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Pandemic polycentricity? Mobility and migration patterns across New York over the course of the Covid-19 pandemic

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The expectation of a mass movement out of cities due to the rise of remote work associated with the Covid-19 pandemic, is counter to longstanding theories of the benefits of agglomeration economies. It suggests centrifugal shifts of economic activity which could boost neighbourhood economies at the expense of the downtown core. Using mobile phone data from SafeGraph, we track migration and daily mobility patterns throughout the New York metropolitan area between July 2019 and June 2021. We find that diverse suburban centres and exurban areas have bounced back more quickly than the dense specialized commercial districts in and around Manhattan.

Keywords: Covid-19, polycentricity, mobility patterns, migration patterns, suburban centres, commercial districts

I. Introduction

The rise of remote work during the Covid-19 pandemic has threatened the economic viability of downtowns. As managerial and professional workers cancel their commutes, commercial districts, whether in the downtown core or suburban sub-centres, have become ghost towns. Not only are office buildings deserted, but the surrounding ecosystem of business support services, restaurants, retail, and hotels also see little activity. This raises the question: Is the downtown doomed?

This article explores the question of which areas are most likely to bounce back as the pandemic eases. A storied debate in economic geography suggests the answer, with the preponderance of evidence pointing to urban diversity as spurring more job growth (Jacobs, 1969; Glaeser, 2000; Dissart, 2003). But the availability of near real-time data on activity patterns, via the geospatial tracking of mobile phone and social media activity, as well as the shifting patterns over the course of the pandemic, provides a new lens on the debate. Instead of evaluating sectoral composition and growth outcomes in the aggregate for cities and regions, we can see how the specific configuration of commercial districts, in terms of land use, sectoral composition, and density, leads to more resilient outcomes.

The specific focus of this research is the impact of changing daily mobility patterns as well as broader migration patterns over the course of the Covid-19 pandemic on downtowns and neighbourhood commercial districts within the New York metropolitan area. This study adopts the tri-state definition of the New York metropolitan area which incorporates 31 counties across New York, New Jersey, Connecticut.

The first case of Covid-19 in the New York metropolitan area was reported on 1 March 2020 and it quickly became the epicentre of the first wave of Covid-19 in the US (Brynjolfsson *et al.*, 2020), with case numbers peaking in April 2020. State-wide stay-at-home orders were put in place in New York and Connecticut on 20 March 2020, and New Jersey followed on 21 March. As of September 2020, over 600,000 Covid-19 cases and 47,500 deaths had been reported across the New York metropolitan area (Regional Plan Association, 2020), representing 24% of all Covid-19 cases across the US, at the time. According to the Regional Plan Association (2020), 1.89 million jobs were lost across the region between February and May 2020.

II. Context

Cities as the focus of economic activity

The role of cities as dense centres of economic activity where valuable knowledge is exchanged has increased in the context of the post-industrial society. Bell (1976) forecast the shift towards a post-industrial knowledge economy over 50 years ago. According to Castells (1989), economic growth within the context of the information society is driven by the accumulation of knowledge and processing of information. Global cities, such as New York, have been observed as the production sites for knowledge industries due to the concentration of firms, talent and expertise across specialized fields (Sassen, 2001).

The agglomeration of knowledge industries in cities is driven by access to dense labour markets, specialized service providers, consumer markets and knowledge spillovers (Marshall, 1920; Jacobs, 1969; Glaeser *et al.*, 1992; Storper and Venables, 2004). Within a region, the most accessible locations, which is most commonly the core of the city, will attract dense clusters of employment (Scott, 1982). Knowledge-based industries are labour intensive and thus access to highly skilled labour both regionally and locally is critical.

The importance of face-to-face contact

Cities have remained dense centres of economic activity, despite advancements in information technology. Over the course of the Covid-19 pandemic, the continued role of cities as economic engines has been debated, particularly in the context of the widespread shift to remote work for certain occupations and industries. At the heart of this debate is whether face-to-face contact remains critical to productivity. Knowledge and information flow more easily between workers in dense cities, than over long distances (Dahl and Pedersen, 2004). Contemporary theories consider that tacit knowledge is unable to be codified and requires face-to-face contact for knowledge to be exchanged (Gertler, 2003; Storper and Venables, 2004; Huber, 2012).

Scholars have emphasized the role of the social and built environment in facilitating knowledge spillovers. Culture, including established conventions and institutional arrangements, shared values and language, is critical to the fluid exchange of knowledge (Gertler, 2003; Bathelt, Malmberg and Maskell, 2004). Storper and Venables (2004) coined the term buzz to describe the social environment where knowledge spillovers occur. Cities with buzz are characterized as having a diversity of industries such as creative and cultural, finance and business, science and technology, as well as power and influence (Storper and Venables, 2004). A diversity of economic activities and a mix of land uses is considered an important component of cities in which knowledge spillovers are facilitated. At a neighbourhood scale, the importance of a mix of land uses has been reflected in the Brookings Institution innovation district model which promotes a mix of office, retail and residential development (Katz and Wagner, 2014), drawing on the work of Jacobs (1961, 1969) who emphasized the importance of a diversity land uses to city economies.

While more 'basic' forms of information could potentially be transmitted through digital technologies, existing research suggests that tacit knowledge cannot. However, whether or not face-to-face interaction requires permanent co-location within cities, or can be facilitated by semi-regular meetings in cities, is a matter of ongoing debate (Bathelt and Turi, 2011). Given the potential widespread shift to hybrid forms of working (combination of remote and in-person) across knowledge-based industries associated with the Covid-19 pandemic, it is expected that the productivity of remote work will continue to be debated (Masayuki, 2020; Felstead and Reuschke, 2021; Mehdi and Morissette, 2021).

Suburbanization of the downtown

A nuance to the 'classic' agglomeration in urban cores is provided by the emergence of suburban downtowns. During the 1970s and 1980s, business parks were developed at the edges of cities containing concentrations of knowledge-based industries and managerial locations that were previously concentrated within the central business district. Improved information technology and expansion of the informational sector did allow for the spatial separation of head office and back office functions within metropolitan regions (Freestone and Murphy, 1998). Within the US, suburban downtowns emerged along major arterial roads and highways, accessible to the managerial workforce who have high rates of car ownership (Noyelle and Stanback, 1984).

The suburbanization of employment has led to varying spatial patterns in different urban contexts leading to debate on whether these patterns represent a 'scatteration' or rather an intensification of polycentricity (Hartshorn and Muller, 1989; Pfister, Freestone and Murphy, 2000; Shearmur *et al.*, 2007). Nonetheless, suburban centres are more typically associated with specialization, in comparison to the diverse CBDs in the urban core with which they are associated. These centres can also serve as retail and leisure destinations (Hartshorn and Muller, 1989) for workers who are increasingly working partially from home, even before the onset of the pandemic (Felstead and Henseke, 2017). Given this trend, the role of suburban centres may have become more pronounced during the Covid-19 pandemic. As the geography of daytime consumption has shifted to residential locations, suburban centres located in closer proximity to places of residence of knowledge workers could see an increase in activity.

Transformation of downtowns

According to Loh and Kim (2021), contemporary downtowns can be defined by the dominance of office floorspace. Across the 30 largest US metropolitan areas, offices comprise, on average, 71% of real estate. New York is considered to have a more diverse downtown (defined as Manhattan below 59th Street) compared to other major cities in the US, with office floorspace representing 48% of downtown real estate (Badger and Bui, 2021). The development of housing through both new construction and the conversion of vacant office space has been promoted in Manhattan since the 1990s as part of various land use revitalization strategies implemented by the city government (Beauregard, 2005). A diverse downtown is considered to be more resilient against economic shocks. There is an expectation that the introduction of housing, in particular, will support the local economy by providing workers for local businesses and customers to support retail and other services, which promotes a functional interdependence between office, residential, retail, entertainment (Beauregard, 2005).

