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Peaked too soon? Analyzing the shifting patterns of PM peak period travel in Southern California

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A R T I C L E I N F O

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A B S T R A C T

Daily vehicle travel collapsed with the onset of the COVID-19 pandemic in early 2020 but largely bounced back by late 2021. The pandemic caused dramatic changes to working, schooling, shopping, and leisure activities, and to the travel associated with them. Several of these changes have so far proven enduring. So, while overall vehicle travel had largely returned to pre-pandemic levels by late 2021, the underlying drivers of this travel have likely changed.

To examine one element of this issue, we analyzed whether patterns of daily trip-making shifted temporally between the fall of 2019 and 2021 in the Greater Los Angeles megaregion. We used location-based service data to examine vehicle trip originations for each hour of the day at the U.S. census block group level in October 2019 and October 2021. We observed notable shifts in the timing of post-pandemic PM peak travel, so we examined changes in the ratio of mid-week trips originating in the early afternoon (12–3:59 PM) and the late afternoon/early evening (4–7:59 PM).

We found a clear shift in the temporal distribution of PM trip-making, with relatively more late PM peak period trip-making prior to the pandemic, and more early PM peak trip-making in 2021. The peak afternoon/evening trip-making hour shifted from 5–5:59 PM to 3–3:59 PM. We also found that afternoon/evening trip-making in each year is largely explained by three workplace-area/school-area factors: (1) the number of schoolchildren in a block group (earlier); (2) block groups with large shares of potential remote workers (earlier), and (3) block groups with large shares of low-wage jobs and workers of color (later, except for Black workers in 2021). We found the earlier shift in PM peak travel *between* pre- and late-pandemic periods to be explained most by (1) higher shares of potential remote workers and (2) higher shares of low-wage jobs and workers of color. These findings suggest that the rise of working from home has likely led to a shift in PM peak travel earlier in the afternoon when school chauffeuring trips are most common. This is especially true for low-income workers and workers of color.

1. Introduction

Commercial and, especially, personal travel collapsed early in 2020 with the onset of the COVID-19 pandemic. Popular news accounts in April of that year marveled at the near-empty streets and dramatically reduced emissions resulting from widespread safer-at-home orders, temporary business closures, and related efforts to slow the spread of the virus (Arieff, 2020; Chicago Tribune, 2020). Since then, overall vehicle and active (walking and biking) travel rebounded quickly, reaching levels similar to those before the pandemic (Bureau of Transportation Statistics, 2023).

But while overall travel and trip-making have largely bounced back, top-line figures obscure both subtle and significant shifts in travel that are persisting post-pandemic. For example, public transit use collapsed even more dramatically than other surface transportation modes in the spring of 2020; its subsequent rebound in the U.S. has been both halting

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and partial. So while U.S. vehicle travel had largely recovered by the end of 2020, public transit ridership reached only 59 percent of pre-pandemic levels by July 2022 (American Public Transportation Association, 2022). In contrast to public transit, rates of walking and cycling increased during the pandemic in many U.S. cities (Doubleday et al., 2021), and travelers anticipated walking and bicycling more as the pandemic receded (Chauhan et al., 2021).

While shifts among travel modes coming out of the pandemic have caught the attention of researchers, shifts in the timing of travel have garnered less attention. Yet such shifts are consequential for transportation systems and likely explained substantially by post-pandemic changes in patterns of working, schooling, shopping, and leisure activities. So, the durability of these post-pandemic changes may tell us much about the future of travel. For example, more flexible work schedules in the pandemic appear to have changed commuting behavior and eased peak-hour, peak-direction traffic congestion (Muller, 2022). Yet little recent research examines the timing and spatial patterns of peak hour travel, particularly with respect to the external factors that might be related to such change, including labor, education, and socio-demographics.

Researchers and policymakers concerned about traffic congestion and vehicle emissions have long hoped that remote work—or "telecommuting"—would reduce the economic and environmental costs of driving (Speroni & Taylor, 2023). But studies of the travel behaviors of workers who shift to working from home full- or part-time find that homeworkers make *more* trips—completing household errands, chauffeuring kids to and from school, and so on—and drive at least as many miles as before (Zhu & Mason, 2014). Further, the growing popularity of e-commerce—which expanded during the pandemic—may also influence long-term travel trends (Le et al., 2022) by replacing personal trips (e.g., to the store) with commercial ones (e.g., when something ordered online is delivered). The longer-term effects of the pandemic on location choices, trip-making, and travel by various modes are far from settled as of writing in 2023. However, in the post-pandemic era, higher levels of working from home, shopping online, and streaming for entertainment appear increasingly likely to endure.

To address gaps in research on shifting temporal patterns wrought by the COVID-19 pandemic, we examine changes in daily patterns of peak travel prior to and during the pandemic in Greater Los Angeles, the second largest U.S. metropolitan area with a population greater than the 15 smallest U.S. states combined (US Census Bureau, 2019). In this analysis, we use location-based service (LBS) data from StreetLight Data. We examine how travel patterns have changed from just before the pandemic (fall 2019) to the early post-pandemic period (fall 2021), about a year after motor vehicle travel had largely returned to pre-pandemic levels. We do this by comparing midweek hourly vehicle trip data from the last two weeks of October 2019 (seven months before the first stay-at-home orders) to the last two weeks of October 2021. After briefly considering changes in AM peak period travel, we focus on the ratio between vehicle trips originating in the early afternoon (12–3:59 PM) and late afternoon/early evening (4–7:59 PM). This is where we observe the most substantial shifts in daily vehicle travel.

2. Background trends and previous research

Virtually all travel dropped sharply in the spring of 2020 in response to public health orders and business closures (Xiong et al., 2020). However, it quickly bounced back over the second half of 2020 (Bureau of Transportation Statistics, 2023). Researchers have examined many dimensions of these travel changes, some of which proved fleeting and others enduring. Among these travel changes, shifts in the *timing* of travel have received less attention.

Transportation policymakers, planners, and engineers often emphasize peak travel periods because they help determine the scale and capacity of transportation infrastructure. Travel peaks have temporal (hour of the day, day of the week, season of the year) and spatial (location and direction) dimensions. The frequency and intensity of weekday morning and afternoon travel peaks, in particular, have implications for both traffic congestion and public transit use (Papacostas & Prevedouros, 1993). Peaking (in both time and direction) is especially important for metropolitan road and transit networks, whose concentrated use leads to both traffic congestion and crowding on buses and trains. These impose significant time and emissions costs on travelers and society at large (Downs, 2005).

So, when are the weekday peak periods? Fig. 1 displays U.S. trends in the temporal distribution of trips (by all modes) over more than three decades. Because the time periods reported in the figure are both asymmetric in length (varying from 3 to 5 h) and do not conform to more traditional measures of peak periods (e.g. 9:00 AM to 12:59 PM covers the tail of the morning peak, the late morning, and the beginning of the midday period), the familiar diurnal weekday morning and afternoon/early evening peak periods are less obvious, though still in evidence. Traditional explanations for these two weekday peak periods center on journeys to and from work, typically inbound commutes to job centers in the morning, followed by a 9-to-5 shift at the office or factory, and then outbound trips home in the late afternoon or early evening. However, commuting accounts for a relatively modest share of overall personal travel. In 2017, for example, 19 percent of trips were journeys to and from work, while 41 percent served household errands (Federal Highway Administration, 2018a). These errand trips often occur on weekdays after work or school and can be "chained" onto commute trips home. Meanwhile, most intra-metropolitan commercial travel occurs during business hours (Dablanc & Rodrigue, 2017). As a result, more overall travel occurs in the early afternoon (from 1 PM to 4 PM) than during the morning peak (from 6 AM to 9 AM).

In terms of trends over time, Fig. 1 shows that the pre-pandemic timing of personal travel remained relatively consistent over the 34 years between 1983 and 2017. However, since 1990 the share of all person-trips made in the morning through early afternoon (9 AM to 3:59 PM) has generally increased, while the share of such trips made in the evening and overnight (7 PM to 5:59 AM) has generally decreased (Federal Highway Administration, 2018a). These longer run trends in the timing of daily travel, combined with the recent shock of the pandemic on work, school, shopping, and leisure patterns, motivate the analysis in this paper.

While the pandemic has changed many things, one of the most notable—and to date persistent—has been the rise of working from home (WFH). Over the past few decades, WFH rates had climbed slowly, to only about five percent of the U.S. workforce just before the pandemic (U.S. Census Bureau, 2022). However, the onset of the COVID-19 pandemic and its early restrictions on all manner of public gatherings, including at worksites, caused WFH rates to jump by a factor of ten, almost overnight. By 2021, rates of commuting rose, as most worksites and schools had reopened once vaccines became widely available. By December 2021, for example, 99 percent of teachers and students in the U.S. had returned to in-person instruction (U.S. Department of Education, 2022).

Yet WFH, at least part-time, appears here to stay for many workers. As of 2022, roughly 30 percent of all U.S. workdays were WFH, a six-fold increase over pre-pandemic levels (Barrero et al., 2021). This persistence partly reflects continued demand from workers to retain the option to telecommute and the flexibility it affords them (Barrero et al., 2021). Further, WFH in the U.S. has traditionally been and remains more prevalent among wealthier (Matson et al., 2021), Asian, and white workers (Asfaw, 2022; Bureau of Labor Statistics, 2021), as well as workers living in urban rather than rural areas (Paul, 2022).

