in Public Admin	2.85%	% Jobs in Public Admin	3.17%	% Jobs in Education	3.49%
Average Commute Time	2.78%	Employment Density	3.16%	% Jobs in Accommodation/Food	2.75%
% Jobs in Education	2.66%	Winter Average Temperature	2.93%	% Jobs in Manufacturing	2.60%
Employment Density	2.64%	% Jobs in Management	2.56%	% Commute Public Transit	2.50%
% Commute Bicycle	2.63%	% Jobs in Education	2.53%	Housing Units Downtown	2.33%
Days of Stay at Home Req.	2.50%	% Jobs in Manufacturing	2.44%	% Jobs in Retail Trade	2.27%
% Jobs in Management	2.41%	Days Large Events Canceled	2.42%	Days of Stay at Home Req.	2.15%
% Residents Bachelor +	2.40%	Average Commute Time	2.33%	% Renter Occupied Housing	2.14%
Median Age of Residents	2.23%	Days All Events Canceled	2.29%	% Jobs in Utilities	2.13%
Days All Events Canceled	2.14%	Days of Workplace Closure	2.23%	% Jobs in Finance	2.04%
Housing Median Year Built	2.13%	Housing Median Year Built	2.22%	% Jobs in Public Admin	2.03%
Days Large Events Canceled	1.99%	% Jobs in Healthcare	2.09%	% Jobs in Admin/Waste	2.01%
% Jobs in Admin & Waste	1.92%	% Jobs in Transport/Warehouse	2.08%	Downtown Housing Density	1.80%
% Jobs in Manufacturing	1.86%	% Jobs in Finance	2.04%	Days of Workplace Closure	1.78%
% Jobs in Finance	1.86%	Housing Units Downtown	2.04%	% Jobs in Transport/Warehouse	1.77%
Days of Workplace Closure	1.83%	% Jobs in Retail Trade	1.98%	Days All Events Canceled	1.70%
% Jobs in Agriculture	1.77%	% Jobs in Agriculture	1.95%	Median Age of Residents	1.70%
% Jobs in Healthcare	1.76%	% Jobs in Accommodation/Food	1.84%	% Jobs in Real Estate	1.69%
Winter Average Temperature	1.73%	Downtown Housing Density	1.82%	Summer Average Temperature	1.67%
% Jobs in Arts/Entertainment	1.64%	% Jobs in Construction	1.78%	% Commute Walking	1.63%
Housing Density	1.63%	Median Age of Residents	1.77%	% Jobs in Management	1.58%
Housing Units Downtown	1.55%	% Jobs in Utilities	1.72%	% Jobs in Arts/Entertainment	1.57%
% Jobs in Accommodation/Food	1.54%	Days of Mask Mandates	1.71%	Housing Median Year Built	1.54%
Median Household Income	1.47%	% Jobs in Arts & Entertainment	1.47%	% Multi-Family Housing	1.52%
% Jobs in Transport/Warehouse	1.44%	Housing Median No. of Rooms	1.42%	Days of Mask Mandates	1.48%
Days of Income Support	1.36%	% Jobs in Admin & Waste	1.37%	% Jobs in Healthcare	1.48%
% Jobs in Wholesale Trade	1.36%	Days of Stay at Home Req.	1.36%	% Jobs in Construction	1.47%
Housing Median No. of Rooms	1.33%	% Jobs in Real Estate	1.32%	% Downtown Housing Vacancy	1.45%
Days of School Closure	1.32%	% Downtown Housing Vacancy	1.30%	% Commute Bicycle	1.36%
% Downtown Housing Vacancy	1.23%	% Jobs in Wholesale Trade	1.27%	Days of Income Support	1.30%
% Jobs in Utilities	1.22%	% Renter Occupied Housing	1.11%	Employment Entropy	1.30%
% Jobs in Retail Trade	1.18%	Employment Entropy	1.06%	Days of School Closure	1.17%
Summer Average Temperature	1.11%	Days of School Closure	1.05%	Housing Median No of Rooms	1.05%
Median Rent Downtown	1.00%	Median Household Income	0.95%	% Jobs in Mining	1.05%
Days of Mask Mandates	0.90%	% Residents Bachelor +	0.91%	Days Large Events Cancelled	1.01%
% Jobs in Real Estate	0.90%	% Jobs in Mining	0.85%	% Jobs in Wholesale Trade	0.95%
% Jobs in Mining	0.72%	Median Rent Downtown	0.78%	% Jobs in Agriculture	0.95%

The results of the RFC show that for the Downtown RQ, concentration of specific industries and commuting variables featured amongst the most important explanatory variables in both Periods 1 and 2. Period 1 also included housing and COVID-19 restriction variables, with housing type and tenure variables among the most important, but these became less important in Period 2. Instead, as the pandemic continued for a second year, the weather and socio-economic features such as the percentage of downtown residents with a bachelor's degree or higher assumed a more prominent role. This speaks to the differences in factors which influenced downtown recovery within the two periods. The most important Downtown LQ determinants came from all categories except COVID-19 policies (Employment by Industry, Environment and Urban Form, and Socio-Economic Variables).