The rise in remote work associated with Covid-19, has implications for downtown commercial districts, particularly the retail and other services which were not only forced to adapt their operations to comply with Covid-19 restrictions, but also experienced a severe reduction in day-to-day foot traffic which was primarily driven by office workers pre-Covid. This raises the question as to what will happen to the local economies of these commercial downtowns if remote workers do not return, or only return part-time to the office. Will downtowns need to become more reliant on residential development to survive?

The impact of Covid-19 on mobility, migration and remote work

The mobility of people and goods, both within and between cities, remains fundamental to the growth of the metropolitan economy. A shift towards full time remote work, or even part time remote work, will inevitably reduce the amount of activity within previously office dominant downtowns. Prior to the pandemic, an increase in remote work had been observed and an associated increase in long-distance commutes, reflecting somewhat of a rural renaissance (Andersson, Lavesson and Niedomysl, 2018). Some cities are even introducing cash incentives to attract remote workers particularly in tech industries; Tulsa Remote offers remote workers $10,000 to move to Tulsa, Oklahoma.[1] A shift towards remote work, whether temporary or

[1] Refer to https://tulsaremote.com/

permanent, has the potential to influence both intra-metropolitan local commutes and inter-regional commutes.

Over the course of the Covid-19 pandemic, the media has reported a 'mass migration' out of cities, particularly a flight of knowledge and tech workers out of central New York and San Francisco and towards the suburbs or other cities (Haag, 2020; Hughes, 2020; Zaveri, 2020; Bowles, 2021). A range of studies have considered the impact of Covid-19 on daily mobility within cities. A study into the shift towards remote work during the early stages of the Covid-19 pandemic (February to May 2020), found that US states with a higher share of employment in knowledge-based industries and occupations were more likely to shift towards remote work, and thus fewer people were laid off from their jobs (Brynjolfsson *et al.*, 2020). According to the study, the shift towards remote work largely occurred by early April. De Fraja et al. (2021) have measured 'Zoomshock', the impact of the shift to remote work on neighbourhoods across the UK, highlighting the potential impact on locally consumed services. Utilizing historic commute patterns and income data, De Fraja et al. (2021) identify positive Zoomshocks where there is a high proportion of workers working from home, typically in residential neighborhoods, and negative Zoomshocks where there is a loss of workers, typically in downtown areas. Our study builds on the work of De Fraja et al. (2021), by using real time mobile phone data (rather than historic commute patterns) to measure shifts in labour mobility during the pandemic.

An analysis of correlation between shifts in daily mobility during Covid-19 and income has been undertaken by a number of scholars utilising mobile phone data to provide an understanding of patterns of movement at various stages during the pandemic. A study looking at Greater Houston in Texas found that wealthier people were more likely to reduce their daily mobility during Covid (Iio *et al.*, 2021), reflecting the nature of their employment in industries which were able to shift easily to remote work. Similarly findings were reported in a study conducted across the US (Weill *et al.*, 2020). Analysis of mobility in New York found that residents of Manhattan and wealthier parts of Brooklyn were more likely to leave the city after the crisis compared to residents of Queens, Brooklyn and the Bronx, reflecting disparities in income (Coven and Gupta, 2020).

These previous studies have primarily focused on residential mobility during the early stages of the pandemic. Few studies have examined fluctuations in these shifts in mobility and broader migration patterns across the course of the pandemic so far, and its impacts specifically on downtown areas and the economy.

III. Research design

Research questions and hypotheses

We propose two research questions to be examined through this analysis:

1. *How have mobility and migration patterns changed throughout the New York metropolitan area during the pandemic?*

   Hypothesis: We anticipate that there was a substantial out-migration of workers from downtown New York to suburban and exurban areas during the first six months of the pandemic. There is likely to be a gradual movement back to downtown areas over the recovery period, we expect that some of this in-migration will take longer to return.

2. *How do mobility and migration patterns vary across downtown and suburban commercial districts within the New York metropolitan area?*

   Hypothesis: We anticipate that changes in mobility, including the share of out-migration that is more long term, depends on the sectoral composition of centers, with more specialized commercial districts (with higher concentrations of office-based sectors) experiencing more long term out-migration compared to locations with a greater diversity of businesses and housing.

Time periods

This research traces mobility and migration over the course of two years, from July 2019 to June 2021. The last six months of 2019 is identified as the Pre-Covid period, and was utilized as a baseline for the analysis. The other 18 months of data was grouped into three Covid periods; Covid Period 1

(January 2020 - June 2020) which includes the first wave of Covid-19 experienced in New York, Covid Period 2 (July 2020 - December 2020) which incorporates the start of the second wave of Covid-19 in New York and Covid Period 3 (January 2021 - June 2021) which includes the vaccine roll-out and potential start of recovery.

Data and method

Neighborhood patterns data from **SafeGraph** (2021)[2] was utilized to identify real-time activity patterns based on device counts each month during the two-year study period. Raw device counts, which are available at the Census Block Group (CBG)[3] geography, represent the number of unique devices that stopped in the CBG for at least one minute, capturing both visitors and residents. Between July 2019 and June 2021, 979 million device counts were captured within the New York metropolitan area. The device count per month ranged from a high of 68.3 million in September 2019 to a low of 19.2 million in April 2020. Device counts were available for 1,230 of the 1,251 zip codes within the New York metropolitan area. In this paper, the device counts are utilized as a proxy for economic activity. The SafeGraph data contains a number of sinks, specific locations that have a disproportionate number of inaccurate counts caused by, for example,

[2] a data company that aggregates anonymized location data from numerous mobile phone applications

[3] Census blocks are the smallest statistical geography for which the US Census collects and releases Census data. A Census Block Group is the second smallest geography and comprises a combination of census blocks.

mobile devices being out of range of GPS satellites and relying on less precise location sensors. Aggregating the data to ZIP Code Tabulation Areas (ZCTA) for the purpose of the analysis helped to smooth some of the sinks, however the sinks cannot be entirely removed from the data.

Three data sources have been utilized to validate the SafeGraph data; United States Postal Service (USPS) Change-of-Address (COA) requests, geotagged Tweets, and Zillow Home Value Index (ZHVI). USPS Change-Of-Address (COA) data was utilized to determine patterns of migration throughout the study period. Although address changes may reflect only temporary moves, in aggregate they provide a picture of movement throughout the region. Outflows were identified based on the Total From ZIP (total COA requests that originated from the zip code) and inflows were identified based on Total To ZIP (total COA requests that are destined to the zip code). A net inflow was calculated by subtracting the outflows from the inflows. A positive result indicates that the zip code had a net in-migration during the relevant time period and a negative result indicates a net out-migration. The analysis focuses on residential COA requests (business COA requests were excluded from the analysis).

Twitter data was accessed using the Streaming API collecting all tweets that have spatial location information associated with the tweet (i.e. geotagged tweets) from July 2019 to June 2021 (Poorthuis and Zook, 2017). During this period a total of 6.7 million tweets were sent from the tri-state area by 221,000 users. To account for both sporadic users as well as power users (most likely algorithmic bots), we filter out the top 0.1% of most active users (who have more than 2,000 tweets during the study period) as well as users with fewer than 10 tweets. We also remove any tweets whose location is likely based on a coarser spatial resolution (e.g. centroid of a larger region) rather than a precise location derived from GPS positioning by removing coordinate pairs that are clearly rounded or used in an unusually high number of tweets. This yields a final filtered dataset of 2.7 million tweets sent by 43,000 users.

Zillow Home Value Index (ZHVI), which is a smoothed, seasonally adjusted measure of the typical home value across a given region and housing type, was utilized to assess shifts in housing prices across the two-year study period.

The USPS (COA), Twitter and ZHVI data validated the patterns observed across the SafeGraph data. The SafeGraph data was the most comprehensive across the study area for the two-year timeframe and thus was utilized in the modelling.

