Title
A Forever Shift or Just a Blip? Gauging the Impact of Pandemic Induced Flexibility on Activity Patterns, Spatial Habits, and Schedule Habits.

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Publication Date
2024

Peer reviewed|Thesis/dissertation

A Forever Shift or Just a Blip? Gauging the Impact of Pandemic Induced Flexibility on Activity Patterns, Spatial Habits, and Schedule Habits.

By

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A dissertation submitted in partial satisfaction of the

requirements for the degree of

Doctor of Philosophy

in

Engineering - Civil and Environmental Engineering

in the

Graduate Division

of the

University of California, Berkeley

Committee in charge:

Professor Joan Walker, Chair
Professor Marta Gonzàlez
Professor Sofia Villas-Boas

Summer 2024

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Abstract

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Doctor of Philosophy in Engineering - Civil and Environmental Engineering

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The COVID-19 pandemic sparked a significant shift in how we work and shop, resulting in wide adoption of remote work and e-commerce. These changes led us to rethink various aspects of our lives, including our living environments, work practices, consumption patterns, and time allocation patterns, among others. The pandemic thus provides a unique opportunity to examine research questions surrounding the adaptability of human behavior and the potential for lasting change in the aftermath of such a global crisis.

The primary aim of this dissertation is to gauge the impact of pandemic-induced flexibility on activity patterns, spatial habits, and schedule habits, exploring whether the changes observed during the COVID-19 pandemic represent permanent shifts or only temporary adjustments. I do this through:

- Collecting a comprehensive, longitudinal national dataset tracking the multifaceted impacts of the pandemic on human behavior, attitudes, and beliefs, using a mix of passive and active data collection methods.

- Proposing a new metric that captures individual schedule regularity over time, while accounting for specific day-of-week characteristics.

- Developing an analytical framework that recognizes the multifaceted nature of impacts of the COVID-19 pandemic and its associated relaxation of spatio-temporal activity constraints on travel behavior, and distinguishes the nature of such impacts across activity patterns, spatial habits, and schedule habits.

- Evaluating the impact of telecommuting, as a key characteristic of the lifestyle changes ushered by the COVID-19 pandemic, on time-use and the diversity of locations visited.

Methodological Contributions

Human mobility has been repeatedly shown to be regular and predictable, as a result of both internal (e.g. circadian rhythms, psychological traits, sociodemographic characteristics, etc.) and external constraints (e.g. commuting requirements, social responsibilities, etc.). Such regularity has been shown to have significant impacts, such as increased social contact rates and playing a significant role in disease spreading. The relaxation of spatio-temporal constraints around key activities during the COVID-19 pandemic indicates a potential reshaping of such regularity and predictability. For example, as employees enjoy more autonomy on their preferred work environment and their schedules, including when to work and on what days to commute, it is reasonable to hypothesize that they would exhibit more irregular schedules, flexibly adjusting their activities to meet their own needs; running errands during regular business hours when work demands are not intense, and following working routines that might be synchronous with colleagues from different time zones. While intrapersonal variability in travel behavior is extensively researched by transportation researchers, such research has often addressed variability in mode use, trip frequency, distance traveled, or activity time use, leaving a missing gap in understanding schedule variability. Further, such research does not account for day-of-week characteristics, despite such consideration being important since outside societal obligations and constraints are usually tied to specific days of the week. In Chapter 3, I build on the extensive intrapersonal travel variability literature by proposing a new metric that captures the intrapersonal schedule similarity across weeks. This metric measures schedule regularity by computing the cosine similarity between the time allocation vectors of each individual for specific days of the week (i.e. Monday, Tuesday, etc.) across several weeks. In doing so, I control for characteristics of specific days of week, such as outside social constraints common to same day of the week. We use this metric to evaluate how the COVID-19 pandemic and the associated spatio-temporal activity constraints affected schedule similarity.

Empirical Contributions

Dataset

Transportation researchers have tried to understand how the COVID-19 pandemic impacted different aspects of travel behavior. However, most of this research is cross-sectional, does not capture non-transportation factors that can influence travel behavior, and uses either active (survey) data or passive data, limiting our collective ability to understand the dynamic and interrelated impacts surrounding the pandemic. In Chapter 2, I present the design and implementation of a study aiming at the collection of data tracking the state of people throughout the COVID-19 pandemic in the U.S. I, along other collaborators, collected a rich panel dataset combining both active survey data and passive data from U.S. residents between January 2020 and September 2022. The fusing of the longitudinal active and passive data helps overcome the limitations of active or passive data when used individually and limitations posed by cross-sectional dataset and allows important research questions to be answered; for example, to determine the factors underlying the heterogeneous behavioral responses to COVID-19 restrictions imposed by local governments. The passive dataset overcomes provides a continuous stream of human mobility, compared to only location traces associated with cell phone activity, or use of specific applications, financial transactions, or transit services. This dataset complements existing datasets by: 1) combining large scale detailed passively collected data with a smaller subset of actively collected survey data, 2) designing a survey that covers broader aspect of participants life and behavior including personality traits, political views, and vaccination intention and status, 3) deploying multiple survey throughout the COVID-19 pandemic to overcome the limitations of cross-sectional studies, 4) deploying the survey to participants across the US, and 5) making our collected data accessible to other researchers. We acknowledge, however, that by being broader than other studies, we might not be able to capture deeper information on any singular aspect of human life during the pandemic. This dataset was the foundation of the remaining research presented throughout this dissertation, and supported other studies by several researchers.

Impact of COVID-19 on Activity Patterns, Spatial Habits, and Schedule Habits

One of the key COVID-19 impacts was the relaxation of spatio-temporal constraints of key activities, notably work and shopping, allowing for greater flexibility in work hours, work locations, and consumption mediums. Such shift can disrupt the historically documented regularity of human mobility, opening up the potential for a wide array of impacts. These include changes in frequency, range, and time, as well as the diversity of travel destinations and schedules. Yet, much of the existing research has been limited to examining narrow aspects of the pandemic's impact on activity pattern, often considering only short-term impacts. In Chapter 3, I propose a framework that evaluates the impacts of the COVID-19 pandemic and its associated relaxation of spatio-temporal constraints around key activities on multiple aspects of activity patterns, and whether such impacts are temporary or permanent. I relied on well-documented metrics from both the traditional travel behavior literature (i.e., trip frequency, dwell-time, trip-timing) and "mobility science" literature (i.e., radius of gyration, location entropy, exploration rate) to evaluate the COVID-19 impact on activity patterns and spatial habits. I also proposed a new metric to measure schedule habits by computing the cosine similarity between the time allocation vectors of each individual for specific days of the week (i.e. Monday, Tuesday, etc.) across several weeks. The analysis results reveal a mixed picture; while some metrics have reverted to their pre-pandemic baselines, others have not. Regarding the schedule habits, we observe a paradox, that while large sectors of the workforce have shifted towards flexible work arrangements, schedule habits have strengthened rather than weakened.

Impact of Telecommuting on Out-of-home Nonwork Time-use and Diversity of Visited Locations

Recognizing the persistence of telecommuting well beyond the COVID-19 pandemic, I quantify the impact of telecommuting on time-use at out-of-home nonwork locations and the diversity of locations visited in Chapter 4. This analysis is motivated by the well-documented research that demonstrates the strong links between well-being and both the amount of time spent in out-of-home nonwork locations, and the diversity of such locations. I use quasi-experimental designs and the fused passive and active dataset described in Chapter 2 to control for unobserved individual confounders, thereby overcoming limitations of majority of existing research relying on cross-sectional observational data. Further, I build on current studies by assessing the impact of telecommuting on weekly time-use, moving beyond the conventional focus on daily time-use. I find evidence that during pre-pandemic, individuals spend an average of 114 minutes at out-of-home nonwork locations on telecommuting days relative to commute days, dropping significantly to approximately 64 minutes in the early phases of the pandemic, and slowly recovering to approximately 119 minutes post pandemic, or pre-pandemic levels, with the largest share ($\approx 85\%$) of this time spent at discretionary locations. Further, I do not find evidence that this increase in time use on telecommuting days at out-of-home nonwork locations is additive at the weekly level, with this time being shifted from other days of the week. In terms of the diversity of locations visited, I find evidence suggesting that an additional day of telecommuting results in an average reduction of 0.35 in the number of unique out-of-home nonwork locations visited, split unevenly between discretionary (0.23) and maintenance (0.13) locations. These results contribute to the large body of evidence on the documented impacts of telecommuting on travel behavior and help further bridge the gap between travel behavior and causal inference.

Summary

In conclusion, this dissertation aims to understand the dynamic impacts of the COVID-19 pandemic on activity and travel patterns. Methodologically, I build on the set of existing methods aiming to understand intrapersonal travel behavior variability by proposing a new metric that captures individual schedule regularity over time. Empirically, we collect a unique national, longitudinal, dataset mixing both passive and active data collection methods tracking the state of people throughout the COVID-19 pandemic. I analyze this dataset to evaluate the impacts of the COVID-19 pandemic on activity patterns, spatial habits, and schedule habits, relying on well-documented metrics from the travel behavior and mobility science bodies of literature. Finally, I use causal inference methods to evaluate the impact of telecommuting on workers time use and diversity of locations visited.

Findings from this research reflect the dual nature of travel behavior following the COVID-19 pandemic, illustrating a balance between behavioral inertia and adaptability to a new post-pandemic world. First, within the framework proposed in Chapter 3, I find that while some mobility metrics have returned to their pre-pandemic baselines as early as 2021 (Weekly trips, Radius of Gyration, Share of peak trips, exploration rate) as people started emerging out of pandemic-induced lockdowns, other mobility metrics have yet to reverse to pre-pandemic baselines (At-home dwell time, location entropy), with people spending on average more time at home and visiting a less diverse set of destinations. Perhaps most interestingly, we find that despite the relaxation of spatio-temporal constraints of key activities, schedule habits have strengthened as opposed to weakened. This finding is striking, going against our initial hypothesis, and possibly that of many other researchers, that the flexibility induced by the COVID-19 pandemic will result in people exhibiting less regular schedules. Finally, in my analysis of telecommuting, I find that while telecommuting results in an increase in time-use at out-of-home nonwork locations on telecommute days, relative to commute days, such increase only represents a shift of time allocation at out-of-home nonwork locations across days of the week. Going beyond time use, I also find that telecommuting results in workers visiting less unique locations. Collectively, the findings reveal a complex picture of how the COVID-19 pandemic, and its associated relaxation of spatio-temporal activity constraints, has impacted activity patters, spatial habits, and schedule habits, with such impacts being neither fully temporary nor completely new.

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Acknowledgments

As I close up my graduate studies, I reflect on these past few years and find myself grateful. I am grateful to have had the opportunity to complete my doctoral studies at such a special place and surrounded by brilliant and kind-hearted individuals. Despite my name being at the front of this dissertation, I am grateful for the numerous people, without whom, this research would never see the light of day.

First of all, I am grateful for my advisor, Joan Walker. Joan, you have been such an impactful person in my life, it gets hard to express it in words. Your constant support and encouragement is everything any graduate student could dream of. Thank you for helping me shape the way I think about research, for allowing me to pursue research I am interested in and for teaching me to be patient with it when it in those difficult times. Beyond everything else, thank you for cheering on me during the many ups and downs of this journey.

I owe a debt of gratitude to my doctoral committee. To Marta, your mastery of our subject matter is astounding. Thank you for challenging me with thought-provoking questions that pushed my research further, for introducing me to key literature that shaped my understanding, and for your insightful feedback during our many discussions. To Sofia, my appreciation knows no bounds. Your incredible attention to detail has significantly improved the quality of my work. I'm deeply grateful for your generosity with your time, whether in lengthy discussions that helped clarify my ideas or in your thorough reviews of my drafts.

I am grateful to all the colleagues who became the closest of friends during this journey. To the homie Hassan, I am forever grateful for being able to go through this journey with you. Thank you for pushing me to be better every day, and thank you for the great times we've had during this journey, from DC to San Diego. To Teddy, thank you for the good times we shared, and by good times I mean all times. To Tim, thank you for being real, all day everyday. To the masters friends: Andrew, Jessica, Catalina, and Jason, thank you for the amazing times we had! To the 116 crew; Juan, Anu, Alex, Carlos, Qianhua, Phoebe, and Aqshems, thank you all for the stimulating conversations and lovely work environment, I am extremely happy to have been part of the group.

I am grateful to my family. What is one without family? To my parents, Khadija and Omar, I would never be who I am without you. Thank you for supporting me through this long and difficult journey. Thank you for letting me follow my own path, despite it meaning that it will take me away from you and from home. Most importantly, thank you both for sacrificing so much to give me whenever I needed it. To grandma Fatima and Zahra, thank you for always praying for me and for being the most amazing source of light and inspiration in my life.

Finally, and most importantly, I am forever grateful to my life partner, Kat. I am forever grateful to you for accompanying me through this crazy journey/ More than that, I am grateful for your accompanying me through life. Thank you for seeing in me what I do not see in myself, and for always having my back. Thank you for being patient with me when you did not have to. None of this would have been possible without you.

Chapter 1

Introduction

Starting my doctoral studies at the height of the COVID-19 pandemic felt like stepping onto a roller coaster blindfolded, not knowing when the next twist would come. There I was, all ready to dive deep into my research and eager to exchange ideas with peers and mentors face-to-face. Instead, I found myself navigating through a series of virtual mazes, trying to make meaningful connections through a screen. The vibrant campus life I had envisioned was replaced by my own four bedroom walls, and the spontaneous department hallway chats that could spark new ideas were now just scheduled video calls that somehow always started or ended with, "Can you hear me? Ah! sorry I was on mute." The excitement of attending research conferences was also "Zoomified", where interactions were as likely to be interrupted by a bad connection as by a thought-provoking question.

Even with the pandemic throwing curveballs left and right, I embraced resilience, weaving through the pandemic with grit. Social apps became spaces where casual hangouts weren't just possible but were the main event. I reconnected with old friends and family members I hadn't spoken to in ages, and we'd gather in these digital rooms to simply "chop it up." These sessions, filled with laughter, shared memories, and the venting about pandemic life, became a cherished part of my routine. On a personal note, I also found solace in the kitchen, where cooking and baking became my new mindfulness practice. Experimenting with recipes became a form of creative expression and a way to physically engage with the world around me. This blend of virtual connection and culinary exploration helped balance the scales, reminding me that peace can be found in the midst of chaos.

As the pandemic stretched on from weeks, into months, and then into a seemingly indefinite state, it forced a deep introspection about my core values and lifestyle choices. Questions began to swirl in my mind with more intensity: "If flexible work is here to stay, should I relocate to a different region in the country?" This thought was quickly followed by concerns about the potential trade-offs: "Would such a move enhance my creativity and productivity, or would it diminish the vibrancy and stimulation I draw from living in a vibrant urban center?" Another consideration emerged around social interactions: "In a world where virtual connections are predominant, how much value should I place on physical proximity to friends and family?" Similarly, mundane tasks like grocery shopping came under scrutiny: "Is the convenience of online shopping a better use of my time?" In fact, it wasn't just me wrestling with such questions. Everywhere, individuals were reassessing what truly mattered to them, spurred by the realization that the world might never revert to its pre-pandemic state. These reflections were not just thought, but rather catalysts for significant life changes. Friends and acquaintances began making bold decisions, like relocating to quieter, more rural areas. Others chose to pivot careers entirely, seeking fulfillment in professions that offered more purpose or better work-life balance. The pandemic, in all its disruption, became a crucible for reevaluation, prompting a widespread reimagining of how we live, work, and connect.

Despite the individuality of each person, human mobility was repeatedly shown to follow regular and predictable patterns (Gonzalez et al. 2008; Song, Qu, et al. 2010). This includes, the probability of traveling a certain distance, the way we allocate time across space, and the tendency to explore new locations at a constant rate (Gonzalez et al. 2008; Song, Qu, et al. 2010; Alessandretti, Lehmann, et al. 2018; Pappalardo, Simini, et al. 2015). Such regularity is a result of both internal (e.g. circadian rhythms, psychological traits, sociodemographic characteristics, etc.) and external constraints (e.g. commuting requirements, social responsibilities, etc.) and has been shown to have significant impacts, such as increased social contact rates and playing a significant role in disease spreading, and have been at the core of transportation planning. The COVID-19 pandemic disrupted such regularity primarily as a result of the wide adoption of telecommuting and e-commerce. With more autonomy on their work location and work schedules, it is easy to imagine how workers can adjust how, when, and where they schedule their activities to meet their own needs; choosing to work from different locations, adjusting their schedule to run errands during regular business hours when work demands are not intense, and following working routines that might be synchronous with colleagues from different time zones.

As a result of these observations, the primary aim of this dissertation is to gauge the impact of pandemic-induced flexibility on activity patterns, spatial habits, and schedule habits, exploring whether the changes observed during the COVID-19 pandemic represent permanent shifts or only temporary adjustments. I do this through:

- Collecting a comprehensive, longitudinal national dataset tracking the multifaceted impacts of the pandemic on human behavior, attitudes, and beliefs, using a mix of passive and active data collection methods.
- Proposing a new metric that captures individual schedule regularity over time, while accounting for specific day-of-week characteristics.
- Developing an analytical framework that recognizes the multifaceted nature of impacts

of the COVID-19 pandemic and its associated relaxation of spatio-temporal activity constraints on travel behavior, and distinguishes the nature of such impacts across activity patterns, spatial habits, and schedule habits.

- Evaluating the impact of telecommuting, as a key characteristic of the lifestyle changes ushered by the COVID-19 pandemic, on time-use and the diversity of locations visited.

In the following sections of this chapter, I outline the motivations behind each study conducted within this dissertation, detailing the research methodologies employed and how each study overcomes existing limitations and builds upon current studies. Next, I provide an overview of the dissertation's diverse contributions, both methodological and empirical. To conclude, I describe how the rest of this dissertation is organized.

1 Tracking the state of people

Impacts of the pandemic such as loss of life, persistent health effects, changes in levels of employment and economic activity, and even changes in mobility, education, and civic and political engagement have been heavily documented. Such impacts have proven to be dynamic, apply at multiple spatial scales, and unevenly distributed across individuals and space. In response, both our individual and collective responses to them follow suit. This necessitated the importance of being comprehensive in the outcomes considered and how they change over time.

Transportation researchers explored the impact of the pandemic on the number of trips (Abdullah et al. 2020; Beck et al. 2020; Fatmi 2020), mode use and mode shift (Abdullah et al. 2020; Beck et al. 2020; Bucsky 2020; Haas et al. 2020; Shamshiripour et al. 2020; Eisenmann et al. 2021; Shakibaei et al. 2021; Meister et al. 2022), trip purpose (Abdullah et al. 2020; Beck et al. 2020; Haas et al. 2020; Parady et al. 2020), distance traveled (Abdullah et al. 2020; Fatmi 2020; M. Lee et al. 2020; Molloy, Tchervenkov, et al. 2020), public transit and active transportation (Jenelius et al. 2020; Nikiforiadis et al. 2020; Pawar et al. 2020; Teixeira et al. 2020; Chang et al. 2021; Dong et al. 2021; Eisenmann et al. 2021; Hu et al. 2021; Przybylowski et al. 2021), commuting behavior (Abdullah et al. 2020; Pawar et al. 2020; Shakibaei et al. 2021; Matson et al. 2021), time spent traveling (Borkowski et al. 2021), and driving behavior (Katrakazas et al. 2020). Collectively, the research community addressed a wide spectrum of COVID-19 related research questions, though singularly, each study maintained a narrow research scope, limiting our ability to understand and address the complexities created by interrelated impacts surrounding the pandemic.

It is possible that the narrow nature of these studies individually is a result of practical constraints. After all, understanding the complex impacts of the pandemic requires collecting extensive data on multiple aspects of human life. While surveys have historically been popular in collecting behavioral data, they pose significant burden on participants, an aspect critical to minimize when researchers try to capture high quality, detailed, comprehensive behavioral information over time. The adoption of smartphones helps cover and While detailed travel diaries have been the most widely used approach for collecting data, they pose significant participation burden and suffer from memory recall issues that lead to misreporting of behaviors (Janzen et al. 2018).

Thanks to technological advances of recent decades, extensive, long-term data can now be collected from smartphones and other distributed sensor systems. As a result, we now passively generate large amounts of data of our GPS traces, smartphone use behaviors, financial transactions, physical activities, to name a few. These data help address issues often present across survey datasets by allow for detailed, uninterrupted data collection with little to no burden on participants. As a result, these data can be used to understand human behavior at deeper levels than ever before. Despite these advantages, these data themselves can still suffer from some limitations. For example, passive data is often limited to what can be collected automatically, often lacking individual level socio-demographics and unable to capture the nuanced reasons behind people's actions. This limitation is particularly relevant in contexts where it is critical to understand the 'why' behind the 'what'. As a result, requiring direct input from participants through surveys becomes necessary.

By leveraging both passive and active data sources, researchers can have the best of both worlds, combining the breadth of information captured through passive means with the depth of understanding that comes from direct participant feedback, thereby enabling researchers to develop a richer, more nuanced understanding of complex behaviors and phenomena. Within the context of the COVID-19 pandemic, all research, with the exception of data collected by Molloy, Castro, et al. (2022) relies on either passive or active data, often in cross-sectional form. Collecting both data types in a longitudinal fashion provides researchers with time-varying information allowing to control for many observed and unobserved confounders when answering questions surrounding the pandemic.

In Chapter 2, we address this gap by designing a study capturing the impacts of the pandemic on several aspects of daily life as well as the longitudinal dynamics in human behavior, attitudes, and beliefs in response to the COVID-19 pandemic, using both passive and active data collection methods. We do so by: 1) combining large scale detailed passively collected data with a smaller subset of actively collected survey data, 2) designing a survey that covers broader aspect of participants life and behavior including personality traits, political views, and vaccination intention and status, 3) deploying multiple survey throughout the COVID-19 pandemic to overcome the limitations of cross-sectional studies, 4) deploying the survey to participants across the US, and 5) making our collected data accessible to other researchers. This mix of active and passive data collection methods, gathered over several waves and covering a range of domains, stands in contrast to the majority of pandemic-related studies that have been more narrowly substantively focused and have made use of either active or passive data collection, but rarely both. Additionally, our data reflects the different scales at which behavior can be influenced; from the individual to the regional scale, making our data collection consistent with socio-ecologic approaches to understanding human behavior. Our data's coverage of several domains is useful in addressing interdisciplinary questions and is the result of collaboration between transportation and non-transportation researchers. A holistic retrospective understanding of the impacts of the COVID-19 pandemic is fundamental to an effective management of the current state of the pandemic as well as future pandemics. More broadly, the development of this data infrastructure will help researchers explore frontiers in behavioral science useful in the management of large-scale disasters.

The passive mobility data has been collected since January 2020 and throughout the COVID-19 pandemic. Our longitudinal survey consisted of six survey waves between August 2020 and September 2022. The dataset includes approximately 5900 responses from 2655 individuals, some of which only participated in some survey waves due to the nature of the panel. The response rates of each of the survey waves varied between 2% and 51%, with low response rates occurring on waves targeting a large sample of panelists. Our survey of survey incompletion patterns provides key insights on the importance of survey design for participant retention, as we observe a significant share of survey abandonment occurring at sections not properly suitable for display on smartphone screens.

2 Activity Patterns, Spatial Habits, and Schedule Habits

There is significant empirical evidence showing that human mobility exhibits high levels of regularity and predictability (Song, Qu, et al. 2010; Schneider et al. 2013; Lu et al. 2013; Cuttone et al. 2018). At the same time, human mobility and its regularity are intricately linked to the many constraints one faces (Aubourg et al. 2020; K. Zhao et al. 2016; Susilo and Axhausen 2014). For instance, transit accessibility, work schedules, and caregiving responsibilities play critical roles in shaping one's travel decisions (e.g. commute timing, frequency, etc.) and their long-term regularity. As a result, such regularity and predictability is useful in the proper planning for transportation infrastructure (Gonzalez et al. 2008), and beyond, playing a role in explaining social contact rates (Leng et al. 2021) and disease spreading mechanisms (Pappalardo, Simini, et al. 2015).

However, the COVID-19 pandemic has potentially reshaped this landscape. A case in point is the growing adoption of hybrid work models, which liberate individuals from traditional spatio-temporal work constraints. Remote and hybrid employees enjoy more autonomy on both their work environment and work schedules (Caros et al. 2023). Further, large shares of workers favor more flexible work arrangements in a post-pandemic world (K. Parker et al.

2021; Alexander et al. 2021). As a result of this shift, beyond its immediate effects on activity patterns, people could start exhibiting new spatial exploration patterns and less structured activity schedules. The persistent preference for hybrid working models and e-commerce by employees and consumers well beyond the pandemic suggests the possible stickiness of behavioral shifts brought upon by the pandemic (Said et al. 2023; K. Parker et al. 2020; K. Parker et al. 2021).

While there was much interest from researchers on investigating several dimensions such as trip making, mode use, travel distance, among others (Abdullah et al. 2020; Beck et al. 2020; Molloy, Tchervenkov, et al. 2020; M. E. Parker et al. 2021; Shakibaei et al. 2021; Luo et al. 2023), much of the research has been myopic to the broader impacts of the COVID-19 pandemic on human mobility, focusing on singular aspects of travel behavior. Second, much of the research addressed short-term impacts, with little attention to potential long-term impacts, indicating our lack of collective understanding of what a post-pandemic landscape world shape up to be. Most importantly, investigating the impacts the COVID-19 pandemic and its associated relaxation of spatio-temporal constraints on schedule habits remains missing. Improving this understanding is critical to transportation planning in a post-pandemic world, as behavior and demand predictability are important to transport planning.