In terms of *travel behavior,* the degree to which continued demand for WFH options influences travel patterns arises from a simple question: does WFH substitute for or complement trip-making? If it is a substitute, we should expect to see overall declines in travel as WFH replaces commuting. But if it is a complement, former commute trips may be replaced with others (such as dining out or shopping). This could result

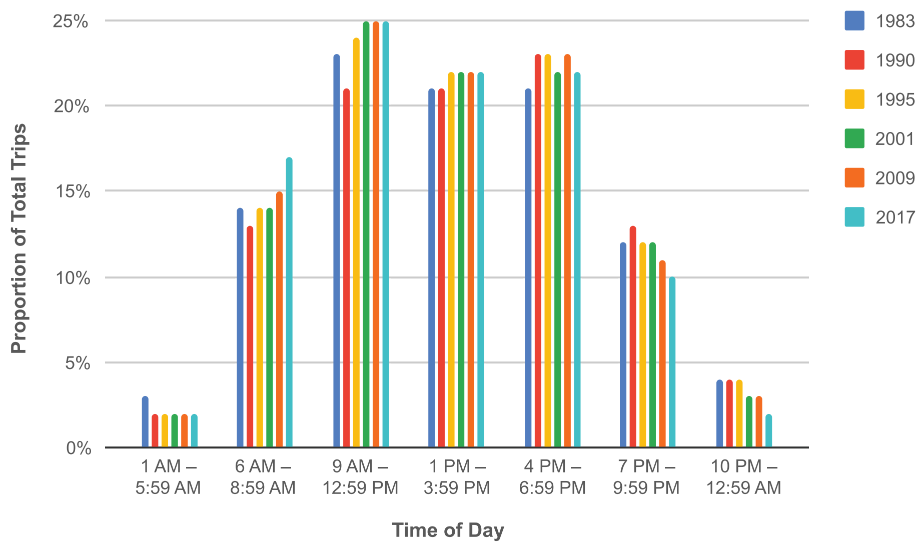

Fig. 1. Trends in temporal distribution of trips in the U.S., 1983 to 2017 (Federal Highway Administration, 2018b). Note: The duration of the seven time periods varies by length and are thus not directly comparable in terms of hourly rates of trip-making.

in as much — or even more — vehicle travel than before, as workers have greater time and flexibility to travel during less congested times (Zhu, 2012).

Newer studies diverge from older ones on this question. Over three decades ago, Mokhtarian (1991) reviewed the (then available) research and found that teleworkers[5] commuted less, did not take more non-commute trips, and tended to restrict their travel closer to home. More recently, however, Andreev et al. (2010) conducted a meta-analysis of the now much larger number of telework studies. They found strong evidence that new trips tended to replace foregone commute trips, at least in the short-term. Indeed, no study using data from the past 25 years has suggested that remote work—apart from pandemic restrictions—was associated with less daily travel (Speroni & Taylor, 2023). In fact, several recent U.S. studies (Chakrabarti, 2018; Zhu, 2012; Zhu et al., 2018) found that trip-making may actually increase alongside WFH, though increased travel often occurs outside of traditional peak periods and peak routes. For example, Su et al. (2021) examined data from California telecommuters in 2017 and found that commuters tended to travel more during peak periods than did telecommuters. Similarly, Stiles and Smart (2021) analyzed national data to examine changes in travel patterns among teleworkers. They also found that full-day teleworkers were more likely to forgo peak-hour travel. Further, while full-day teleworking appears to reduce demand for travel during both the morning and evening peaks, the effect is more pronounced in the morning (Stiles & Smart, 2021).

Finally, two recent studies examining the temporal distribution of travel have suggested that teleworking may substantially affect peak travel. Bhagat-Conway and Zhang (2022) found evidence of the spreading of the peak in California during the pandemic. They conclude that the rise of WFH was the likely cause. Teleworkers may take more non-work-related trips during the off-peak hours, or they may start their workday at home and commute to work later during traditional off-peak hours (Stiles & Smart, 2021). Both of these may lead to the spreading of the peak. Gao and Levinson (2022) examined the morning peak travel patterns in six California cities. They found that the morning peak indeed has changed from a single to a bifurcated peak, and attribute this to both increased telework and changes in the composition of commuters.

3. Data

3.1. StreetLight data

This study relies on passively collected data from StreetLight Data's Insight platform on vehicle trip originations for the last two weeks of October 2019 and October 2021. StreetLight uses data from location-based services (LBS), global positioning system (GPS) trips, and vehicle counts from fixed traffic recorders to estimate trip-making using machine-learning models. Data from StreetLight include trips by various modes and can be disaggregated spatially and temporally across a variety of strata. StreetLight does not report data for any combined spatial and temporal analysis frame when the sample of LBS and GPS data points fall below a certain threshold, which was the case for a small share (<0.01 %) of our block groups (usually rural) and hourly time periods (usually in the very early morning hours).

In this research, we analyze how trip counts have changed temporally (primarily) and spatially (secondarily) relative to similar time periods prior to the pandemic. To do this we examine average daily trip originations for each hour during the midweek (Tuesday through Thursday) at the census block group level for the Southern California Association of Governments (SCAG) megaregion. Hourly data are the most granular temporal disaggregation that StreetLight allows while still maintaining significance thresholds.

At about 100,000 square kilometers (SCAG, 2021), the SCAG region is about the size of South Korea (CIA, n.d.), and its 19 million residents (SCAG, 2021) are greater than the populations of Cambodia, Chad, Ecuador, or the Netherlands (CIA, 2023). The region, which includes the Los Angeles metropolitan area and adjacent mountain and desert areas, is comprised of Los Angeles and 190 other cities in Southern California (not including the San Diego and Santa Barbara metropolitan areas) (SCAG, 2021). So, while we are analyzing a single region in this analysis, the Greater Los Angeles/SCAG megaregion is an enormous one. By

[5] We use the terms work from home, WFH, remote work, telecommuting, and telework largely interchangeably in this article, as they are often treated as such in the literature. Technically speaking, however, they all mean slightly different things. *Working from home* (*WFH*) refers to any work for pay conducted at home that (1) may or may not be away from a typical worksite (for example, the home may be the typical worksite for a self-employed worker), (2) may or may not entail the use of information and communications technologies (ICT), but (3) is not conducted at a third location (such as a coffee shop); *Remote work* refers to work for pay conducted away from the typical worksite (at home or at a third location) which may or may not entail ICT use; and *Telecommuting* and *Telework* refer to any work for pay conducted away from the typical worksite (at home or a third location) that entails the use of ICT.

almost any measure, the region is demographically diverse as well: almost seven in ten residents are people of color (i.e., not of white, European origin); 30 percent of the region's households are headed by women; and one in ten residents has limited English proficiency (SCAG, 2022).

The U.S. Census Bureau divides the country into various geographic units for the collection and reporting of data. At a high level, these entities include states and counties within states. Smaller units include census tracts and census block groups within tracts. The latter—our unit of analysis in this paper—typically consist of about 600 to 3,000 people. As a subdivision of a census tract, the census block group provides a more localized breakdown of the population and housing characteristics than tracts, which are almost three times larger on average (US Census Bureau, n.d.). The SCAG region used in our analysis is part of one state (California) and is comprised of six counties, 3,956 census tracts, and 10,783 block groups.

We downloaded our data from the StreetLight InSight web platform for 2019 and 2021 separately and then pooled the data, organized by census block group and time period. StreetLight's sample collected data from about 1.7 million devices for October 2019 and 900,000 devices for October 2021 in our study region, providing information on roughly 30.6 and 19.2 million trips, respectively. After data collection, StreetLight applies its proprietary machine-learning algorithm to estimate the number of trips that commenced in each period for each census block group (StreetLight Data, Inc., 2022b).

We focus our study on midweek days because their daily travel patterns tend to be similar to one another. The typical work week in the U.S. is Monday through Friday, though this varies across occupations and industries. The weekend-adjacent days of Monday and, especially, Friday typically have daily travel patterns that differ somewhat from the midweek (Mallig & Vortisch, 2017). For example, workers are more likely to leave work early on Fridays or take a single vacation day on Mondays to lengthen a weekend getaway. We also focus our analysis on Tuesdays, Wednesdays, and Thursdays because data on post-pandemic working from home suggest that remote work tends to be lower on those days, compared with Mondays and Fridays; we didn't want to bias our sample by mixing potentially high (Mondays, Fridays, weekends) and low (Tuesdays, Wednesdays, and Thursdays) WFH days (Bureau of Transportation Statistics, 2016; Zetlin, 2021). If we observe notable post-pandemic shifts in midweek travel timing, we can be relatively confident that these effects were not overly influenced by an outlier day (perhaps Fridays) in our sample.

Many traditional transportation data sources are not well-suited to studying fast evolving changes in travel. Administering, coding, and cleaning travel survey data are expensive and time-consuming, and thus collected relatively infrequently. Many researchers have thus turned to using passively collected data, such as LBS and connected vehicle data. Prior to the pandemic, transportation researchers had already begun to use private sources that draw on cellphone data. These include studies of the connection between street network design, congestion, and collision rates (Choi & Ewing, 2021), traffic forecasting for a new highway project (Sarvepalli & Davis, 2020), and first- and last-mile access to light rail stations (McCahill, 2017), among many others. In addition to StreetLight, researchers have used GPS and LBS data from other companies for transportation studies, including from Safegraph (Brough et al., 2021), INRIX (Lee et al., 2020), and AirSage (Huntsinger, 2017).