A location quotient (LQ) was calculated comparing device counts for each zip code during Covid Period 1 to the Pre-Covid period, accounting for overall activity levels in the New York metropolitan area. The LQ provides an indication of which areas experienced an increase in activity based on device counts during the pandemic compared to the pre-covid period. The formula for the LQ calculation is provided below.

$$LQ = \frac{(Device\ count\ in\ ZCTA\ Covid\ Period\ 1 / \ Total\ device\ count\ for\ NY\ Covid\ Period\ 1)}{(Device\ count\ in\ ZCTA\ Pre-Covid\ /\ Total\ device\ count\ for\ NY\ Pre-Covid)}$$

An LQ was also calculated comparing Covid Period 3 against Covid Period 1 to identify which zip codes experienced an increase in activity, and thus have 'recovered' the fastest, if at all. The population, employment and land use characteristics of six office precincts have been analysed to uncover the characteristics that differentiate these locations and their pandemic recovery. Office precincts were selected based on the absolute number and proportion of total jobs in office sectors[4].

To determine the potential explanatory variables for changes in mobility patterns during Covid-19, a multivariate regression analysis was conducted using the SafeGraph data.

The regression equation for the subsequent analysis is:

$$\begin{aligned} DEVICE\ COUNT\ = \ & \beta_1 * DEVICE\ COUNT\ PREV\ PERIOD + \beta_2 * POP\ DENSITY + \beta_3 \\ & * EMP\ DENSITY + \beta_4 * INDUSTRIAL\ + \beta_5 * OFFICE\ + \beta_6 * RETAIL\ + \ \beta_7 \\ & * LOGISTICS\ + \ \beta_7 * ACCOMM\ + \ \beta_8 * INCOME\ + \ \beta_9 * RENT + \ \beta_{10} * AGE \\ & + \ \beta_{11} * ENTROPY \end{aligned}$$

The independent variables (summarised in Table 1) include the

[4] Office includes North American Industry Classification System (NAICS) sectors 51-55

device counts during the previous period as a baseline or control variable. We include two density-based variables based on population and employment as we hypothesize that dense employment and population centres might exhibit slower recovery from COVID. We also include a number of variables that capture the percentage of businesses in specific sectors of the economy (i.e. industrial, office, retail/food, logistics, and accommodation). We expect areas with certain specialisations (office, retail/food, accommodation) to make a slower recovery than others (industrial, logistics). On a similar note, we also add an entropy index of land use diversity (for further details on the entropy index, see explanation below). Finally, we add three indicators that reflect the demographic characteristics of each area: median rent, median income and median age. Here, we expect areas with lower rent, income or age to experience a lower impact on total device count. The spatial unit for the regression analysis is always the ZCTA.

We conduct the regression using Generalized Linear Model (GLM) with a Gaussian distribution (i.e. linear regression). For robustness, we also include model estimates based on a quasi-Poisson and Negative Binomial specification in our results, which are theoretically well-suited for modelling the device count. As the model residuals exhibited spatial autocorrelation (Moran's I: 0.24, p: <0.001), we also include a spatial lag model. Since the model fit is consistently better for the Gaussian model and the linear regression can be extended more easily to a spatial lag model, we focus our discussion on this specification.

<Table 1 near here>

An entropy index for land use mix was calculated to provide an indication of the diversity of land uses within each zip code and precinct. Data from the 2019 American Community Survey (ACS) and 2019 Zip Code Business Patterns were utilized as these data sources are consistently available at the zip code level across the New York metropolitan area. The calculation incorporates the number of housing units and number of businesses by broad industry category (Accommodation, Arts and Recreation, Education and health, Industrial, Logistics, Office, Retail and Food and Other)[5]. The entropy index formula applied to each zip code is:

$$Entropy\ index = -\sum_{j=1}^{k} p_j \log(p_j)$$

where:
k = number of land use categories
p_j = proportion of businesses/dwellings of jth land use category in ZCTA (=nj/n)
n_j = businesses/dwellings of jth land use category in ZCTA
n = total number of businesses and dwellings in ZCTA

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[5] Accommodation includes NAICS 721, Arts and Recreation includes NAICS 71, Education and health includes NAICS 61 and 62, Industrial includes 23, 31-33 and 42, Logistics includes NAICS 48-49, Office includes NAICS 51-55, Retail and Food includes NAICS 44-45 and 722, and Other includes all other NAICS categories not previously captured.

Each zip code was assigned a number between 0 and 1, with 0 representing a low diversity of land uses and 1 representing a high diversity of land uses. Although this entropy index is not covering all aspects of land use diversity, we use it here as a proxy indicator to assess how land use diversity has mediated the impact of the pandemic for different areas.

III. Mobility and migration analysis

Population and employment densities

To provide a baseline, Figure 1 shows the population and employment densities in the New York metropolitan area at the zip code level. On a regional scale, both population and employment density follow similar patterns with much higher densities in and around Manhattan compared to the rest of the region. The ring around the New York City urban core, with a population density of between 30 and 100 people per hectare, can be considered mostly suburban, with the remaining part of the tri-state area being rural or ex-urban[6]. Employment density follows a largely similar pattern with corridors of density extending outwards from Manhattan east onto Long Island, west into New Jersey and north-east into Connecticut.

<Figure 1 near here>

[6] According to Spencer et. al (2015), less than 4 people per hectare is generally considered non-urban (or ex-urban)

Migration patterns

To ascertain changes in the population density during the pandemic, we utilize USPS COA data. During the last six months of 2019, this data shows a net outflow of residents from New York City and surrounds with a net inflow of residents into parts of Connecticut and New Jersey (see Figure 2). During the first six months of 2020, Covid Period 1, there is a clear ‘flight’ to the suburbs represented by a net inflow of residents to the majority of suburban areas, that is, outside downtown New York and New Jersey. This trend continues during Covid Period 2 and Covid Period 3, however to a lesser extent. During Covid Period 1 and Covid Period 2, there is also a much larger number of change of address requests relating to moving out of Manhattan. Comparing the net change in inflow between the Pre-Covid period and Covid Period 1, alongside Covid Period 1 and Covid Period 3, we can see that the net outflow of people from Manhattan increases during the first Covid period and decreases during the 'recovery period' (refer to Figure 3).

The observed patterns are consistent with previous analysis of USPS change of address data published in *The New York Times* (Kolko, Badger and Bui, 2021). The analysis, which was conducted across the US, identified that migration patterns during 2020 were generally in line with previous pre-pandemic trends. However, San Francisco and New York experienced a more pronounced increase in net out-migration driven by an increase in out-migration and a decrease in-migration (Kolko, Badger and Bui, 2021). Part of the decrease in in-migration can be attributed to restrictions on international migration into the US during the pandemic, in addition to changes in migration patterns domestically.

<Figure 2 near here>

<Figure 3 near here>

Mobility patterns

Figure 4 shows the overall distribution of device count and density. This pattern has a strong correlation with the Twitter data (Pearson's correlation coefficient: 0.62) but is based on a much higher number of observations (median device count per zip code in Covid Period 1 is ~100,000). This also allows for a more in-depth evaluation of the evolution of activity during the different post-covid periods. In Figure 5(C and D), the device count in the first period is compared with the device count in the third period, giving an indication of the potential recovery of different areas. While the island of Manhattan is still experiencing a decrease in relative activity overall, an increase can be observed in residential suburbia as well as several suburban centres such as Great Neck, NY; Newark, NJ; and the corridor from Union City to Englewood in New Jersey. These patterns support commentary that small businesses in NY suburbs have observed an increase in the amount that local residents are spending on local businesses (Bayrakdarian and Armstrong, 2021).