4.3 Cluster Associations with Employment by Industry

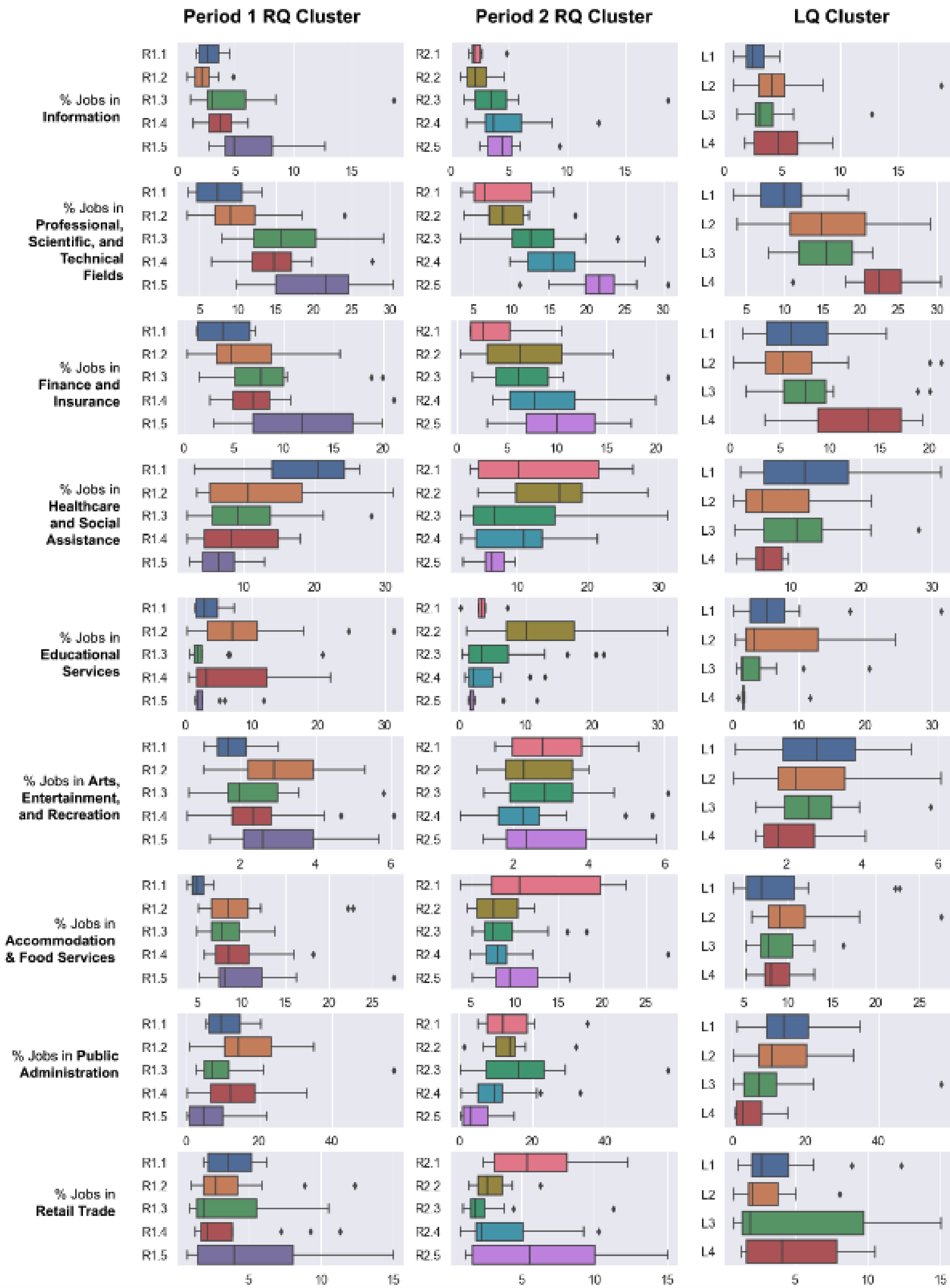


Figure 8: Cluster Association with Employment by Industry Variables

Specific industries are strongly associated with levels of sustained or depressed visitation throughout the period of study. For example, the industry concentration of information (including tech), finance & insurance, and professional, scientific, & technical fields is negatively associated with both downtown recovery levels throughout the study period, and are consistently factors of high importance in random forest classification. These fields had the highest propensity to work from home more days a week, which not only reduced the visit counts to office POIs, but also POIs of related economic activities such as business lunches and conferences. Downtowns in Clusters R1.5, R2.5, and L4, which had the highest concentrations of these three industries (at up to 53% of total downtown employment), saw the most significant depression in downtown activity, hovering between 20% and 50% of pre-pandemic raw visit counts and 40% to 50% of the proportion of pre-pandemic raw visit counts throughout the study period. In contrast, downtowns in Clusters R1.1, R2.1, and L1, which sustained levels of downtown visits around or above 80% of pre-pandemic levels throughout the pandemic, were primarily defined by low concentrations in these three industries, while intermediate clusters also saw a negative gradient between these industry concentrations and downtown activity levels. Thus, we can observe that the high concentrations of office real estate occupied by firms from these industries was a significant contributor to depressed downtown activity.

Concentrations of six other key industries - healthcare, education, arts & entertainment, accommodation & food, public administration, and retail trade - showed interesting associations with pandemic-era downtown activity. In Period 1 under widespread COVID-19 restrictions which only allowed essential workplaces to operate, these industries varied in activity. However, by Period 2, downtowns with higher industry concentrations of healthcare, arts & entertainment, and public administration tended to be placed in clusters with higher levels of activity (although this positive association is not as strong as the negative association of information, finance, and professional services). Cluster R2.1, which comprised downtowns that recovered or even exceeded their pre-pandemic visits, was also characterized by high industry concentrations in accommodation and food services, while Cluster R2.2, which trailed just behind Cluster R2.1, was characterized by high industry concentration in education (although for these examples, counter-examples exist and there is less of a clear trend across cities). This suggests that these five industries could offer viable paths for downtowns to reinvent their land use and industry mix to address depressed foot traffic and vacant real estate, given that they are compatible with existing office land use. In fact, downtowns which moved from a lower RQ cluster to a higher RQ cluster between Periods 1 and 2 (such as Las Vegas, San Diego, and Nashville), or downtowns which were on an uptrend towards the end of the analysis period (such as New York City), tended to have high concentrations in the arts & entertainment and accommodation & food industries, showing strong rebounds after early impacts of COVID-19 operating restrictions. Downtowns with high concentrations of employment in retail trade were classified in both high-performing and low-performing clusters. Recovery of the retail sector is hence likely to be dependent on the nature and target audience of retail offerings. It is likely that specialty or tourist-oriented retail showed a strong recovery together with a strong leisure activity recovery, and that retail targeting office crowds or retail which can be otherwise found outside the downtown lagged in recovery.