In Chapter 3, I propose a framework that goes beyond investigating the impact of the COVID-19 pandemic on traditionally reported mobility metrics, and extends to metrics that capture spatial and schedule habits. I use this framework to answer two key questions: 1) Are post-pandemic mobility behaviors are different their pre-pandemic baselines, and 2) whether post-pandemic mobility behaviors exhibit stability. I suggest that the relaxation of spatio-temporal constraints following the COVID-19 pandemic have a broader influence on mobility behavior, affecting not just activity patterns, but also spatial and schedule habits. I rely on well-established mobility metrics characterizing human activity patterns, namely frequency of travel, radius of gyration, dwell-time, trip timing, spatial exploration, and spatial diversity (as measured by entropy). Additionally, I propose a new metric to measure individual schedule regularity across weeks, contributing to the literature on intrapersonal travel behavior variability. I hypothesize that with the relaxation of spatio-temporal activity constraints during the COVID-19 pandemic, people will exhibit less schedule regularity post-pandemic compared to pre-pandemic. I use passive mobility tracking dataset from a panel of approximately between January 2020 and September 2022 to attempt to address these limitations. In doing so, I shed light on the long term impacts of the pandemic on travel behavior, providing more clarity on what a "new normal" is shaping up to be.

Our findings present a mixed picture; while several mobility indicators have recovered to their pre-pandemic levels (trip frequency, radius of gyration, peak period demand), others have not (i.e. at home dwell-time). I find that while people's explorative behavior recovered to their pre-pandemic levels, they exhibit on average lower diversity (as measured by entropy) in their time distribution across space compared to pre-pandemic. Finally, I find evidence that despite the loosening of spatio-temporal activity constraints during the pandemic, schedule habits strengthened compared pre-pandemic, presenting a counterintuitive picture to our initial hypothesis.

3 Role of Telecommuting

Despite telecommuting gaining massive popularity across different sectors of the workforce during the COVID-19 pandemic, its origins date back to the 1970s oil crisis, where it was considered as a tool to reduce demand and ease pressures on the commodity's price. Since then, there has been significant interest among transportation researchers on telecommuting, along with its impacts. With a series of work concluding its effectiveness as a cheap and easy to implement travel demand management strategy (Kitamura, Mokhtarian, et al. 1991; Koenig et al. 1996; Mokhtarian 1998; Choo et al. 2005; Kim et al. 2015; Kim 2017; Obeid, M. L. Anderson, et al. 2024; Wang 2023). Beyond eliminating the need to commute, telecommuting has the potential to reshape other aspects of travel behavior, reshaping activity participation patterns, consumption patterns, time-use patterns. Since previous research, rooted in the activity-based approach of travel demand modeling, has established the connection between time-use and diversity of locations visited on one hand and well-being on the other (Archer et al. 2013; Krueger et al. 2009; Bergstad et al. 2012; Ettema et al. 2010; Kahneman et al. 2004; J. K. Stanley et al. 2011; J. Stanley et al. 2011; Alessandretti, Lehmann, et al. 2018), policymakers should look beyond the environmental impact of telecommuting, as such benefits could come at the cost of deteriorating our societal well-being (Gärling et al. 2002). This becomes especially relevant as telecommuting as the child of the COVID-19 pandemic, is here to stay, with 26% of U.S. workers expecting to telecommute at least a few times a week beyond the pandemic, compared only to 13% before the pandemic (Salon et al. 2021).

Given the established correlations between well-being and out-of-home time-use and the diversity of visited locations, I quantify the impact of telecommuting on both metrics in Chapter 4. While many studies have explored similar topics and presented significant insights on the impacts of telecommuting on non-commute activity participation and time use, they often suffer from limitations. First, none of the reviewed research investigates the impact of telecommuting on the diversity of visited out-of-home nonwork locations. Second, majority of the research does not account for or control for any unobserved confounding or self-selection problems, primarily because it relies cross-sectional datasets (e.g.: household travel surveys, time use diaries), Other researchers have tried to address these limitations using instrumental variable approaches, propensity score matching, or endogenous-switching modeling approaches, but such approaches either make strong assumptions or only adjust for observable biases. Fourth, time-use focused research does not capture weekly behaviors, possibly resulting in biased findings as the result of the use of single day data. Fourth, majority of the research relies on self-reported behavioral measures, making it prone to errors due to self-reporting biases. Fifth, our current understanding of the impacts of telecommuting is from before COVID-19 pandemic, when telecommuting was less prevalent, making it necessary to update revise such findings to reflect post-pandemic context. Finally, there is inconsistency in the populations of interest across studies, making their findings less comparable and less generalizable to the entire workforce. I overcome these limitations by: 1) relying on a panel dataset and a quasi-experimental design (i.e. fixed effects and first-differences) to account for unobserved confounding, 2) using passively tracked data to avoid self-reporting and recall biases, 3) answering the questions within the COVID-19 context, with telecommuting rates at all-time highs, hence provide more generalizable and time relevant results on the impacts of telecommuting.

On time use, I find strong evidence that workers spend significantly more time at out-of-home nonwork locations, relative to commute days. This effect is unequally divided between discretionary and maintenance activities and fluctuates throughout the COVID-19 pandemic. Furthermore, I do not find evidence for such effect to be additive. In other words, this increase in time spent at out-of-home nonwork locations is shifted from other days of the week, with the effect of an additional day of telecommuting on the total weekly time-use at out-of-home nonwork locations being null. On the number of unique nonwork locations visited, I find strong evidence suggesting that an additional day of telecommuting results in an average decrease of 0.35 in the number of unique locations visited, unequally distributed between discretionary and maintenance locations.

4 Contributions

In aiming to gauge the impact of pandemic-induced flexibility on activity patterns, spatial habits, and schedule habits, this dissertation a variety of contributions, both methodological and empirical contributions:

I, along other collaborators, collected a rich panel dataset tracking the state of people throughout the COVID-19 pandemic in the U.S., combining both active survey data and passive data from U.S. residents between January 2020 and September 2022. The fusing of the longitudinal active and passive data allows important research questions to be answered; for example, to determine the factors underlying the heterogeneous behavioral responses to COVID-19 restrictions imposed by local governments. This dataset complements existing datasets by: 1) combining large scale detailed passively collected data with a smaller subset of actively collected survey data, 2) designing a survey that covers broader aspect of participants life and behavior including personality traits, political views, and vaccination intention and status, 3) deploying multiple survey throughout the COVID-19 pandemic to overcome the limitations of cross-sectional studies, 4) deploying the survey to participants across the US, and 5) making our collected data accessible to other researchers. Beyond being the foundation of research studies presented throughout this dissertation, this dataset supported a variety of other studies, including M. E. Parker et al. (2021), Obeid, M. L. Anderson, et al. (2024), and Obeid, M. Anderson, et al. (2024).

I propose a framework that evaluates the impacts of the COVID-19 pandemic and its associated relaxation of spatio-temporal constraints around key activities on activity patterns, spatial habits, and schedule habits. I relied on well-documented metrics from both the traditional travel behavior literature (i.e., trip frequency, dwell-time, trip-timing) and "mobility science" literature (i.e., radius of gyration, location entropy, exploration rate) to evaluate the COVID-19 impact on activity patterns and spatial habits. Within this framework, I make a methodological contribution, by proposing a new metric to measure schedule habits while controlling for specific days of the week (i.e. Monday, Tuesday, etc.) across several weeks.

Recognizing the persistence of telecommuting well beyond the COVID-19 pandemic, I use quasi-experimental design to quantify the impact of telecommuting on time-use at out-of-home nonwork locations and the diversity of locations visited. This analysis builds on the large body of literature on the impact of telecommuting on daily time-use by addressing the self-selection and unobserved confounding issues often present in existing literature through the use of a panel dataset. Going beyond daily analyses, I quantify the impact of telecommuting on weekly time-use at out-of-home nonwork locations, an aspect previously unexplored in the literature. Finally, I provide novel evidence that telecommuting reduces the diversity of locations visited, hinting at possible social implications of telecommuting.

5 Dissertation Outline

The dissertation is organized as follows:

Chapter 2 presents the design and implementation of a data collection effort aimed at tracking the state of individuals throughout the COVID-19 pandemic. We present details about the study timeline, the survey design, sampling strategy, and study participation incentives. We provide an overview of key characteristics of our collected data, including socio-demographic characteristics of the sample and study participation statistics such as participation rates, dropout patterns, and results of series of models estimating determinants of participation in the study.

Chapter 3 presents a framework to analyze how the relaxation of the spatio-temporal constraints of key activities, namely work and shopping, has impacted the different facets of human mobility throughout the COVID-19 pandemic. The framework relies on well-established metrics in the transportation literature. This chapter also presents a new metric to evaluate the variability of schedules week-to-week, while controlling for day-of-week characteristics.

Chapter 4 addresses the question identifying the impact of telecommuting on time-use at out-of-home nonwork locations and the number of unique locations visited using a quasi-experimental approach that overcomes limitations of cross-sectional studies.

Lastly, Chapter 5 concludes this dissertation by providing a summary of its motivation, its key findings and contributions, and suggestions for future research directions.

Chapter 2

Tracking the state and behavior of people in response to COVID-19 through the fusion of multiple longitudinal data streams

Abstract

The changing nature of the COVID-19 pandemic has highlighted the importance of comprehensively considering its impacts and considering changes over time. Most COVID-19 related research addresses narrowly focused research questions and is therefore limited in addressing the complexities created by the interrelated impacts of the pandemic. Such research generally makes use of only one of either 1) actively collected data such as surveys, or 2) passively collected data from sources such as mobile phones or financial transactions. So far, only one other study collects both active and passive data, and does so longitudinally. Here we describe a rich panel dataset of active and passive data from US residents collected between August 2020 and September 2022. Active data includes a repeated survey measuring travel behavior, compliance with COVID-19 mandates and restrictions, physical health, economic well-being, vaccination status, and other factors. Passively collected data consists of Point of Interest (POI) check in data indicating all the locations visited by study participants. We also closely tracked COVID-19 policies across counties of residence of study participants throughout the study period. The combination of the longitudinal active and passive data helps overcome the limitations of active or passive data when used individually as well as the limitations posed by cross-sectional dataset and allows important research questions to be answered; for example, to determine the factors underlying the heterogeneous behavioral responses to COVID-19 restrictions imposed by local governments. Better information about such responses is critical to our ability to understand the societal and economic impacts of the COVID-19 pandemic and possible future pandemics. The development of this

data infrastructure can also help researchers explore new frontiers in behavioral science. This article explains how this approach fills gaps in COVID-19 related data collection; describes the study design and data collection procedures; presents key demographic characteristics of study participants; and shows how fusing different data streams helps uncover behavioral insights often difficult to reveal from either data streams individually.

1 Introduction

The impacts of the COVID-19 pandemic are dynamic, apply at multiple spatial scales, and are unevenly distributed across individuals and space. Impacts such as loss of life, persistent health effects, changes in levels of employment and economic activity, and even changes in mobility, education, and civic and political engagement have been documented. This changing nature of the virus and its impacts, and our individual and societal responses to them, have highlighted the importance of being comprehensive in the outcomes considered and how they change over time. To date, however, most COVID-19 related research is cross-sectional and addresses a set of narrow research questions. Further, except for (Molloy, Tchervenkov, et al. 2020), all research makes use of either active (survey) data or passive data. This limits the ability to understand and address the complexities created by interrelated impacts surrounding the pandemic.

While detailed travel diaries have been the most widely used approach for collecting travel behavior data, they pose significant participation burden and suffer from memory recall issues that lead to misreporting and underreporting of trip details (Janzen et al. 2018). Passive data collection methods help resolve these issues and often allow for uninterrupted data collection, with little to no burden on participants. However, passive data often lack individual level socio-demographic data and individual level preferences key to understanding determinants of behavior. Survey data helps in addressing this limitation. Combining the two data types allows to address the shortcomings of the individual data sources. Collecting both data types in a longitudinal fashion provides researchers with time-varying information allowing to control for many observed and unobserved confounders when answering questions surrounding the pandemic.

To address this gap, we designed a study capture the impacts of the pandemic on several aspects of daily life as well as the longitudinal dynamics in human behavior, attitudes, and beliefs in response to the COVID-19 pandemic, using both passive and active data collection methods. This mix of active and passive data collection methods, gathered over several waves and covering a range of domains, stands in contrast to the majority of pandemic-related studies that have been more narrowly substantively focused and have made use of either active or passive data collection, but rarely both. Additionally, our data reflects the different scales at which behavior can be influenced; from the individual to the regional scale, making our data collection consistent with socio-ecologic approaches to understanding human behavior.

Our data's coverage of several domains is useful in addressing interdisciplinary questions and is the result of collaboration between transportation and non-transportation researchers. A holistic retrospective understanding of the impacts of the COVID-19 pandemic is fundamental to an effective management of the current state of the pandemic as well as future pandemics. More broadly, the development of this data infrastructure will help researchers explore frontiers in behavioral science useful in the management of large-scale disasters.

Our passive mobility data has been collected since January 2020 and throughout the COVID-19 pandemic. Our longitudinal survey consisted of six survey waves between August 2020 and September 2022. The dataset includes approximately 5900 responses from 2655 individuals, some of which only participated in some survey waves due to the nature of the panel. The response rates of each of the survey waves varied between 2% and 51%, with low response rates occurring on waves targeting a large sample of panelists.

The purpose of this article is to present the data collection design and summarize characteristics of the sample collected. We leave the in-depth exploration of COVID-19 related research to other research endeavors. For example, as of the writing of this manuscript, our team has used the combination of these two data sources to explore several research questions, including; 1) Understanding the heterogeneous impacts of COVID-19 on multiple dimensions of travel behavior for transit users (M. E. Parker et al. 2021), 2) the causal impact of getting vaccinated on reversing pandemic mobility trends, more specifically whether getting vaccinated increases individuals' travel frequency, increases public transportation use, and encourages a return to in-person work (Obeid, M. L. Anderson, et al. 2024), and 3) quantifying the causal effect of telecommuting on travel behavior, more specifically on the number of trips and distance traveled by individuals at various time scales (Obeid, M. L. Anderson, et al. 2024).

The rest of the article is organized as follows. Section 2 reviews previous data collection efforts surrounding COVID-19 and presents gaps addressed by our data. Section 3 describes the data infrastructure, study design, and adjustments made during the study period. Section 4 presents summary statistics about the data. Section 5 identifies conclusions and lessons gathered.

2 Literature

During the COVID-19 pandemic, many researchers examined the impacts of the virus on numerous aspects of human life, including mental and physical health, the economy, education, mobility, and the environment. Some researchers used actively collected data such as surveys, while others exploited passively collected data including smartphone use data, wearable technology data, and POI data. This section provides an overview of COVID-19 related research in the transportation literature and the data it used.

We mainly used Google Scholar to identify relevant COVID-19 research efforts. We used “COVID-19" and “coronavirus" as the primary keywords to initially identify relevant research, accompanied by other keywords indicating the research focus area (e.g., “travel behavior", “mode use", “driver behavior", “commute", “shared mobility", “e-commerce"). We examined each relevant result to identify the research questions it addressed, whether it summarized the data collection effort it used, the content of the collected data, and whether the authors made their data available to other researchers or the public. In addition to results directly obtained from Google Scholar, we used the snowballing technique to identify other COVID-19 related research efforts.

Transportation researchers addressed a variety of COVID-19 related research questions. Researchers explored the impact of the pandemic on the number of trips (Abdullah et al. 2020; Beck et al. 2020; Fatmi 2020), mode use and mode shift (Abdullah et al. 2020; Beck et al. 2020; Bucsky 2020; Haas et al. 2020; Shamshiripour et al. 2020; Eisenmann et al. 2021; Shakibaei et al. 2021; Meister et al. 2022), trip purpose (Abdullah et al. 2020; Beck et al. 2020; Haas et al. 2020; Parady et al. 2020), distance traveled (Abdullah et al. 2020; Fatmi 2020; M. Lee et al. 2020; Molloy, Tchervenkov, et al. 2020), public transit and active transportation (Jenelius et al. 2020; Nikiforiadis et al. 2020; Pawar et al. 2020; Teixeira et al. 2020; Chang et al. 2021; Dong et al. 2021; Eisenmann et al. 2021; Hu et al. 2021; Przybylowski et al. 2021), commuting behavior (Abdullah et al. 2020; Pawar et al. 2020; Shakibaei et al. 2021; Matson et al. 2021), time spent traveling (Borkowski et al. 2021), and driving behavior (Katrakazas et al. 2020).

Out of all the studies we reviewed, only Molloy, Tchervenkov, et al. (2020) used both active and passive data, tracking a sample of Swiss individuals throughout the COVID-19 pandemic. This dataset builds on the data infrastructure established by Molloy, Castro, et al. (2022) and has been used in multiple studies investigating the impacts of the COVID-19 pandemic on overall mobility (Molloy, Schatzmann, et al. 2021; Hintermann et al. 2023), mode choice (Meister et al. 2022), time use (Mesaric et al. 2022; Winkler et al. 2022), and micro-mobility (A. Li et al. 2021), among others. All other reviewed studies have made use of either active or passive data collection methods, with 65% of studies relying on survey/questionnaire data.

Out of the studies using solely survey/questionnaire data collection methods Parady et al. (2020), Shakibaei et al. (2021), Shamshiripour et al. (2020), and Beck et al. (2020) collected longitudinal data over short periods of time throughout the pandemic, Matson et al. (2021) collected longitudinal data before and during the early phases of the COVID-19 pandemic, and Chauhan et al. (2021) collected survey responses across two longitudinal waves all throughout the COVID-19 pandemic.

Studies also vary in their geographical coverage. Approximately 85% of the reviewed covered specific countries or narrower geographical regions. However, Abdullah et al. (2020), Fraiberger et al. (2020), and Katrakazas et al. (2020) collected data from multiple countries around the world.

Studies using passive data had access to large sample sizes, with M. Lee et al. (2020) using aggregate level mobility data from 100 million individuals across the United States (US). Out of the articles, Chauhan et al. (2021), Hu et al. (2021), Zheng et al. (2020), and Molloy, Tchervenkov, et al. (2020) made their data available to other researchers, either readily or by request.

In addition to academic researchers, technology companies collecting mobility data from their users have published it during the pandemic to help researchers and public health experts understand how mobility has changed in response to policies aimed at controlling the spread of the virus. Apple published aggregate (on city, county, and country level) mobility data showing the change in routing requests by travel mode (Walking, Driving, and Transit) compared to the baseline on January 13th, 2020 (Apple 2020). Similarly, Google has published aggregate community mobility reports broken down by types of locations visited throughout the pandemic. Locations tracked include residences, parks, grocery and pharmacy stores, transit stations, retail and recreation, and workplaces (Google 2020). Similarly, Grandata formed a partnership with the UN Development Program to make their mobile user data from 12 countries available to researchers (UNDP Latin America and the Caribbean 2020). In Switzerland, Intervista has conducted a study tracking the mobility changes of approximately 2500 individuals through a smartphone application and made this data available to the public. More specifically, Intervista focused on tracking changes in distances traveled for different activity purposes, mode use, and trip purpose (Intervista 2021).

From this review, we learned the following:

- One out of 27 studies use both active and large-scale passive data collection methods
- Three out of 27 studies are longitudinal, two of which collect data throughout the duration of the COVID-19 pandemic
- Eighteen out of 27 studies have a national or international scope
- Four out of 27 studies make the data available to other researchers either openly or by request

Additionally, the content of the reviewed survey based studies varied and can be summarized as follows:

- Four out of 17 studies asked about safety measures taken by participants during COVID-19
- All 17 studies asked about participants' travel behavior, including travel behavior related attitudes
- Two out of 17 studies asked about participants' household dynamics
- Four out of 17 studies asked about participants economic circumstances
- Two out of 17 studies asked about participants' physical health
- Five out of 17 studies asked about participants' mental health and psychological traits
- Nine out of 17 studies attitudinal views towards COVID-19 and its related restrictions
- All studies collected participants demographic information

Our data complements the reviewed data collection efforts by: 1) combining large scale detailed passively collected data with a smaller subset of actively collected survey data, 2) designing a survey that covers broader aspect of participants life and behavior including personality traits, political views, and vaccination intention and status, 3) deploying multiple survey throughout the COVID-19 pandemic to overcome the limitations of cross-sectional studies, 4) deploying the survey to participants across the US, and 5) making our collected data accessible to other researchers. We acknowledge, however, that by being broader than other studies, we might not be able to capture deeper information on any singular aspect of human life during the pandemic. Section 3 goes into detail about our data collection effort.

3 Study design and administration

3.1 Data infrastructure

We used a combination of data collection methods to develop a database that enables a broad understanding of how COVID-19 has affected people's behavior Figure 2.1. First, we included passively collected data by SimilarWeb, a mobile audience analytics company with a recruited panel representative of US smartphone users, which comprises point of interest (POI) visit information and smartphone app use over time, as well as basic user socio-demographic data. Second, we designed a longitudinal survey to capture a broad snapshot of people's behavior, beliefs, and attitudes in response to COVID-19. Third, given the variety in public health measures enacted in response to the pandemic across the US, we tracked county-level COVID-19 related public health policies. We combined these three data sources to create a dataset that captures a wide spectrum of human activity throughout the COVID-19 pandemic. This dataset can be integrated geographically with other external datasets to address a wider range of questions.

3.2 Study timeline

SimilarWeb started collecting passive data from its panelists in January 2020. We started the survey data collection in early August 2020 and collected five subsequent waves (October 2020, December 2020, April 2021, July 2021, September 2022). Simultaneously, we tracked stay-at-home/shelter-in-place and mask mandate policies across the home counties of study participants. We note that there is no official national dataset tracking the different public health policies enacted in the US. At the time of our initial data collection, however, there were several databases by research groups and non-profit organizations tracking these policies at the state level (Raifman et al. 2020; Foundation 2022). Since then, Ritchie et al. (2021) and MultiState (2021) have published databases on COVID-19 public health policy interventions at both the state and county level.

3.3 SimilarWeb panel and passive data

SimilarWeb allows researchers to target recruited panelists based on criteria of interest. For example, one can target panelists based on their socio-demographic characteristics, geographic location, or their smartphone use behavior. In addition to allowing researchers to collect survey data from its recruited panelists, SimilarWeb also partners with third-party partners to collect POI and smartphone app use data. The POI data includes information critical to inferring daily activities of panelists and understanding their daily travel behavior. These data are not continuously tracked GPS traces, but rather inferred individual check-ins at POIs. SimilarWeb uses proprietary technology from a third-party provider to infer the location category from each of the POIs visited. For each individual check-in at a POI, the dataset includes information about the panelist's arrival and departure times, the category and brand of the location visited, the distance and time traveled to get to said location, the distance of the POI from the individual's identified home and work locations, as well as its zip code, city, and Metropolitan Statistical Area (MSA) name. This data can further be processed to compute specific mobility metrics of interest (e.g., distance traveled for specific purposes or locations, variability in commute time, etc..). While it is possible to collect this data via survey instruments, doing so poses additional burden on participants, especially when collecting multi-day data, and is likely to suffer from biases due to data misreporting. The smartphone app use data provides a longitudinal description of smartphone use behavior for each of the recruited panelists. Each observation represents a smartphone activity and includes information about the app used as well as its duration of use.