<*Figure 4 near here*>

<*Figure 5 near here*>

Here we analyse six downtown and suburban office precincts; Downtown Brooklyn Downtown Manhattan, Great Neck, Lakewood, Melville and Parsippany. Downtown Brooklyn and Downtown Manhattan have performed worse on all indicators measuring activity during and after the pandemic (Table 2): outflows (measured by changes of address) have been higher, home values have dropped, and device counts have dropped dramatically over the course of the pandemic. In contrast, Great Neck and Lakewood, in particular, as well as Melville and Parsippany have seen median home value increases and device counts have been relatively stable or slightly above pre-pandemic levels and this has continued into the recovery phase (Covid Period 3).

Population and employment densities are both high in Downtown Brooklyn and Downtown Manhattan, employment densities are much higher in Downtown Manhattan compared to Downtown Brooklyn (Table 3). Many of Downtown Brooklyn core activities – including the Barclays Center, the Brooklyn Academy of Music, and MetroTech (which houses financial, tech, and educational establishments) – closed temporarily during the pandemic, and have struggled to return. Similarly, many companies located in Wall Street/ Financial District of Downtown Manhattan have continued to operate remotely. In contrast, the other office precincts contain more essential businesses (e.g. industrial and logistics), some of which have seen a surge of activity. The resilience of commercial districts in the downtown and suburban areas is closely related to its economic structure.

The entropy index of land use diversity varies across the six precincts with Downtown Manhattan with the highest at 0.88, followed by Melville with 0.80 and Great Neck with 0.78. Melville and Great Neck have higher LQs for Covid Period 3 (compared to Covid Period 1), demonstrating stronger evidence of recovery compared to the other office precincts which were analysed. The link between the recovery and entropy index may only be present within the suburban office precincts, and this will be further explored through the regression modelling.

<Table 2 near here>

<Table 3 near here>

Regression analysis

First wave of Covid

To understand what might explain shifts in the mobility patterns described above, we conduct a regression analysis with several potential covariates. Table 4 summarizes this analysis, with the SafeGraph device count for Covid Period 1 as the dependent variable and Device count in the Pre Covid period as an independent variable.

The coefficients illustrate that areas with high employment density indeed see a lower device count in the first Covid period. The same pattern is visible for median age and median income: higher median age and income are associated with lower device counts. In contrast, higher concentrations of businesses in the logistics sector are associated with higher device counts in Covid Period 1, while the reverse is true for concentrations of accommodation businesses. The observed patterns are consistent with an increase in the proportion of people working from home or being furloughed or unemployed during the first stages of Covid-19. The lack of activity in the downtown commercial districts is reflected in these patterns as well, whereas certain sectors of the economy that are less amenable to work-from-home arrangements (such as logistics) show a relative increase in activity.

<Table 4 near here>

Recovery during pandemic: Covid 1 - Covid 3

To investigate the recovery during the pandemic, Table 5 presents an analysis of the device counts for Covid Period 3, with the count in Covid Period 1 as an independent, control variable. Here we see some differences emerging from the initial response to the pandemic. Higher employment density is still negatively associated with higher device counts in Covid Period 3, but the same can now also be said for population density. This suggests that less densely populated zip codes in the metropolitan area see a faster recovery of activity than the more dense, urban core. Other variables in the model generally exhibit high p-values, although the quasi-Poisson and negative binomial specifications do hint at the impact of the diversity of the underlying economy in each area. Apart from the impact of the logistics and accommodation sectors that we also saw in Covid period 1, in the negative binomial model, we see a positive coefficient for the entropy index that suggests that the areas which potentially 'recovered' faster (in terms of an increase in activity represented by device counts) are those which are more diverse. Therefore, areas which are identified as recovering fast, based on detected activity, are diverse suburban centres, rather than the densely populated and specialized commercial district of Manhattan. This raises questions as to what characteristics separate both the suburban and downtown areas which have recovered compared to those that have not. The analysis of the commercial precincts above suggests that recovery for the suburban areas may be associated with a higher proportion of more essential businesses (e.g. industrial and logistics) and a higher diversity of land uses (reflected in a higher entropy index). However, there is limited evidence so far of downtown areas which have recovered to draw any specific conclusions about the characteristics of downtown areas which have recovered compared to those that have not.

<Table 5 near here>

IV. Conclusion

The first of the two research questions proposed in this paper asked, how have mobility and migration patterns changed throughout the New York metropolitan area during the pandemic? Following the mass migration to the suburbs at the start of the Covid-19 pandemic, there has been a gradual movement back to downtown Manhattan since June 2020, evidenced by an increase in device counts and shifts in change of address requests (consistent with our first hypothesis). Our second research question asked, how do mobility and migration patterns vary across downtown and suburban commercial districts within the New York metropolitan area?

The areas which have bounced back more quickly are the suburban centres, rather than the dense specialized commercial centre of Manhattan (consistent with our second hypothesis that more specialized commercial districts would experience more long term out-migration compared to locations with a greater diversity of businesses and housing). The activity patterns reflect the current office market context. Within Manhattan, office vacancy rates have increased since the end of 2020, with 18.7% of all office space available for lease, as of July 2021, which is more than double the Pre-Covid vacancy rate (Haag, 2021). These vacancy rates do not account for the large amount of office space which is leased by companies which continue to work remotely. In mid-2021, several companies announced that they would be delaying their return to the office to late 2021 or early 2022 due to concerns regarding the spread of the Covid-19 delta variant (and subsequently the omicron variant which has caused further delays). Vacancy rates could continue to increase as office leases expire and companies make decisions about the long-term location of their operations and office space requirements. These decisions will greatly impact the viability of downtown commercial districts, particularly retail, business services and accommodation, which have been supported by the working population.

If remote work continues (even under a hybrid model), increased residential may be sustain commercial downtowns in the longer term, which raises several questions. How much residential is required? What will attract the highly paid knowledge workers to downtowns if they no longer need to be physically present in the office on a day-to-day basis? Florida et al. (2021, p. 2) contend that Covid-19 will not "derail the long-standing process of urbanisation and the economic role of cities". It is anticipated that the vibrancy of cities and opportunity for face-to-face contact (local buzz) will still be attractors for people. However, we expect that workers are likely to make trade-offs, particularly in terms of housing affordability, and this may promote suburban lifestyles over downtowns due to the shift in commuting patterns and potential to access more space at a lower cost, compared to say in Manhattan, for example. The shifts may differ depending on the demographics of the knowledge workers and how much they value proximity. Despite this, there remains questions as to how cities adapt and the role of both urban, suburban, and exurban centres.

The methodology adopted within this study can be applied to additional cities to further validate the approach, and to assess the extent to which these mobility and migration patterns are consistent across different contexts. Real-time mobile phone data provides the opportunity to further analyse these patterns, and the economic viability of downtowns, as the Covid-19 recovery continues. There are several different ways to think about economic recovery. Physical activity (measured by mobility data) is just a narrow slice which may not even be strongly correlated with economic recovery. Similarly, population and employment density and entropy measures are crude, and a finer scale might tell a different story. The Covid-19 pandemic is not yet over and with time we will understand more about longer term shifts in mobility and migration and how this reshapes the role of cities and downtown commercial districts, as well as the most compelling cases for recovery.