4.4 Cluster Associations with Socio-Economic and Housing Factors

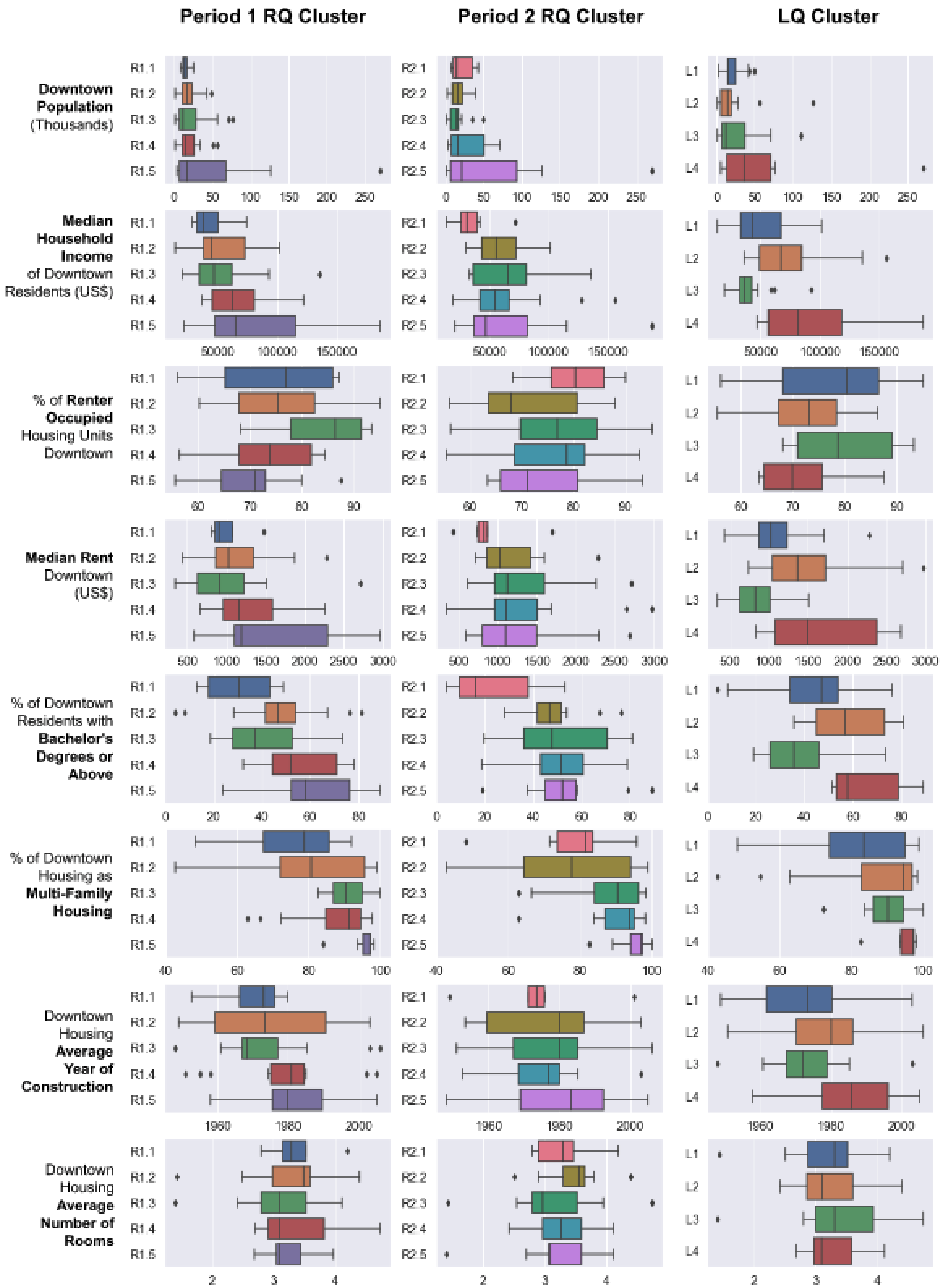


Figure 9: Cluster Association with Socio-Economic and Housing Factors

There was also substantial association of downtown recovery with some housing and socio-economic characteristics of residents who live in or directly adjacent to the downtown area. While data shows that downtowns with larger populations tended to perform more poorly in raw recovery numbers, a handful of downtowns with medium-sized populations were classified in the exceptionally-performing R2.1 cluster in Period 2. Most downtowns with larger populations were also classified in Cluster L3, indicating that they maintained a stagnant 50% to 60% of visit proportions throughout the study period. This indicates that a larger population may have helped prevent downtowns from reaching the lower 30% to 40% of visit proportions observed by Cluster L4 Downtowns, but also does not become a determinant of greater recovery over time.

Median household income, median rent, and percentage of residents with a bachelors degree and above were negatively associated with raw visit recovery, mirroring the trend of information, professional, and financial industry concentrations. In other words, the downtowns with more affluent residents initially fared worse. However, by Period 2, this trend disappears for the bottom-most cluster R2.5, and instead we see the second-lowest Cluster R2.4 having the highest income, education levels, and rent prices, which indicates that the association of these socio-economic variables alone did not stand the test of time, and other factors were more deterministic of recovery in Period 2. We also observe that Clusters L2 and L4, where LQs increase over time, tended to be associated with higher income, education, and rent, while Clusters L1 and L3, which showed more stagnant LQs over time, tended to be associated with lower income, education, and rent. This speaks to the higher mobility of higher-wage workers to shift commuting patterns and work location, influencing the business activity in downtown districts.

Interestingly, Cluster R1.3, which stagnated between 40% and 50% of recovery quotient in Period 1, was characterized by a high proportion of renter-occupied housing units. This goes against the gradual recovery pattern of Clusters R1.2, R1.4, and R1.5. High proportions of renters may have had greater degrees of mobility, causing stagnations in downtown activity as rental prices dropped significantly during Period 1 commensurate with strong out-migration from the urban core during the initial phases of COVID-19. This variable recovery direction was not seen in Period 2, where downtowns in all cities trended in the general upwards direction of recovery.

There were no significant relationships between age of housing stock and number of rooms with raw recovery, although downtowns with newer housing stock tended to be classified in the lowest performing LQ cluster L4. This may reflect the small size of new downtown units, which pushed larger households out to exurban areas with larger houses.