In terms of their strengths, LBS data are available on an ongoing basis, are relatively inexpensive per unit sampled, and draw on enormous samples (Bricka et al., 2020). However, researchers have identified issues—including data quality and privacy concerns—with using these sources (Welch & Widita, 2019). For example, the data may overestimate travel on low-volume roadways (Turner et al., 2020). Further our analysis of the data suggests that information on trip purpose is less consistent than the vehicle trip data (particularly at small geographic units like census blocks).

These particular weaknesses are less of a concern in this analysis for a few reasons. We analyze vehicle trips aggregated to moderately sized geographic units (block groups) in a major metropolitan area, and do not consider trip purpose, individual public transit routes, or individual road segments. StreetLight's reported data validation checks suggest that their estimates improve as the number of trips increases, and they report better estimates in urban rather than rural areas (StreetLight Data, Inc., 2022a); the vast majority of our census block groups are urban or suburban.[6] Additionally, analyses conducted and reported by StreetLight suggest that their estimates for several locations in the U.S. and Canada, when compared with in-road sensor data, accurately captured the decline in traffic volumes during the COVID-19 pandemic (StreetLight Data, Inc., 2022a).

Lastly, these data may experience two issues regarding representativeness. First, not everyone owns a smartphone with a locational tracking option, although the share of the population owning a smartphone is quite high in the U.S. According to the American Community Survey Public Use Microdata Sample, the share of the population owning smartphones in the US was 89 percent in 2019 and 91 percent in 2021 (Pew Research Center, 2024). However, smartphone ownership is less common among elderly people, people in low-income households, and people living in rural areas. Therefore, people from these demographic groups may be underrepresented in our data. Second, beginning in 2022, smartphone devices and services began shifting from a default of "opt out" for location tracking to a default of "opt in," according to staff at StreetLight. Pre-2022 smartphone apps typically tracked user locations in the background without asking, unless the user turned off location tracking in the settings; from 2022 on, upon first use, smartphone apps typically ask users whether they would like their location tracked and/or data shared. This means that, in our data, most subjects whose devices provided our fall 2019 and fall 2021 data would have needed to affirmatively "opt out" of tracking if they did not wish to be included. Because research has shown that people are far more likely accept default options rather than affirmatively opt for some alternative, even if that alternative is preferred (Thaler & Sunstein, 2008), the post-2021 norm of requiring users to opt in to data tracking suggests that LBS data circa 2022 and later are both smaller and more biased samples. To avoid this potentially significant sample bias issue, we chose not to analyze LBS data collected after 2021.

3.2. Supplementary data

We supplemented these vehicle trip data with three additional data sources and one additional analysis from StreetLight. To maintain consistency across all supplementary data, we draw pre-pandemic data for the year 2019 or the closest period to the final two weeks of October 2019.

First, we drew on the 2019 Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics (LODES), which are administrative data from the U.S. Census Bureau's Center for Economic Studies (U.S. Census Bureau, 2019). The LODES provide information on worker and job location, including various residential and workplace area characteristics. We analyze trips that start in the afternoon, which we expect for most commuters will entail more trips from work to home than vice versa. Accordingly, we primarily use the LODES Workplace Area Characteristics (rather than Residential Area Characteristics) data in our analyses.

[6] Among the 10,783 block groups in our study, nearly 98 percent are urban or suburban areas. Although most of the land area of the study region is rural, census block groups are a measure of both population and area. Rural block groups make up only two percent of the study's block groups and cover roughly two percent of the region's workers. However, they represent nearly 75 percent of the area's land. So, while trip-making per square mile may be sparse in rural block groups, these block groups tend to be very large geographically when StreetLight is counting trips in those areas.

Second, in considering afternoon trips, schools emerge as important afternoon trip generators, given the gradual rise in parent/guardian chauffeuring of students to and from school over time in the U.S. (McDonald et al., 2011). Therefore, we also include data on student enrollment by school and home location. The school-area data come from the U.S. Department of Education's Common Core of Data (U.S. DoEd CCD) and include student enrollment numbers for every public school serving kindergarten through 12th grade (K-12) for the beginning of the 2019–2020 school year (National Center for Education Statistics, 2020). We aggregate the enrollment of schools by block group, such that the data include the number of K-12 students attending a public school located there.

Third, we include the neighborhood typology of built environment and transportation system characteristics—urban, suburban, and rural—for each block group by pairing it with its parent census tract as defined by Voulgaris et al. (2016).[7]

And finally, we use data on transit use from StreetLight. We examined StreetLight's bus trips and rail trips indices each aggregated across all stops to the block group level for October 2019 across the six-county region. We use these data only to derive an independent variable for our models, which we describe in the next section.

The increase in working from home necessitates examination of workers' home areas. For reasons explained below, we focus primarily on the workplace-/school-areas; however, we draw parallel data as needed to construct residential-area data for each block group. We use the LODES Residential Area Characteristics data as a parallel to the LODES Workplace Area Characteristics, and we use the 2019 American Community Survey (ACS) five-year estimates (US Census Bureau, 2019), which are the most recent for the 2010 census geographies, as a parallel to NCES data about students by residential location. We include all K-12 students who enrolled in public schools.[8] Other variables, like categorical variables for the county and transit use, remain the same in all models.

4. Methods

Because our analysis focuses on travel changes in the PM peak period, we chose to study trip origins rather than destinations, as most afternoon commutes begin at the workplace. To explore these data and compare the two PM peak time periods, we first present a series of descriptive analyses. Then, to explore what predicts the changes we identify between October 2019 and October 2021, we construct and present a model that explains the shift in a ratio of early- to late-PM trip-making.

4.1. Measures and descriptive calculations

Our analysis took three forms, based on the topics, questions, measures, and purposes described and defined in Table 1 and detailed below.

Table 1
Measures for analyzing change in temporal distribution of trips.

Topic	Research Question(s)	Measure(s)	Purpose
Total trip originations by hour	How does the temporal distribution of trip originations vary between before and late in the pandemic?	Count of number of trips that commenced in each hour of the day	Identify how trip-making has changed throughout the day from the fall of 2019 to the fall of 2021
Top-ranked hour for trip-making for each block group	How do each block group's vehicle trips peak throughout the day?	Relative rank of trip generation across the 24 h for each block group	Identify how trip-making peaks during the day, and how those patterns have shifted between 2019 and 2021
Temporal shift of trip-making in the PM Peak period	Did trip-making change in the PM Peak period during the pandemic? If so, what factors, if any, explain these changes?	Ratio of the number of trips originating in the Early PM Peak period (12–3:59 PM) to the number of trips originating in the Late PM Peak period (4–7:59 PM)	Examine how afternoon peaking and trip-making distribution has shifted from 2019 to 2021, especially considering revealed changes in the classic two-peaked distribution of daily travel

We begin by counting the number of trips that commenced in each hour during the two respective time periods. We chart these for each of the 24 h in the day and examine the differences between the last two weeks each of October 2019 and October 2021, focusing particularly on three peak time periods: the AM Peak (6–8:59 AM), the Early PM Peak (12–3:59 PM), and the Late PM Peak (4–7:59 PM). The latter two-part, eight-hour PM peak period might seem to stretch the notion of an afternoon peak period too far. Yet the data we present below support this definition. The other times of day include the overnight (12–5:59 AM), late morning (9–11:59 AM), and evening (8–11:59 PM) periods. We focused on the spatial and temporal shifts in trip-making. Upon analyzing these initial results, we observed notable changes in the diurnal two-peaked weekday trip-making pattern between October 2019 and October 2021, particularly in the afternoon. So, we then turned our focus to the evolving PM peak period between October 2019 and October 2021.

Second, to examine more specifically how each block group's vehicle trips peak throughout the day, we calculated the relative rank of trip generation across the 24 h for each block group. Thus, the top-ranked hour for a block group was the one with the most vehicle trip originations. We then compared the top-ranked hour across all SCAG-region block groups between the 2019 and 2021 time periods and noted broadly shifting trip patterns in the morning (less peaking) and afternoon/early evening (peak shifting and spreading) peak periods. Turning to the PM peak period, we then identified the peak trip generation hour for each block group between 12 and 7:59 PM.

And third, we sought to more deeply examine the shifting distribution of trips between the early and late PM peak periods. To do this, we calculated the ratio of trips between the two; this is the crux of our analysis. We refer to this ratio from here on as the Early-to-Late PM Ratio. For each block group, we calculated the ratio as the number of trips originating in the Early PM Peak period (12–3:59 PM) divided by the number of trips originating in the Late PM Peak period (4–7:59 PM). We calculated the Early-to-Late PM ratio for both October 2019 and October 2021. This ratio allows us to focus on the relative *distribution* of trips within the two time periods, which in turn provides evidence of how travel patterns have changed. We consider this measure first descriptively and then second spatially with maps.

4.2. Modeling approach

Following this descriptive analysis, we sought to identify how pre-pandemic characteristics of a given block group predict a shift in afternoon and evening trip-making in that block group from 2019 to 2021.

[7] Neighborhood type is drawn from Voulgaris et al.'s (2016) typology of seven neighborhood types—three urban (mixed use, old urban, urban residential), three suburban (established suburb, patchwork, new development), and one rural—based on a set of 20 built environment and transportation system variables for most census tracts in the U.S. We use the three generalized area types – urban, suburban, and rural – in this analysis.