3.4 Survey design

We asked study participants about their economic well-being, mental health, physical health, personality type, political orientation, household dynamics, mobility behavior, living conditions, sheltering behaviors, preventative measures taken throughout the COVID-19 pandemic, and additional demographic information not collected by SimilarWeb. In designing

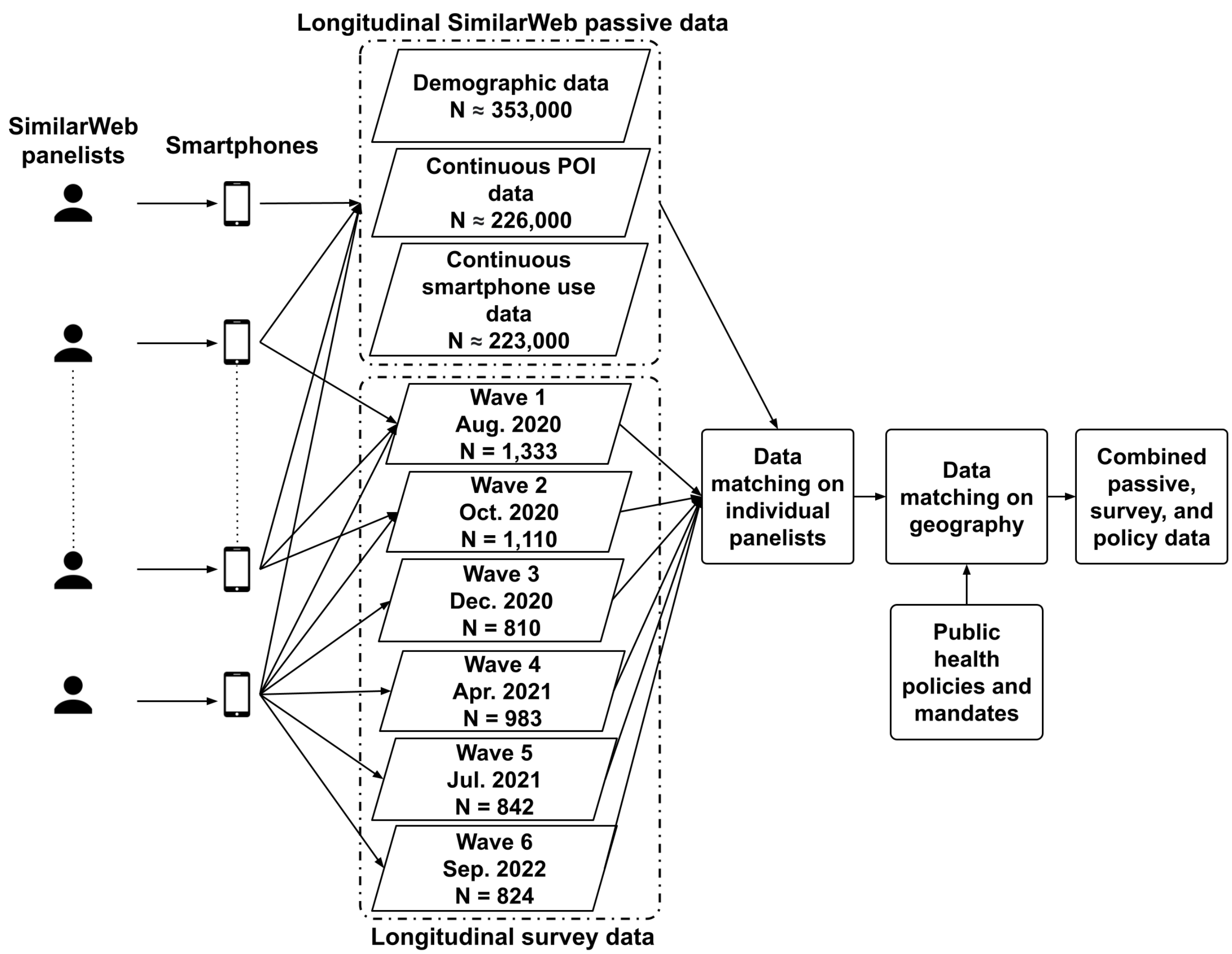

Figure 2.1: Data infrastructure, N indicates the number of unique individuals in the dataset

our survey, we aimed to draw from validated survey questions in the literature and national datasets such as the US Census and the US National Household Travel Survey. As such, our questionnaire contained a mixture of validated and newly developed questions. Table 3.4 summarizes the contents of the survey, including the source of any validated questions. The first survey wave included 11 sections, each of which focused on a distinct theme. The last section of the survey included open-ended questions providing study participants the opportunity to share their thoughts on the pandemic, in addition to feedback about the survey questionnaire itself. In subsequent survey waves, we modified the survey to reflect the changing pandemic context within the US (e.g., relaxation and reimposition of restrictions, US presidential elections, and vaccine availability). The length of the survey changed as we added and removed questions, but the main sections of the survey remained the same.

We required study participants to respond to all survey questions, with the exception of open ended questions. However, we included a "I prefer not to answer" option allowing respondents to opt out of responding to any question and to comply with the Institutional Review Board (IRB) guidelines. To minimize experienced survey burden on participants, we implemented conditional display logic whenever applicable. Further, to ensure high data quality, we implemented two attention check questions in different sections of the survey. The attention check questions specifically asked respondents to follow instructions and select specific choices. If a respondent failed to follow the instructions of any of the attention check questions, they were not allowed to continue the survey. We changed the placement of the attention check questions within the survey across the various survey waves to further reduce low-quality responses resulting from people remembering the survey flow from previous survey waves. The survey was approved by the University of California Committee for Protection of Human Subjects (CPHS). We used the Qualtrics survey platform to host and administer our survey. The questionnaire for the first survey wave is included in Appendix 1.

Table 2.1: Survey structure

Survey section	Section content (bolded questions are excerpted from validated surveys)	Source of validated questions	Changes in subsequent waves
Safety measures	COVID-19 related safety measures, including hand-washing and mask-wearing frequencies, the sizes of gatherings attended		Included question on natural disasters
Mobility	Respondents' recent travel behavior, commuting/telecommuting behavior, **main commute transportation modes, vehicle ownership,** attitudinal questions on use of ridesharing and public transit during COVID-19, recent purchases due to COVID-19	US National Household Travel Survey	
Household dynamics	Respondents' household dynamics throughout the pandemic, including the number of individuals living in their household, the status of their relationship with their household members compared to before COVID-19, and whether the relationship with their household members affect their ability to spend time at home		Added questions on changing primary residential location
Economic factors	Respondents' change of employment since the beginning of COVID-19, changes in household income, **financial stability,** ability to sustain the economic and emotional impacts of the pandemic	US Census, US Federal Reserve	
Political	Respondents' pandemic news sources, knowledge and opinion of local pandemic restrictions, **political affiliation, willingness to get vaccinated,** importance of religion, and opinion about various pandemic related statements	PEW Research Center	Added questions on vaccination status and political affiliation
Personality	**Questions to measure personality**	BFI-10	Removed for returning respondents
Physical health	Questions about the respondents' physical health, their insurance status, level of worry about COVID-19, COVID-19 symptoms, COVID-19 testing status		
Psychological factors	Respondents ability to be productive, feeling lack of companionship, **anxiety and depression diagnosis**	PHQ-4	
Demographics	**General demographic information including details about the respondents living situation,** number of children in household, whether respondents provide care for a child or an elderly	US Census	Added questions on disability, sexual orientation, school attendance
Open ended	Open ended questions asking about additional information on positive and negative aspects of the COVID-19 pandemic as well as feedback from respondents about the survey		

3.5 Sampling strategy

We developed a stratified sampling strategy to obtain a sample of panelists that was fairly geographically representative of the US population. Assuming a 10% response rate, we targeted the survey to approximately 14,500 panelists with a diverse mixture of metropolitan and rural counties across the US. We primarily focused on counties within 16 major MSAs across the US and selected a subset of counties within each to balance the number of panelists, area type and geographic distribution. To further balance our sample between rural and non-rural areas, we selected a set of rural counties across the US with the largest concentration of panelists. In total, 85% of targeted panelists are from metropolitan counties and 15% are from rural counties. Figure 2.2 illustrates the geographical distribution of the targeted panelists from the first wave.

The targeted sample over-represented people of color and lower income people compared to the US population. For example, only 50% of the targeted panelists were White/Caucasian, in comparison to 72% of the US population. People with annual household income lower than $25,000 constituted 44% of the targeted sample, whereas only 20% of the US, population fall into this income category.

Due to a decrease in retention rates, we augmented the targeted set of panelists with sets of randomly selected panelists who have not been previously targeted in the second, fourth, and sixth survey waves.

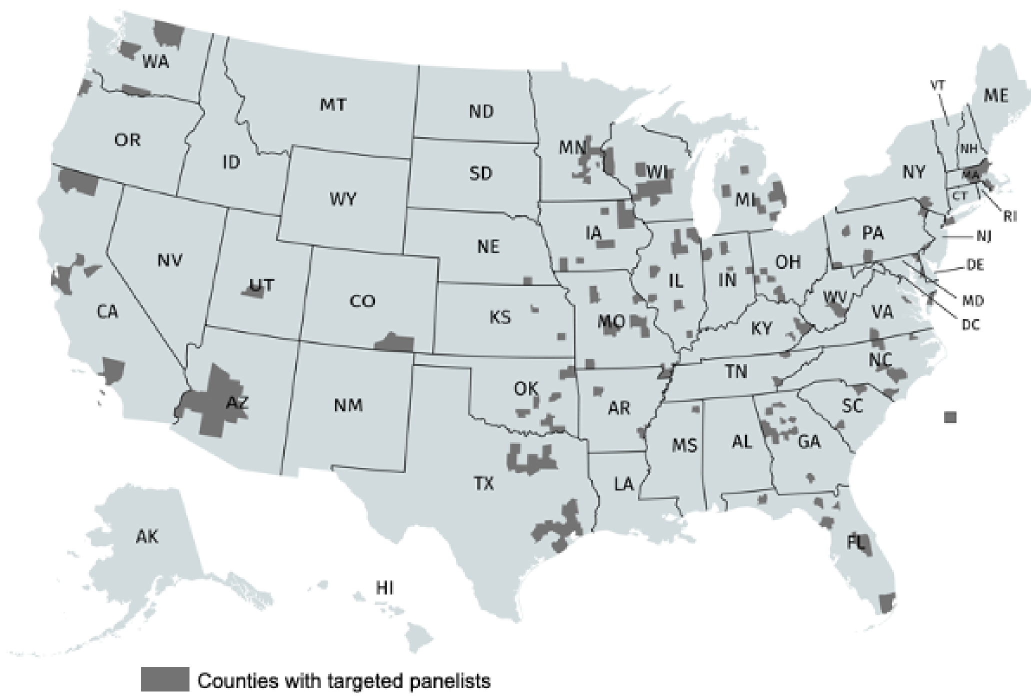

Figure 2.2: Geographical distribution of targeted panelists in the first wave

3.6 Survey pretesting

Due to the urgency of the study and our budget constraints, we conducted only informal pre-tests of the survey instrument with several graduate students from UC Berkeley and other individuals not affiliated with UC Berkeley. We pre-tested the survey on smartphones (iOS and Android) and laptops. Following the feedback, we modified the survey by rearranging the order of several survey questions and added several survey cosmetic changes to improve the survey flow and user experience. Additional comments from the survey pre-testers were mainly about the duration of the survey. Due to the large similarity between the different survey waves, we only tested subsequent surveys to ensure that the overall survey flow was not broken due to the modification of certain survey sections. Prior to fielding the survey to our targeted panelists, we also tested the survey with a small random sample of 20 SimilarWeb panelists.

3.7 A-priori survey assessment

Determinants of response rates in any questionnaire include the questionnaire's complexity and length. We use the point scheme presented by Axhausen et al. (2015) to calculate the maximum survey burden score for each deployed wave. The maximum survey burden is the

Table 2.2: Respondent burden assessment using the point-based system proposed by Axhausen et al. (2015)

	Wave 1 (Aug. 2020)	**Wave 2 (Oct. 2020)**	**Wave 3 (Dec. 2020)**	**Wave 4 (Apr. 2021)**	**Wave 5 (Jul. 2021)**	**Wave 6 (Sep. 2022)**
Deployment period	Aug. 3, 2020 - Sep. 12, 2020	Sep. 26, 2020 - Nov. 2, 2020	Dec. 4, 2020 - Jan. 3, 2021	Mar. 26, 2021 - May 3, 2021	Jun. 22, 2021 - Aug. 13, 2021	Sep.14, 2022- Sep.30, 2022
Number of questions	76	75	67	72	73	58
Survey burden (points)	716	690	617	672	656	539
Largest burden section	Mobility	Mobility	Mobility	Political	Political	Mobility

sum of individual survey question burdens for the longest possible survey path a respondent could take.

Table 3.7 presents fielding dates, the total number of questions, and the maximum calculated survey burden for each survey wave. The first survey wave has the largest a-priori survey burden because it has the most questions out of all survey waves. With the exception of wave 4 and wave 5, the mobility section had the greatest burden in the survey. Within this section, the question asking participants to identify the purposes for which each transportation mode was used has the largest survey burden. This question presents seven different transportation modes, for which up to six purposes could be selected. The political section has the largest burden in wave 4 and wave 5. This is the result of the addition of several vaccination related questions as vaccines became more available within the US For a detailed breakdown of the response burden of each survey wave, we refer the reader to Appendix 2.

3.8 Study participation

Given that all study participants had the SimilarWeb application installed on their smartphones, beyond answering the surveys, no additional effort was required from them to participate in our study. After each survey wave was made available, targeted panelists received notifications directly from the SimilarWeb smartphone application alerting them that they could answer the survey. Survey availability notifications stated that the survey was related to COVID-19, and provided recipients with a survey burden estimate and the participation incentive amount.

Participants were presented with a consent form detailing the purpose and scope of the data collection, a description of how the data was stored, protected and used. Potential participants were also provided with contact information of the principal investigator and were instructed to retain a copy of the informed consent form for their records. Only panelists providing consent for participations were allowed to continue with the survey. Once a participant starts the survey, they can abandon it at any time. However, only participants who completed the survey are eligible for receiving the survey incentive.

3.9 Participation incentives and reminders

Research shows that compensating study participants boosts participation rates (James and Bolstein 1992; Laguilles et al. 2011; Pedersen and Nielsen 2016) and makes it more likely to retain respondents in a longitudinal study (Yu et al. 2017). Our collaboration with SimilarWeb allowed us to access their panel, infrastructure, and data, free of charge. The most significant share of costs associated with this study were related to participant incentive. Only participants who answered all survey questions were compensated. Participants who failed the attention check questions were not allowed to complete the survey and were not compensated for their partial participation. Participant retention proved to be a significant challenge throughout the study. As such, we increased financial compensation in several waves to retain as many panelists as possible. The total cost across the six completed survey waves added up to $43,500.

To further boost response rates, we sent reminders to targeted panelists starting in the second wave. Participation reminders were found to boost response rates (Kongsved et al. 2007; Svensson et al. 2012; Van Mol 2017). We sent a single participation reminder in the second wave and daily reminders in the subsequent waves. We present detailed statistics on incentives, response rates, and completion times for each survey wave in the results section.

3.10 Policy tracking

Throughout the COVID-19 pandemic, state and local governments took regulatory actions, known in the literature as Non-Pharmaceutical Interventions (NPIs), to decrease the transmission of the virus causing COVID-19. We initially tracked policies for all the counties of origin of our study participants (191 counties) for stay-at-home orders, with the intention of tracking the same counties for mask mandates as well. However, we kept tracking mask mandates for counties with at least one participant in our sample (141 counties). Given this data collection was extensive due to the dynamic nature of the public health policy landscape, we examined numerous sources in an effort to find a county-level database with a rigorous data collection process. After not finding such a database at the time and due to budget constraints, we further reduce the number of counties tracked; following the first survey wave (August 2020) we stopped tracking counties with 2 participants or less in our sample and continued to track NPIs for 65 counties and 21 states. Figure 2.3 shows the geographical distribution of these 65 counties.

There were several occasions where county and state level orders co-occurred. In each of these circumstances, we checked for any state-level preemption of county orders. If that was the case, we recorded the current state regulations for that county. If there was no preemption, we recorded the stricter order of the two. For example, if the state did not have a stay-at-home order and the county did, we recorded a stay-at-home order being present in the county.

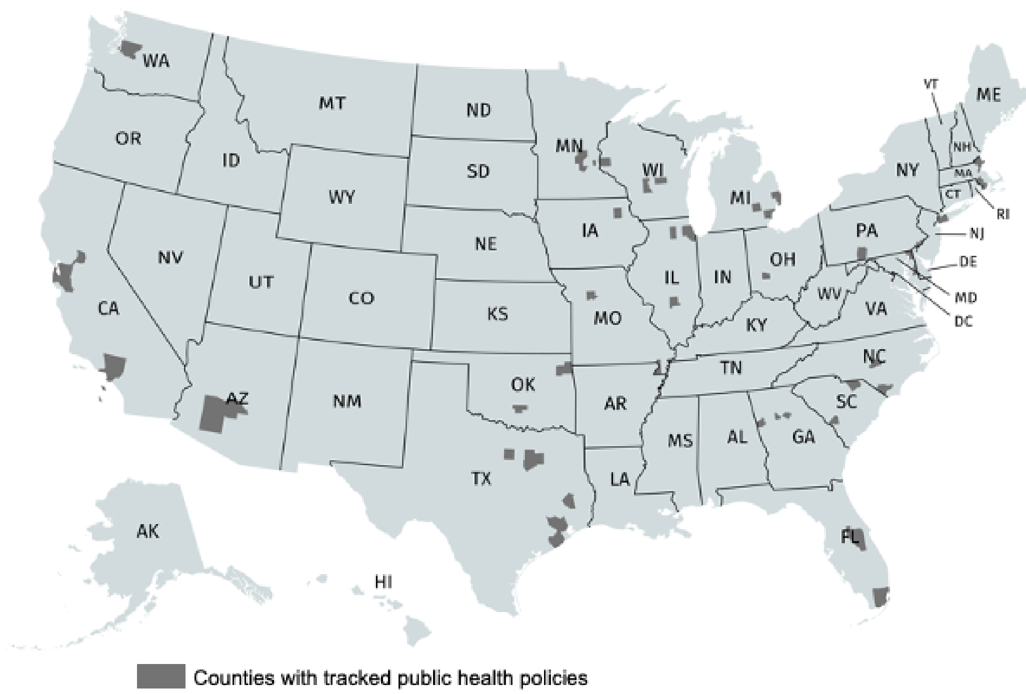

Figure 2.3: Geographic distribution of counties with tracked public health measure

4 Data and results

In this section, we present key results as related to the study participation and details of the collected data. More specifically, we discuss the study's participation rates and participant retention, present key demographic statistics for study participants, analyze possible factors related to several aspects of study participation and retention, present descriptive information the tracked policies, and present several insights that can be gleaned combining the passive and active data sources. We leave the in-depth exploration of specific research questions on the evolution of travel behavior throughout the pandemic for other research endeavors.

4.1 Response rates

Response rates for the surveys were calculated based on the web-based survey methodology and standards described by the American Association for Public Opinion Research (The American Association for Public Opinion Research 2016). We used the Response Rate 5 (RR5) model, which estimates the proportion of completed surveys out of all eligible participants. We categorized participant responses as follows: Completed surveys, accepted partial surveys, blank survey responses indicating consent, other surveys that were incomplete or failed the attention check, and unopened surveys. We defined “accepted" responses as those that answered all survey questions and did not fail any attention checks.

Table 4.1 presents the study's response rates, sample sizes, retention rates, survey incentives, and survey completion times detailed by wave. The response rate for the first wave was approximately 19%. The second, fourth, and sixth survey waves targeted additional panelists, and had response rates of 14%, 18%, and 2% respectively. The third and fifth survey waves targeted only panelists who had responded to previous survey waves, and had significantly higher response rates, 51% and 42% respectively. Participant retention has proved to be a challenge in the study; out of the initial first wave participants, 63% (847 panelists) completed the second wave, 42% (556 panelists) completed the first three waves, 25% (336 panelists) completed the first four waves 20% (262 panelists) completed five survey waves, and approximately 4% (50 panelists) completed all six survey waves. A possible reason for the decreasing retention is the long time span of the study and the continuously decreasing interest in COVID-19 related topics. The median survey completion time continuously decreased from the first to the sixth survey waves. This could be due the decreasing number of questions in each new survey wave and the possible familiarity with the survey instrument for repeat participants. Additionally, the survey length also plays a role in this decline, as the survey length decreased since the first wave.

Figure 2.4 illustrates panelist retention across all deployed survey waves by presenting the breakdown of participants in each survey wave by the most recent wave they participated in. We should note that due to the additional targeting in the second, fourth, and sixth survey waves, this figure does not present a comprehensive listing of the different participant cohorts. We include the detailed breakdown of all our study cohorts in Appendix 3. The largest participant drop occurred between the fifth and sixth survey waves, partly due to the long duration between the two survey waves (July 2021 vs September 2022). Additionally, with the exception of the sixth survey wave, the majority of participants in each wave participated in the preceding survey wave.

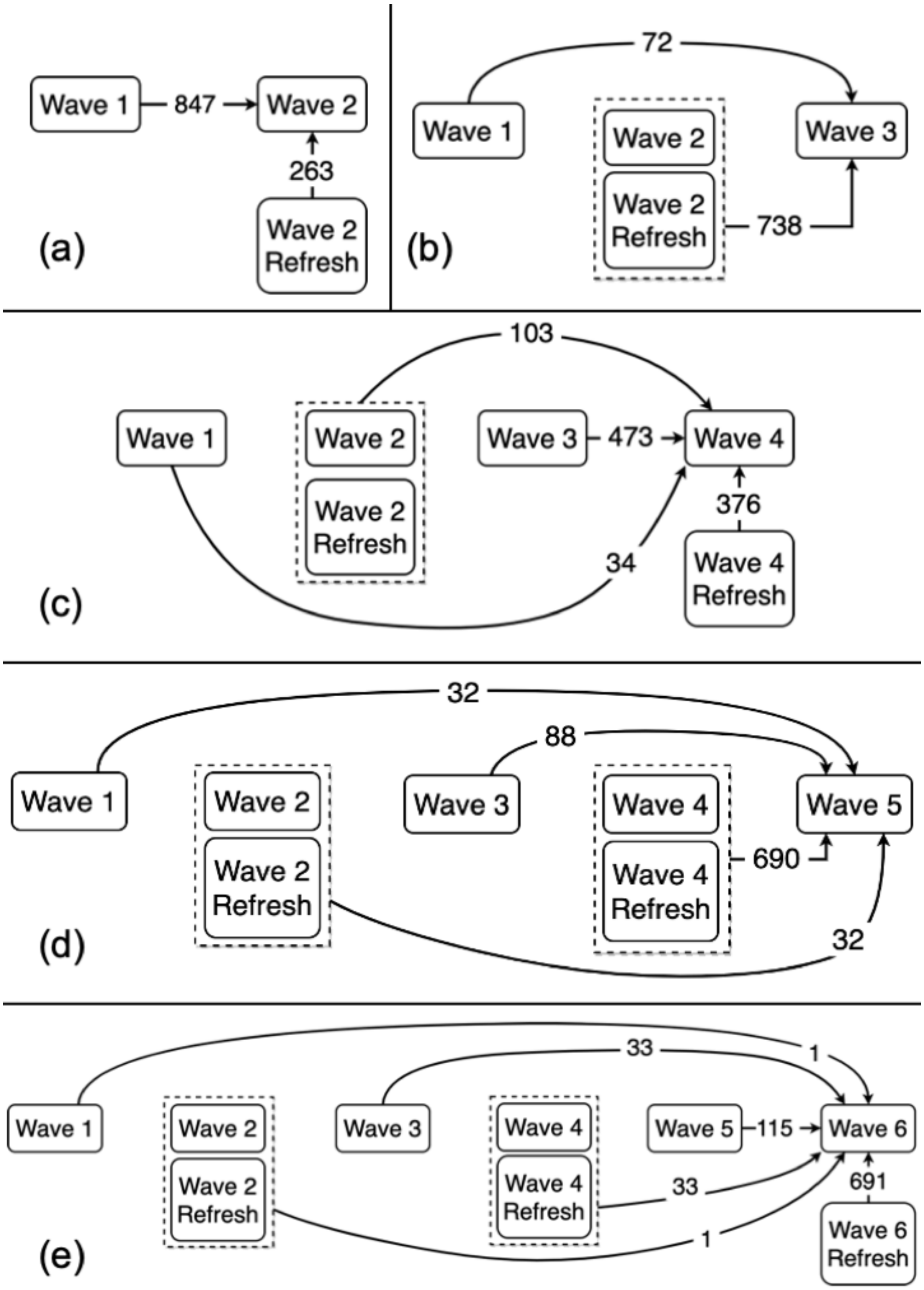

Figure 2.4: Retention of study participants throughout the study

Table 2.3: Survey response rates, retention rates, incentives, and completion times

		Wave 1 (Aug.2020)	Wave 2 (Oct.2020)	Wave 3 (Dec.2020)	Wave 4 (Apr.2021)	Wave 5 (Jul.2021)	Wave 6 (Sep.2022)
Targeted sample (N)		6968	7686	1586	5504	1962	51034
Response rate (%)		19	14	51	18	42	2
Sample size (N)		1333	1100	811	983	842	824
Share of repeaters (%)		-	85	100	62	100	16
Number of participants with previous waves	**One wave**	-	847	255	53	277	5
	Two waves	-	-	556	218	86	25
	Three waves	-	-	-	336	217	12
	Four waves	-	-	-	-	262	39
	Five waves	-	-	-	-	-	50
Average survey incentive ($)		4.0	5.0	5.0	8.7	11.3	12.6
Completion time (min)	**Median**	20.0	17.0	16.0	17.0	14.5	12.0
	75th Percentile	28.0	24.0	24.0	25.0	20.5	17.0

Figure 2.5 illustrates the number of daily survey returns after deploying each of the six survey waves. The figure also shows when survey participation reminders were sent out to the panelists in each of the survey waves and when survey incentives were increased to increase response rates and maintain participant retention. The number of daily returns is high immediately after each wave launch, albeit not in the sixth wave. This could be due to several reasons, including the panelists' loss of interest in pandemic related matters in 2022. We sent survey participation reminders starting from the second survey wave. Sending survey participation reminders in the second wave of the survey increased the daily returns immediately after sending the reminder. In the third wave of the survey, we sent daily reminders to the panelists, resulting in a slight increase in the number of daily responses immediately after the launch of the survey. In addition to sending daily participation reminders and refreshing the targeted panelists' pool, we also increased survey compensation in the fourth and fifth survey waves. While Figure 2.5.d shows an increase in daily returns immediately after increasing survey incentives, Figure 2.5.e does not reflect a similar increase in daily returns following the increasing of survey incentive. Figure 2.5.b, Figure 2.5.d, and

Figure 2.5.f indicate that targeting additional panelists resulted in a significant increase in daily returns. This is especially notable for the sixth wave where the majority of responses came from the additional pool of panelists.