4.5 Cluster Associations with Environment, Urban Form, and Commute Factors

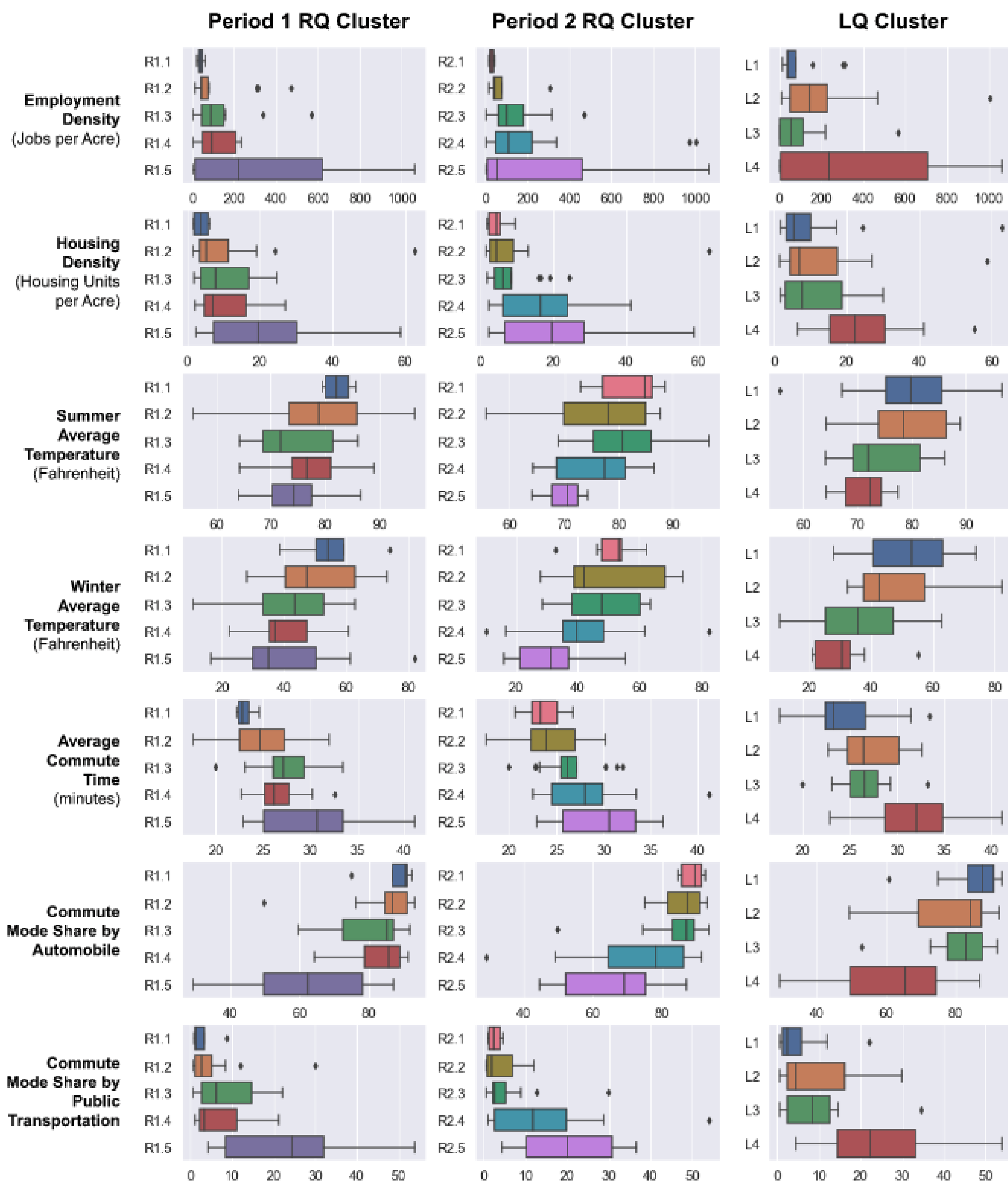


Figure 10: Cluster Association with Environment and Urban Form, and Commute Factors

Analysis of the environment, urban form, and commute variables also revealed that these factors had a strong association with RQ and LQ clusters, and became especially important in Period 2.