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Table 1: Dependent and independent variables

Variable	Data source	Count	Mean	Std Dev
Dependent variable				
Device counts Covid Period 1 OR	SafeGraph, 2021	1,230	114,937	132,146
Device counts Covid Period 3	SafeGraph, 2021	1,230	101,765	113,153
Independent variables				
Device counts Pre-Covid period OR	SafeGraph, 2021	1,230	174,355	225,478
Device counts Covid Period 1	SafeGraph, 2021	1,230	114,937	132,146
Population density (people per ha)	ACS, 2019	1,172	36	75
Employment density (jobs per ha)	ZCBP, 2019	1,172	29	178
Percent of businesses in industrial sectors	ZCBP, 2019	1,146	22%	14%
Percent of businesses in office sectors	ZCBP, 2019	1,146	21%	11%
Percent of businesses in retail & food sectors	ZCBP, 2019	1,146	22%	11%
Percent of businesses in logistics sectors	ZCBP, 2019	1,146	3%	4%
Percent of businesses in accommodation sectors	ZCBP, 2019	1,146	1%	6%
Median income	ACS, 2019	1,143	$98,033	$40,270
Median rent	ACS, 2019	1,068	$1,578	$469
Median age	ACS, 2019	1,171	43	7
Entropy index	Calculated	1,172	0.33	0.19

Table 2. Case Study Pandemic Outcome Indicators

Precinct	Brooklyn - Downtown	Manhattan - Downtown	Great Neck	Lakewood	Melville	Parsippany
Zip codes	11201	10004,10005, 10007,10013, 10038	11021	08701	11747	07054
Cluster	Downtown - declining	Downtown - declining	Suburban - recovering	Suburban - recovering	Suburban - recovering	Suburban - stable
Device Count Pre-Covid	1,063,741	3,440,982	194,479	348,856	318,183	361,327
Device Count Covid 1	531,772	1,607,231	129,199	256,609	200,609	242,732
Device Count Covid 2	405,485	1,404,447	126,388	251,123	221,201	222,339
Device Count Covid 3	358,679	950,022	123,152	253,456	199,314	220,584
LQ Covid 1 vs Pre-Covid	0.76	0.71	1.01	1.12	0.96	1.02
LQ Covid 3 vs Covid 1	0.76	0.67	1.08	1.12	1.12	1.03
USPS LQ outflow Covid 1	1.62	1.72	0.80	0.84	0.76	0.73
USPS LQ outflow Covid 3	1.30	1.31	0.79	0.84	0.70	0.84
% Median Home Value Change Covid 3 vs Covid 2*	-5.97	-2.02	5.63	13.12	6.72	6.25

*Median values are included for the largest zip code (based on area) for Manhattan - Downtown (10013)

Table 3. Case Study Population and Employment Characteristics

Area	Brooklyn - Downtown	Manhattan - Downtown	Great Neck	Lakewood	Melville	Parsippany
Zip codes	11201	10004,10005, 10007,10013, 10038	11021	08701	11747	07054
Total businesses	3,294	11,255	1,963	3,206	2,023	1,749
% office	38.0%	46.9%	43.5%	28.2%	52.4%	45.3%
% industrial	6.6%	7.0%	13.8%	18.9%	12.9%	14.0%
% logistics	0.5%	0.7%	1.1%	2.1%	4.0%	2.2%
% retail/ food	23.3%	19.9%	10.3%	18.9%	8.2%	14.9%
% accommodation	0.2%	0.4%	0.0%	0.3%	0.2%	0.7%
% health/ edu	13.1%	8.4%	17.1%	15.9%	8.7%	10.2%
% arts/ recreation	4.7%	3.4%	1.1%	0.8%	1.9%	0.9%
% other	13.5%	13.3%	13.2%	14.9%	11.8%	11.8%
Employment (jobs)	53,005	275,667	17,070	45,197	50,172	60,093
Employment density (jobs per ha)	145	657	28	7	15	17
Population	63,378	71,554	18,245	102,466	18,288	29,144
Population density (people per ha)	174	171	30	16	5	8
Housing units	31,445	37,962	8,377	26,035	8,007	11,564
Housing density (dwellings per ha)	86	91	14	4	2	3
Job to housing ratio	1.7	7.3	2.0	1.7	6.3	5.2
Entropy index of land use diversity	0.47	0.88	0.78	0.53	0.80	0.59
Median age*	34.9	37.9	46.0	19.3	50.1	40.7
Median income*	$129,248	$113,191	$102,596	$52,148	$126,607	$99,251
Median rent*	$2,523	$1,692	$1,859	$1,427	$2,351	$1,377

*Median values are included for the largest zip code (based on area) for Manhattan - Downtown (10013)

Table 4: Results of OLS (Gaussian), Quasi-Poisson and Negative Binomial models: Covid 1

Variable	OLS (Gaussian)		Quasi-Poisson		Negative Binomial		Spatial Lag	
(Intercept)	72,419.765 (11,994.811)	***	12.160 (0.237)	***	11.598 (0.236)	***	69,673.97 (12,867.04)	***
Device count Pre Covid	0.581 (0.005)	***	2.16e-6 (5.93e-08)	***	4.23e-06 (1.04e-07)	***	0.575 (0.006)	***
Population density	8.055 (17.340)		3.54e-4 (2.32e-4)		4.82e-04 (3.41e-04)		-12.335 (16.110)	
Employment density	-149.382 (8.264)	***	-1.63e-3 (1.30e-4)	***	-1.03e-3 (1.62e-4)	***	-149.268 (8.089)	***
% industrial	-25,842.717 (14,064.442)		-0.977 (0.289)	***	-1.113 (0.277)	***	-27,336.468 (14228.801)	*
% office	11,938.617 (16,941.444)		0.284 (0.343)		0.573 (0.334)		10583.684 (15739.465)	
% retail/food	-11,879.539 (15,212.767)		-0.307 (0.320)		-0.185 (0.300)		-14,680.271 (14741.864)	
% logistics	72,813.946 (30,450.942)	*	1.610 (0.447)	***	3.595 (0.600)	***	60,539.330 (31910.381)	
% accommodation	-134,962.187 (52,749.726)	*	-7.073 (0.447)	**	-5.576 (1.040)	***	-124,590.35 (27,070.716)	
Median income	-0.118 (0.039)	**	-4.27e-6 (7.65e-7)	***	1.39e-6 (7.59e-7)		-0.111 (0.037)	**
Median rent	-0.086 (3.062)		2.65e-4 (5.85e-5)	***	6.42e-5 (6.04e-5)		-0.967 (2.031)	
Median age	-828.784 (172.798)	***	-0.021 (0.000)	***	-0.026 (0.003)	***	-781.250 (172.122)	***
Entropy index	-6,771.896 (7,731.051)		0.153 (0.128)		0.455 (0.152)	**	-6759.397 (7916.592)	
Spatial Lag Covid 1 Device Count							0.0394 (0.014)	**
AIC	24,569		NA		25,473		24,562	

* p<0.05, ** p<0.01, *** p<0.001

Table 5: Results of OLS (Gaussian), Quasi-Poisson and Negative Binomial models: Covid 3

Variable	OLS (Gaussian)	Quasi-Poisson	Negative Binomial	Spatial Lag
(Intercept)	-19,026.984 (11,794.727)	11.239 *** (0.207)	10.605 *** (0.221)	-20945.721 (5907.245)
Device count Covid 1	0.875 *** (0.008)	4.44e-6 *** (8.36e-8)	7.13e-6 *** (1.59e-7)	0.865 *** (0.009)
Population density	-69.600 *** (16.881)	-2.33e-4 (2.09e-4)	-6.13e-4 (3.13e-4)	-85.948 *** (15.969)
Employment density	-96.056 *** (7.909)	-1.125e-3 *** (1.17e-4)	-8.897e-4 *** (1.48e-4)	-94.168 *** (7.664)
% industrial	7,034.217 (13,745.741)	-0.500 * (0.252)	-0.74 ** (0.258)	5691.752 (9844.508)
% office	10,645.654 (16,540.979)	0.423 (0.300)	0.577 (0.311)	9564.619 (12950.021)
% retail/food	17,569.701 (14,849.323)	-0.104 (0.278)	0.136 (0.279)	15068.189 (11227.564)
% logistics	-11,756.070 (29,777.066)	1.062 ** (0.409)	2.355 *** (0.559)	-22632.296 (26819.225)
% accommodation	-8,819.748 (51,528.149)	-3.811 * (1.600)	-3.689 *** (0.968)	435.891 (26,421.146)
Median income	0.060 (0.038)	-1.63e-6 * (6.4e-7)	1.03e-8 (7.08e-7)	0.063 (0.032)
Median rent	0.203 (2.990)	1.74e-4 *** (5.00e-5)	7.76e-5 (5.61e-5)	-0.577 (1.495)
Median age	245.462 (169.549)	-0.012 *** (0.003)	-0.014 *** (0.003)	275.045 (133.226)
Entropy index	5,961.330 (7,525.634)	0.170 (0.114)	0.553 *** (0.141)	5715.635 (6483.349)
Spatial Lag Covid 3 Device Count				0.043 ** (0.015)
AIC	24,569	NA	25,136	24,511