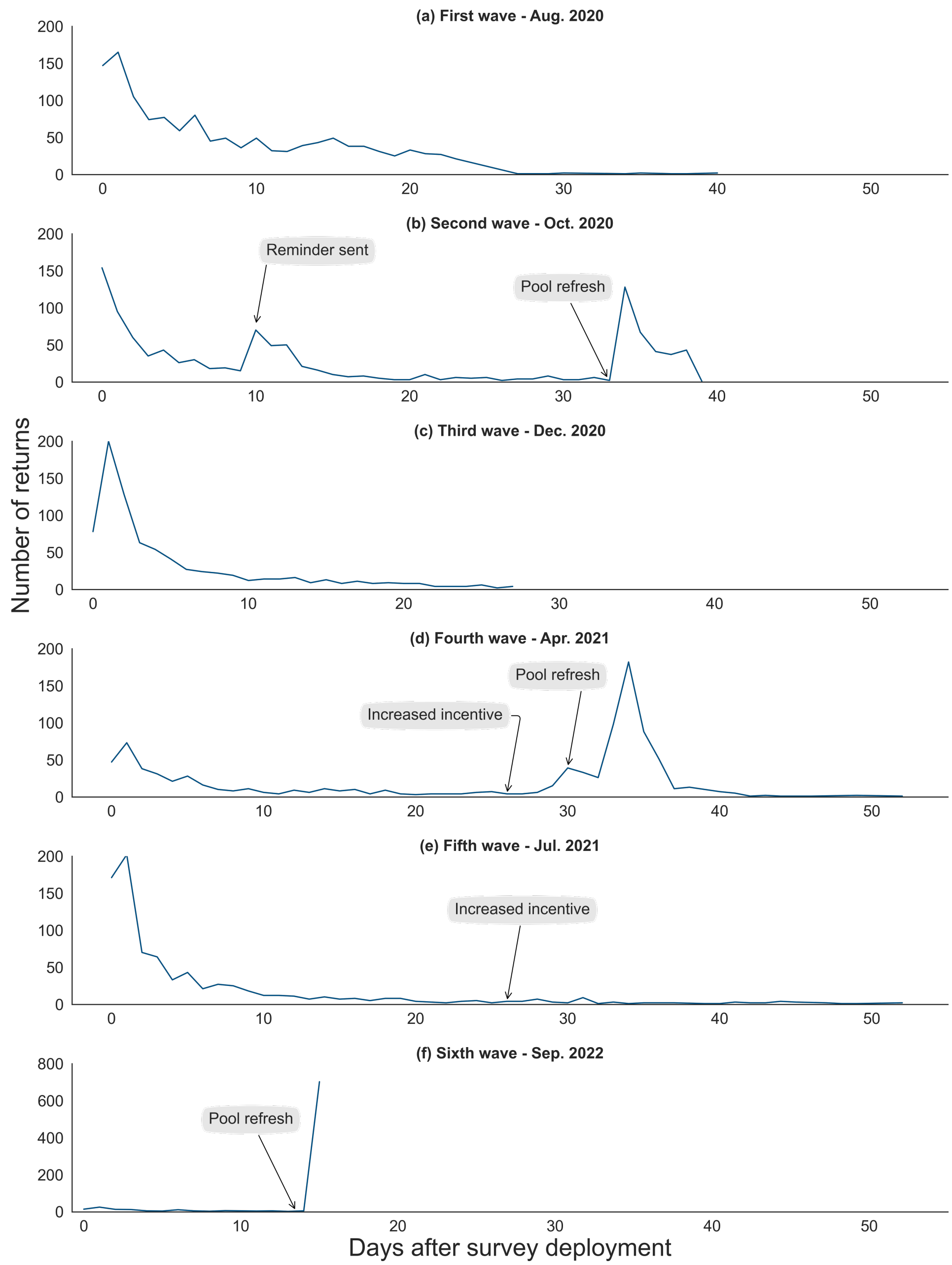

Figure 2.5: Number of daily survey returns after deployment

4.2 Demographic summary

In this section, we present key demographic statistics for each survey wave and compare it to statistics from the US census for the targeted counties and US population where applicable (Table 4.2 and Table 4.2). Our data oversamples women and undersamples men when compared to the targeted counties and the US population; women respondents represent 55% to 60% of survey participants, compared to about 51% across the targeted counties and the US population.

Our sample across all waves is heavily skewed towards young respondents, those between 25 and 54 years old. These respondents represent about 69% to 73% of all six survey waves, compared to 41% and 39% within the targeted counties and the US population, respectively. Our sample also significantly undersamples individuals 19 years or younger and individuals 65 years and older across all survey waves compared to the target counties and the US population.

Our sample overrepresents low and medium income households. Between 59% and 65% of the respondents' households have an income of less than $50,000 compared to 36% across the targeted counties and 40% in the US population; and 10-11% of respondents have an income of $100,000 or higher, compared to about 35% in the targeted counties and 31% in the US population. It is possible that lower income individuals are more likely to be part of an online panel to earn income from survey incentives.

Apart from the sixth survey wave, all survey waves undersample white Americans and oversample other racial groups. Caucasians represent approximately 72% of the US population compared to approximately 52-56% of our respondents across the first five waves. On the other hand, African American participants represent 18% of our respondents across the first five waves compared to 13% within the targeted counties and the US population. The racial breakdown of participants in the sixth survey waves closely track those of across the targeted counties and the US population.

The first five waves of our sample underrepresent non-Hispanics/Latinos when compared to the US population, with 75-77% identifying as a non-Hispanic/Latino compared to 82% of individuals in the US However, this share is much closer to that within the targeted counties. The share of non-Hispanic/Latino individuals in the sixth wave (83%) closely tracks that of the US population (82%) but overestimates it within the targeted counties (75%)

Our sample significantly underrepresents individuals with a high school education or less, who comprise 45-55% of our survey respondents, compared to 65% across the targeted counties and 62% of individuals in the US Those with a university or college degree represent between 39% and 46% across all survey waves compared to only 27% across the targeted counties and 29% within the US population. Finally, 5-7% of our respondents hold a postgraduate degree, compared to 14% across the target counties and 11% within the US population.

Our study also undersamples smaller households. The share of 2-person or less households hovers around 40-47% in our sample, compared to 60% within the targeted counties and 62% within the US population. On the other hand, 5-person or larger households comprise about 14-20% across the different waves, compared to less than 10% within both the targeted counties and the US population.

The majority of our survey respondents have access to either 1 or 2 vehicles, representing 58-79% of respondent households across all but the fourth survey wave. The share of panelists reporting working from home continuously decreased throughout the study, from 35% in the first survey wave to approximately 14% in the sixth survey wave. This share is still significantly higher than that of within the targeted counties and across the US population pre-COVID19. Conversely, the number of individuals driving or carpooling to their workplaces increased from 50% in the first wave to 68% in the sixth wave, indicating the increasing propensity of individuals to commute to drive to work since the beginning of the COVID-19 pandemic, although still significantly less than the share of car commuters across the targeted counties and the US.population pre-COVID19. Our sample is representative of public transit and active mode users (walking and biking). The share of these users has remained constant around 9% across the first five but increased to 13% in the sixth survey waves. Further, our sample does not fully reflect the sinking share of transit use reported in the early stages of the pandemic by other researchers. Several factors behind changes in respondents' primary commute mode throughout the pandemic include reopenings across the nation and businesses requiring people to return to offices and places of work.

4.3 Survey abandonment

As with all surveys, some participants do not stay through to completion. Survey abandonment could be due to several reasons, including experienced survey burden, nature of the survey questions, relevancy of the questions to participants, survey incentive amounts, or technical difficulties. However, when survey abandonment is not random, it could prevent results from being generalizable to the population. Galesic (2006) found that survey incompletion is associated with higher experienced survey burden and overall lower interest in participation. Given the context of our study and overall conditions within the US throughout the COVID-19 pandemic, the research team suspected that the University of

Table 2.4: Demographic characteristics of study participants

	Wave 1	Wave 2	Wave 3	Wave 4	Wave 5	Wave 6	Targeted counties	Population
Gender								
Male	40.8	40.4	40.5	43.9	45.2	41.0	49.1	49.2
Female	59.2	59.6	59.5	56.1	54.8	59.0	50.9	50.8
Age								
< 19	3.8	3.8	3.5	4.3	3.9	1.2	25.2	25.3
20 - 24	9.7	9.0	8.1^*	10.2	9.4	7.5^*	6.7	6.8
25 - 34	23.7	22.4	23.0	23.7	24.1	22.2	14.6	13.9
35 - 44	27.4	26.1	26.8	27.2	27.0	26.8	13.1	12.6
45 - 54	20.2	21.2	22.0	20.4	21.3	20.9	13.3	13.0
55 - 59	6.7^*	7.3^*	6.7^*	5.7^*	5.6^*	7.6^*	6.6	6.7
60 - 64	4.4	4.7^	4.7^	4.0	3.6	5.9^*	5.9	6.2
> 65	4.3	5.5	5.5	4.6	5.2	7.8	14.5	15.6
Household income								
$0 - 25K	35.1	31.8	30.4	30.0	27.8	36.8	17.7	19.3
$25K - 50K	30.1	32.5	30.8	28.7	29.1	28.4	19.2	21.2
$50K - 100K	24.5	25.4	27.3^*	30.6^*	31.1^*	22.9	28.7	29.9
$100K - 150K	6.9	6.4	7.6	6.7	7.6	6.8	16.1	15.1
$150K - 200K	1.4	2.1	2.1	2.0	2.1	2.2	8.1	6.8
$200K or more	1.8	1.7	1.8	1.9	2.1	1.6	10.2	7.7
Race								
Asian/Pacific Islander	7.4*	7.7^	8.4^	10.7^	11.0^	6.7*	8.9	5.7
African American	18.1	18.9	17.4	18.4	18.1	13.3^*	13.4	12.7
Mixed Race	6.5	6.4	5.7	7.1	6.8	4.5^*	3.6	3.3
Native American/ Alaskan Native	2.5	2.8	3.1	1.9	1.9	1.3^*	0.6	0.9
Caucasian	54.5	54.7	56.5	52.2	53.3	68.4^	65.6	72.5
Other	8.0^	7.0^	6.5^*	6.3^*	6.9^	3.9*	7.8	4.9
Hispanic status								
Hispanic or Latino	20.3*	18.9*	18.8*	18.8*	19.5*	13.2	24.8	18.0
Not Hispanic or Latino	75.8^	77.9	77.5^	77.0^	77.3	83.7*	75.2	82.0
Education level								
Less than High School	3.5	3.1	2.8	3.8	2.9	5.5	13.1	10.1
High School	46.4	46.2	45.8	44.8	42.8	49.5*	51.6	51.5
University/College	43.8	44.4	44.7	44.9	47.3	38.5	21.5	27.5
Post-graduate Education	6.1	6.2	6.5	6.4	7.1	5.2	13.7	11.0
Household size								
1	15.1	16.3	14.2	15.4	14.8	16.5	27.0	28.0
2	25.2	25.8	26.3	26.3	26.3	30.6^	31.9	34.0
3	20.8	21.5	24.1	20.4	23.1	24.4	16.2	15.6
4	18.3	16.2	16.8	19.6	18.7	13.9^*	14.0	13.0
5	10.6	11.2	9.6	8.4	7.7^*	7.5^*	6.6	6.0
6+	9.8	8.4	8.4	9.2	8.4	6.2	2.6	2.3

^indicates a statistic representative of the population at the targeted counties at the 5% level
*indicates a statistic representative of the US population at the 5% level

Table 2.5: Transportation-related descriptive statistics of study participants

	Wave 1	Wave 2	Wave 3	Wave 4	Wave 5	Wave 6	Targeted counties	Population
Household vehicle ownership								
0	12.4^	12.3^	11.7^	10.2^*	8.9*	11.8^	11.4	8.6
1	38.2	39.9	37.0	36.7	39.0	46.3	32.9	32.7
2	32.5	33.1^	34.1^	21.0	34.5^*	32.2	35.6	37.2
3 or more	16.6	14.0	16.5	31.5	17.2	9.2	19.9	21.4
Primary commute mode								
Not Applicable	34.3	24.3	28.0	21.2	19.5	13.8	5.3	5.2
Car †	50.8	61.0	58.2	65.6	67.7	68.2	80.4	85.3
Carsharing	0.8	0.6	0.9	0.3	0.0	1.1	N/A	N/A
Ridehail or Taxi	2.0	1.2	1.7	2.3	1.9	2.7	0.1	0.2
Transit	6.0*	6.1*	6.7*	5.5*	5.5*	7.9^	9.5	5.0
Bicycle	0.6^*	0.9^*	0.4^*	0.7^*	0.4^*	2.0	0.6	0.5
Walking	2.2^*	3.3^*	3.1^*	2.5^*	2.7^*	2.6^*	3.0	2.7
Other	1.6^	1.4^*	0.5^*	0.3	0.6^*	0.7*^	1.1	1.1

† Drive Alone and Carpooling are aggregated into one category to compare US census statistics to our survey data
^indicates a statistic representative of the population at the targeted counties at the 5% level
* indicates a statistic representative of the US population at the 5% level

California brand could impact our response rate and data quality. Fang et al. (2012) show that a research project's sponsoring corporation reputation can have a significant impact on people's willingness to participate in a web-based survey.

Table 4.3 summarizes the share of complete and incomplete survey responses. Incomplete responses can further be categorized into those due to respondents dropping out of the survey and those due to the respondent's failure to properly answer the attention check questions. These statistics are computed relative to the number of participants who opened the survey, as opposed to all individuals initially targeted. In this study, the share of survey completes increased between the first and fifth wave from 65% to 90%. The share of survey incompletion was 11% in the first survey wave, consistent with findings from Hoerger (2010) and decreased to a low of 3% in the fifth wave. This decrease can possibly be explained by the commitment and interest of panelists staying on the panel throughout the study period. Similarly, and possibly due to similar reasons, the share of panelists failing the attention check question decreased by upwards of 70% from the first survey waves (from 24% to 7%). Comparing the waves with additionally targeted panelists (wave 2, wave 4, and wave 6) to waves without panelist pool refresh (wave 3 and wave 5) shows that incompletion rates are higher for waves with a pool refresh. Lower survey incompletion rates in later survey waves without additionally targeted panelists suggests that retained panelists are panelists with greater interest and attention.

Table 2.7: Share of survey abandonment at key survey sections

	Wave 1	Wave 2	Wave 3	Wave 4	Wave 5	Wave 6
Incomplete (%)	10	5	1.7	10	3	6
Before mobility section (%)	3	1	0	3	0	0
At mobility section (%)	4	3	0.7	3	2	3
After mobility section (%)	3	1	1	4	1	3

Table 2.6: Share of participants with complete, incomplete, and failed attention check responses

	Wave 1	Wave 2	Wave 3	Wave 4	Wave 5	Wave 6
Complete (%)	66	79	85	73	90	69
Incomplete (%)	10	5	2	10	3	6
Failed Attention Check (%)	24	16	14	17	7	25

Table 4.3 illustrates the share of study participants abandoning the survey at key points through the survey: before the mobility section, at the mobility section, and after the mobility section. We present the breakdown of survey abandonment in this fashion because the mobility section included high burden questions according to the point system suggested by Axhausen et al. (2015). The table shows that a significant share of survey incompletion occurred immediately at the beginning of the survey in the first survey wave. This initially high dropout rate was also significant in the fourth wave as we targeted a large pool of additional panelists. The dropout rate was also significant at the mobility section across all six survey waves, higher than that of any other section throughout the survey. Several questions in this section had large burden scores. For example, a series of questions in this section ask about the participants' pandemic transportation behavior (e.g., frequency and usage purpose of several transportation modes). These questions were designed a matrix format with several options to select, which was displayed in a repetitive fashion on smartphone screens and as a result might have been difficult to answer. We include examples of such questions in Appendix 4.

4.4 Study participation models

We estimated several binary logit models to help describe the factors associated with several aspects of study participation, more specifically the following outcomes:

- Whether a targeted panelist opened the survey
- Whether a participant abandoned the survey
- Whether a participant failed the attention check questions
- Whether a participant returned to at least one additional wave after their initial participation

In addition to key demographic variables, we explore the impact of the participants proximity to UC Berkeley as well as their tenure as active panelists on all four outcomes. We also explore the impact of the experienced survey burden on retention; more specifically, whether one's experienced survey burden being greater than the expected survey burden estimated by the survey platform impacts their likelihood to participate in follow up survey waves. Table 4.4 presents the estimation results of the four models.

The model results are mixed. Panelist tenure is the variable most highly associated with whether a targeted panelist opens the survey, with individuals on the panel for longer than 30 days being significantly less likely to open the survey. This suggest that panelists with longer tenure are more selective with the studies they participate in. Surprisingly, out of the pool of targeted panelists, individuals with higher household income are more likely to open the survey. Our model also suggests that full-time workers are less likely to open the survey, suggesting a possible lack of available time to participate.

The results also indicate that out of the panelists who opened the survey, non-white participants are more likely to not complete the survey. It is plausible that this could be explained by the distrust of minority racial and ethnic groups in researchers (Corbie-Smith et al. 2002; Gilmore-Bykovskyi et al. 2019), especially that our survey asks participants on the impact of the COVID-19 pandemic on their physical and mental health. Similarly, out of the panelists who opened the survey, non-White, Hispanic, less-educated, and lower income participants are more likely to fail the survey's attention check questions included in the survey. Full-time workers are also more likely to fail attention check questions. This could suggest that out of the targeted full-time workers, those who opened the survey tried to complete it quickly and could have missed the instructions shown in the attention check questions.

When it comes to participant retention, our models suggest that while panelists with long tenure might be more selective with the studies they participate in, once recruited, they are more likely to exhibit higher retention in longitudinal studies. Our model also indicates that participants with survey burden greater than that estimated by the survey platform were less likely to participate in follow-up waves.

4.5 Tracking COVID-related policies

Figure 2.6 shows that as many as 93% of our initially tracked counties had implemented stay-at-home orders. This share has continuously decreased after April 2020. After this rush of stay-at-home and shelter-in-place orders in the early weeks of the pandemic, governments began mandating the use of masks and face coverings in public places. Initially, public health experts discouraged the use of face masks to ensure there were enough masks and personal protective equipment for frontline healthcare workers (Panetta 2020). As COVID-19 continued to spread, and research supporting the effectiveness of masks emerged, many regions implemented face covering mandates (Molteni et al. 2020). Figure 2.7 shows that 33% of the tracked counties implemented mask mandates before July 2020 and 37% of the counties implemented mask mandates post July 2020, and the remaining 30% not implementing any mask mandates.

Table 2.8: Model results presented as odds ratio and 95% confidence interval

	Open Survey	Abandon survey	Fail attention check	Participate in subsequent wave
Intercept	0.423***	0.07***	0.22***	1.55
	[0.32, 0.56]	[0.02, 0.15]	[0.11, 0.43]	[0.82, 2.93]
Age (decades)	1.06***	1.10*	0.92*	1.11**
	[1.02, 1.10]	[0.98, 1.24]	[0.84, 1.00]	[1.01,1.21]
Male	0.77***	0.87	1.53***	1.05
	[0.70, 0.85]	[0.64, 1.19]	[1.21, 1.94]	[0.83, 1.31]
Race: Non-white	0.93	1.89***	1.33**	1.00
	[0.84, 1.02]	[1.38, 2.58]	[1.05, 1.68]	[0.8, 1.26]
Hispanic	1.12*	0.88	1.49***	0.98
	[0.98, 1.26]	[0.60, 1.26]	[1.14, 1.96]	[0.74, 1.29]
Household size	0.95***	1.08*	1.02	0.98
	[0.92, 0.98]	[0.99, 1.17]	[0.95, 1.08]	[0.91, 1.05]
Education Level				
University/College	1.06	0.92	0.62***	0.90
	[0.95, 1.18]	[0.66, 1.27]	[0.48, 0.80]	[0.71, 1.14]
Postgraduate	1.07	0.82	0.78	0.97
	[0.86, 1.33]	[0.40, 1.66]	[0.46, 1.33]	[0.58, 1.61]
Household Income				
\$25,000 - \$49,999	1.16**	0.89	0.53***	1.23
	[1.02, 1.31]	[0.61, 1.29]	[0.39, 0.72]	[0.93, 1.62]
\$50,000 - \$99,999	1.37***	0.75	0.55***	1.37**
	[1.19, 1.58]	[0.48, 1.16]	[0.39, 0.77]	[1.00, 1.86]
\$100,000 - \$149,999	1.69***	0.71	0.52**	1.44
	[1.34, 2.11]	[0.34, 1.48]	[0.29, 0.92]	[0.85, 2.41]
\$150,000 - \$199,999	1.94***	0.53	0.85	1.56
	[1.26, 2.97]	[0.12, 2.35]	[0.34, 2.13]	[0.62, 3.9]
\$200,000 or more	1.88***	0.86	0.80	2.03
	[1.28, 2.74]	[0.28, 2.61]	[0.34, 1.87]	[0.68, 6.05]
Full-time worker	0.89**	0.93	1.40***	0.95
	[0.80, 0.99]	[0.66, 1.30]	[1.09, 1.82]	[0.74, 1.21]
Tenure on panel > 30 days	0.31***	0.98	1.02	1.63**
	[0.25, 0.38]	[0.58, 1.65]	[0.68, 1.54]	[1.08, 2.44]
Dist. from Berkeley (100s of miles)	1.00	1.00	1.01	1.00
	[0.99, 1.01]	[0.99, 1.01]	[1.00, 1.02]	[0.99 1.1]
Experienced survey burden > Burden estimated by Qualtrics	N/A	N/A	N/A	0.81*
				[0.64, 1.02]
Observations	14,581	1,871	1,871	1,955
ρ^2	0.019	0.021	0.046	0.011

*p<0.1; **p<0.05; ***p<0.01

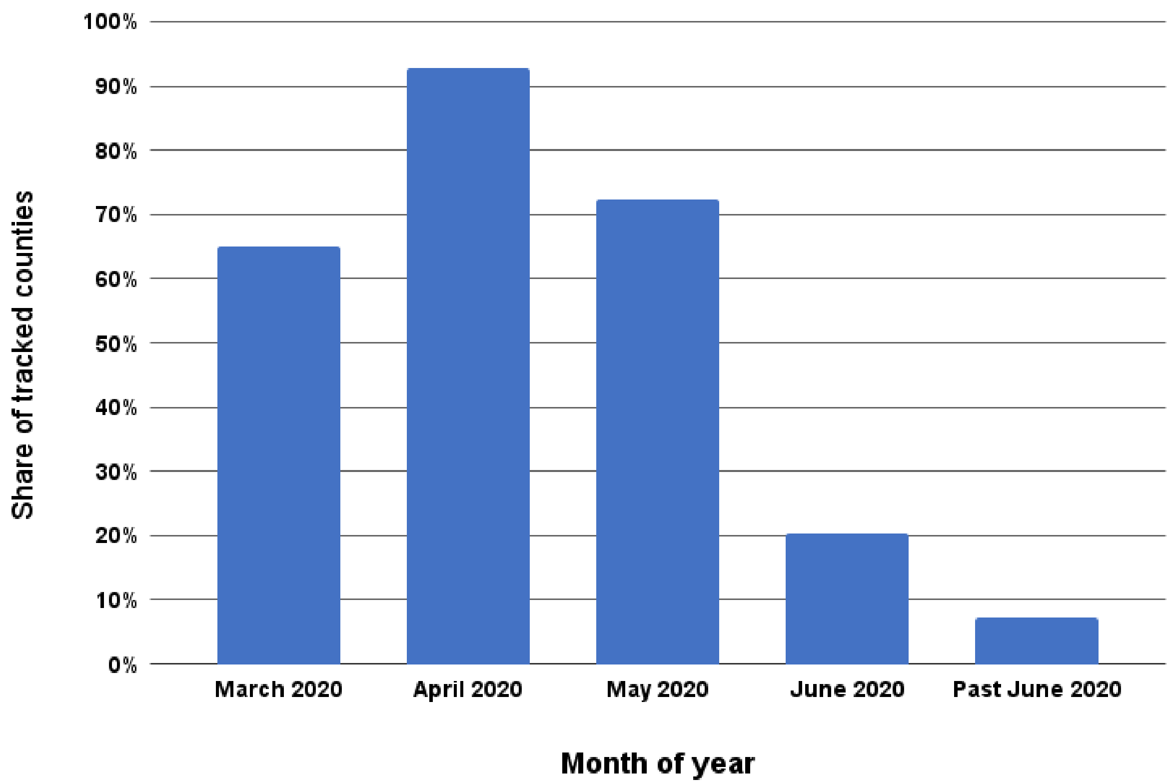

Figure 2.6: Share of counties with active stay-at-home orders by month

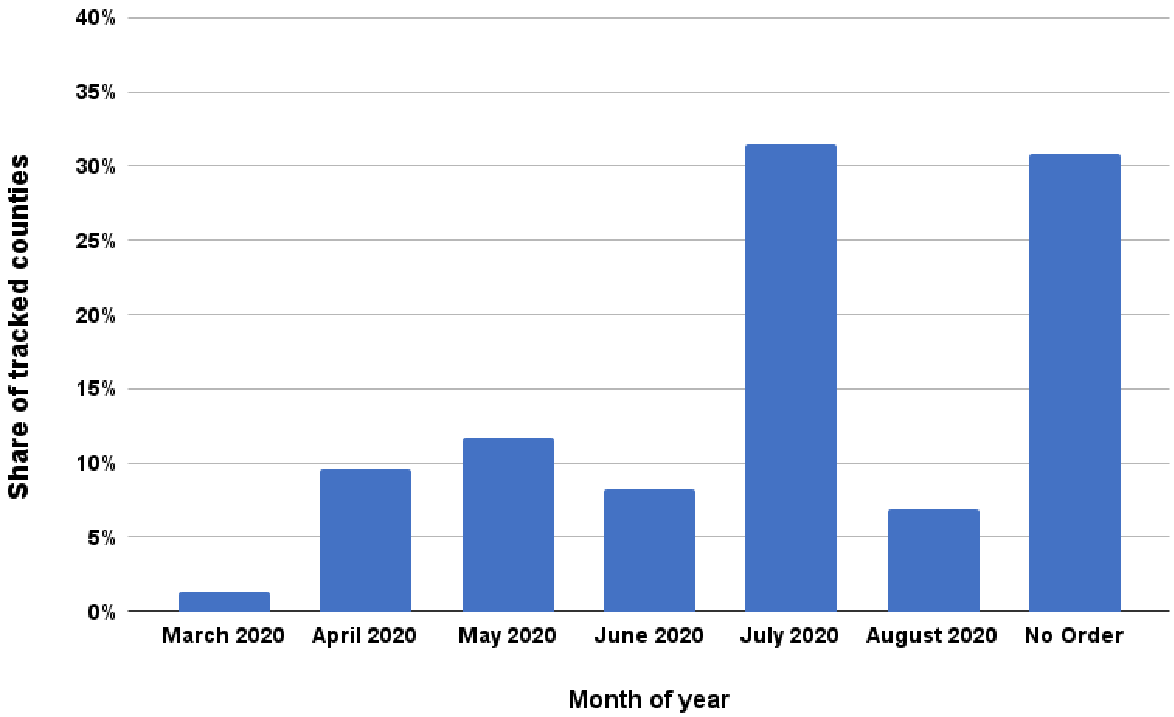

Figure 2.7: Distribution of mask mandates starting dates by month for tracked counties

4.6 Fusing passive and active data

In this section, we show how the fusing of survey and POI data can help uncover underlying factors explaining behavioral change. These results are exploratory in nature, and we do not attempt to make any claims about their implications. Instead, we defer the in-depth exploration of such findings to other research endeavors.