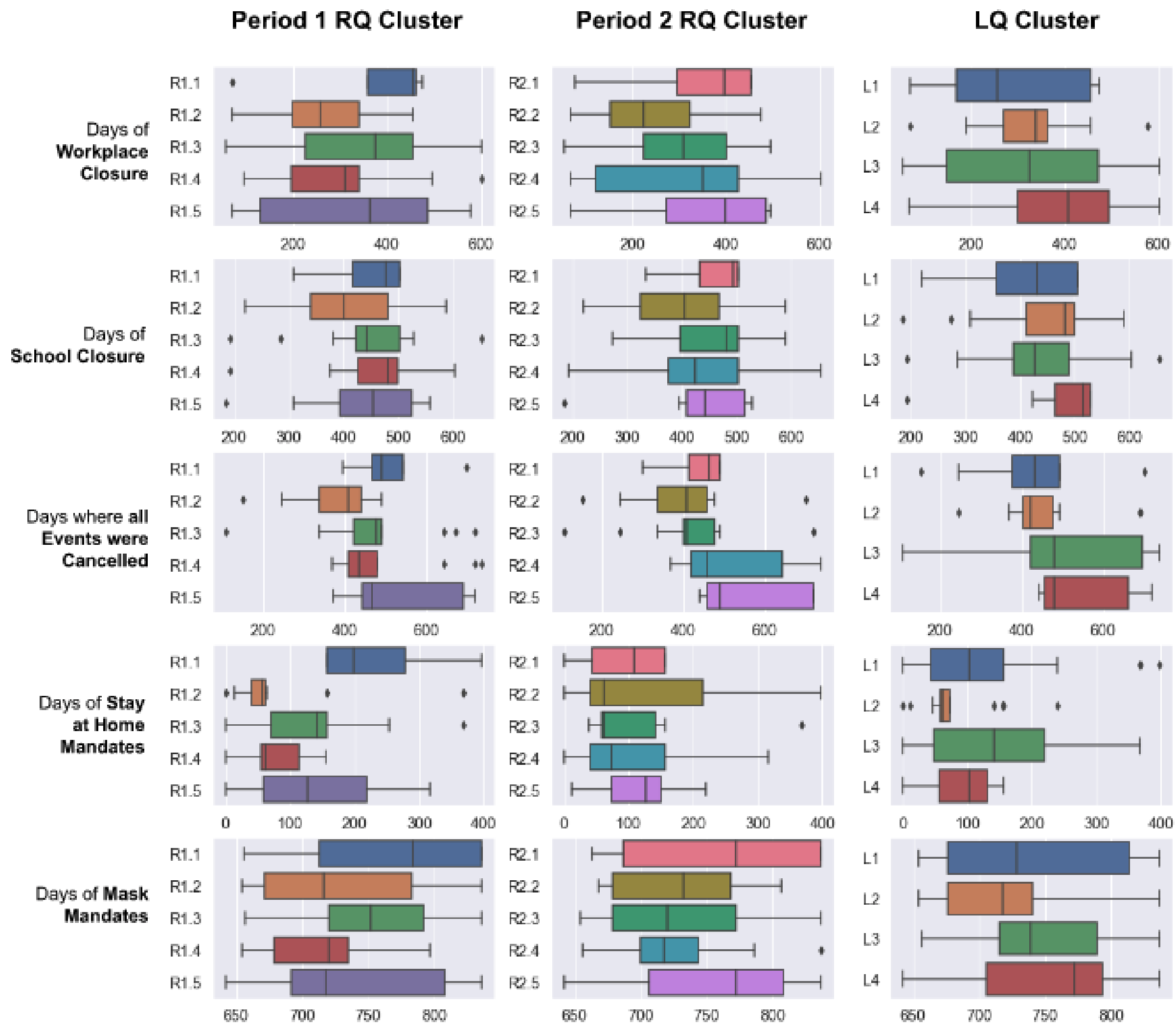
Firstly, the downtowns with the highest employment densities and housing densities placed into the lowest recovery clusters 1.5 and 2.5, indicating they struggled the most retaining both raw visitation numbers and visitation proportions relative to the rest of their respective cities. These trends were more pronounced in Period 1 than Period 2, but still hold significance in Period 2. Cities with the highest housing density tended to be placed in Cluster L4, indicating they struggled to retain proportions of visits. However, employment density was less consequential for LQs, as although many cities with high employment density were classified into Cluster L4, cities with low employment density were spread out across all clusters. The downtowns with the highest proportions of multi-family housing were also placed in the lowest clusters of both recovery quotients and location quotients. These trends could result from two possible causes - behavioral change induced by pandemic-era public health advisories against the visitation of crowded areas, and outmigration by affluent downtown residents, i.e., the “donut effect” of moving to exurban areas. The combination of these findings suggest that housing had little positive effect on downtown recovery metrics over the period of study. However, this finding may reflect shortcomings of the analysis (e.g., omitted variable bias).

Secondly, we observe that there is a more pronounced influence of weather and average commuting time in Period 2 compared to Period 1. Clusters R2.5 and L4 comprised downtowns with harsher winter temperatures and longer commute times compared to stronger recovery clusters, which suggests that the propensity to commute (which is reduced by longer commute times or extremely cold or warm temperatures) may have had a large influence on the willingness of the population to return downtown if their work or activities could be performed remotely. This classification also correlates with studies showing higher rates of snowbirding amongst the working population during the pandemic (Yale, 2021), where many colder cities would have experienced a temporary population loss altogether. These findings of negative recovery associations with extreme winter weather and long commute times may pose a particular challenge to downtowns in large cities or cities with less desirable winter climates.

Thirdly, the commuting mode shares of automobiles and public transportation experienced an inverse relationship with both RQs and LQs throughout the period of study, indicating that workers were quicker to return to automobile commutes than public transit commutes. This could be largely due to the association of public transportation with COVID-19 risk and the reduction of public transit service levels during the pandemic (Solomonow, 2020; Gkiotsalitis, 2021), both of which induced a modal shift to private automobiles. These patterns are similar to the negative associations of urban density and social interactions early in the pandemic, and suggest that these associations may be sticky over time even if they were untrue (Richter, 2022). The lag in return to public transit commutes could also reflect the phenomenon that flexible work arrangements have caused the spatial and temporal patterns of commuting to change, whilst most public transportation systems cater to pre-pandemic commuting patterns (Shaver, 2022).

Lastly, we note that even after COVID-19 became less of a public health concern in Period 2 of our study, many cities had experienced other issues which affected the propensity of workers to return to downtown offices. Loh & Love (2023) document that in large cities such as New York, office workers increasingly cite increases in crime during the COVID-19 pandemic instead of fear of COVID-19 infection as reasons they are uncomfortable with returning to downtowns

4.6 Cluster Association with COVID-19 Restrictions



Our study finds that there is a very limited association between downtown recovery and COVID-19 restrictions. The number of days where all events were canceled had the most significant association for both periods, where generally a higher number of days with event cancellations were characteristic of depressed downtown visitation. Downtowns in Cluster R1.5 and Cluster R2.5, which included downtowns that performed well-below average, had a maximum number of days of approximately 650. In contrast, well-performing clusters such as Cluster R1.1, R1.2, R2.1, and R2.2 had a much lower total of days where all events were canceled. Downtowns dependent on large events such as conferences and concerts likely experienced disproportionate impacts from their cancellation. Additionally, the prolonged cancellation of events during the pandemic and relative success at large virtual events has shifted the long-term preferred modality of large events to include hybrid and virtual events (Yuniati et al, 2022), which could continue to threaten the future of event-reliant downtowns in both the business and entertainment sectors.

Interestingly, neither blanket COVID-19 restrictions like stay-at-home orders nor school and workplace closure revealed any significant trend between Period 1 and Period 2. Well-performing cluster R1.1 had a higher number of days with stay-at-home orders compared to the below-performing clusters in R1.5; similarly, in Period 2 all clusters had similar number of stay-at-home dates, with cluster R2.5 having a slightly lower maximum days than R2.1. These findings indicate that contrary to popular opinion, the severity of COVID-19 restrictions and mandates did not have a strong association with downtown recovery patterns, and other sets of variables such as industries, urban form, and socio-economic factors had more influence over recovery patterns.

5. Discussion

This section examines the implications and limitations of our analysis and results during continually dynamic times for cities. Section 5.1 provides a summary of findings in Section 4 and links them to policy implications for downtowns and cities, while Section 5.2 identifies contributions to literature and Section 5.3 identifies limitations to the analysis.