[8] Although census data include private school students, private school enrollment data are not widely available and thus we exclude private school students' residential locations to match the available school location area data.

To do so, we investigated two related questions: What characteristics of workplace and/or residential areas predict the temporal shift toward earlier afternoon trip-making? More specifically, to what extent does remote work explain this shift? To answer these questions, we estimated an Ordinary Least-Squares (OLS) regression model with cluster-robust standard errors to predict the ratio of Early-to-Late PM trip originations in both 2019 and 2021. Predictors include workplace or residential area characteristics, school enrollment, locational characteristics, and the time period. We fit one model for workplace- and school-area characteristics (Model 1), a second model for residential area characteristics (Model 2), and a third model with both workplace and residential area characteristics (Model 3). Because the ratio of Early-to-Late PM trip originations is positively skewed, it requires a logarithmic transformation to meet the OLS assumption of normality. The models all follow variations of the basic form shown in Equation (1):

$$\ln\left(\frac{EarlyPMTripOriginations}{LatePMTripOriginations}\right) = f(\boldsymbol{W}, \boldsymbol{R}, \boldsymbol{E}, \boldsymbol{L}, \boldsymbol{T}, \boldsymbol{I}) \tag{1}$$

Where:

W denotes a vector of workers' characteristics at the workplace area (number of workers and the percentages of workers whose jobs can be done remotely, who have low-wage jobs, are female, are Hispanic/Latino/a, are Asian, and are Black[9]).

R denotes a vector of workers' characteristics at the residential area (number of workers and the percentages of workers whose jobs can be done remotely, who have low-wage jobs, are female, are Hispanic/Latino/a, are Asian, and are Black).

E denotes a vector of school enrollment characteristics (number of K–12 public school students enrolled at a school in the block group, number of K–12 public school students residing in the block group).

L denotes a vector of locational characteristics (neighborhood type, county, and high pre-pandemic transit use).

T denotes a dummy variable indicating the 2021 data period.

I denotes the interaction term for the 2021 year with the other variables.

We focus this article on Model 1 (the workplace- and school-area characteristics model) because Model 2′s (the residential-area characteristics model) explanatory power proved far weaker for reasons we discuss later. Model 3 included all relevant workplace and residence area controls, but many of its variables were multicollinear, and this more complex model provided very little additional predictive power beyond the more parsimonious and interpretable workplace- and school-area model. Models 2 and 3 and their outputs are available in Supplemental Material. Table 2 shows which variables are present in each of the three models and displays descriptive statistics for the dependent and independent variables, first for continuous variables and then for categorical variables.

n = 10,783.

All data except *Ratio Early/Late PM 2021 are for 2019 unless otherwise noted.*

As we described earlier, most of our data are drawn directly from StreetLight, LODES, NCES, and the Voulgaris et al. (2016) neighborhood typologies. Beyond that, we constructed four predictor variables from supplementary data.

First, we derive the percentage of workers who are able to work from home (WFH) using a method defined by Dingel and Neiman (2020). They use work activity data like email use, workplace dangers, disease exposure, physical tasks, and machinery use to estimate the share of jobs that can be done remotely. They apply these measures to the 20 primary industries as defined by the North American Industry Classification System (NAICS). We pair their unweighted-by-wage estimates (to avoid correlation with our wage variable) with the LODES, which include the number of workers in each census block by NAICS code. By this measure, 37 percent of U.S. jobs can be done remotely, and the workers in those jobs are likely to have higher levels of educational attainment and higher incomes than average. Dingel and Neiman (2020) also provide a list of the top-ten and bottom-ten U.S. metropolitan areas by this measure, ranging from 51 percent in San Jose-Sunnyvale-Santa Clara, California (known colloquially as Silicon Valley), to 28 percent in Cape Coral-Fort Myers, Florida. At 34 percent, the six-county SCAG region rests just below the national average. Within the block groups of the region, this measure is approximately normally distributed with a slight positive skew.

Second, we categorize the percentage of low-wage workers in a block group by combining the two lowest wage categories in the LODES: jobs with earnings of $1,250 per month or less and jobs with earnings between $1,251 and $3,333 per month. We combine these categories to capture a larger share of the bottom half of wage earners. Although this does not capture household income (and thus poverty status), it reasonably captures lower wage earnings by individuals, similar to a per-capita adult income measure. In the Greater Los Angeles region, per-capita income among adults was $43,838 (US Census Bureau, 2019), meaning that any worker we designate as low-wage (presumably earning less than $39,996 annually) would very likely lie below the per-capita adult income line for the region.

Third, we estimate the percentage of workers in industries likely to have traditional office-based schedules that begin roughly at 9:00 AM and end at roughly 5:00 PM. We calculate the percentage of workers in a block group whose jobs are classified in the NAICS as either Information; Finance and Insurance; Professional; Scientific; and Technical Services; Management of Companies and Enterprises; or Public Administration. Our intent was to capture those workers who are not prone to irregular work schedules (like retail and service industry workers), or those with schedules unlikely to follow the "9-to-5" workday (like teachers and healthcare workers).

Finally, we derive an indicator for high-transit-use block groups based on the October 2019 StreetLight bus and rail trip indices. We designate any block group as high transit if it falls in the top decile of the bus ridership or rail ridership indices. We use the top decile of transit use block groups because it emphasizes areas where transit was a major player in travel behavior prior to the pandemic.[10]

By controlling for the year, we can identify the effects of our independent variables on the 2019 Early-to-Late PM ratio, 2021 Early-to-Late PM ratio, and the difference between them. For each of these parameters, we include standardized coefficients (betas) to measure the relative effect size of each predictor. In controlling for 2021, our model yields coefficients for 2019 as well as coefficients for the change between the years. To include coefficients for predicting the 2021 ratio, we calculate the marginal effects of each variable by taking their derivatives.

We employ cluster-robust standard errors to address the issue of multiple observations from the same block group. This is necessary because all predictor data come from 2019, the latest date for which the independent variable data were available at the time of our analysis. As a robustness check, we also estimated a linear mixed effects model with random intercepts by block group; these results were nearly identical to our OLS model.[11] Because of their similarities, we chose to report the

[9] Due to collinearity issues, we omit the percentage of white workers, both in *W* and in *R*.

[10] Unlike the other variables in these models that are likely to have changed minimally from 2019 to 2021, the transit index may well have changed substantially, as transit systems have adjusted service to reflect substantially shifting demand. However, like our other independent variables, the high transit use variable is only available for 2019. While data limitations preclude us from obtaining 2021 reliable transit data from StreetLight, the 2019 top-decile allows us to see how these pre-pandemic high transit use areas have changed, and it does so in a consistent manner with other control variables.

[11] These models are available from the authors upon request.

Table 2
Descriptive statistics, block groups in Greater Los Angeles Region.

	Variable in Model							
Variable	**1**	**2**	**3**	**Mean**	**St. Dev.**	**Min.**	**Max.**	**Source**
Ratio of Early-to-Late PM Vehicle Trips								
October 18–31, 2019	X	X	X	1.00	0.31	0.20	4.80	
October 18–31, 2021	X	X	X	1.11	0.37	0.22	5.59	
Workplace Area Characteristics								
Number of Workers	X		X	773.3	3,017	2	138,875	
% Workers Able to WFH	X		X	34.2 %	14.3 %	4.0 %	83 %	Dingel & Neiman (2020)
% Low-wage Jobs	X		X	68.6 %	16.6 %	0 %	100 %	
% Female	X		X	54.7 %	12.4 %	0 %	100 %	
% Hispanic/Latino	X		X	43.1 %	16.3 %	0 %	100 %	
% Asian	X		X	14.4 %	13.3 %	0 %	94.9 %	
% Black	X		X	8.9 %	11.5 %	0 %	100 %	
Number of K–12 Students Attending School in block group	X		X	266.9	604.7	0	7,390	U.S. DoEd CCD
Residential Area Characteristics								
Number of Workers		X	X	771.5	415.0	1	5,221	
% Workers Able to WFH		X	X	37.3 %	5.3 %	21.0 %	72 %	Dingel & Neiman (2020)
% Low-wage Jobs		X	X	54.4 %	9.9 %	25.4 %	100 %	
% Female		X	X	49.0 %	2.9 %	25.0 %	100 %	
% Hispanic/Latino		X	X	41.5 %	22.6 %	0 %	95.2 %	
% Asian		X	X	13.9 %	12.5 %	0 %	78.8 %	
% Black		X	X	8.0 %	9.5 %	0 %	100 %	
Number of K–12 Students Residing in block group		X	X	272.3	238.3	0	3,296	ACS (2019)
Variable	**1**	**2**	**3**	**Freq.**	**%**			
Neighborhood Type								Voulgaris et al. (2016)
Urban	X	X	X	4,433	41.1 %			
Suburban	X	X	X	6,106	56.6 %			
Rural	X	X	X	244	2.3 %			
County								U.S. Census Bureau
Imperial	X	X	X	94	0.9 %			
Los Angeles	X	X	X	6,339	58.8 %			
Orange	X	X	X	1,817	16.9 %			
Riverside	X	X	X	1,024	9.5 %			
San Bernardino	X	X	X	1,082	10.0 %			
Ventura	X	X	X	427	4.0 %			
Top Transit block group	X	X	X	1,053	9.8 %			StreetLight

OLS results for ease of interpretation.