Our POI data can be processed to compute various mobility metrics (e.g., number of trips, distance traveled, time use, radius of gyration, etc...) at various time scales (e.g., daily, weekly, etc.). For our purposes, we illustrate the evolution of the number of weekly trips throughout the COVID-19 pandemic for different groups. Overall, the number of weekly trips made by first wave study participants confirms other research showing a sharp decrease in mobility in the early weeks of the pandemic, followed by a steady recovery since Figure 2.8.

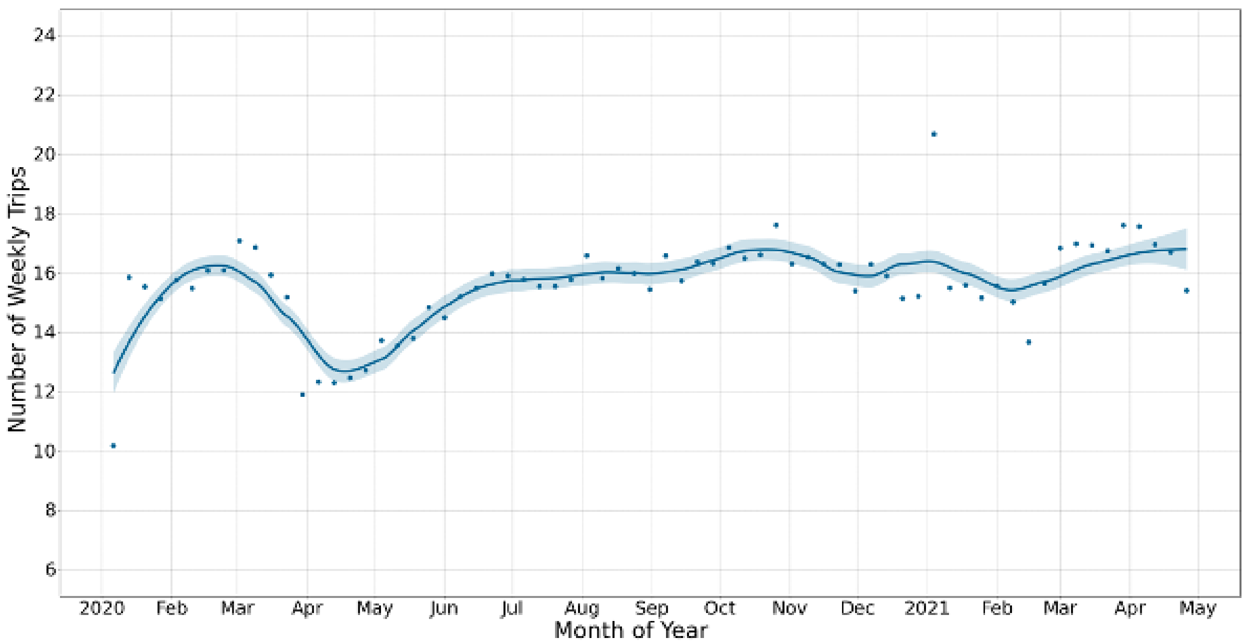

Figure 2.8: Number of weekly trips by study participants

Next, we illustrate the evolution of weekly trips taken throughout the COVID-19 pandemic across several individual characteristics collected from the survey data. Figure 2.9 shows that individuals with access to a car traveled significantly more than those without, both before and after the beginning of the pandemic. The difference in the number of weekly trips taken by the two types of individuals has continued to widen throughout the COVID-19 pandemic, reaching its highest in February 2021.

Figure 2.10 illustrates the number of weekly trips taken by individuals with different extraversion levels as indicated by the personality questionnaire included in our survey. We find that highly extroverted individuals have quickly recovered to their pre-pandemic mobility levels only a few months into the pandemic, compared to low extraversion individuals who exhibited lower than pre-pandemic mobility levels well into the pandemic. This suggests that introverted individuals might have reduced their out-of-home non-mandatory activities.

We also explored whether differences in the evolution of mobility behavior throughout the pandemic can be distinguished across populations with different beliefs about the pandemic. More specifically, we plot the number of weekly trips for people who believe in the efficacy of social distancing in reducing the spread of the virus compared to those who do not. Figure 2.11 shows that participants who do not believe that social distancing reduced COVID-19 spread took more weekly trips, especially in the early phases of the pandemic. As vaccines started becoming available, however, the trend started reversing, with individuals believing in the efficacy of social distancing taking only slightly more weekly trips than those who do not.

Additionally, we explore whether differences in the evolution of mobility behavior throughout the pandemic can be identified along characteristics of the participants' home location. Figure 2.12 shows a widening gap in the number of weekly trips taken by the individuals living in low population density counties compared to individuals living in high population density counties throughout the pandemic, with individuals living in the lowest tercile population density counties taking significantly more weekly trips than those in highest tercile population density counties.

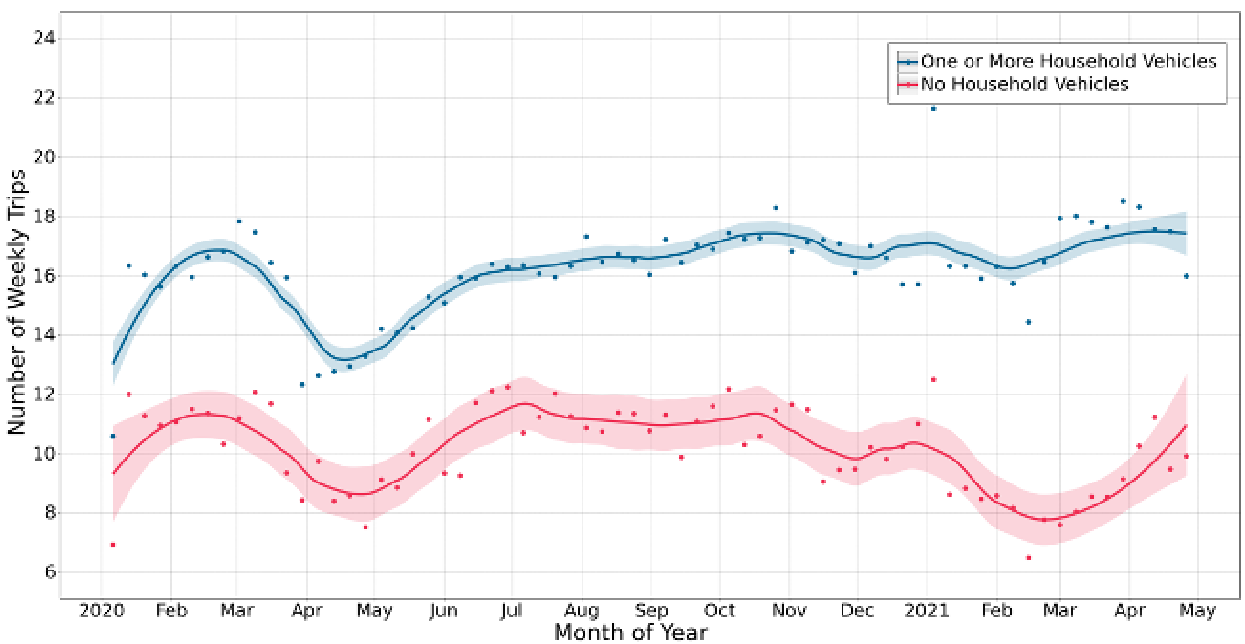

Figure 2.9: Number of unique places visited weekly by study participants with and without access to a household vehicle and the share of survey participants

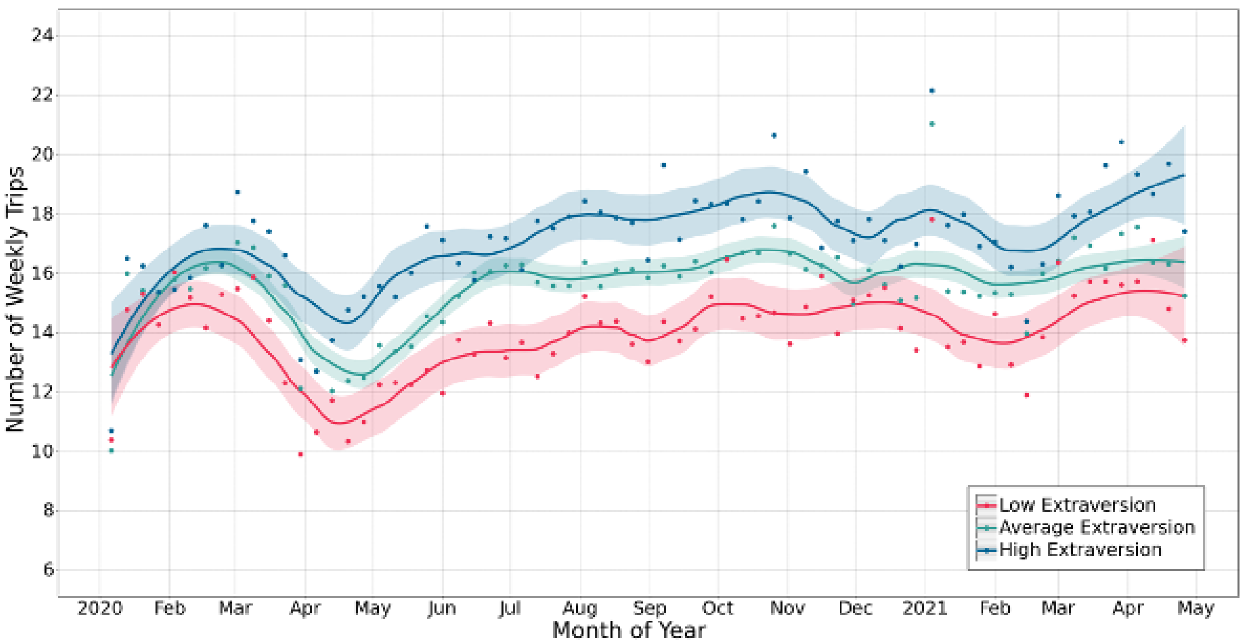

Figure 2.10: Number of weekly trips by study participants with low, average, and high extraversion levels as measured by BFI-10 (Rammstedt and John 2007)

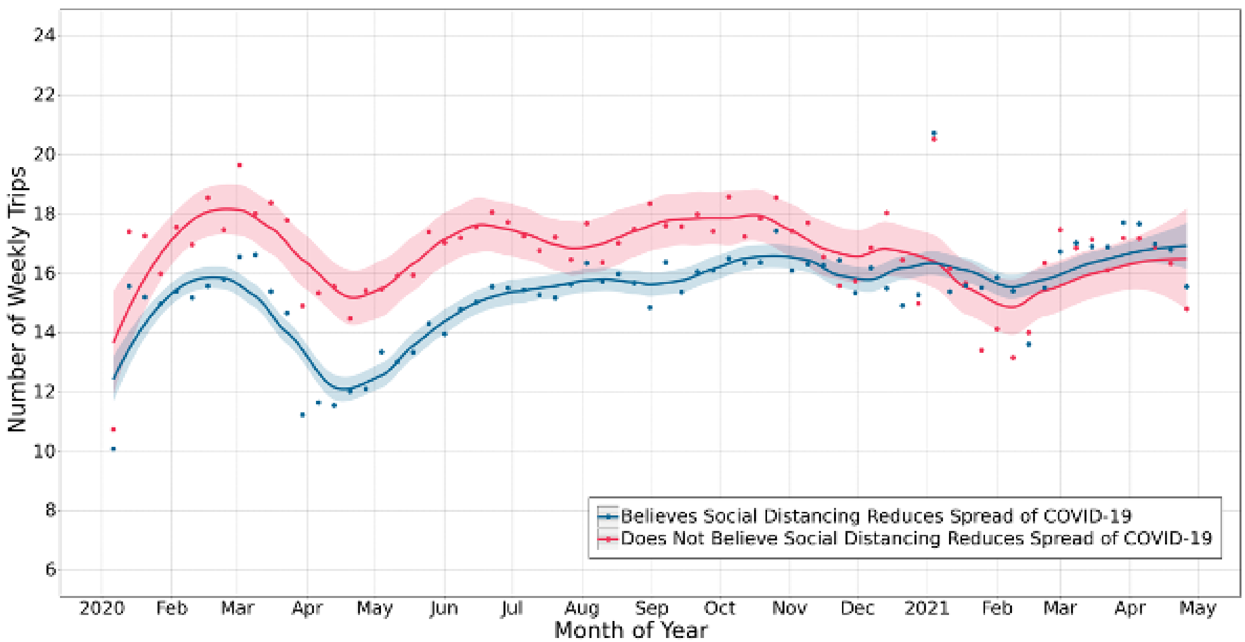

Figure 2.11: Number of weekly trips by study participants who believe social distancing helps reduce COVID-19 spread vs. those who do not

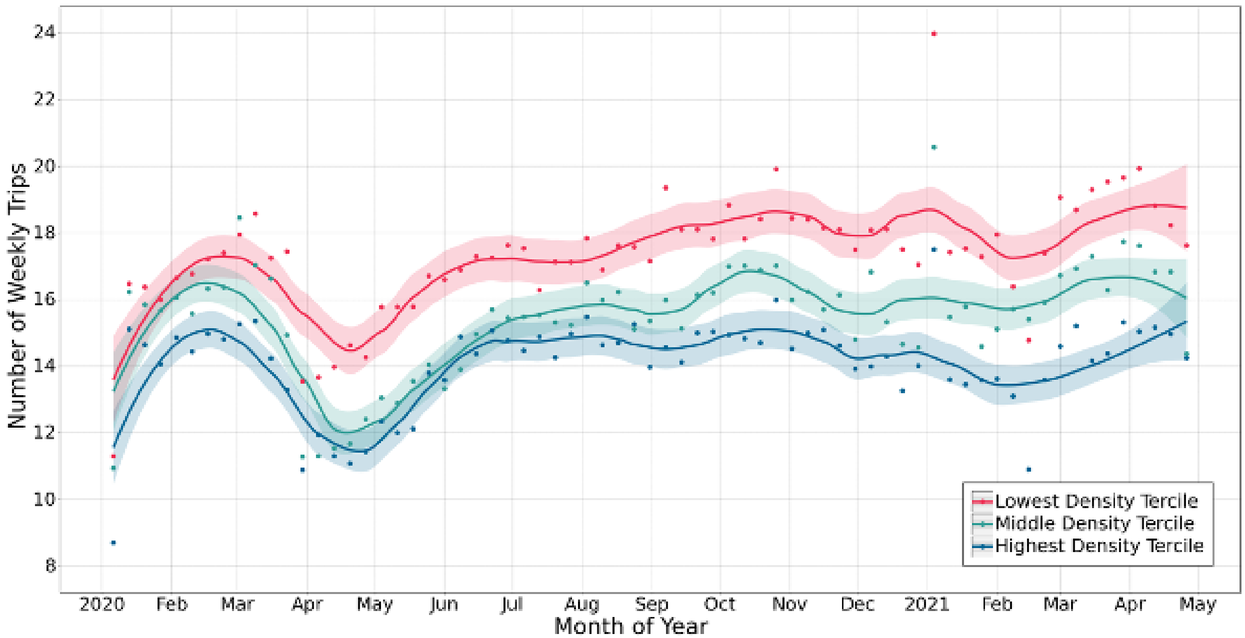

Figure 2.12: Number of weekly trips by study participants from counties with the lowest, middle, and highest population density terciles

5 Conclusions

In this paper, we presented the summary of the data collection processes used for a comprehensive COVID-19 study. We collected longitudinal passive and active data from a set of US panelists throughout the COVID-19 pandemic, starting in August 2020. The passive data consisted of individual level spatial POI data, which provides invaluable insight into human mobility behavior throughout the pandemic. From a review of the literature, and to the best of our knowledge, only one other study combining both individual passive (POI) and broad active (survey) data exist, particularly for a panel. Our longitudinal data reflects the different levels at which behavior can be influenced (individual vs. aggregate) and captures phenomena that vary at different time scales; we measure individual mobility on a daily basis, identifying several characteristics of daily travel behavior over time and capture COVID-19 related policies which are adjusted less frequently and are likely to have a broad impact on local or regional behavior. As a result, our longitudinal dataset helps address the unobserved confounding resulting from cross-sectional dataset and helps overcome the limitations of solely using either passive or active data.

This study collected data from six survey waves, across two years between August 2020 and September 2022. The surveys were slightly modified between waves to capture information relevant to the context of the pandemic in the US. All study participants were compensated for their participation in the study, with varying amounts in each of the survey waves to maintain quality survey responses and participant retention. Increases in the response rates through the survey waves suggest that the participants remaining on the panel are more reliable panelists. Nonetheless, the research team still faced difficulties in achieving the desired response rates in later survey waves despite increasing survey incentives. This difficulty of getting the desired response rates could be due to several factors, including respondent survey fatigue. To overcome this hurdle, the research team targeted more panelists to refresh the respondents pool.

Our sample is not fully representative of the US population, as it overrepresents low and medium income households, non-White Americans, and individuals with a college or university degree. This oversampling is a result of the characteristics of the SimilarWeb panel, which is geographically representative of US smartphone users, but is not fully representative of the US population across several demographic characteristics. Oversampling lower income households and non-White Americans presents a unique opportunity to garner insights on how the pandemic has specifically impacted these communities. Our sample is fairly representative of public transit and active mode users, but our longitudinal data does not reflect the drop in public transit use reported by other research in the early phases of the pandemic.

Our survey incompletion analysis also shows that our survey design might not have been properly suited for smartphones. A significant share of survey abandonment occurs at the mobility section of the survey. Several mobility questions asked for several layers of information in a repetitive format, which might not have been not properly suited for smartphones. However, we notice that the overall survey incompletion rate has continuously decreased across the several survey waves, indicating that returning participants became more comfortable with the survey flow and design.

We also estimated several binary logit models to explore associations between sociodemographic characteristics and several aspects of study participation. Model results show that non-White respondents are more likely to abandon the survey and fail the surveys' attention checks. Additionally, while panelists with a long tenure on the SimilarWeb are significantly less likely to participate in the study, perhaps due to being more selective with what studies to participate in, they were more likely to return for follow-up waves once successfully recruited.

Our passive POI data confirms findings by other researchers, finding a significant drop in mobility activity in the early phases of the COVID-19 pandemic, followed by a consistent recovery since. We illustrate how fusing the passive POI data with active data could reveal mobility behavior heterogeneity across different groups; most notably, individuals without access to a car continued to exhibit significantly lower mobility when compared to individuals without one throughout the COVID-19 pandemic.

This study succeeded in collecting a comprehensive longitudinal panel dataset giving detailed insight into people's lives in response to the COVID-19 pandemic. The dataset has been used in multiple research efforts as outlined in the introduction and could be used in conjunction with other data sources to address a wider range of retrospective questions aiming at fully understanding the impacts of the COVID-19 pandemic and help shape our collective response to similar public health threats in the future.

6 Acknowledgements

The authors would like to thank SimilarWeb for providing access to the passive data used in this research, as well as access to their mobile platform to administer surveys to their panelists. The authors of this paper would like to thank the University of California Center for Information Technology Research in the Interest of Society (CITRIS) for funding support. Additionally, the authors would like to thank all the individuals who provided feedback throughout the duration of the study. The authors would also like to thank the participants for their valuable time. Any omissions are unintentional.

Chapter 3

Human Mobility Reshaped? Deciphering the Impacts of the COVID-195 Pandemic on Activity Patterns, Spatial Habits, and Schedule Habits

Abstract

Despite the historically documented regularity in human mobility patterns, the relaxation of spatial and temporal constraints, brought by the widespread adoption of telecommuting and e-commerce during the COVID-19 pandemic, as well as a growing desire for flexible work arrangements in a post-pandemic work, indicates a potential reshaping of these patterns. In this paper, we investigate the multifaceted impacts of relaxed spatio-temporal constraints on human mobility, using well-established metrics from the travel behavior literature. Further, we introduce a novel metric for schedule regularity, accounting for specific day-of-week characteristics that previous approaches overlooked. Building on the large body of literature on the impacts of COVID-19 on human mobility, we make use of passively tracked Point of Interest (POI) data for approximately 21,700 smartphone users in the US, and analyze data between January 2020 and September 2022 to answer two key questions: 1) has the COVID-19 pandemic and its associated relaxation of spatio-temporal activity patterns reshaped the different aspects of human mobility, and 2) have we achieved a state of stable post-pandemic "new normal"? We hypothesize that the relaxation of the spatiotemporal constraints around key activities will result in people exhibiting less regular schedules. Findings reveal a complex landscape: while some mobility indicators have reverted to pre-pandemic norms, such as trip frequency and travel distance, others, notably at-home dwell-time, persist at altered levels, suggesting a recalibration rather than a return to past behaviors. Most notably, our analysis reveals a paradox: despite the documented large-scale shift towards flexible work arrangements, schedule habits have strengthened rather than relaxed, defying

our initial hypotheses and highlighting a desire for regularity. The study's results contribute to a deeper understanding of the post-pandemic "new normal", offering key insights on how multiple facets of travel behavior were reshaped, if at all, by the COVID-19 pandemic, and will help inform transportation planning in a post-pandemic world.

1 Introduction

Human mobility has been repeatedly shown to be regular and predictable (Song, Qu, et al. 2010; Schneider et al. 2013; Lu et al. 2013; Cuttone et al. 2018). Such regularity is the result of both internal and external constraints. These include circadian rhythms (Aledavood et al. 2022; Aubourg et al. 2020), the need to eat, spatio-temporal commuting requirements (K. Zhao et al. 2016), psychological traits (Alessandretti, Lehmann, et al. 2018), social responsibilities (Susilo and Axhausen 2014), and socio-economic characteristics (Eric I Pas et al. 1987; Susilo and Axhausen 2014). For example, it is easy to imagine how a parent with childcare duties and a fixed work location is constrained to follow a regular schedule with activities that are, for the most part, well-planned ahead of time and regular. Similarly, it is also easy to imagine how a young urban remote worker can flexibly adjust their activities to meet their own needs; not being limited by a fixed work location, this worker can choose to work from different locations, adjust their schedule to run errands during regular business hours when work demands are not intense, and follow working routines that might be synchronous with colleagues from different time zones. Temporal mobility regularity has been shown to lead to increased social contact rates (Santana et al. 2023; Leng et al. 2021; Sun et al. 2013) and play a critical role in disease spreading processes (Pappalardo, Simini, et al. 2015).