5.1 Summary of Findings and Policy Implications

Downtowns are currently facing an inflexion point as remote and hybrid work patterns appear more permanent, and downtown districts cannot fully rely on business activity to maintain their economic significance and cultural vibrancy. Our analysis helps enumerate the multiple pathways which downtowns could take to recover, with an emphasis on data from Period 2 of our study (June 2021 to May 2022), when widespread availability of COVID-19 vaccinations allowed many people and businesses to resume some degree of normalcy in activities. In the downtown districts that have recovered to greater extents measured against pre-pandemic levels, traffic is not fueled by the traditional white-collar industries occupying Class A office space, but rather industries not traditionally associated with modern office towers, such as education, accommodation and tourism, entertainment, government services, or healthcare. These industries did not see widespread demand changes for in-person interactions throughout the pandemic. Factors which may continue to challenge the economic success and vitality of downtown districts include large sizes of surrounding metro areas and long commutes, high density, extreme winter or summer weather, and reliance on public transportation, where more innovative solutions need to be developed to counteract the observed behavioral trends.

While many scholars, planners, and investigative journalists advocate for the conversion of empty downtown real estate to housing (Sands, 2021; Hutson et al., 2022, Arroyo, 2022; Marino, 2022; McGahey, 2022), our analysis suggests that this alone may not revive downtown vibrancy to 2019 levels, even if it prevented them from reaching the lowest levels during the pandemic. In our analysis, the quantity, density, or characteristics of housing were not seen to influence recovery trajectories, and while this does not imply that housing had no effect on recovery trajectories, it suggests that restoring the vibrancy of downtowns to 2019 levels does not only rely on making introducing more downtown residents, but also land uses with greater attractive potential to bring large masses of people back downtown in volumes similar to pre-pandemic offices. It has also been documented that many office buildings have floor plans which are not easily convertible to residential development, and developers would incur higher costs converting existing offices to residences than building completely new residences. For these reasons, we suggest that in addition to housing, empty office real estate could be converted into alternative land use forms such as vertical universities, medical facilities such as individual specialist clinics, research facilities such as laboratories, hotels, or public administrative buildings, creating anchor tenants and institutions with a large visitation volume and sphere of influence. Food, entertainment, retail, and public spaces which do not specifically target office workers and instead attract a specific patronage on their own are also land uses that could increasingly be incorporated into the ground floors of office complexes to generate more foot traffic at the street level of the city. Large event venues such as stadiums are also seen to be key drivers of urban activity and public transportation ridership in the post-pandemic era, however these would rely on a consistent schedule of events to meaningfully influence business cycles downtown.

The negative associations of recovery with longer commute times and colder winter temperatures present an uphill battle which cities may face in trying to retain their pre-pandemic visitation bases. More interventions to address these difficulties, such as restoring service levels and improving public transit, improving connections between transportation facilities and buildings, and building more weather-resilient infrastructure, may be needed to entice a greater return of commuting or leisure travel. However, the fact that strong associations do not exist with COVID-19 lockdown restriction variables show that restrictions likely did not have a significant long-term impact on cities, and low levels of downtown foot traffic in some cities are the result of factors other than lockdown restrictions. This gives cities a ‘fresh slate’ and identifies concrete areas which are associated with greater downtown recovery in other cities.

The two most extreme cases of our analysis - San Francisco, CA being the slowest downtown to recover and Salt Lake City, UT being the fastest downtown to recover - provide contrasting examples of how the types and diversity of land uses affected foot traffic during our period of study. San Francisco’s downtown employment by industry is extremely specialized - with 31% of employment in Professional, Scientific, and Technical Services (the highest in the US and Canada), 9% of employment in information, and 12% of employment in finance and insurance (totalling 52% in these three industry categories). In contrast, Downtown Salt Lake City has 36% of the total employment in these industries, and instead has a higher percentage of jobs in retail trade (9%, second in the US only to Las Vegas) and accommodation (12%). Local reports also indicate that Salt Lake City is in the midst of a strategic transition to the healthcare tech and innovation industry (Wittenberg, 2020), another industry area positively associated with in-person work. Salt Lake City was ranked amongst the top in the nation for job growth during the COVID-19 pandemic (Berube & Byerly-Duke, 2022), and has benefited from substantial out-migration from the largest metro areas during the pandemic, along with increased domestic tourism to Utah’s national parks when international travel was limited (Leaver, 2021). Increased housing development in Salt Lake City, a trend which started before the pandemic, however, also likely contributed to the recovery (Russell, 2022). This dynamic is despite the relatively mild winter weather in San Francisco and the colder winter weather of Salt Lake City, which would have provided tailwinds and headwinds, respectively, to recovery.

New York City also provides an interesting contrast to other cities with large financial and professional industries, such as Chicago, IL; Boston, MA; Charlotte, NC; Toronto, ON; and Vancouver, BC. While all of these cities were grouped in the lowest two clusters of RQ and LQ rankings, New York bucked the trend towards the end of our analysis period, recovering to 78%

of pre-pandemic visits. New York's designated downtown areas (which, for consistency with other city definitions, included parts of Midtown Manhattan in addition to Downtown Manhattan), is characterized by high amounts of entertainment and hospitality offerings within the same areas as dense employment districts, along with housing in close proximity, which we believe helped maintain vibrancy amidst a shortfall in foot traffic from office workers. This shows that despite its professional and financial-heavy office mix, New York was able to ride the wave of recovery that lifted downtowns with similarly high accommodation and entertainment land uses, such as San Diego and Las Vegas.

The cases of Bakersfield and Fresno in California also illustrate a dynamic emerging from cities with less traditional downtowns, buoyed by substantive outmigration from larger metropolises nearby. While Bakersfield and Fresno's downtown RQs are high, their LQs are not; and since the entire cities in both cases saw more activity compared to pre-pandemic time periods, increased downtown activity is likely a function of an increased population in each city, instead of specific policies to initiate downtown recovery. These two cities also house a large share of healthcare and agricultural businesses instead of professional, financial, and information, which likely helped to keep their downtown areas resilient.