* p<0.05, ** p<0.01, *** p<0.001

Figure 1

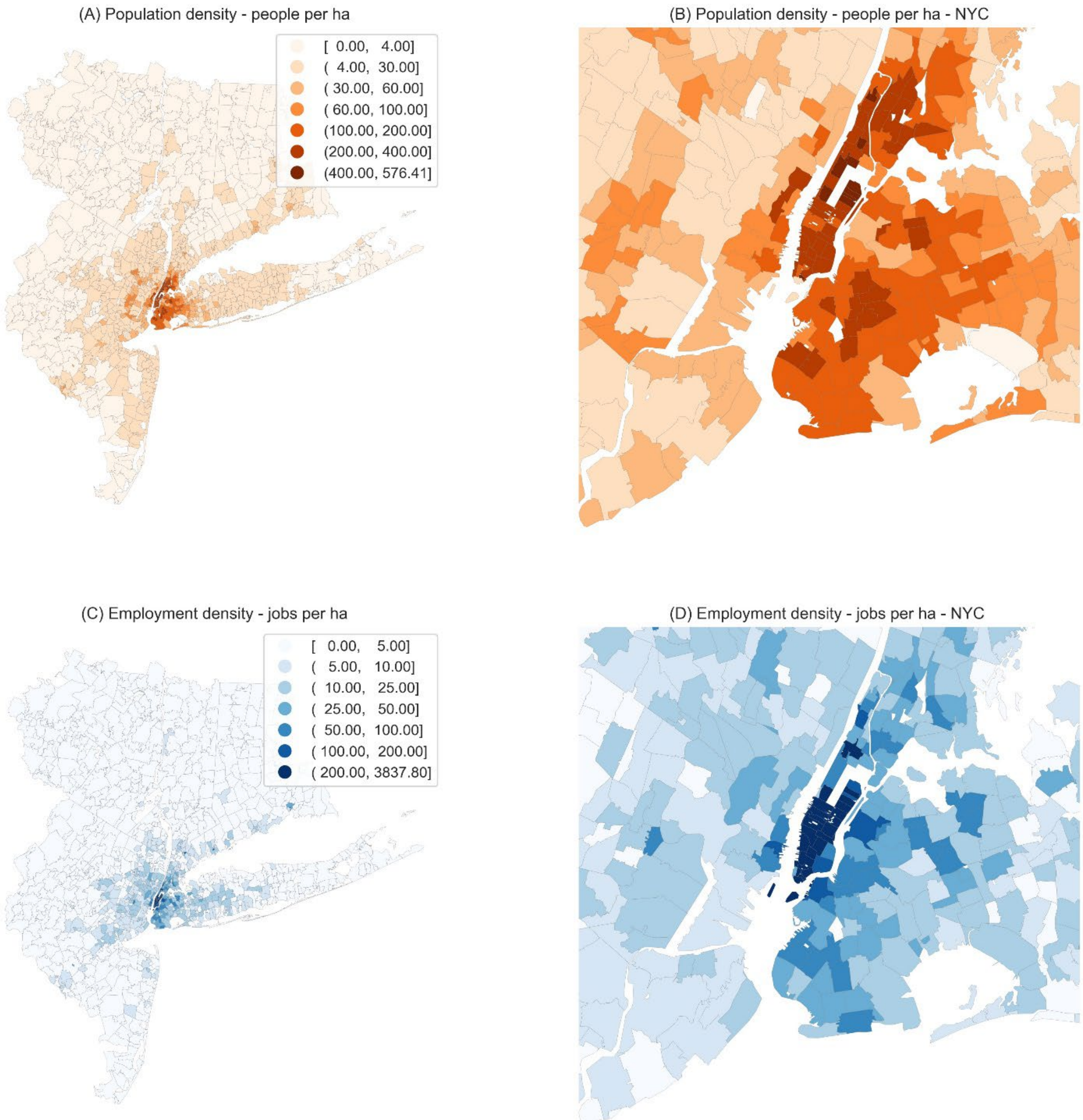

(A) Population density - people per ha
[0.00, 4.00]
(4.00, 30.00]
(30.00, 60.00]
(60.00, 100.00]
(100.00, 200.00]
(200.00, 400.00]
(400.00, 576.41]
(B) Population density - people per ha - NYC
(C) Employment density - jobs per ha
[0.00, 5.00]
(5.00, 10.00]
(10.00, 25.00]
(25.00, 50.00]
(50.00, 100.00]
(100.00, 200.00]
(200.00, 3837.80]
(D) Employment density - jobs per ha - NYC