5. How trip originations have changed throughout the day

5.1. Total trip originations by hour

The daily temporal patterns of trip origin counts in Greater Los Angeles were in many ways similar just before (fall 2019) and late (fall 2021) in the pandemic. For both periods, the number of trips per hour during the afternoon peak was higher than during the morning peak, on average. Yet while the total number of trip originations declined notably from 2019 to 2021, the decrease was not consistent throughout the day. Fig. 2 shows the highest number of morning trips occurred during the same period—between 7 AM and 7:59 AM—in both 2019 and 2021, but

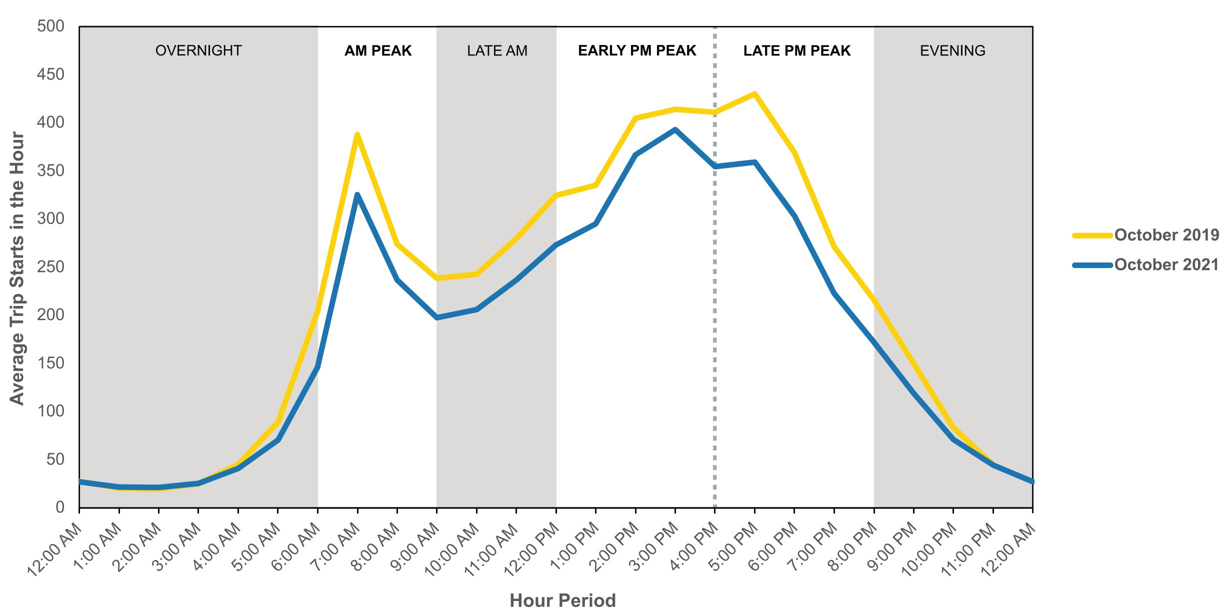

Fig. 2. Average vehicle trip originations by hour, Greater Los Angeles Region block groups, midweek, October 2019 and 2021.

the distribution of afternoon trip origins in 2021 differed from that of 2019. The highest number of afternoon trips was between 5 PM and 5:59 PM in 2019, but this peak-of-the-PM-peak shifted two hours earlier (3–3:59 PM) in 2021. Across all hours of the day, the number of trips declined most between 2019 and 2021 from 5 PM and 6:59 PM. These various shifts collectively suggest a substantial change in afternoon trip-making during the pandemic.

5.2. A shifting PM Peak: Examining block groups by hour

Given this observed decline in overall trip originations in both the morning and afternoon peaks (particularly during the 7 AM and 5 PM hours), we sought to identify not only how trip originations changed, but how *peaking* changed as well. Accordingly, we calculated the top trip-origination-hour for each block group in the Greater Los Angeles region. This measure identifies the hour (among the 24 in a day) that hosts the most midweek trip originations. Fig. 3 displays this top-peak hour for October 2019 (in blue), overlaid with data from October 2021 (in yellow).

The figure shows that the morning peak—measured by the number of block groups with the highest number of trips during the morning peak—declined notably between 2019 and 2021. The drop in the number of block groups with trip-making peaks in the 7 AM hour was especially notable, with a slight increase in the 8 AM hour. These changes are striking, but they are confined largely to the 7 to 8:59 AM period. More importantly, the shift from the 7 AM hour does not appear to be simply to the 8 AM hour, as their changes between 2019 and 2021 are not the inverse of one another. Thus, the number of block groups peaking in the AM has fallen relative to peak trip-making at other parts of the day. As we shall see, this shift occurs most notably toward the early afternoon.

While the character of the morning peak changed in the pandemic, afternoon and early evening trip-making patterns shifted even more notably. Most conspicuously, the peak one-hour trip origins in the afternoon shifted earlier in the day. The dashed line in Fig. 3 represents the divide between our two periods of analysis: early and late PM peak. The number of block groups where the peak one-hour of trip origins was between 5 PM and 5:59 pm (the classic PM peak hour) decreased, while that number increased between 2 PM and 3:59 PM.

We constructed Fig. 3 above and Fig. 4 below slightly differently. For Fig. 4, we identified the top trip-origination count hour across the two PM peak periods (the eight hours between 12 PM and 7:59 PM) for each block group. This allowed us to isolate changes in the afternoon and early evening from 2019 to 2021. Again, the dashed vertical line represents the divide between the early PM and late PM periods. In 2019 (blue shading), most block groups peaked during the 5 PM hour (by a noticeable margin), while the 6 PM hour saw the second-most block group peaks.

However, peak patterns changed by 2021 (yellow shading). First, the PM peak hours spread considerably: by 2021, the number of block groups with peak PM trip origins becomes roughly similar between 2 PM and 7 PM. Second, the 5 PM peak-of-the-PM-peak hour was replaced by the 3 PM hour — though the difference between this new peak-of-the-PM-peak hour (3 PM) and the old one (5 PM) is modest. More dramatic, however, was the change for 6 PM: it went from being the second highest trip-generating hour to a lowly fifth place out of eight. Together, these data suggest that the PM peak has both spread out and shifted earlier.

5.3. Ratio between early PM and late PM trip originations

We move now from our analysis of peak one-hour trip origins to the temporal distribution of trip origins across our two PM peak periods. To assess the relationship between trips beginning in the early PM (12–3:59 PM) and late PM (4–7:59 PM) peak periods, we calculated the ratio of trips beginning in the former to the latter period by block group. If this ratio is one, a block group had the same number of trips beginning in the early PM period as in the late PM period. If the ratio is above one, more trips commenced in the early PM period; a ratio below one indicates a block group had more trips beginning in the late PM. In 2019, and by a remarkable coincidence, the mean of this ratio across our sample rounds to exactly one.

By October 2021, however, this ratio changed dramatically in the Greater Los Angeles region. Fig. 5 shows the distribution of this ratio

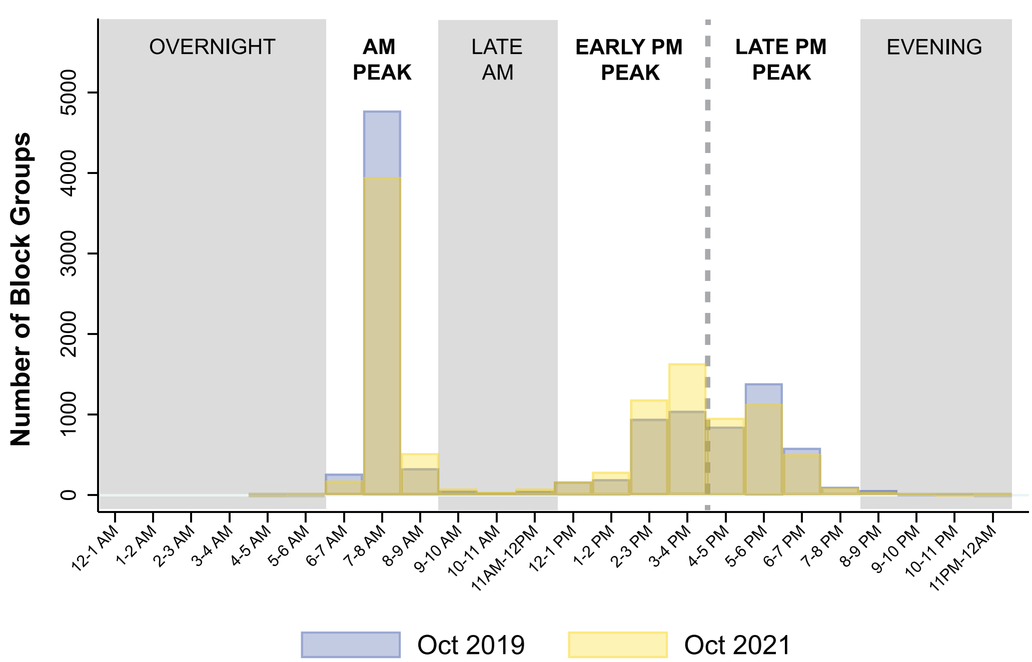

Fig. 3. Top trip origination hour for Greater Los Angeles Region block groups, midweek, October 2019 and 2021. Note: The yellow (2021) data are overlaid on the blue (2019) data, and the darker shading shows where the data from the two years overlap. (If this figure appears in black and white, we refer the reader to the color web version of this article.)