5.2 Research Contributions

In recent decades, the conventional wisdom about how to spur activity in downtowns has been to bring in diverse uses, including retail, entertainment, accommodation, and residential, to attract new visitors and residents. This led to a so-called "back-to-the-city" movement that made many downtowns into lively, 24-hour spaces. As the COVID-19 pandemic emptied out downtowns, however, it has become clear these new uses are not sufficient (albeit possibly necessary) to bring activity back. Instead, our research shows that the downtowns that have recovered benefit from a specific economic structure. They are not over-specialized in professional services and information, but instead supported the significant presence of diverse industries such as education, healthcare, entertainment, retail, and public administration, where the retention of in-person activity was more robust throughout the pandemic. This leads to concrete policy implications for downtowns trying to reinvent themselves post COVID-19.

This paper also offers several methodological contributions, including the processing of LBS data and recovery metrics as a new method to comparatively quantify downtown activity, as well as a framework to cluster these trajectories and correlate them with explanatory variables. By comparing outcomes across cities, we shift conversations about revitalizing downtowns from a local level to a national level, and create a standardized basis for cities to compare and contrast their recovery rates and explanatory variables. Through our framework, cities are able to jointly visualize and quantify what drives recovery in various cities, using a comparison which was previously not standardized from city to city. This framework can also be applied to analyze and compare other insights from time-series data and explanatory variables, or to analyze the differences in global recovery patterns or recovery patterns in different regions.

5.3 Limitations of Analysis

While this paper is focused on examining the earlier phases of recovery until mid 2022, future research can include the later phases of recovery such as late 2022 and 2023. However, ongoing research has revealed that there has yet to be a distinctive shift in downtown activity or hybrid work patterns for US and Canadian cities at the time of publication in mid-2023, and the dominant narrative is likely to shift from 'recovery' to 'change' as 2019 becomes a more distant past. International tourism, however, likely rebounded substantially after May 2022. Future research may be less interested in the recovery trajectories starting from 2020, and more interested in the increasingly independent actions which cities and downtowns are taking in the age where the habits of a hybrid workforce have stabilized, as well as the impact of specific post-pandemic initiatives such as new construction, increases in tourism, large institutional changes, or other relevant public initiatives.

Despite being a key achievement of our study, the definitions of downtown districts using zip codes also provided some limitations to our analysis and could be improved in future studies. While our zip code definitions were designed to provide compact, understandable, and nationally comparable definitions of downtown districts, there were some cases where zip codes did not align well with downtowns. In such examples like Phoenix, AZ; Honolulu, HI; and Cleveland, OH, the downtown definition included some areas outside the area commonly perceived as downtown. While the use of employment density was able to identify most downtown districts, in the future, if downtowns successfully diversify their land uses, they may also have to be defined with alternative metrics beyond employment such as with the inclusion of housing units, or with pure activity density from LBS data. Future research can also examine redefining downtowns more compactly with units such as with census tracts or block groups, and performing additional sensitivity analyses to understand the impact of using census tract-level data compared to zip code level data for LBS data analysis. Although downtown recovery rankings may change slightly with redefined boundaries, there is reason to believe explanatory factors and city trajectories will not change significantly.

Secondly, the use of cities to determine the denominator of downtown activity proportions in the LQ metric also limited our ability to capture the effects of changes in popularity of regional subcenters compared to the downtown, which often in a North American context are also located in neighboring cities within the same economically dependent metropolitan area. While influence of the core downtown area generally wanes with distance from the city itself, analysis of corresponding recovery rates in suburban subcenters may provide more insights into relative performance of the downtown area within each region more broadly, especially if some metropolitan areas have become more polycentric since COVID-19.

Thirdly, due to the time delay in publication of corresponding socio-economic and census data, this study used the latest available US census data from 2019, US LODES data from 2018, and Canadian Census and Business Patterns data from 2016. While many of these factors likely changed as a result of movement during the pandemic, they were not captured in the static variables used as explanatory variables. Future research should update this data to create a more consistent baseline, especially when full pandemic-era datasets are gradually released. In addition, future work should explore in more detail the role of residential development in generating foot traffic and revitalizing downtowns, as well as examine factors not included here, such as crime, real estate market inventory, and the effects of specific types of residential development and conversions in downtowns.

Lastly, while our study seeked out a wide range of explanatory variables to test the influence of several widely hypothesized determinants of downtown recovery, our results imply associations and not causations. We recognize some co-variability may exist between certain variables, which are not strictly independent of each other. For example, the associations of high employment density, high public transit usage, and colder winter weather are common definitions of many cities in the Northeast United States and Eastern Canada, however these variables are not strictly independent of each other. The highly correlated variables (over 0.8

correlation) in our analysis are listed in Appendix D, and they included unsurprising relationships such as income and education, population and housing density, density and public transit, or winter and spring weather. We also understand that despite the extremely wide range of data which we covered, our results still likely suffer from omitted variable bias. Future studies could research into articulating the causal relationship between some of these variables, especially as variability in public health and economic conditions stabilizes in 2023.

6. Conclusion

Over the period of March 2020 to May 2022, this study found that there were substantial variations in recovery of foot traffic in downtown areas across North America, as well as in the recovery relative to the rest of their respective cities. While the majority of downtowns have yet to witness a full recovery to pre-pandemic visits and visit proportions, some have come close, and a select few even exceeded 2019 levels. Lower-performing downtowns were often associated with high industry concentrations in professional services, information, finance and insurance, high employment and housing density, cold winter temperatures, longer commute times, and higher commute mode shares of public transportation. This is in contrast to higher-performing downtowns, which were often associated with higher industry concentrations in hospitality, entertainment, healthcare, education, and public administration, lower density, shorter commute times, and higher commute mode shares in automobiles. The research also suggests that COVID-19 restrictions and the amount of housing stock did not have a significant impact on long-term recovery trajectories, and that variation in activity recovery is due to other economic factors. These results enumerate possible interventions and challenges for the transformation of post-pandemic downtown districts, suggesting that they benefit from a specific economic structure maximizing face-to-face interaction and connectivity.