Figure 2

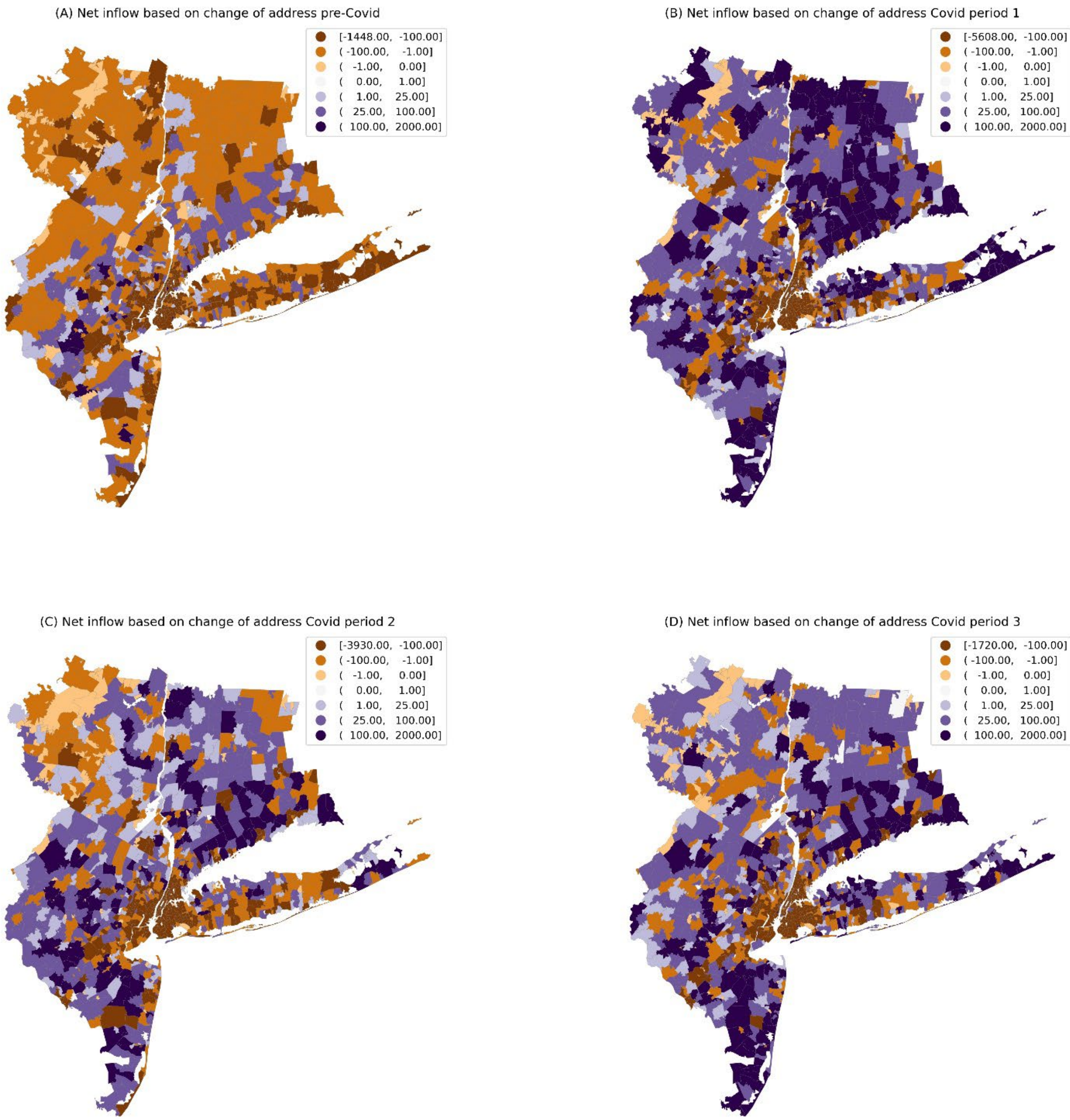

(A) Net inflow based on change of address pre-Covid
[-1448.00, -100.00]
(-100.00, -1.00]
(-1.00, 0.00]
(0.00, 1.00]
(1.00, 25.00]
(25.00, 100.00]
(100.00, 2000.00]
(B) Net inflow based on change of address Covid period 1
[-5608.00, -100.00]
(-100.00, -1.00]
(-1.00, 0.00]
(0.00, 1.00]
(1.00, 25.00]
(25.00, 100.00]
(100.00, 2000.00]
(C) Net inflow based on change of address Covid period 2
[-3930.00, -100.00]
(-100.00, -1.00]
(-1.00, 0.00]
(0.00, 1.00]
(1.00, 25.00]
(25.00, 100.00]
(100.00, 2000.00]
(D) Net inflow based on change of address Covid period 3
[-1720.00, -100.00]
(-100.00, -1.00]
(-1.00, 0.00]
(0.00, 1.00]
(1.00, 25.00]
(25.00, 100.00]
(100.00, 2000.00]

Figure 3

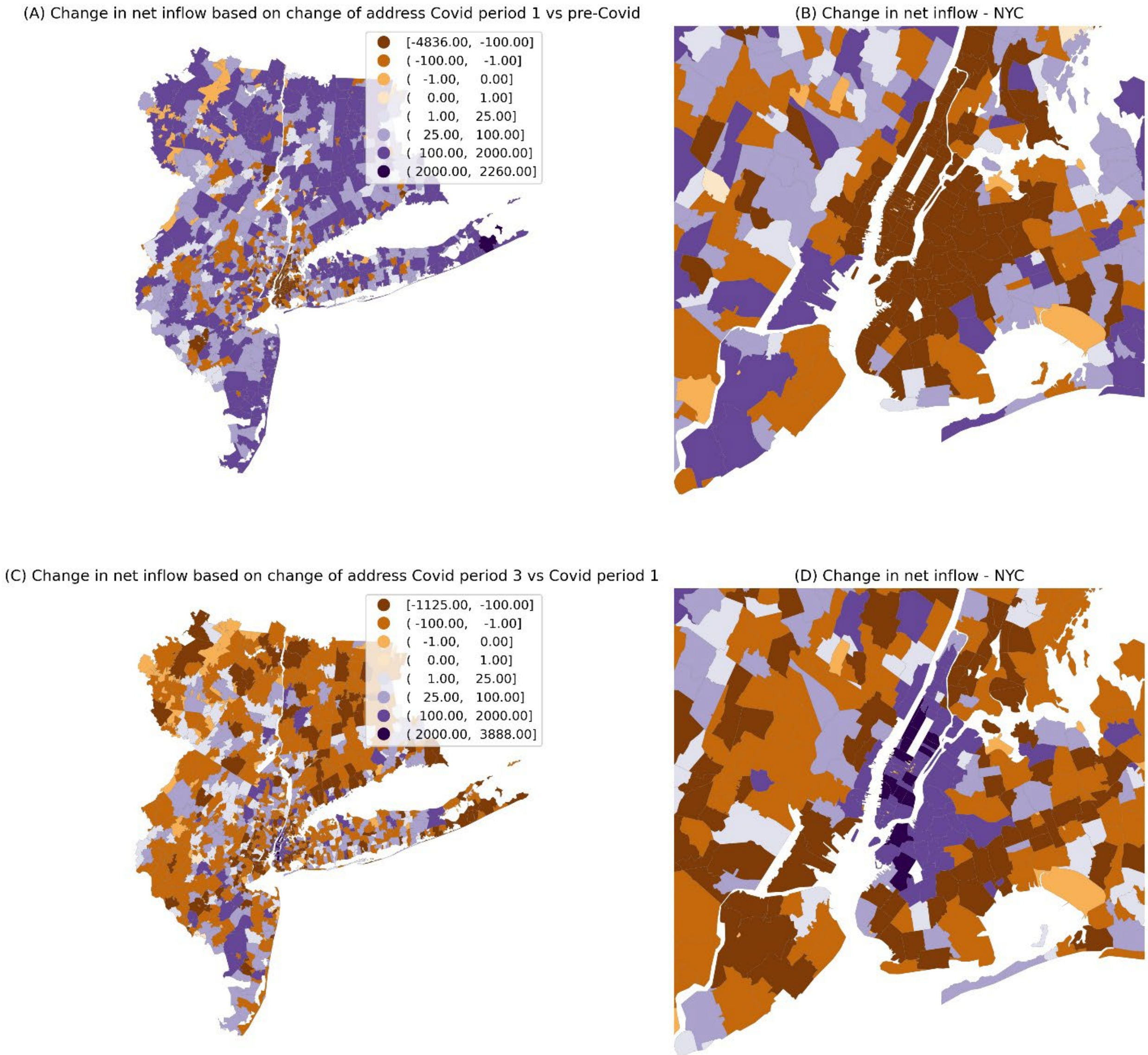

(A) Change in net inflow based on change of address Covid period 1 vs pre-Covid
[-4836.00, -100.00]
(-100.00, -1.00]
(-1.00, 0.00]
(0.00, 1.00]
(1.00, 25.00]
(25.00, 100.00]
(100.00, 2000.00]
(2000.00, 2260.00]
(B) Change in net inflow - NYC
(C) Change in net inflow based on change of address Covid period 3 vs Covid period 1
[-1125.00, -100.00]
(-100.00, -1.00]
(-1.00, 0.00]
(0.00, 1.00]
(1.00, 25.00]
(25.00, 100.00]
(100.00, 2000.00]
(2000.00, 3888.00]
(D) Change in net inflow - NYC