In the wake of the COVID-19 pandemic, human behavior underwent significant shifts. Governments, especially during the pandemic's early stages, leaned heavily on non pharmaceutical interventions (NPI) to curb the virus's spread. These interventions had significant impacts on human behavior, reducing mobility levels, changing lifestyles, and causing ripple effects on physical and mental well-being. A standout change during this period was the large scale adoption of telecommuting by employers and the increase in e-commerce adoption by consumers. The persistent preference for and adoption of hybrid working models and e-commerce by employees and consumers, even after the easing of pandemic restrictions, hint at lasting behavioral shifts (Said et al. 2023; K. Parker et al. 2020; K. Parker et al. 2021). Fundamentally, this evolution reflects a relaxation of spatio-temporal constraints around several activities. In a hybrid work paradigm, employees enjoy more autonomy to choose their preferred work environment, be it their home, the office, or some alternative location like cafes, libraries, or coworking spaces (Caros et al. 2023). Further, they enjoy more flexibility in their schedules, including when to work and on what days to commute.

The impacts of the COVID-19 pandemic on human mobility have garnered significant attention from transportation researchers. Researchers addressed the impacts of the pandemic on numerous aspects of travel behavior, such as trip-making (Abdullah et al. 2020; Beck et al. 2020; Fatmi 2020), mode use (Beck et al. 2020; Bucsky 2020; Haas et al. 2020; Eisenmann et al. 2021), trip purpose (Abdullah et al. 2020; Beck et al. 2020; Haas et al. 2020; Parady et al. 2020), distance traveled (M. Lee et al. 2020; Molloy, Tchervenkov, et al. 2020), public transit and active transportation (Jenelius et al. 2020; Nikiforiadis et al. 2020;

Pawar et al. 2020; Dong et al. 2021; M. E. Parker et al. 2021), commuting behavior (Pawar et al. 2020; Matson et al. 2021; Shakibaei et al. 2021), e-commerce (Luo et al. 2023; Said et al. 2023), and time-use (Mesaric et al. 2022; Sullivan et al. 2021; Shi et al. 2023; Batur et al. 2023), among others.

However, these works have several limitations. First, majority of the research has been myopic to the broader impacts of the COVID-19 pandemic on human mobility, often focusing on singular aspects of travel behavior. Second, this body of work has predominantly addressed the short-term impacts of the pandemic on travel behavior, with little attention given to potential long-term impacts, indicating our lack of collective understanding of what the post-pandemic landscape is shaping up to be. Most critically, our current understanding of the impacts the COVID-19 pandemic and its associated relaxation of spatio-temporal constraints on schedule habits remains missing. Improving this understanding will help inform transportation planning in a post-pandemic world.

In this article, we use passive mobility tracking dataset from a panel of approximately 21,700 U.S. smartphone users, spanning January 2020 (2 months before the onset of the pandemic) to September 2022 (14 months after widespread vaccine availability in the U.S.) to attempt to address these limitations. First, we propose a framework to explore the impacts of the COVID-19 pandemic and its associated relaxation of spatio-temporal activity constraints on multiple dimensions of mobility behavior. We choose well-established mobility metrics from the literature characterizing human activity patterns, namely frequency of travel, radius of gyration, dwell-time, trip timing, spatial exploration, and spatial diversity (as measured by entropy). Second, within this framework, we propose a new metric to measure individual schedule regularity over time, contributing to the literature on intrapersonal travel behavior variability. Finally, we build on the vast COVID-19 travel behavior literature by investigating the long term impacts of the pandemic on travel behavior, providing more clarity on what a "new normal" is shaping up to be. We hypothesize that with the relaxation of spatio-temporal activity constraints during the COVID-19 pandemic, people will exhibit less schedule regularity post-pandemic compared to pre-pandemic.

Figure 3.1 provides a comprehensive review of our key findings. Our findings present a mixed picture; while several mobility indicators have recovered to their pre-pandemic levels (trip frequency, radius of gyration, peak period demand), others have not (i.e. at home dwell-time). We further find that while people's explorative behavior recovered to their pre-pandemic levels, they exhibit on average lower diversity (as measured by entropy) in their time distribution across space compared to pre-pandemic. Finally, we find that despite the loosening of spatio-temporal activity constraints during the pandemic, schedule habits remain stronger than pre-pandemic, presenting a counterintuitive picture to our initial hypothesis.

The rest of the manuscript is organized as follows; in Section 2, we summarize our data,

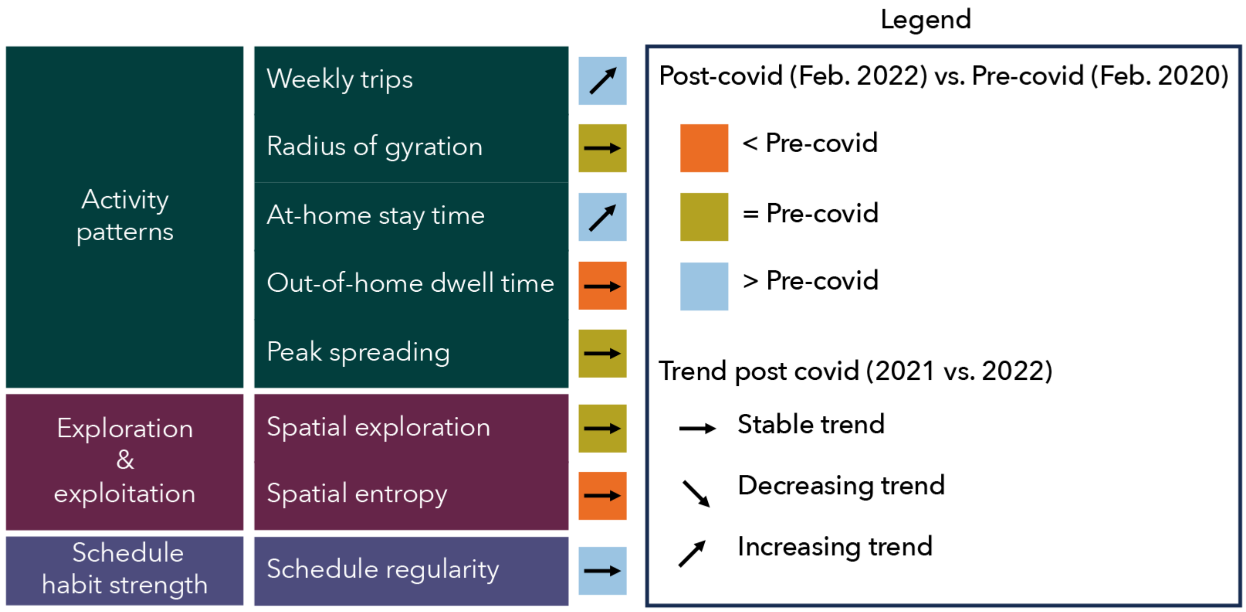

Figure 3.1: Summary of study findings

its pre-processing, as well as the analysis framework and approach; in Section 3 we present our findings; we conclude with summarizing the study and discussing the possible broader impacts of our findings in Section 4.

2 Data and Methods

2.1 Data

We leverage passively collected tracking data from a panel of U.S. smartphone users who have consented to give access to their location data. The data was provided by SimilarWeb for research purposes and spans between January 2020 and September 2022, effectively capturing critical long-term behavioral impacts of the COVID-19 pandemic.

These data are not continuously tracked GPS traces, but rather inferred individual check-ins at Points of Interest (POI). SimilarWeb uses proprietary technology from a third-party provider to infer the location category from each of the POIs visited. Further, to preserve the individuals' privacy, SimilarWeb obfuscates the individuals' inferred home and work locations by randomly placing it within a 1000 meters radius from its detected location. For each individual check-in at a POI, the dataset includes information about the panelist's arrival and departure times, the category of the location visited, the distance and time traveled to get to said location, the distance of the POI from the individual's identified home and work locations, as well as its zip code, city, and Metropolitan Statistical Area (MSA) name.

In addition to the POI check-in records, the dataset contains self-reported information about individuals' gender, age, race/ethnicity, household size, household income, educational level, and employment status.

One key advantage of our data is our ability to capture a continuous trajectory of individuals, instead of sparse records depending on the call activity under call detail records data (CDR) or location-based service use for location based service (LBS) data (Z. Zhao et al. 2016; Çolak et al. 2015). However, one main limitation of our data is the lack of information about travel modes used for each inferred trip, preventing us from understanding the modal impacts of the COVID-19 pandemic.

To ensure accuracy of our analyses, we undertake rigorous pre-processing to clean our data from any inconsistencies or noise. First, we aggregate each of the POIs visited by each individual into geographical locations based solely on their spatial proximity. This is particularly useful considering that detected spatial coordinates of visited locations can often be noisy (Alessandretti, Sapiezynski, et al. 2018). We use the DBSCAN algorithm (Ester et al. 1996) to cluster the check-ins for each individual using a maximal distance ε. We use a maximum distance $\varepsilon = \mathbf{50}$ meters and **min_samples** $= \mathbf{1}$, to produce places of the approximate size of a building, consistent with previous literature (Alessandretti, Sapiezynski, et al. 2018; Cuttone et al. 2018; Hong et al. 2023). The result of this pre-processing clustering is an assignment of cluster label to each inferred POI check-in, where the label refers to a geographical place of the POI check-in record.

Second, to maintain high quality observations, we select only individuals observed for a long period of time with small change in tracking coverage over time, consistent with previous literature (Alessandretti, Sapiezynski, et al. 2018; Yang et al. 2023; Hong et al. 2023). In our context, time coverage is defined as the share of time one's location is known. More specifically, we select panelists observed for at least 20 weeks between January 2020 and September 2022, and showing little variability in time-coverage over time. We use the coefficient of quartile variation (Bonett 2006), to measure the individual variability of time-coverage over time, defined as:

$$\frac{Q_3 - Q_1}{Q_3 + Q_1} < 0.25 \tag{3.1}$$

Where Q_3 and Q_1 are the 75^{th} and 25^{th} percentiles of the individual's weekly time coverage over time, respectively.

Our final sample includes approximately 21,700 individuals. The median individual time coverage across the data collection span is depicted in Figure 3.2. While the median time coverage remains consistent between 75% and 80% for most of the data collection period, there was a notable decline in July and August 2021 due to an unexplained data collection issue. To maintain data integrity, we exclude the data from these two months in our analysis. Further, we find that time-coverage quality was consistent across diverse sociodemographic categories throughout the data collection period.

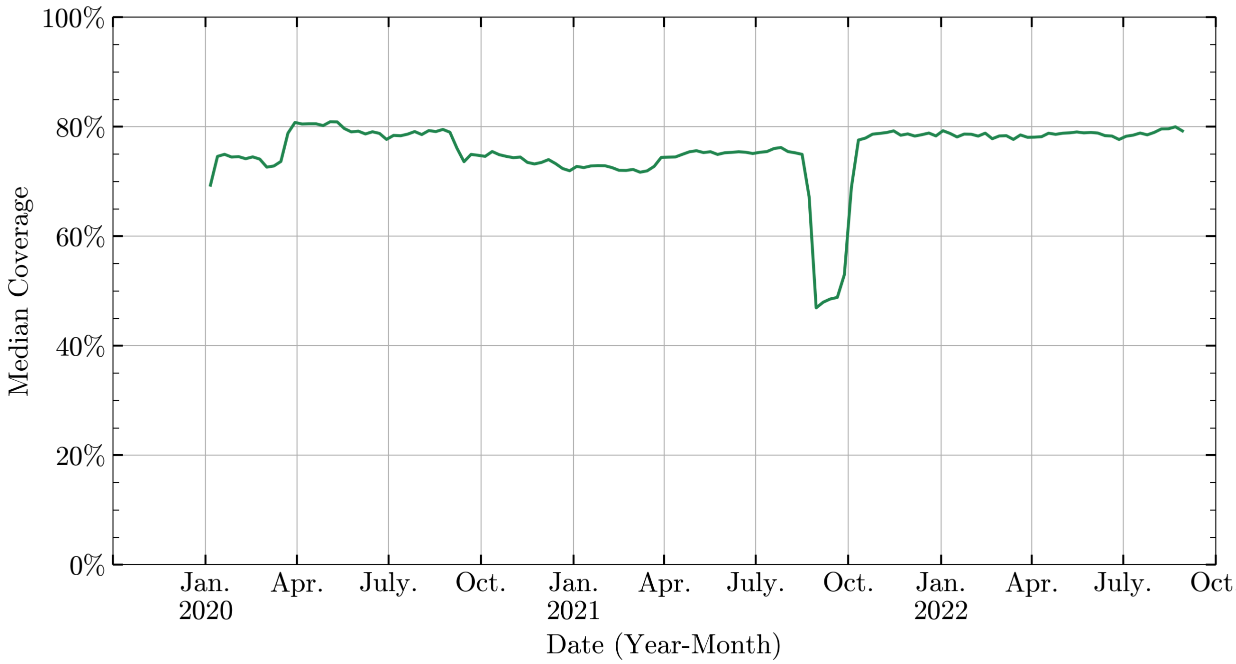

Figure 3.2: Median weekly temporal tracking coverage across the population as a function of time. A significant drop in coverage occurs in August and September 2021.

Table 2.1 presents a summary of the sociodemographic characteristics of our sample, compared to the U.S. population based on data from the 2019 U.S. census. Notably, our sample is over-representative of females, lower income households, racial minorities and individual with at least a college degree.

We can further process this to compute individual mobility measures of interest (e.g. distance traveled for specific purposes or locations, variability in commute time, dwell time at locations, etc.). In the next section, we present our proposed methodology and the mobility metrics we used to achieve the research objectives.

Table 3.1: Sample demographic characteristics compared to the US population

	Data (%)	US Population (%)
Female	56.0	50.8
Household Income $<$ 50K USD	71.1	40.4
White	66.1	72.5
College Degree or More	40.1	38.5

2.2 Framework and metrics

Travel behavior and its regularity are intricately linked to the many constraints one faces (Aubourg et al. 2020; K. Zhao et al. 2016; Susilo and Axhausen 2014). For instance, transit accessibility, work schedules, and caregiving responsibilities play critical roles in shaping one's travel decisions (e.g. commute timing, frequency, etc.) and their long-term regularity.

However, the COVID-19 pandemic has potentially reshaped this landscape. Beyond its immediate effects on activity patterns, the pandemic-induced relaxation of the spatio-temporal constraints around key activities might be a precursor to newly emerging behaviors emblematic of the post-pandemic "new normal". A case in point is the growing adoption of hybrid work models, which liberate individuals from traditional spatio-temporal work constraints. In fact, large shares of workers favor more flexible work arrangements in a post-pandemic world (K. Parker et al. 2021; Alexander et al. 2021). As a result of this shift, people could start exhibiting new spatial exploration patterns and less structured activity schedules.

Our research objectives are twofold:

- First, to determine if post-pandemic mobility behaviors are different from pre-pandemic baselines
- Second, to assess if post-pandemic mobility behaviors exhibit stability and, if not, identify post-pandemic trends

Our hypothesis in this research is that the relaxation of spatio-temporal constraints following the COVID-19 pandemic have a broader influence on mobility behavior, affecting not just activity patterns, but also spatial and schedule habits. To test this hypothesis, we present a framework (Figure 3.3) that goes beyond investigating the impact of the COVID-19 pandemic on traditionally reported mobility metrics (namely, travel frequency, distance traveled, activity duration, and activity timing), and extends to metrics that capture spatial and schedule habits.

In the case of activity patterns and spatial habits, build upon the existing literature, emphasizing the pandemic's long-term effects and understanding what a post-pandemic new normal is shaping up to be. Regarding schedule habits, we propose a new metric capturing the regularity of individual schedules over time, while controlling for day-of-week characteristics. The following sections present, in greater detail, each of these dimensions and the metrics we use to capture their evolution throughout the COVID-19 pandemic.

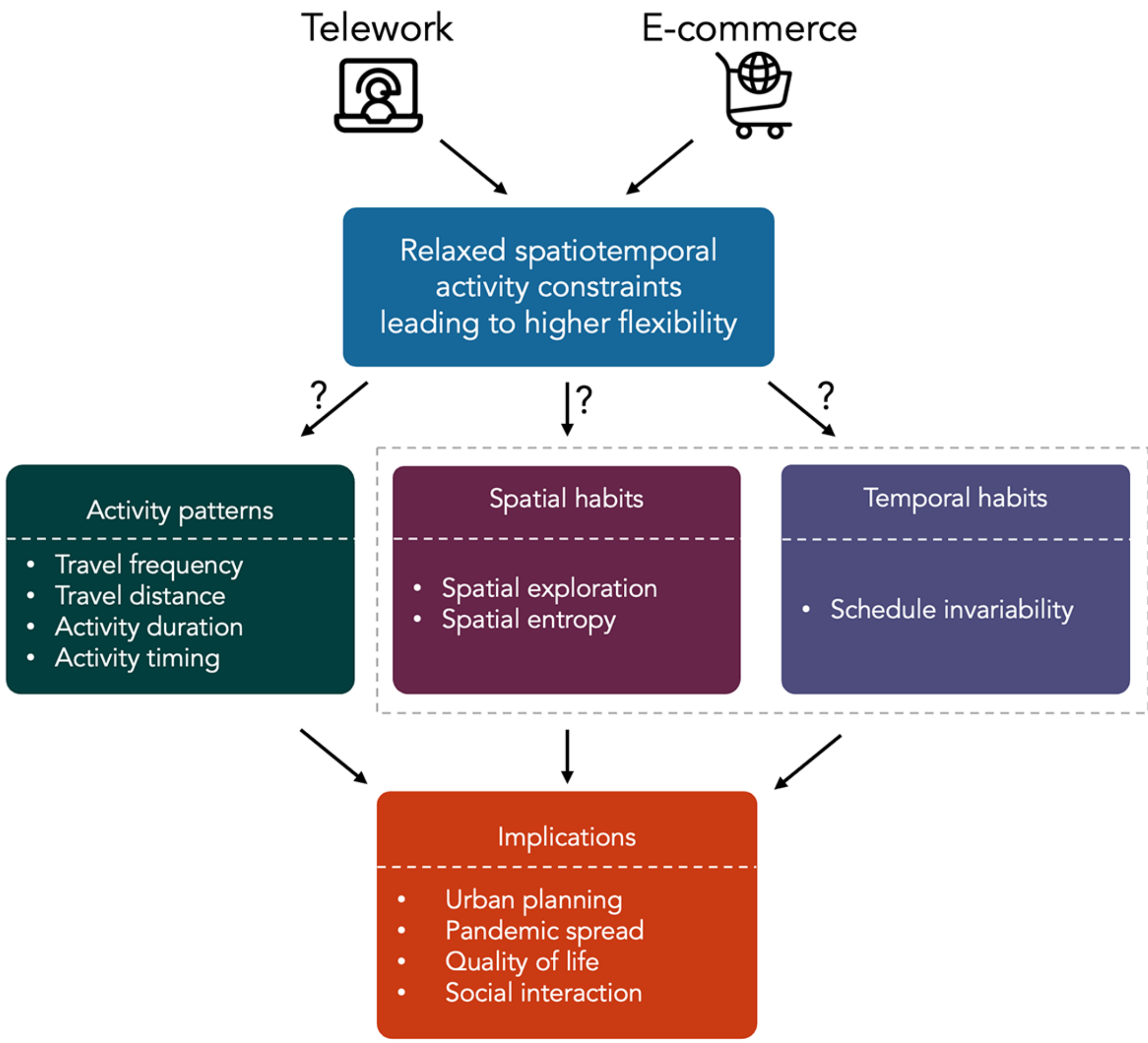

Figure 3.3: Proposed research framework, highlighting the impacts of relaxed spatio-temporal constraints on human mobility and its possible implications

Activity patterns: First, the loosening of spatio-temporal activity constraints throughout the pandemic can impact activity patterns. For example, individuals with flexible working arrangements can decide take fewer trips or avoid commuting during peak periods. Previous work has explored the impact of the COVID-19 pandemic on many widely reported mobility metrics including trip frequency (Beck et al. 2020), travel distance (M. Lee et al. 2020; Hintermann et al. 2023), and time-use (Mesaric et al. 2022). In this work, we characterize activity patterns by the following quantities:

- **Travel frequency**: We characterize travel frequency by the number of weekly trips taken by an individual.
- **Travel distance**: We use the radius of gyration to characterize the typical distance traveled by an individual (Gonzalez et al. 2008). The radius of gyration is defined as:

$$r_g = \sqrt{\frac{1}{n}\sum_{j=1}^{n} dist(r_j - r_{cm})^2} \tag{3.2}$$

  Where r_j is a two-dimensional vector of the spatial coordinates of the j^{th} location, and r_{cm} is the center of mass of the locations visited by the individual, $dist(r_j - r_{cm})$ is the haversine distance between the j^{th} location and the center of mass, and n is the total number of locations visited.
- **Stay duration**: We use dwell time at each POI to measure the typical stay duration of an individual i at any visited location. Dwell-time is a key component of mobility models (Song, Koren, et al. 2010; Pappalardo, Simini, et al. 2015). Further, as the pandemic has forced many people to stay at home, especially in its early phases, we distinguish between total daily at-home dwell time and out-of-home dwell-time to investigate any possible shifts in dwell-time across different location types. We present results on at-home total stay duration in the main text and include additional results on out-of-home visit dwell-time in Appendix B.
- **Trip timing**: We measure peak demand concentration by identifying the share of trips during the AM peak (i.e. 6-9AM) that fall between 7-8AM.

Spatial habits: Beyond activity patterns, the relaxation of spatio-temporal activity constraints during the COVID-19 pandemic could also reshape individuals' spatial habits. While research suggests individuals balance exploring new places with revisiting known ones (Pappalardo, Simini, et al. 2015), the pandemic's influence on this balance is yet to be fully understood. In particular, the relaxation of spatio-temporal activity constraints might redefine how individuals explore their surroundings.

Further, while the use of geographical space tends to be uneven, with people spending the majority of their time in a limited number of locations, notably work and home, looser spatio-temporal constraints might alter this distribution, possibly resulting in higher heterogeneity of use of geographical space.

We use the following measures to quantify how the propensity of exploration and exploitation:

- **Spatial exploration**: We use the spatial exploration rate, σ_p (Moro et al. 2021), which measures the fraction of total visits to new places to capture the propensity for exploration for each individual, defined as:

$$\sigma_p = \frac{S}{N} \tag{3.3}$$

  Where S is the number of unique locations visited and N is the total number of visits made by the individual.

- **Spatial entropy**: We use entropy to measure the heterogeneity of time distribution across geographical space. Spatial entropy has been used in previous works (Pappalardo, Vanhoof, et al. 2016; Pappalardo, Pedreschi, et al. 2015; Y. Xu et al. 2018) and is defined as:

$$H_{\text{norm}} = \frac{-\sum_{i=1}^{N} p_i \log(p_i)}{\log(N)} \tag{3.4}$$

  Where $p_i = \frac{T_i}{\sum_i^N T_i}$ is the probability of finding the individual at location i and T_i is the total time spent at location i, and N is the total number of unique locations visited by the individual. Lower entropy values indicate lower heterogeneity in one's whereabouts.

Schedule habits: Temporally, a loosening of spatio-temporal constraints could induce people to be less habitual in their schedules from week to week. For example, an employee with a hybrid work schedule can decide to commute to their workplace on different days from week to week. We use the cosine similarity to calculate the similarity between any pair of daily schedules. In this context, we describe a schedule by the distribution of time spent across different locations. The cosine similarity is defined as follows:

$$Cosine(\mathbf{d_{(i,t,j)}}, \mathbf{d_{(i,t,k)}}) = \frac{\mathbf{d_{(i,t,j)}} \cdot \mathbf{d_{(i,t,k)}}}{\|\mathbf{d_{(i,t,j)}}\| \cdot \|\mathbf{d_{(i,t,k)}}\|} \tag{3.5}$$

Where:

- $\mathbf{d_{(i,t,j)}}$, $\mathbf{d_{(i,t,k)}}$ represent the normalized time allocation vectors for the same individual i on day of week t (i.e., Monday, Tuesday, etc.) from distinct weeks j and k.

- $\mathbf{d_{(i,t,j)}} \cdot \mathbf{d_{(i,t,k)}}$ represents the dot product of vectors $\mathbf{d_{(i,t,j)}}$ and $\mathbf{d_{(i,t,k)}}$.
- $\|\mathbf{d_{(i,t,j)}}\|$ and $\|\mathbf{d_{(i,t,j)}}\|$ represent the Euclidean norm (magnitude) of vectors $\mathbf{d_{(i,t,j)}}$ and $\mathbf{d_{(i,t,k)}}$, respectively.

The time allocation vectors (i.e., $\mathbf{d_{(i,t,j)}}$ and $\mathbf{d_{(i,t,k)}}$ in equation 3.5) for an individual i are L_i-dimensional vectors (where L_i is the number of unique locations visited by individual i, identified from the aggregating individuals' POI locations into geographical locations, see Section 2.1) containing the normalized time spent in any of the different locations on any specific day. The cosine similarity measures the cosine of the angle between the two non-zero vectors in the L_i dimensional activity location space, in this context the angle between the vectors representing the allocation of time across geographical space on two distinct days.

We evaluate schedule similarity for the same individual through pairwise daily schedule comparisons to the same type of day (i.e. Monday vs. Monday, Tuesday vs. Tuesday, etc.). Evaluating similarity in this manner controls for characteristics of specific days of week, such as outside social constraints common to the same day of week (e.g. specific commute schedule, recurring social commitments on specific days, care-taking responsibilities, etc.).