The combination of effects from the COVID-19 pandemic, changes in behaviors and attitudes toward working, living, and traveling as a result of the COVID-19 pandemic, and uncertainty over the emerging “new normal” in cities post-pandemic has created both a crisis and opportunity to reinvent downtowns. Despite these headwinds, our analysis also shows that it is possible to recover foot traffic to 100% of pre-pandemic levels, or even in some extraordinary cases, exceed 100%. Our analysis also suggests that the future of a vibrant downtown will continue to rely on bringing large masses of people together. However, people may not all visit downtown for work, but instead a mix of leisure, entertainment, healthcare, education, and tourism, in addition to some degree of hybrid and some degree of foot traffic from residential development. We recognize that a complete downtown reinvention is a complex effort that requires a vision, and needs to involve city governments, business associations, real estate owners, and communities - but the existing infrastructural, cultural, and economic significance of the downtown presents a scenario where cities have too much to lose if downtowns die. This analysis presents some clues and strategies to help revive and reinvent our great downtowns to emerge stronger than ever before into the post-pandemic structure of activity.

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Appendix A – US Downtown Definitions

City	State	Downtown Definition by Zip Codes	Employment Density (jobs/sqmi)
New York	NY	[10004, 10005, 10006, 10017, 10018, 10174, 10165, 10168, 10170, 10169, 10172, 10177, 10167, 10036, 10112, 10020, 10111, 10110, 10271]	580,255
Los Angeles	CA	[90013, 90014, 90017, 90071]	62,629
Chicago	IL	[60601, 60602, 60603, 60604, 60606]	394,267
Houston	TX	[77002, 77010]	37,536
Phoenix	AZ	[85003, 85004]	14,733
Philadelphia	PA	[19102, 19103, 19106, 19107, 19109]	71,349
San Antonio	TX	[78205]	14,653
San Diego	CA	[92101]	6,790
Dallas	TX	[75201, 75202, 75270]	35,244
San Jose	CA	[95113]	32,801
Austin	TX	[78701]	30,489
Jacksonville	FL	[32202]	12,431
Fort Worth	TX	[76102]	7,805
Columbus	OH	[43215]	12,052
Indianapolis	IN	[46204]	35,183
Charlotte	NC	[28202, 28282, 28244, 28280]	35,287
San Francisco	CA	[94104, 94105, 94111]	236,548
Seattle	WA	[98101, 98104, 98154, 98164, 98174]	132,284
Denver	CO	[80202, 80293]	47,022
Washington DC	DC	[20005, 20006, 20036]	81,072
Nashville	TN	[37201, 37219]	23,471

Oklahoma City	OK	[73102]	14,544
El Paso	TX	[79901]	4,071
Boston	MA	[02109, 02110]	186,334
Portland	OR	[97204]	63,238
Las Vegas	NV	[89101]	6,390
Detroit	MI	[48226, 48243]	31,658
Memphis	TN	[38103]	740
Louisville	KY	[40202]	12,940
Baltimore	MD	[21201, 21202]	31,955
Milwaukee	WI	[53202]	19,161
Albuquerque	NM	[87102]	3,486
Tucson	AZ	[85701]	6,172
Fresno	CA	[93721]	4,853
Sacramento	CA	[95814]	16,446
Kansas City	MO	[64105, 64106]	5,372
Atlanta	GA	[30303]	34,149
Omaha	NE	[68102]	4,347
Colorado Springs	CO	[80903]	4,370
Raleigh	NC	[27601]	6,457
Miami	FL	[33131]	16,088
Oakland	CA	[94612]	34,665
Minneapolis	MN	[55402, 55415]	109,040
Tulsa	OK	[74103, 74119]	11,047
Bakersfield	CA	[93301]	716
Wichita	KS	[67202]	7,870
Tampa	FL	[33602]	124,446
New Orleans	LA	[70112, 70130, 70139, 70163]	24,443
Cleveland	OH	[44114]	18,615
Honolulu	HI	[96813]	9,154
Cincinnati	OH	[45202]	12,177
Pittsburgh	PA	[15219, 15222]	22,715

Salt Lake City	UT	[84101, 84111]	13,588
St Louis	MO	[63101]	29,275
Orlando	FL	[32801]	15,089

Downtowns in Canada defined by Statistics Canada.

Appendix B - Recovery Quotients and Location Quotients

(uploaded to Mendeley)

Leong, Michael (2023), "Downtown Recovery and Polycentricity Quotients for US and Canadian Downtowns", Mendeley Data, V1, doi: 10.17632/fkjzfkhbd5.1

Appendix C - Explanatory Variables

(uploaded to Mendeley)

Leong, Michael (2023), “Explanatory Variables for US and Canadian Downtowns”, Mendeley Data, V1, doi: 10.17632/b27vjdvg35.1

Appendix D – Highly Correlated Explanatory Variables

Variable 1	Variable 2	Correlation Value
Total Population Downtown	Housing Units Downtown	0.994054429*
Population Density Downtown	Housing Density Downtown	0.975293318*
Fall Average Temperature	Spring Average Temperature	0.964376426*
Median Rent Downtown	Median Household Income Downtown	0.947203758*
Fall Average Temperature	Winter Average Temperature	0.918997434*
Spring Average Temperature	Winter Average Temperature	0.918720881*
% Commute Mode Share Public Transit	% Commute Mode Share by Walking	0.862124828
% Commute Mode Share Public Transit	Housing Density (City)	0.849493013
% Mobile Home & Others (City)	% Downtown Jobs Real Estate	0.831602696
% Commute Mode Share Public Transit	Average Commute Time	0.828772348
% Multi-Family Homes (City)	Housing Density (City)	0.817278091
% Mobile Home & Others (Downtown)	% Downtown Jobs in Other Industries	0.81546276
% Multi-Family Homes (City)	% Renter-Occupied Units (City)	0.813465437
Fall Average Temperature	Summer Average Temperature	0.812787314
% Multi-Family Homes (City)	% Commute Mode Share Public Transit	0.806068098
Spring Average Temperature	Summer Average Temperature	0.805318639
% Jobs in Retail Trade	% Mobile Home & Others (Downtown)	0.801847168
% Commute Mode Share Auto	Average Commute Time	-0.807427037
% Commute Mode Share Auto	% Commute Mode Share Walking	-0.899730588
% Commute Mode Share Auto	% Commute Mode Share Public Transit	-0.976316594*
% Multi-Family Homes (Downtown)	% Single-Family Homes (Downtown)	-0.996746793*

*Where 2 variables had a correlation magnitude above 0.9, one was excluded from the Random Forest Classifier analysis.