Figure 4

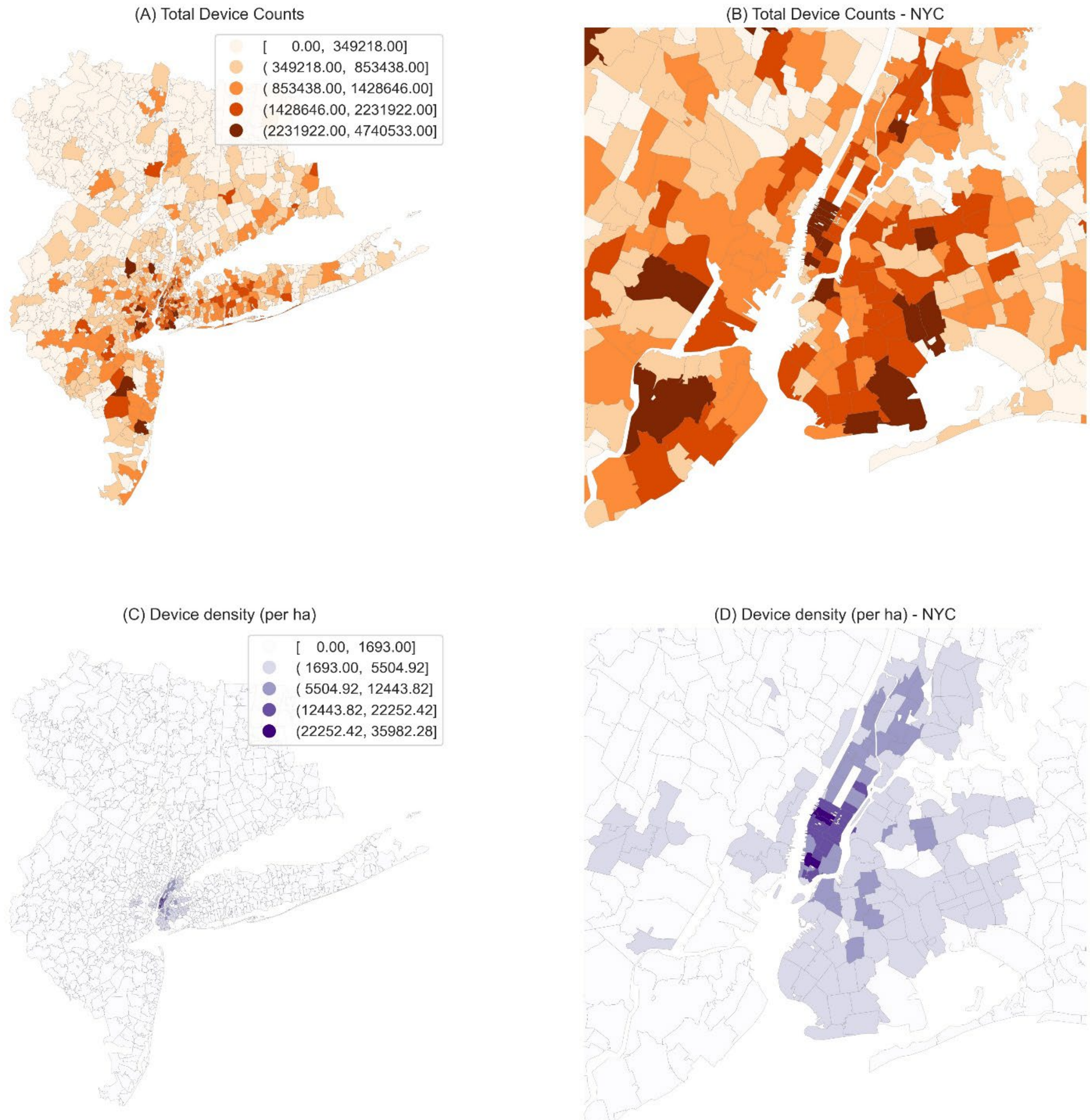
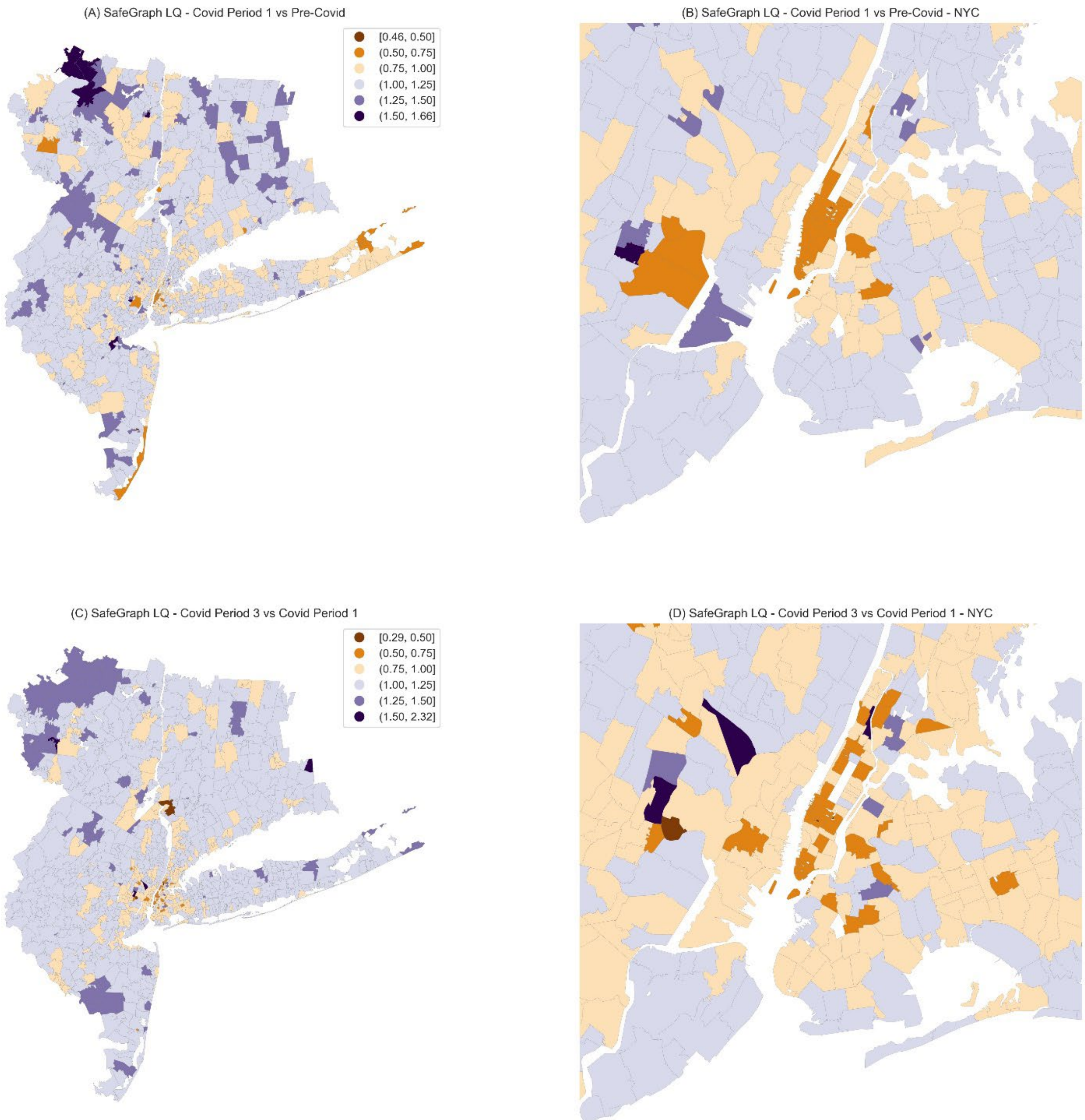

(A) Total Device Counts
[0.00, 349218.00]
(349218.00, 853438.00]
(853438.00, 1428646.00]
(1428646.00, 2231922.00]
(2231922.00, 4740533.00]
(B) Total Device Counts - NYC
(C) Device density (per ha)
[0.00, 1693.00]
(1693.00, 5504.92]
(5504.92, 12443.82]
(12443.82, 22252.42]
(22252.42, 35982.28]
(D) Device density (per ha) - NYC

Figure 5


(A) SafeGraph LQ - Covid Period 1 vs Pre-Covid
[0.46, 0.50]
(0.50, 0.75]
(0.75, 1.00]
(1.00, 1.25]
(1.25, 1.50]
(1.50, 1.66]
(B) SafeGraph LQ - Covid Period 1 vs Pre-Covid - NYC
(C) SafeGraph LQ - Covid Period 3 vs Covid Period 1
[0.29, 0.50]
(0.50, 0.75]
(0.75, 1.00]
(1.00, 1.25]
(1.25, 1.50]
(1.50, 2.32]
(D) SafeGraph LQ - Covid Period 3 vs Covid Period 1 - NYC