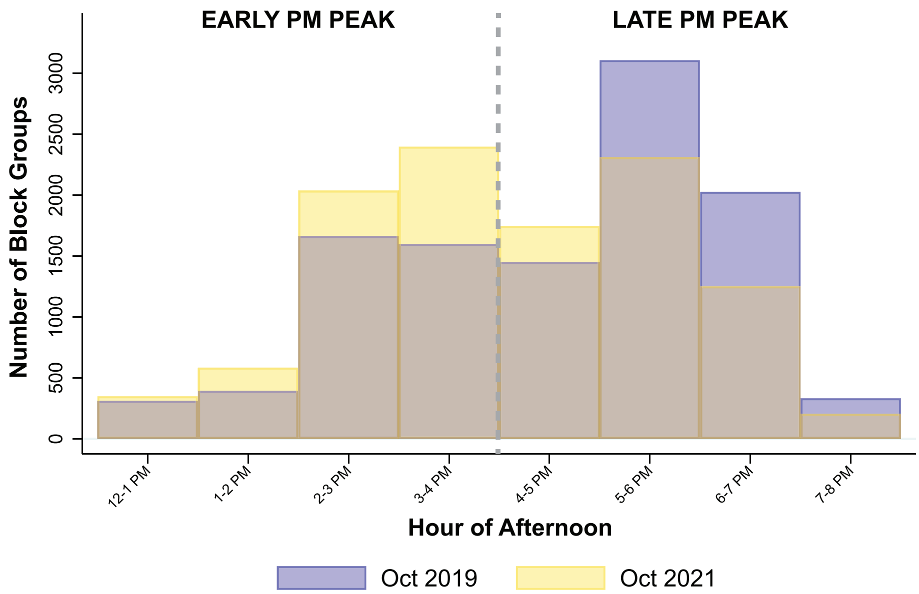

Fig. 4. Top PM Peak Period Trip Origination Hour for Greater Los Angeles Region block groups, midweek, October 2019 and 2021. Note: The yellow (2021) data are overlaid on the blue (2019) data, and the darker shading shows where the data from the two years overlap. (If this figure appears in black and white, we refer the reader to the color web version of this article.)

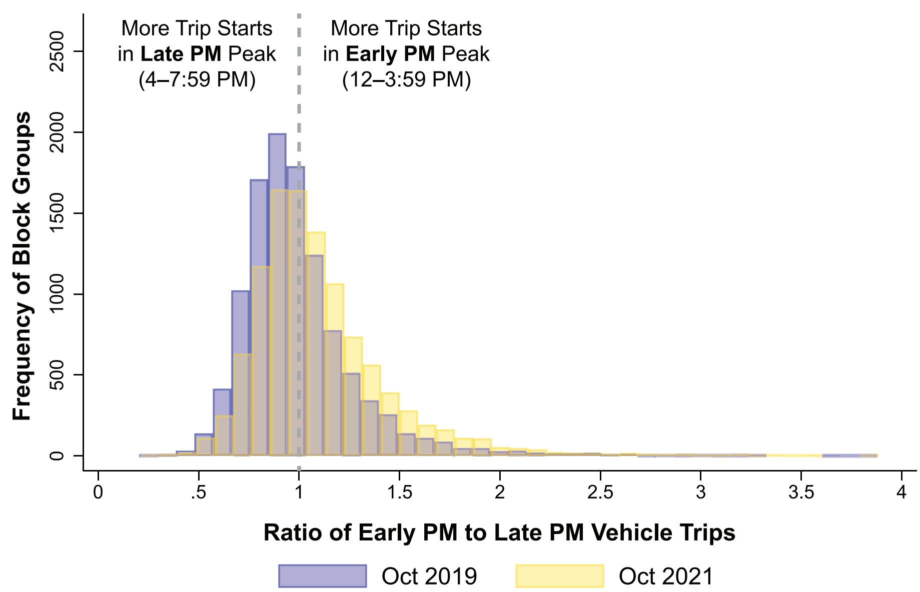

Fig. 5. Early-to-Late PM Vehicle Trips Ratio, Greater Los Angeles block groups, midweek, October 2019 and 2021. Note: The blue shading shows 2019 data, the yellow shading shows 2021 data, and the darker shading shows where 2019 and 2021 data overlap. (If this figure appears in black and white, we refer the reader to the color web version of this article.)

among the 10,765 valid block groups, again with October 2019 in blue and October 2021 in yellow.[12] A ratio closer to zero (the left of the chart) indicates a substantially greater number of trips in the late PM period; as the ratio moves right on the chart, the share of trips in the early PM period increases.

We find that the distribution of the ratio prior to the pandemic was more temporally clustered and centered close to the mean at one. Two years later, however, the ratio shifted to the right, as the share of trips for mean block groups moved earlier into the 12–3:39 PM period. Additionally, the ratio in 2021 is more temporally dispersed.[13] The important measure is the number of block groups in each year above the overlapping shaded area. In 2019, all of these were below one (except for two extreme block groups with ratios above 3.5); in 2021, they were all above one, indicating a clear shift in peak hour trip-making distribution

[12] We exclude 18 block groups in the SCAG region from the analysis because they have incomplete data, either due to insufficient vehicle trip originations or because they exist primarily on the beach and in the ocean.

[13] Of note is that the ratio treats the two sides differently; that is, a block group with 500 hypothetical vehicle trips beginning between 12 and 7:59 PM and 300 of those in the Early PM period (300/200 = 1.50) has a greater ratio distance from one than a block group with the same number of total trips but with 300 beginning in the Late PM period (200/300 = 0.67).

from later to earlier.

We also analyzed this ratio during these two PM peak time periods spatially. Fig. 6 shows maps of the Los Angeles Basin (the central part of Greater Los Angeles) in October 2019 and October 2021. Higher ratios (more trips in the early PM) are in graduated shades of gold (think afternoon sun), lower ratios (more trips in the late PM) are in graduated shades of purple (think twilight sky), and ratios close to neutral are in tan (think… neutral). The symbology is constant across the two years based on 2019 ratios. We conducted this analysis for the Greater Los Angeles region but zoomed in here on urbanized Los Angeles and Orange counties, as they contain most of the region's block groups, population, and trips.

In 2019, the share of block groups shaded purple—representing block groups with relatively more trips in the late PM period (a ratio of less than one)—substantially exceeded the share of gold-shaded block groups—those with relatively more trips in the early PM period (a ratio greater than one). This was especially true along the dense, employment rich Wilshire Corridor between downtown Los Angeles and Santa Monica; in the substantially industrial areas of the Southbay northwest of Long Beach and south of Santa Monica; in the "Gateway Cities" north of Long Beach; around Pasadena northeast of downtown LA; and in Orange County between Long Beach and Anaheim, home to Disneyland.

By 2021, these patterns had changed significantly. A substantially greater share of block groups is shaded gold, with more relative trip-