This approach builds on the large body of literature addressing intrapersonal travel behavior similarity. Previous works, primarily based on self-reported travel diaries, has explored the depth of variability in travel decisions (Eric Ivan Pas 1980; E. Pas 1986; Schlich et al. 2003; Kang et al. 2010; Susilo and Axhausen 2014), finding a significant degree of intrapersonal variation, the extent of which depends on the nature of travel decisions (Susilo and Axhausen 2014) and socio-economic characteristics (Susilo and Kitamura 2005). However, these studies overlook the likelihood that travel habits, influenced by societal constraints, can differ based on the specific day of the week. More specifically, they do not account for possible shared characteristics between observations on the same day of week, at most comparing weekdays to each other and weekend days to each other (Kang et al. 2010; Susilo and Axhausen 2014). Accounting for day-of-week characteristics is crucial in understanding the regularity of schedules, as societal obligations and constraints are often tied to specific days. For example, a parent might have a consistent obligation to drive their child to an after-school activity every Wednesday afternoon, while Thursdays might involve weekly parent-child community group meetings, leading to distinct schedules on those days, even if they are both weekdays.

The cosine similarity has been used extensively in the human mobility literature, measuring similarity in individuals' activity spaces over time (Alessandretti, Sapiezynski, et al. 2018), clustering individuals based on their mobility patterns (Toole et al. 2015; Fan et al. 2017; Di Clemente et al. 2018), and measuring similarity of neighborhoods according to their mobility patterns (Morales et al. 2019), among many others (Alhazzani et al. 2021).

To ensure that our results are not an artifact of our choice of metric, we use other metrics proposed by B. Lee et al. (2019) and find that our results remain consistent.

2.3 Analysis approach

On January 21, 2020, the United States reported its first COVID-19 case in the state of Washington. By late February, concerns about community spread intensified. In response, several states declared states of emergency in early March, a move that many states would soon emulate. On March 13, 2020, the Federal government declared a national emergency, mobilizing federal resources to manage the pandemic. By mid-March, many states and local jurisdictions had initiated measures such as school closures, large gathering restrictions, and social distancing protocols. By the end of April and into May, while most states still had declared emergencies and stay-at-home orders in place, several began outlining phased reopening plans, balancing economic needs with public health concerns. By the end of 2020, a range of vaccines had become available, marking a pivotal turning point in the pandemic. This development heralded the start of a nationwide vaccination drive in early 2021. By May 2021, vaccinations had become widely available in the US. By end of 2021, approximately 83% of U.S. adults had already received at least one vaccine shot (Disease Control 2021). Figure 3.4 presents key milestones throughout the COVID-19 pandemic in the U.S., including the number of reported cases and significant markers throughout the pandemic, such as state reopenings, vaccination rollouts, and the emergence of COVID-19 variants.

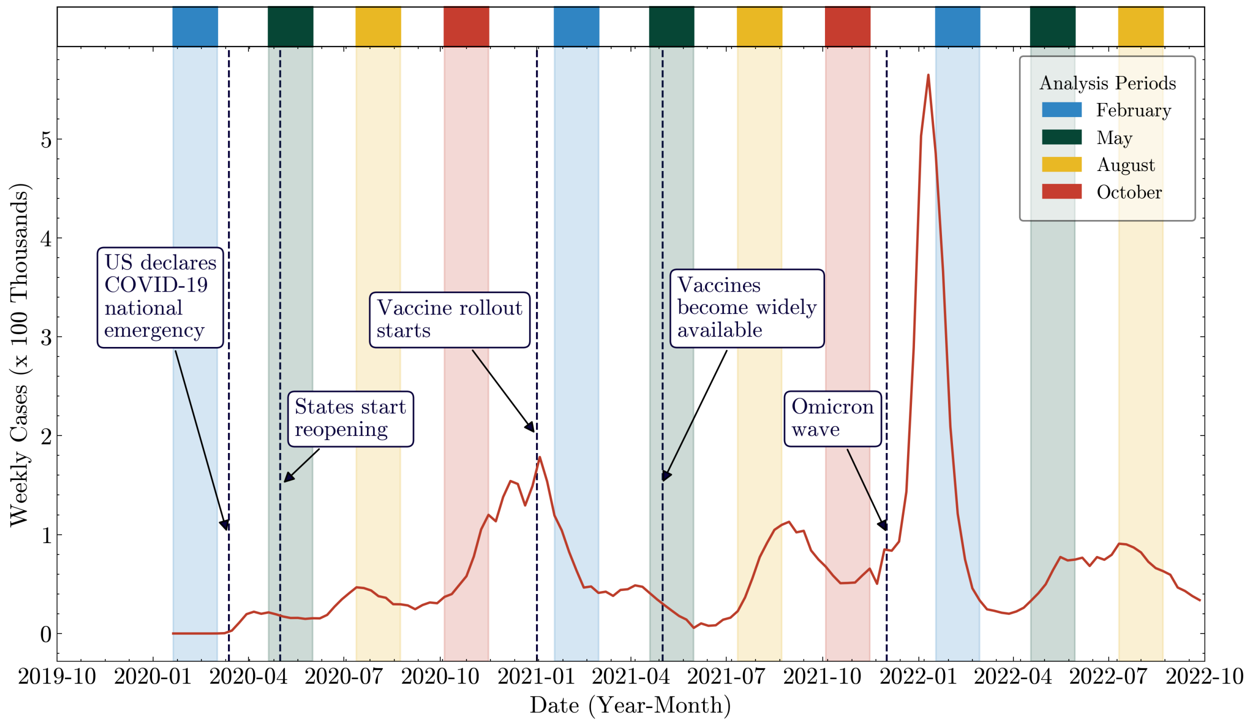

Figure 3.4: COVID-19 cases in the United States and key pandemic milestones

With this backdrop in mind, we investigate the impact of the COVID-19 pandemic and its associated loosening of spatio-temporal activity constraints on activity patterns, spatial habits, and schedule habits. To achieve our research objectives, we proceed as follows:

- To determine if post-pandemic mobility behaviors are different from pre-pandemic baselines: We compare mobility metrics across three pivotal periods: February 2020 (representing pre-pandemic mobility), February 2021 (one year into the pandemic), and February 2022 (two-year outlook, after wide vaccination). This allows us to discern shifts and continuities in mobility trends over these critical junctures.
- To assess if post-pandemic mobility behaviors exhibit stability and, if not, identify post-pandemic trends: We analyze metrics from May 2021, marking the period post widespread vaccine availability, and compare them to May 2022. This comparison helps decipher whether behavioral changes observed after the vaccine rollout have persisted or are continuing to evolve.

We compute our proposed metrics at key times throughout our data collection period, shown with colors vertical stripes in Figure 3.4 and employ 2-tailed t-tests to compare mobility metrics across key periods. By consistently comparing data from similar months across different years (e.g., February 2020, 2021, and 2022), we aim to negate the influence of any seasonal factors that might affect mobility, such as weather patterns, holidays, or school cycles, ensures that any observed differences in mobility patterns can be more confidently attributed to the pandemic's influence. For our first objective, we use data from February 2020, 2021, and 2022 (shown in blue stripes). For our second objective, we use data from February 2021 and February 2022 (shown in blue stripes), as well as May 2021 and May 2022 (shown in green stripes). The other time periods provide us with further indication on how each of the metrics evolved throughout the pandemic and their levels post-pandemic. We should note the deliberate omission of August 2021 due to the data coverage quality issues summarized in Section 2.

3 Results

Within our framework, we identified seven metrics to investigate how the COVID-19 pandemic and its associated relaxation of spatio-temporal activity constraints has impacted activity patterns. The following subsections summarize the results of three categories of metrics identified in the framework presented in Figure 3.3.

3.1 Activity patterns

In this section, we present our analysis results of four key metrics identified to understand the impact of the relaxation of spatio-temporal activity constraints through the COVID-19 pandemic on activity patterns. We summarize the results in Figure 3.5.

Figure 3.5a summarizes the evolution of the average number of weekly trips throughout the COVID-19 pandemic. We observe the initial dip in the number of weekly trips between February 2020 and May 2020 from 22 trips to approximately 20.5 trips. While this decrease might not seem as significant as what was reported in the literature (M. Lee et al. 2020), it reflects conditions after several states have started reopening (Disease Control 2022). Since then, we observe a continuous increase in the number of weekly trips individuals take all throughout the pandemic. When comparing post-pandemic conditions (February 2022) to pre-pandemic conditions (February 2020), we observe that the number of trips has recovered to its pre-pandemic baseline (as early as February 2021), with an average of 26.9 weekly trips in February 2022 compared to 22 weekly trips in February 2020 ($p < 10^{-3}$). Further, we observe an increasing trend in the number of weekly trips taken after the wide vaccine availability (May 2021 vs. May 2022, $p < 10^{-3}$).

Figure 3.5b summarizes the evolution of the radius of gyration throughout the pandemic. We observe a decrease in the range of the radius of gyration in the early phases of the pandemic (between February 2020 and May 2020), from 21.5 to 16.7 km ($p < 10^{-3}$), indicating that people have reduced their mobility's spatial range, consistent with the observation that people were spending most of their time at home, and when traveling, traveling to areas close to their home location. We observe a continuous recovery of the average radius of gyration after the initial phases of the pandemic, despite the seasonal fluctuations, consistent with other findings in the literature (Santana et al. 2023). In February 2021, shortly after the beginning of the vaccine rollout in the U.S., the radius of gyration was still lower than its pre-pandemic levels in February 2020 ($p < 10^{-3}$). However, in February 2022, the radius of gyration has recovered to its pre-pandemic level ($p = 0.23$). Post-pandemic, we observe that the radius of gyration is stable between May 2021 and May 2022 ($p = 0.49$). In October 2021 (i.e. after wide availability of vaccines), we observe that people exhibit higher radius of gyration than October 2020. Similarly, in August 2022, we notice larger radius of gyration compared to August 2020, likely due to the recovery of out-of-home travel. Further, we observe that the radius of gyration shows strong seasonal patterns, with summer months exhibiting higher radius of gyration levels than winter months, possibly due to summer travels. When juxtaposed to the evolution of trip frequency during the pandemic, we observe that even as people started more trips in 2021 compared to pre-pandemic, the spatial extent of such trips has not expanded beyond its pre-pandemic ranges.

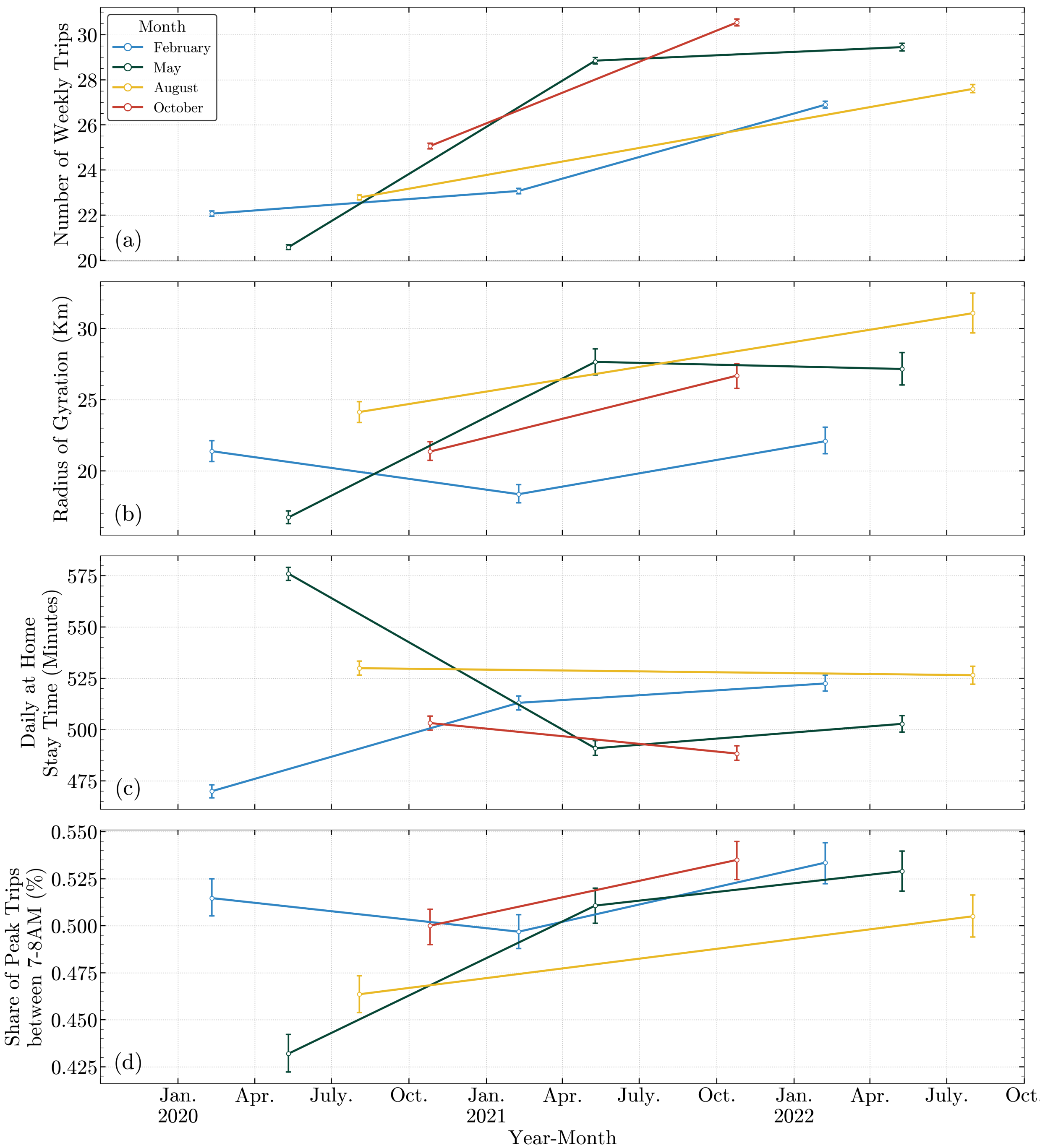

Figure 3.5: Evolution of activity patterns throughout the COVID-19 pandemic. (a) weekly trips, (b) radius of gyration, (c) at-home stay duration between 6AM-9PM, (d) peak demand. The error bars represent the 95% confidence interval around the population mean. ($N \approx 21,700$ individuals)

3.2 Schedule habits

Beyond spatial habits, understanding the regularity of routines from week to week is key in understanding the predictability of human behavior. Within the COVID-19 context, we hypothesized that as people experience less spatio-temporal activity restrictions, they would tend to exhibit less similarity in their day-of-week schedules over time. Further, we suggest that controlling for day-of-week in evaluating intrapersonal schedule variability is critical in understanding predictability of human behavior, as social constraints are often associated with set temporal constraints on distinct days.

Figure 3.6 summarizes the cosine similarity of day-of-week distribution of time and illustrates that schedule habits show strengthening in the early phases of the COVID-19 pandemic (February 2020 vs. May 2020, $p < 10^{-3}$), likely as a result of people spending large shares of time at home. However, contrary to our initial hypothesis, individuals exhibit stronger schedule habits in post-pandemic compared to pre-pandemic, with people showing stronger habits in February 2022 compared to February 2020 ($p < 10^{-3}$). Additionally, we also find evidence for stability in schedule habits post-pandemic (May 2021 vs. May 2022, $p = 0.14$).

The lack of evidence for less structured schedules is surprising, as previous works find strong evidence that workers favor more flexible work arrangements in a post-pandemic world (Alexander et al. 2021). Our finding indicates that while people prefer flexibility, they might take advantage of it by setting an individual schedule that remains strong over time. Further, our finding does not necessarily mean that people returned their pre-pandemic behaviors, but show that while they might have adopted new behaviors, they exhibit strong habits in such behaviors.

3.3 Relationship between spatial habits and schedule habits

In the previous sections, we find evidence for changes in both spatial and schedule habits of human mobility post-pandemic. In this section, we investigate the association between these two aspects of mobility habits (i.e. diversity in spatial habits and schedule regularity). More specifically, we present this association at two distinct points in time, February 2020 and February 2022. Figure 3.7 presents the contour plots for the kernel density estimation of the distribution of cosine similarity (schedule habits) vs. spatial entropy (spatial habits) at three distinct levels of the probability density function.

First, regardless of the time period, we observe a negative relationship between spatial entropy and cosine similarity. This indicates that, on average, people with higher spatial diversity are likely to exhibit less regular day-of-week schedules across weeks. Further, we observe higher heterogeneity in cosine similarity (schedule habits) at higher levels of spatial entropy indicating that despite having high spatial diversity, distinct individuals can exhibit a wide range of schedule regularity. Second, we observe a shift in the population distribution

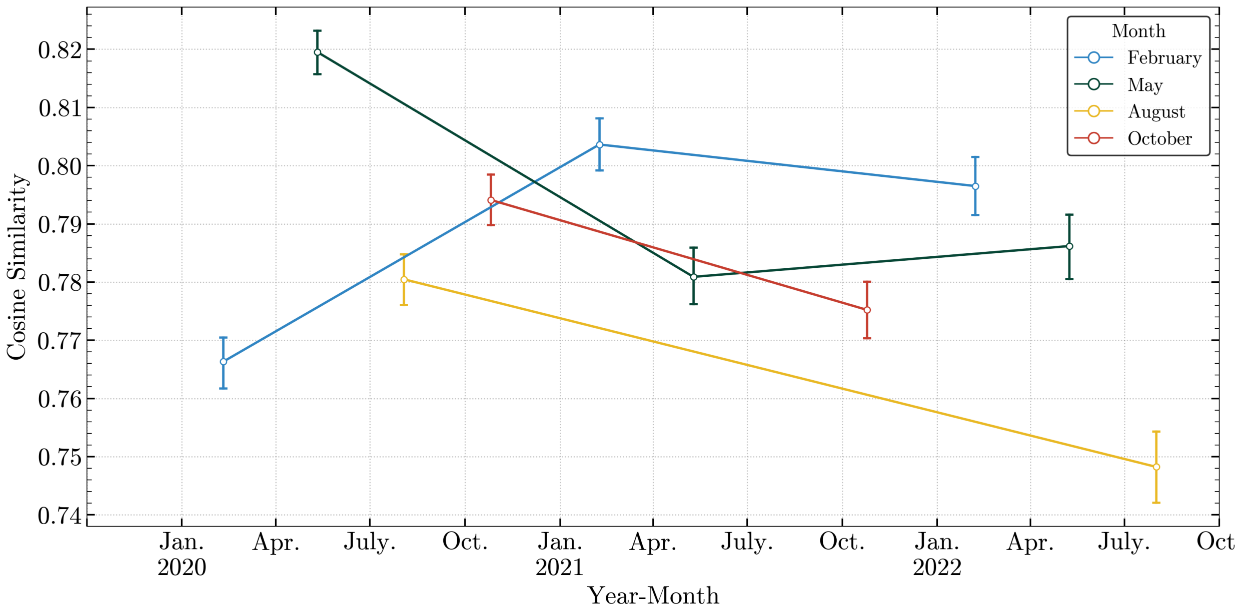

Figure 3.6: Day-of-week schedule cosine similarity throughout the COVID-19 pandemic. Schedule similarity is calculated between 6AM-9PM. Error bars represent the 95% confidence interval around the estimated population means. ($N \approx 21,700$ individuals)

between February 2022 and February 2020, highlighting a coupled shift in both dimensions, with the population shifting more towards both less spatial diversity and stronger schedule habits.

4 Conclusion

In this study, we contribute to the extensive body of literature aiming to understand the impacts of the COVID-19 pandemic on human mobility behavior. Motivated by the relaxation in spatio-temporal constraints of key activities such as work and shopping, we go beyond investigating the impacts of the pandemic using traditionally reported key metrics since these metrics do not convey the full complex picture of human mobility behavior and how it was reshaped.

Using passively tracked POI data from a panel of smartphone users in the U.S. between January 2020 and September 2022, we propose an analytical framework that distinguishes the impacts of the relaxation of spatio-temporal activity constraints on activity patterns, spatial habits, and schedule habits. Within this framework, we use a suite of metrics each designed to capture distinct aspects of human mobility. Most notably, we propose a new metric to measure schedule habits, more specifically to measure the similarity of weekly

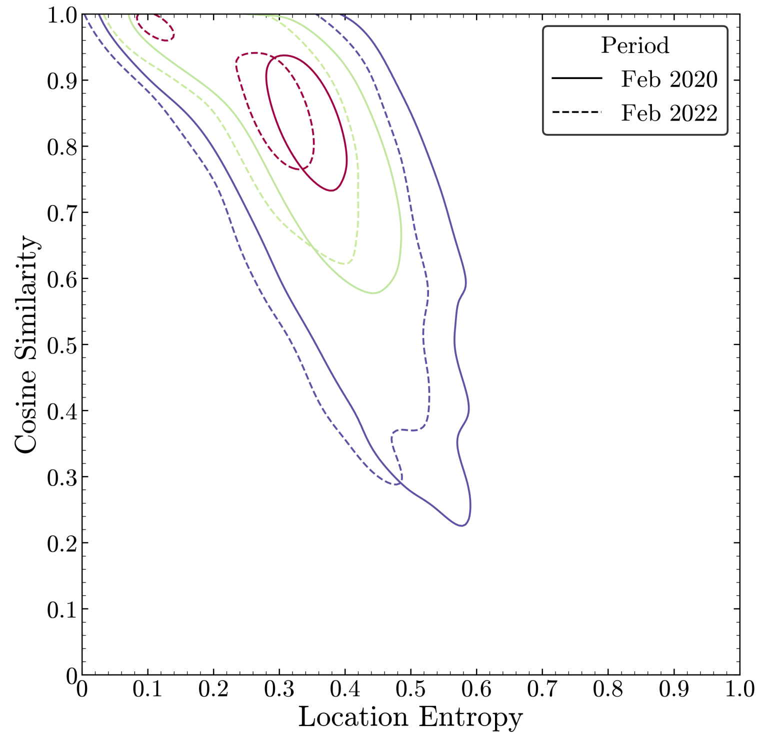

Figure 3.7: Correlation between cosine similarity and spatial entropy in February 2020 (continuous) and February 2022 (dashed line)

schedules over time, controlling for differences between different days of the week. In doing so, we also contribute to the large body of literature on intrapersonal variability in mobility behavior.

Our findings paint a complex picture, as summarized by Figure 3.1. Our data reveals that, while there was a significant impact on multiple aspects of human mobility during the early phases of the pandemic, such impacts were not permanent across all explored metrics. In terms of activity patterns, we find that with the exception of dwell-times, key aggregate mobility metrics have recovered to their pre-pandemic baselines, even exceeding them by 2022 as in the case of number of weekly trips. Dwell-times have been reshaped, with out-of-home visit dwell-times still remaining lower than their pre-pandemic baselines. Further, we find that despite exploration patterns being on average similar to their pre-pandemic baselines, there is less heterogeneity in people's distribution of time across space. Surprisingly, our data reveals the strengthening of schedule habits in a post-pandemic world, challenging our initial hypothesis that people would take advantage of looser spatio-temporal constraints and exhibit more variable schedules from week to week. We also document the relationship between spatial and schedule habits, showing that higher levels of spatial entropy (i.e. spatial diversity) are associated with lower schedule regularity.

These findings, however, are not without limitations. Our most notable limitation is the lack of data for a long period of time before the onset of the pandemic. Having more data before the pandemic would allow us to draw more robust conclusions, and we encourage other researchers to replicate our results using other data. Second, although we have used well-established mobility metrics in drawing our conclusions, our analysis might still suffer from possible biases relating to our data's sociodemographic profile and possible uncertainties in the data collection and location inference algorithms. Future research should aim to address these limitations.

5 Acknowledgements

We would like to thank SimilarWeb for providing access to the passive data used in this research. The opportunity to undertake this research was also made possible by the Dwight D. Eisenhower Transportation Graduate Program, which is administered by the Federal Highway Administration. Any omissions are unintentional.

Chapter 4

Influence of telecommuting on out-of-home time use and diversity of locations visited: Evidence from the COVID-19 pandemic

Abstract The COVID-19 pandemic has led to unforeseen changes in travel and activity behavior, most notably the wide adoption of telecommuting across various sectors of the workforce. This paper investigates the impact of telecommuting on time use and the number of unique locations visited, both of which have been shown to be closely linked to well-being. Previous telecommuting research often relies on cross-sectional data for which it is difficult to control for unobserved confounding, only analyzes impacts of time-use at the daily level, and has yet to quantify the impact of telecommuting on diversity of locations visited. We use quasi-experimental designs to control for unobserved confounders and extend previous research to identify whether the daily impacts of telecommuting on time-use are additive or substitutional at the weekly level. We use passively collected Point of Interest (POI) data between January 2020 and September 2022, supplemented by five waves of survey responses throughout the COVID-19 pandemic (August 2020, October 2020, December 2020, April 2021, and July 2021) from a panel of U.S. smartphone users. We find that on telecommuting days, workers spend significantly more time at out-of-home non-work locations, estimated to be 114 minutes prior to the COVID-19 pandemic, decreasing in the early stages of the pandemic to 63 minutes, and recovering to approximately 120 minutes in 2022, estimates that are within the range of estimates presented in previous literature. While existing literature focuses on single day analyses, our weekly analysis suggests that daily differences due to telecommuting are substitutional, with the effect of an additional day of telecommuting on time-use at the weekly level being null. Our extension to analyze the impacts of telecommuting on the number of unique locations visited shows that an additional day of telecommuting results in an average decrease of 0.35 in the number of unique weekly loca-

tions visited. Collectively, our findings suggest that while telecommuting does not diminish the overall weekly time spent at out-of-home non-work locations, it decreases the diversity of such locations on a weekly level.