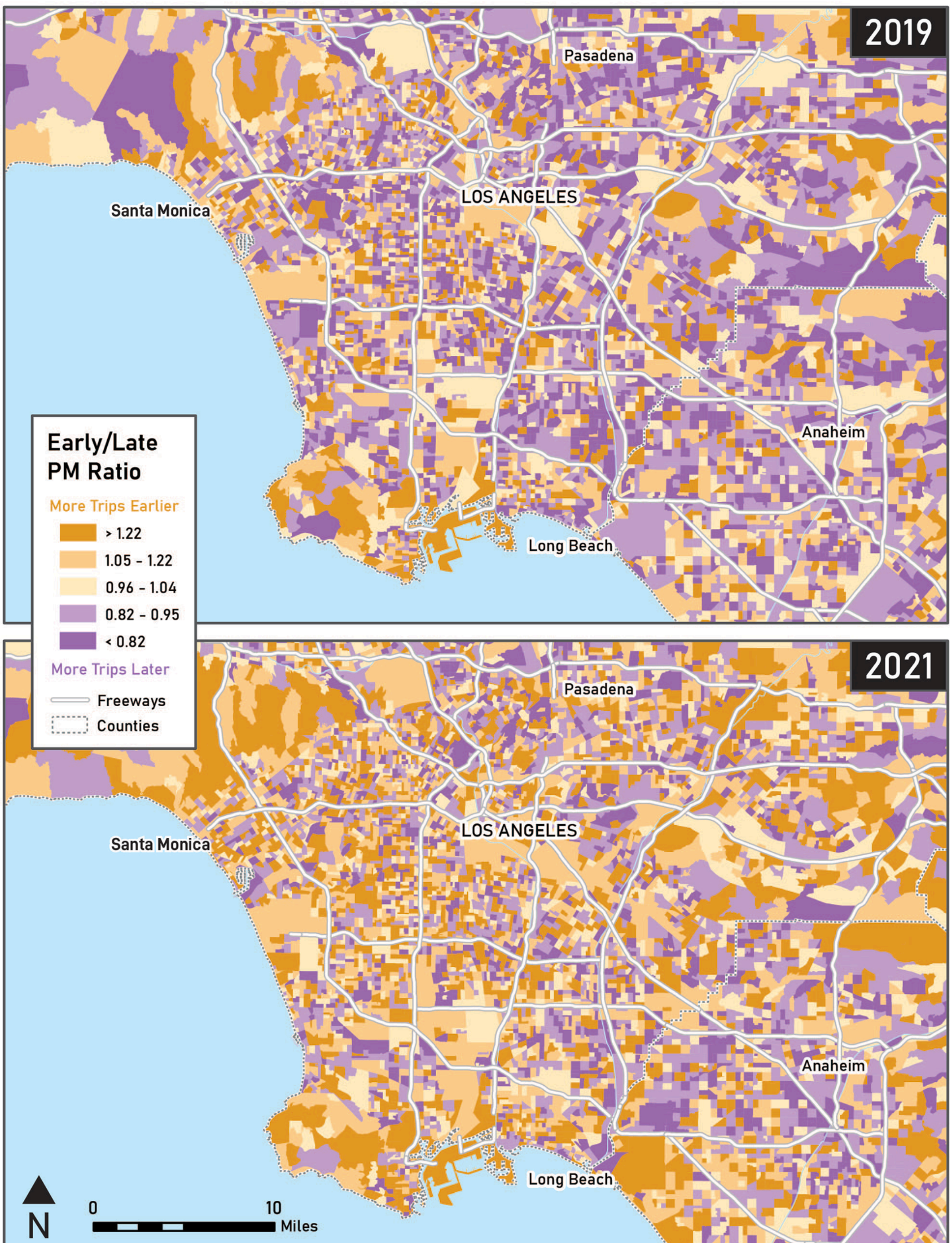

Fig. 6. Maps of Early-to-Late PM Trip Start Ratios, Greater Los Angeles block groups, midweek, October 2019 and 2021.

making in early PM period (ratio > 1). Further, spatial patterns also changed. The Wilshire Corridor, Pasadena, South Bay, and Gateway Cities areas all shifted earlier (shaded gold instead of purple) in 2021. This shift from late PM purple to early PM gold also happened in relatively low-income and predominantly non-white South Los Angeles, areas east of downtown LA, and in the relatively low-income and industrial areas between the freeways running north and south between LA and Long Beach. However, we still see several purple block groups in northern Orange County south and west of Anaheim.

6. What explains the change in the afternoon peak period?

Our model yields results for four related effects on the ratios of early PM peak period (12–3:59 PM) trip origins to late PM peak period (4–7:59 PM) trip origins: 1) the pandemic year 2021, 2) the predictors on the 2019 ratios, 3) the predictors (as they were in 2019) on the *2021* ratios, and 4) the predictors (as they were in 2019) on the *change between* the 2019 and 2021 ratios.

Table 3 compares the explanatory power of all three of our models. We find that workplace- and school-area characteristics explain far more of the variance in the relative distribution of early- to late-PM trip-making and the change in that distribution—over *three times* more. Because the workplace- and school-area model explains so much more than the residential-area model, and because the combined workplace-/school-area and residential area model has the aforementioned issues with multicollinearity, we focus our interpretation of the results on the workplace- and school-area model.

We display the full results of Model 1, the workplace- and school-area model, in Table 3. Then, we discuss the four parts of the model clockwise from top to bottom: we present the year variable before the first gray line, the 2019 and 2021 effects in the middle, and the change effects—which represent the interaction between the year 2021 and the predictors—at the bottom. We include variables for neighborhood type, county, and transit use for both the single-year and change effects. The effect of the year variable is not significant, meaning that the variables in our model explain a substantial part of the change in the Early-to-Late PM Ratio between 2019 and 2021; thus, we focus our analysis primarily on the single-year and change effects.

As in Fig. 5, we shade the positive and statistically significant coefficients gold, and negative and statistically significant coefficients purple. Thus, a predictor associated with relatively more early PM trips is gold, while one suggesting relatively more late PM trips is purple. For changes in the ratio, an increase between 2019 and 2021 means the distribution of trips occurring in the block group between 12 and 3:59 PM has increased. Because we measure relative effects, this could indicate a variety of underlying outcomes: 1) increased early PM trips without change in late PM trips; 2) decreased late PM trips without change in the early PM; 3) simultaneously increased early PM trips and decreased late PM trips; and so on.

6.1. *Single-year effects*

The workplace-/school-area model presented in Table 4 accounts for about a quarter of the variability in this ratio across the two-period sample. Turning first to the results for 2019, recall that the block group average Early-to-Late PM ratio in 2019 was 1.0. This means that, just before the pandemic, an equal share of trips began between 12–3:59 PM and 4–7:59 PM. Our model results suggest that high percentages of Latino/a workers and low-wage jobs in a block group pushed that ratio to the later side, as did (to a lesser extent) shares of Asian workers and the total number of block group workers. For these factors, then, as their numbers or percentages in a block group rose, PM peak trips tended to occur later in the day. Relative to Los Angeles County, late-peaking Orange County (to the southeast of downtown Los Angeles) also had a significant and negative effect on the ratio. Predictors associated with early PM trip-making in 2019 include: the percent of female workers, the block group belonging to an urban or rural tract (relative to suburban), and the block group being in less-dense and more outlying Imperial, Riverside, or San Bernardino counties. But these effects were all relatively modest, as was our variable of interest—the percent of workers able to work from home in 2019. However, the strongest predictor in 2019 *by far* was the number of students attending a public school located in the block group. It explained better than three times more than any other variable. We discuss this finding further below.

What can we surmise about the Early-to-Late PM ratio in October 2021 based on our predictor data from before the pandemic? We observed a shift in both how several predictors affected the ratio and in their relative effect sizes. First, the number of students in the block group still had the strongest effect, by far. However, the influence of the share of able-to-work-remotely jobs shifted from the eighth-strongest predictor before the pandemic to second strongest by late in the pandemic. Further, the number of workers and the percentages of low-wage, Latino/a, and Asian workers continued to have modest negative effects on the ratio. And the effect of Black workers from 2019 reversed; in 2021, that effect was now modestly and significantly positive. Further, compared to suburban areas, rural block groups were associated with earlier peaking. However, the modest effect of urban neighborhoods reversed and became associated with more later trips. The county effects also changed. In 2019, the "Inland Empire" of Riverside and San Bernardino counties were associated with earlier PM peaking relative to more urban Los Angeles. By 2021, however, the Inland Empire was no different from Los Angeles County, while Ventura County joined Orange County in trending significantly toward the late PM period. Finally, high transit ridership block groups were associated with significantly later trip origin distributions compared to those with low transit ridership.

6.2. *Change effects*

The bottom section of Table 4 answers our primary research questions: which factors affected the change in the Early-to-Late PM ratio between the two time periods, and to what extent was the ability to work from home one of them? The purple shading indicates that many factors are associated with pushing the ratio toward the late PM period, despite the clear overall shift in the Early-to-Late PM ratio between 2019 and 2021. These predictors of later PM trip origins include the number of workers in the block group, the percent of workers who are female, urban neighborhoods relative to suburbs, all other counties in the region relative to Los Angeles, and block groups with high 2019 transit use. Even the number of students in a block group has a very small effect on a later distribution of trips.

What then predicts these early PM peak period effects? Chiefly, the traits of the jobs in the block group—the ability to conduct a job remotely and the presence of more low-wage jobs in 2019—predict a shift toward earlier PM peak trip making. Additionally, higher percentages of Asian, Black, or Latino/a workers also modestly influence an earlier shift, albeit by no more than half of the effect of the job trait variables. In short, working remotely strongly predicts this shift toward earlier afternoon trip-making, as we would expect given the effects of the global pandemic on work. The ability to work from home is likely related to the other variables that predict an earlier shift too, as the pandemic opened remote and flexible work opportunities for population groups traditionally excluded from those options. We elaborate on this in the next section.

Table 3
Model explanatory power comparison.

Model	R^2	F	Pr > F
1. Workplace- and School-Area	0.246	123.73	0.000
2. Residential Area	0.075	77.39	0.000
3. Combined	0.275	99.86	0.000

Note: Model 3 has multicollinearity issues and is included here for illustrative purposes only.

Table 4
Model Results with Workplace- and School-Area Controls, Early-to-Late PM Trip Start Ratio.

	Model Results ***(2019 effects)***			**Marginal Effects** ***(2021 effects)***		
	Coeff.	**St. Err.**	**Beta**	**Coeff.**	**St. Err.**	**Beta**
Year						
2019	—					
2021	3.449	2.133	0.061			
Workplace-/School- Area Characteristics						
Number of Workers (100s)	−0.037 ***	0.009	−0.037	−0.057 ***	0.128	−0.063
% Workers Able to WFH	0.080 **	0.024	0.041	0.203 ***	0.026	0.104
% Low-wage Jobs	−0.153 ***	0.018	−0.090	−0.080 ***	0.021	−0.048
% Female	0.085 ***	0.022	0.038	0.023	0.027	0.010
% Hispanic/Latino	−0.191 ***	0.018	−0.111	−0.137 ***	0.020	−0.080
% Asian	−0.177 ***	0.020	−0.084	−0.115 ***	0.023	−0.055
% Black	−0.034	0.024	−0.014	0.104 ***	0.029	0.043
Number of K–12 Students (100s)	1.744 ***	0.064	0.375	1.610 ***	0.062	0.347
Neighborhood Type						
Urban	1.225 **	0.455	0.021	−1.253 *	0.523	−0.022
Suburban	—			—		
Rural	10.975 ***	2.182	0.058	12.323 ***	2.114	0.065
County						
Imperial	15.402 ***	2.452	0.051	6.909 *	3.178	0.023
Los Angeles	—			—		
Orange	−1.748 **	0.645	−0.023	−5.297 ***	0.713	−0.071
Riverside	6.505 ***	0.861	0.068	0.750	0.902	0.008
San Bernardino	5.704 ***	0.799	0.061	0.282	0.864	0.003
Ventura	−0.141	1.156	−0.001	−5.908 ***	1.283	−0.041
Top Transit Block Group	0.050	0.688	0.001	−1.849 *	0.779	−0.020
	Interactions with 2021 (change effects)					
Workplace-/School-Area Characteristics						
Number of Workers (100s)	−0.023 **	0.008	−0.018			
% Workers Able to WFH	0.124 ***	0.025	0.087			
% Low-wage Jobs	0.072 **	0.021	0.093			
% Female	−0.062 *	0.026	−0.064			
% Hispanic/Latino	0.054 **	0.021	0.049			
% Asian	0.062 **	0.023	0.026			
% Black	0.139 ***	0.031	0.046			
Number of K–12 Students (100s)	−0.134 ***	0.037	−0.021			
Neighborhood Type						
Urban	−2.479 ***	0.527	−0.036			
Suburban	—					
Rural	1.348	2.149	0.005			
County						
Imperial	−8.493 **	2.645	−0.020			
Los Angeles	—					
Orange	−3.549 ***	0.682	−0.035			
Riverside	−5.756 ***	0.821	−0.044			
San Bernardino	−5.421 ***	0.841	−0.042			
Ventura	−5.767 ***	1.210	−0.029			
Top Transit Block Group	−1.900 **	0.726	−0.015			
Constant	4.247 *	1.936	—			

$n = 21{,}566$ $R^2 = 0.246$ Gold = relatively more trips earlier Purple = relatively more trips later.
* $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$. All predictors based on 2019 data.

7. Discussion and conclusion

Coming out of the pandemic, the PM "peak" period is perhaps a misnomer. As of October 2021, the PM peak in our Greater Los Angeles data now runs a full five hours, from 2 PM to 7 PM on midweek days. "PM mountain range period" might today be a more apt descriptor.

But in addition to lasting more than 20 percent of each day, a clear shift in the temporal distribution of PM trip-making occurred from 2019 to 2021, moving from the late afternoon and early evening (4–7:59 PM) to the early afternoon (12–3:59 PM). What explains this shift in the temporal distribution of trips to the early afternoon over this two-year period, in the context of the COVID-19 pandemic? Our model suggests that earlier PM travel in general and the distributional shift nearly two years into the pandemic were explained best by three factors: (1) the number of public schoolchildren in a block group in 2019 (earlier peaking); (2) block groups with large shares of potential work-from-home jobs in 2019 (earlier peaking), and (3) block groups with high percentages of low-wage workers and workers of color (later peaking). In addition, we find changes to work and the workplace have had a far greater effect on the temporal shifts in afternoon trip-making than any changes in residential area characteristics.

First, the number of students attending a K-12 public school in a block group was associated with significantly higher levels of early afternoon trip-making in that block group both prior to and late in the pandemic. The measure was more than three times stronger than any other predictor in both 2019 and 2021. Why? We see two reasons. First, the pandemic upended many aspects of life, particularly in terms of the workplace, and many of those effects remained in October 2021. By then, however, California's public schools had largely returned to normally scheduled in-person learning. That the school-area effects remained similar while work-related effects changed between 2019 and 2021 reflects these divergent recovery patterns. Second, schools and many office jobs begin at similar times in the morning, but schools tend to dismiss earlier in the afternoon — and they dismiss students all at once, creating a pulse of travel activity over a very short period of the day. In 2017, more than 80 percent of California students departed school between 2 and 4 PM; in addition, more than two-thirds of California schoolchildren are driven or drive to school, which adds millions of early afternoon vehicle trips (Federal Highway Administration, 2018a). This is true, in part, because less than a third of students live within a mile of school, and because California makes relatively little use of school buses compared with most other U.S. states (Federal Highway Administration, 2018a; McDonald & Howlett, 2007).

Second is the role of working-from-home, both as a pandemic-related phenomenon and as an influencer of the ratio of early-to-late PM trips. In 2019 the ability to work from home had a strong effect, at least relative to the other work-related variables in our workplace-/school-area model. However, and not at all surprisingly, its predictive power grew by 2021. We suspect that the ability to work from home was such a strong predictor in the workplace-/school-area model because it *removed* trips from the late PM period. The LODES data—used to derive our work-from-home measure—captures employment based on employer address data. A significantly higher percentage of these workers worked remotely in 2021, either for the full day or for part of it (Barrero et al., 2021). Thus, higher rates of the ability to WFH suggest that fewer workers travel from those workplace location block groups, especially during the late PM period. Workers who previously left the office at 5 PM are now by that time already at home or elsewhere engaging in non-work travel. This shift has turned 3 PM into the "new" 5 PM.

Third, while we are unable to account for the percentage of workers in a block group *actually* working from home either in 2019 or 2021, previous research shows that the share of workers who work remotely rose dramatically from pre-pandemic levels by a factor of about six well into the pandemic (Barrero et al., 2021). The ability to do a given job remotely may not have changed much since 2019, but the *opportunity* for and uptake in doing so has dramatically increased and persisted. Relatively early afternoon trip-making in block groups with high percentages of low-wage workers and workers of color may reflect a disproportionate expansion of remote and flexible work opportunities among these workers. Prior to the pandemic, most workers, especially low-wage workers and workers of color, did not have the opportunity to work from home, which had traditionally been the domain of white, higher-income office workers (Speroni & Taylor, 2023). The stark and sudden nature of the workplace changes caused by the pandemic may have thus extended the opportunity to WFH to a wider range of workers. The measure we use for approximating the number of jobs able to be completed remotely does not account for worker wage or race, both of which our model accounts for at the block group level. The remote work, low-wage, and worker of color coefficients in our change model collectively suggest that a substantial increase in working from home – particularly among workers less likely to WFH prior to the pandemic – has in turn affected the timing of afternoon trip-making.

There are other possible explanations for this relative shift toward early PM peak trip-making and other ways of assessing the changes. This analysis examined trip origins; a similar analysis could examine trip destinations. We briefly explored this option and found that trip destination patterns roughly mirror those of trip originations, but further research could explore this in greater depth. Further, people could have replaced fewer, longer trips with relatively more, shorter trips. We also explored—and dismissed—this possibility because trip lengths were largely stable between the two time periods. In comparison, by October 2021 trip origination and destination counts recovered to 85 percent of October 2019 levels; similarly, vehicle miles traveled recovered to 93 percent. Further research could explore how and why these recoveries differed.

These patterns—especially the shift toward earlier afternoon travel—deserve careful attention as the pandemic becomes endemic. If these patterns hold, transportation professionals should consider several policy implications. Transportation planners and engineers have long sought to address temporal and directional peaking of travel through a variety of means, including traffic signal timing, time-of-day parking restrictions, high-occupancy vehicle lanes, variable road tolls and transit fares, directional capacity shifting (such as with zipper lanes), and commuter-oriented transit services. An earlier and longer PM peak requires reevaluating how we plan, time, and deploy these various approaches. This temporal shift in peak period travel has also illuminated the importance of schools to transportation systems. At the end of the day, adult workers often trickle out of offices and other workplaces gradually—if they commute to work at all. Yet most primary- and secondary-school students depart school buildings upon being dismissed by a uniform bell, and these pulses have ramifications for transportation systems. Many planners and policymakers may fail to consider these pulses, instead emphasizing workers commuting during the traditional 5 PM peak.

Temporal shifts away from traditional peak periods may bode poorly for public transit. Transit competes most effectively with private vehicles for trips into and out of large employment centers, like downtowns, where parking is scarce and expensive. In such places, concentrated passenger demand justifies frequent service, which lowers average wait times, which then attracts more riders (Manville et al., 2018). Additionally, for people motivated to ride transit to avoid sitting in traffic, diminished or spread peak period traffic delays may draw them off transit and into cars and onto (somewhat) less congested roads (Downs, 2005). If the number of trips to and from downtowns and other job centers remains depressed post-pandemic, frequent peak period transit service becomes harder to justify. In such a case, peak hour, peak direction transit demand and service supply could enter a downward spiral (Ansari Esfeh et al., 2021). On the other hand, the marginal cost of accommodating peak period, peak direction transit demand has long been very high, as new vehicles and workers are typically required that operate for just a few hours each day (Taylor et al., 2000). Thus, the temporal and spatial "flattening" of transit demand could conceivably shift transit service in ways that reduce costs to a surprising degree.

Finally, the overarching question raised by this analysis is whether these temporal changes in daily travel patterns are transient or long-lasting. Comparative analyses of pre-, during, and post-pandemic travel data can shed light on this issue, and passively collected data hold promise for such analyses given their prompt availability. However, researchers must be careful about conducting longitudinal analysis with passively collected data, as these data sources may not remain consistent over time (Ullrich, 2023).

CRediT authorship contribution statement

Samuel Speroni: Conceptualization, Methodology, Formal analysis, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Fariba Siddiq:** Conceptualization, Formal analysis, Writing – original draft, Writing – review & editing. **Julene Paul:** Conceptualization, Writing – original draft, Writing – review & editing. **Brian D. Taylor:** Conceptualization, Resources, Writing – original draft, Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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