Keywords: COVID-19, telecommuting, time use, unique locations, quasi-experimental, fixed effects

1 Introduction

The origins of telecommuting trace back to the oil crisis of the 1970s, when skyrocketing fuel prices and energy shortages spurred the search for alternatives to traditional commuting. In parallel, technological advancements starting to take place during that era provided the necessary infrastructure to start enabling remote work Nilles et al. 1976; Julsrud 1996. Since then, there has been significant interest among transportation researchers on telecommuting, along with its impacts. Previous work has suggested telecommuting as an easy and cheap travel demand strategy, reducing vehicle miles traveled (VMT) and vehicle emissions (Kitamura, Mokhtarian, et al. 1991; Koenig et al. 1996; Mokhtarian 1998; Choo et al. 2005; Kim et al. 2015; Kim 2017; Obeid, M. L. Anderson, et al. 2024; Wang 2023). Telecommuting's benefit of eliminating the daily commute allows for work from home (or other third party locations), can also result in other changes to travel behavior. (Niles 1994; Mokhtarian 1998; Mokhtarian and Salomon 2002), which can in turn have implications on people's well-being (Mokhtarian 2019).

The activity-based approach to travel demand modeling posits that travel is derived from the demand for activity participation. As such, researchers have shown interest in understanding the connection between one's activity participation and allocation of time on one hand, and their well-being on the other hand (Archer et al. 2013; Krueger et al. 2009; Bergstad et al. 2012; Ettema et al. 2010; Kahneman et al. 2004; Goulias et al. 2013). Using time use diaries collected through this method, Krueger et al. (2009) found that time spent in maintenance and discretionary activities outside the home was associated with higher happiness, in contrast to mandatory activities such as working or education. Archer et al. (2013) showed that the duration of out-of-home social and maintenance activities positively influences one's well-being. In two distinct studies, J. Stanley et al. (2011) and J. K. Stanley et al. (2011) found that people who are engaged in social and community activities report higher levels of well-being, while those with lower (or zero) number of trips report feelings of social exclusion and lower well-being, and that higher social exclusion is significantly associated with lower levels of well-being. In a more recent study, Alessandretti, Lehmann, et al. (2018) find a positive relationship between the one's social network size and the number of unique locations they recurrently visit. The synthesis of this finding with those identified by J. K. Stanley et al. (2011) elucidates a possible relationship between the number of uniquely visited locations and well-being levels, where people who visit a higher number of unique locations could exhibit higher well-being levels. Putting all of these findings in context, we conclude that time use in out-of-home non-work activities and the number of unique locations visited are associated with higher well-being levels.

The COVID-19 served as a catalyst for telecommuting, accelerating its adoption across several sectors of the workforce. Businesses, as well as governments, have quickly transitioned to telecommuting to continue their business operations and avoid disruptions to critical government services. Statistics reveal that as much as 70% of U.S. workers have reported working remotely during the pandemic, a remarkable increase from the reported 20% before the onset of the pandemic (K. Parker et al. 2021). This transition was not without its own set of challenges, partly contributing to increased social isolation (Van Tilburg et al. 2021; Krendl et al. 2021; Czeisler et al. 2020) and mental health issues (Giallonardo et al. 2020; Czeisler et al. 2020). In a recent study, Attfield et al. (2021) investigated the impacts of telecommuting on workers in the COVID-19 pandemic and found that 85% of their sample of telecommuters felt some degree of social isolation.

Despite the increased time spent at home as a result of telecommuting and its possible associated social isolation, telecommuting remains very popular among workers. Attfield et al. (2021) find that despite telecommuters feeling socially isolated, 75% of them would continue telecommuting at least two-thirds of the time. The desire for telecommuting was shown to be strong in several studies, with Salon et al. (2021) showing that 26% of U.S. workers expect to work at least a few times a week post-pandemic, compared to only 13% before the pandemic. The lasting nature of telecommuting well beyond the pandemic necessitates strengthening our understanding of how telecommuting impacts travel behavior.

Motivated by this discussion, policymakers should look beyond the environmental impact of telecommuting, as such benefits could come at the cost of deteriorating our societal well-being (Gärling et al. 2002). Given the established correlations between well-being and out-of-home time-use and the diversity of visited locations, as highlighted in previous research, this research has two objectives. Our first objective focuses on assessing how telecommuting affects time use in out-of-home non-work locations. We build on previous time-use related studies to determine whether these impacts are complementary or substitutional at the weekly level. In other words, we aim to uncover if there's an increase or mere displacement of time allocation in activities between telecommute and non-telecommute days. Secondly, we explore whether telecommuting influences the diversity of non-work locations visited on a weekly basis, as measured by the number of unique locations visited.

To achieve the stated objectives, we use a longitudinal dataset comprising passively tracked mobility behaviors from a panel of over 100,000 U.S. smartphone users, enriched with five waves of survey responses from a subset of them. The COVID-19 context and the longitudinal nature of our dataset are critical in implementing quasi-experimental causal designs, allowing us to address common limitations found in majority of previous research.

In doing so, our analysis contributes to the large body of findings on the impact of telecommuting on travel behavior. Further, while our study does not directly measure well-being, it provides valuable insights by examining how telecommuting impacts factors (time use and number of locations visited) that contribute to it. By understanding how telecommuting impacts time-use and the diversity of locations visited, we indirectly capture elements that have been robustly linked to well-being in prior research.

2 Literature

The ultimate goal of transportation planners is to provide access to goods, opportunities, and services that improve the well-being and as a result the quality of life across society (Kitamura, Fujii, et al. 1997; Ettema et al. 2010). This means that successful transportation policies, such as those reducing car ownership or promoting public transit use, should also positively influence well-being. As a result, researchers have proposed several ways in which travel affects well-being, discussed at length by Mokhtarian (2019). One of which follows the conventional derived demand perspective of travel, in which travel plays a role to fulfill an underlying need of participation in out-of-home activities, which represent the direct source of individuals' well-being. In this way, travel indirectly impacts well-being through enabling people to participate in activities.

There has been a large body of literature investigating the relationship between travel behavior and well-being over the last decades. Specifically, several studies have examined the relationship between travel and well-being through participation in activities. Cognizant that time use and activity participation are strongly linked to their well-being, Kahneman et al. (2004) proposed the Daily Reconstruction Method to facilitate data collection to study well-being. This study eventually influenced the incorporation of a well-being module to the American Time Use Survey (ATUS) in 2010 (Stone et al. 2013). Ettema et al. (2010) found that people experience greater well-being when they participate in enjoyable activities. In a sample of Swedish residents, Bergstad et al. (2012) found that participation in out-of-home activities is associated with better well-being and mood. Lucas (2012) find that people who do not travel may experience social exclusion. Building on this finding, Alessandretti, Lehmann, et al. (2018) used several passively tracked datasets from across the world and found that people who visit less locations are likely to have smaller social circles. Mokhtarian and Pendyala (2018) reported that people experience more positive emotions in out-of-home activities compared to in-home activities. Yamashita et al. (2017) find that older adults who engaged in active leisure time activities experienced significantly greater happiness.

The COVID-19 pandemic resulted in significant shifts in human behavior. In a step to protect workers' health and preserve millions of jobs, many businesses have shifted their operations to be primarily teleworking based. This increased the share of U.S. workers working remotely from 20% to 70% at the peak of the pandemic (K. Parker et al. 2021).

This shift towards telecommuting seems likely to last beyond the COVID-19 pandemic, with 26% of U.S. workers expecting to work at least a few times a week post-pandemic, compared to only 13% before the pandemic (Salon et al. 2021).

Telecommuting has long been suggested as a travel demand management strategy, with the goal of reducing emissions and vehicle miles traveled (VMT) by reducing commuting trips (Kitamura, Mokhtarian, et al. 1991; Mokhtarian 1998). In a study that played a significant role in shaping our current understanding of the transportation impacts of telecommuting, Pendyala et al. (1991) report that telecommuters not only eliminated commute trips, but also reduced peak travel 60%, VMT by 80%, and freeway use by 40%. These transportation impacts have broader societal impacts, including reductions in agglomeration and traffic congestion, air pollution, population centrality and energy consumption (Sampath et al. 1991; Safirova 2002). More closely related to activity participation, several studies conducted in different countries, find that telecommuting induces non-commute travel (Kim et al. 2015; Kim 2016; Kim 2017; Melo et al. 2017; Silva et al. 2018; Budnitz et al. 2020; Obeid, M. L. Anderson, et al. 2024). Beyond activity participation, telecommuting frees up time previously used to commute and reshapes the time allocation patterns of workers, making workers spend more time working at home.

Despite the unpopularity of telecommuting before the COVID-19 pandemic, there was significant research on the impact of telecommuting on time use. This research mainly relied on data from the ATUS. For instance, Wight et al. (2009) used data from the 2004 ATUS to analyze time use decisions of adult U.S. workers, and find that telecommuters work one less hour compared to commuters, fathers who work at home spend less time on primary childcare, but find no difference in leisure time between commuters and telecommuters. Using a longer span of ATUS data between 2003 and 2015, Giménez-Nadal et al. (2020) find differences in work schedules between commuters and telecommuters, with less than 60% of telecommuters working during regular work hours, compared to 80% of commuters and note that telecommuters spend more time on leisure activities and unpaid work (e.g.: household chores) compared to commuters, which provides evidence for the hypothesized work-life balance advantages of telecommuting. Restrepo et al. (2020) leveraged more recent ATUS data between 2017-2018 and found that telecommuters spent less time working but more time on leisure, sleep, and food production relative to commuters. In parallel, a series of studies used household travel surveys for their analyses. Asgari et al. (2016) use data from the 2010-2011 New York Regional Household Travel survey to evaluate the impact of telecommuting on nonmandatory activity time use and find that despite telecommuters spending more time at work, they also spend more time in non-mandatory activities compared to commuters. In a more recent study, Su et al. (2021) use the 2017 California National Household Travel Survey dataset and use motif and sequence analysis methods first introduced by Schneider et al. (2013), and revealing more diverse time use patterns among telecommuters compared to commuters. Looking beyond the U.S., Nätti et al. (2011) use the Finnish Use of Time Data from 1999 and 2000 to analyze time use differences between commuters and telecommuters and conclude that telecommuters experience less free time and spend more time working.

Research on the relation between telecommuting and time use was notably present among the COVID-19 related research. Building on their pre-pandemic studies, Restrepo et al. (2022) examined differences in time allocation patterns between telecommuters and commuters during the COVID-19 pandemic using ATUS data. They find that in 2020, telecommuters spent significantly more time working but less time socializing, shopping, and eating outside the home, relative to commuters. In a different study, Barrero et al. (2020) surveyed 10,000 Americans between May and July 2020 and found that 44% of saved commute time is allocated to work, 11% to childcare, 11% to outside leisure, 19% to inside leisure, and 15% to chores though these findings might reflect only early pandemic trends. In a more recent study, Tahlyan et al. (2022) rely on 1-day activity diaries collected in March and April 2022 to analyze time allocation decisions of workers in the later phases of the pandemic and found that on telecommuting days, workers spend less time on out-of-home activities. We present a summary of research findings on the impact of telecommuting on time-use in Table 2, and include a summary of the literature on travel impacts of telecommuting in Appendix 1.

This large body of research provides important insights on the impacts of telecommuting on travel behavior, specifically non-commute activity participation. However, it has several limitations. First, majority of time-use research relies on cross-sectional datasets (e.g.: household travel surveys, time use diaries), preventing researchers from being able to control for any unobserved confounding or self-selection problems. Researchers have tried to address these issues using several approaches, including propensity score matching (Zhu 2012), instrumental variables (Melo et al. 2017), and endogenous-switching regression models (Wang 2023). These methods can also have pitfalls; propensity score matching methods can only adjust for selection bias on observable characteristics; instrumental variable approaches require the identification of valid, strong instruments, backed by theoretical evidence for their relevance and exogeneity; and endogenous-switching regression models require strong assumptions about the selection model. Second, time-use focused research does not capture weekly behaviors, possibly resulting in biased findings as the result of the use of single day data. Third, previous research is primarily based on self-reported measures of time-use or activity participation, making its results susceptible to self-reporting biases. Fourth, much of the reviewed literature was based on data from before the onset of the COVID-19 pandemic, when telecommuting was less prevalent across many sectors of the workforce, making it important to bolster them with new findings reflecting the post-pandemic context. Fifth, none of the reviewed research investigates the impact of telecommuting on the diversity of visited out-of-home non-work locations. We overcome these limitations as follows: 1) by relying on a panel dataset and a quasi-experimental design, we are able to control for both fixed and time-variant confounders, overcoming the shortcomings of most cross-sectional surveys, 2) we analyze data during the COVID-19 context, where telecommuting rates were at all-time highs, helping us address self-selection issues, 3) instead of relying solely on detailed self-reported behavior or time-use diary data, we use a combination of detailed passively tracked data and minimal self-reported data to overcome self-reporting and recall biases (we only asked participants to report their weekly behaviors rather than more detailed activity diaries), 4) building on COVID-19 studies that primarily focused on daily time allocation, we extend the analysis to investigate whether telecommuting's impact on time-use is additive or substitutional at the weekly level, and 5) while recent COVID-19 research investigated telecommuting's impact on time-use, we go further by analyzing the impact of telecommuting on the number of unique locations visited, a factor not previously explored in existing studies, pandemic-era or otherwise. In doing so, we build on recent COVID-19 findings by examining factors - particularly time use and location diversity - that have been strongly linked to well-being in prior research. By incorporating these well-being related outcomes, our study bridges the gap between telecommuting research and well-being studies, offering a broader understanding of telecommuting's potential impacts on individuals, beyond just travel behavior outcomes.

In the next section, we present our data and our analysis methodology in detail.

3 Data and methods

3.1 Data

As part of a larger research effort, we designed a data infrastructure that combines several data sources to develop a dataset enabling a wide understanding of the impacts of COVID-19 on travel behavior. Our data infrastructure combines two key data sources: passively collected travel behavior data and self-reported survey responses gathered at various stages of the COVID-19 pandemic. This approach helps us overcome two major limitations found in previous studies: the inability of cross-sectional studies to control for unobserved confounding, and the self-reporting biases often associated with survey-based studies.

First, the passively tracked travel behavior dataset was collected by a mobile audience analytics company (SimilarWeb) with a recruited panel of U.S. smartphone users. This data captures detailed information for each point of interest (POI) check-in, including information about arrival time, departure time, category of the POI visited as inferred by SimilarWeb (i.e.: home, work, dining, etc.), distance and time traveled to get to the POI, the POI's proximity to the inferred panelist's home and work location, its zip code, city, and Metropolitan Statistical Area name. SimilarWeb uses proprietary technology from a third-party provider to infer POI categories for each of the visited POIs. The data collected by SimilarWeb also includes self-reported sociodemographic characteristics. Despite this level of detail on panelists' travel behavior, a key limitation of our dataset is its lack of information on the transportation modes used by panelists to travel to each POI. We note that these data are

Table 4.1: Literature findings on telecommuting impact on time-use (per telecommuting occasion)

Study	Year	Population	Data	Finding - Per telecommuting occasion
Wight et al. (2009)	2004	18-65 year old workers	ATUS	≈ -60mins work time = leisure time
Giménez-Nadal et al. (2020)	2003-2015	15-65 year old employees	ATUS	≈ +30mins leisure time ≈ -100mins work time
Restrepo et al. (2020)	2017-2018	25-54 year old workers	ATUS	less time working ≈ +94mins leisure time
Restrepo et al. (2022)	2010-2020	All workers	ATUS	≈ +67-84mins leisure time before COVID-19 ≈ +110-174mins leisure time during COVID-19
Asgari et al. (2016)	2010-2011	All workers	New York Regional Household Travel Survey	+65-77mins on maintenance and discretionary activities
Nätti et al. (2011)	1999-2000	15-64 year old employees	Finnish Use of Time survey	≈ +50mins work time ≈ - 16mins free time
Barrero et al. (2020)	2020	20-64 years old workers	Cross sectional-survey	44% of saved commute time to work, 11% to childcare, 11% to outside leisure, 19% to inside leisure, and 15% to chores
Tahlyan et al. (2022)	2022	18 years or older workers	Online cross-sectional survey	≈+75mins in out-of-home nonwork activities

not continuously tracked GPS traces of panelists' movements, but rather inferred individual check-ins at POIs. Despite this difference, this data provides complete trajectories of individuals, in contrast to call detail records (CDR) or location based service (LBS) data, which only captures location data during call activity, or when LBS applications are used. The passive data were collected between January 2020 and September 2022 and can be processed to compute travel behavior metrics of interest. In this study, we compute both the daily and weekly time use and the number of unique weekly non-work locations visited.

Second, we designed an extensive longitudinal survey to track the evolution of a wide array of behaviors, attitudes, and beliefs throughout the COVID-19 pandemic. We distributed the survey in five waves throughout the COVID-19 pandemic, specifically in August 2020, October 2020, December 2020, April 2021, and July 2021, as contextualized in Figure 4.1. Initially, we distributed the first survey to a random sample of approximately 15,000 individuals from the SimilarWeb panel, stratified by U.S. region, that was fairly geographically representative of the US population. We primarily focused on counties within 16 major MSAs across the US and selected a subset of counties within each to balance the number of panelists, area type, and geographic distribution. To further balance our sample between rural and non-rural areas, we selected a set of rural counties across the US with the largest concentration of panelists. In total, 85% of targeted panelists are from metropolitan counties and 15% are from rural counties. In subsequent waves, we supplemented our sample from the original pool of 15,000 panelists from across the U.S. to account for dropouts between survey waves.

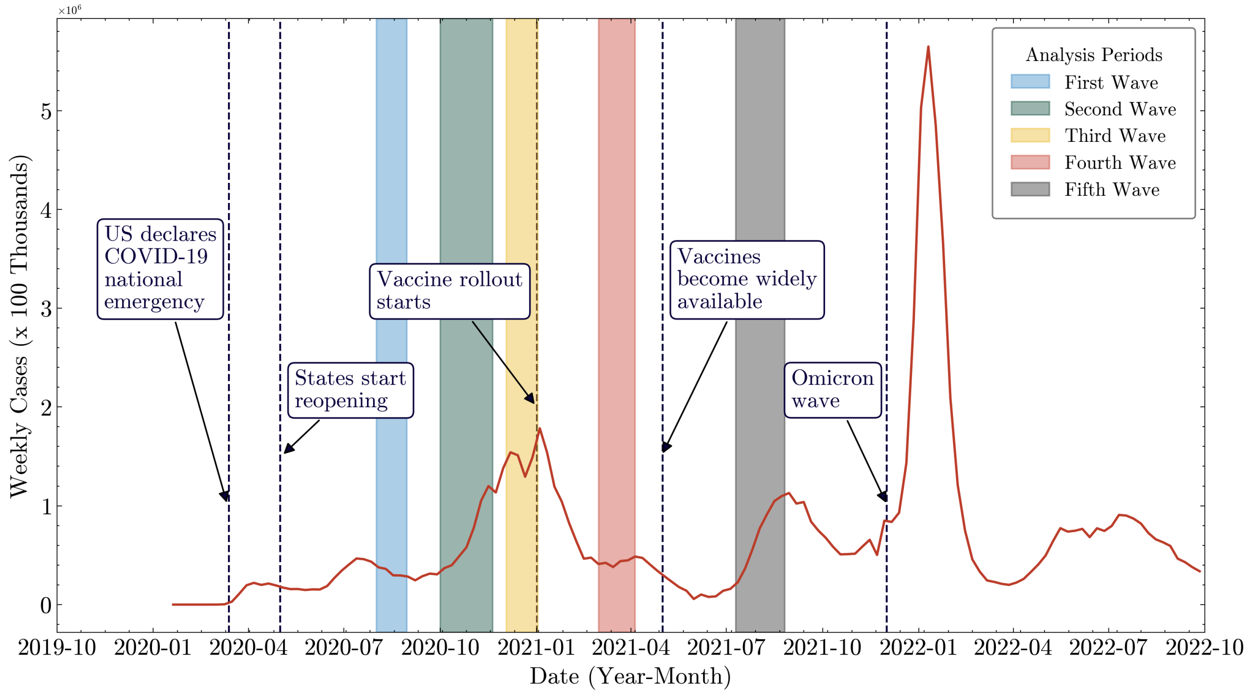

Figure 4.1: COVID-19 cases in the United States, key pandemic milestones, and timing of wave distribution

In each survey wave, participants were asked about their mobility behavior, preventative measures and sheltering behaviors, ideological beliefs, vaccination status, and additional sociodemographic information not collected by SimilarWeb. Most relevant to this research, we asked participants in every survey wave to report both the total number of days worked and the number of telecommuting days in the preceding week, because our passively tracked POI data only enables us to identify whether an individual has commuted to work and does not distinguish telecommute days from non-work days. We include a summary of the survey content in Appendix 1.

The number of participants varies per wave as a result of panel attrition. Our final dataset consists of survey responses from 1962 unique individuals. While not all panelists have participated in all survey waves, 1431 (72%) have participated in at least 2 survey waves. Bouzaghrane et al. (2023) provides more details on the data collection process and the response rates across the different waves.

One of the main strengths of our data infrastructure is being able to link individual survey responses with passively tracked POI check-in data. Each participant has a unique identifier shared between the survey responses and the POI data, allowing us to easily match participants' survey responses to their passively tracked POI data. This combination of data sources allows us to supplement the survey responses from study participants with observed behavioral data from the passively tracked POI data, enabling us to compute mobility metrics at several temporal aggregation levels without the additional burden of asking respondents to report such behaviors.

3.2 Data processing

We preprocess our passively collected POI data to compute outcome metrics of interest. Prior to any data processing, we verified our data quality by computing the median individual time coverage across the data collection period, as depicted in Figure 4.2. While the median time coverage remained consistent between 75% and 80% for most of the data collection period, there was a notable decline in August and September 2021 due to an unexplained data collection issue. To avoid any bias in our analysis due to drop in data coverage, we exclude data during August and September 2021 from our analysis. To further ensure the validity of our POI data, we conducted a comparison of a random subset of approximately 200 records from our study participants. We cross-referenced the inferred POIs from SimilarWeb with those obtained through the Google Maps API.

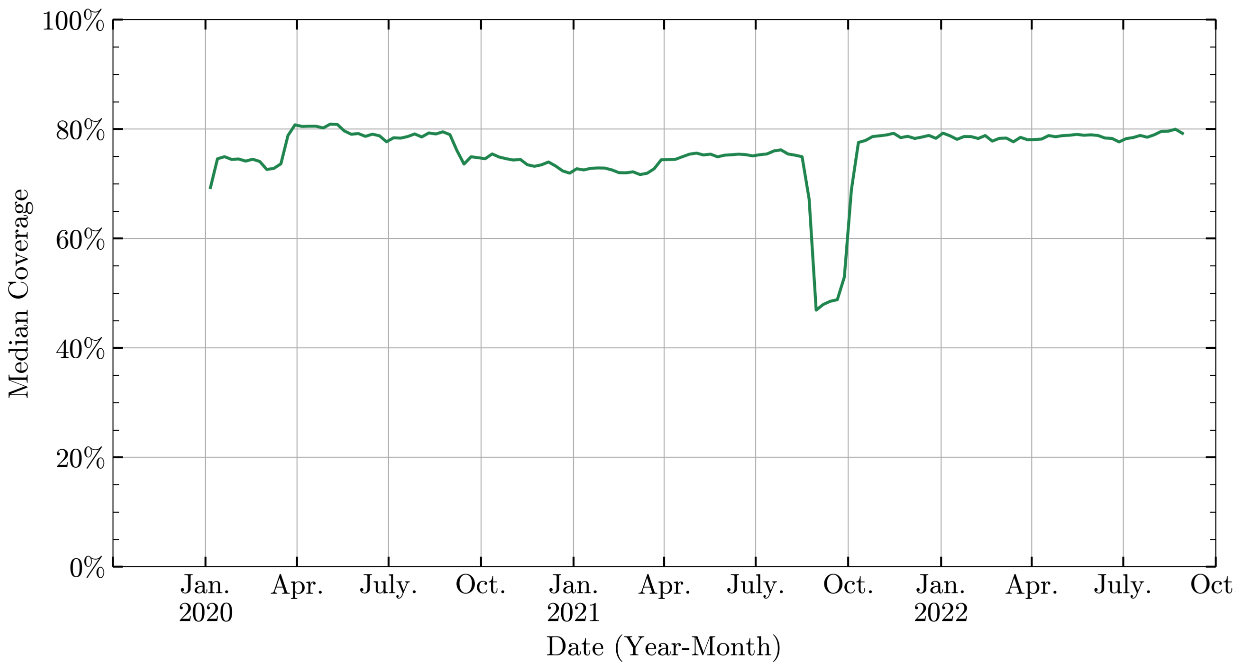

Figure 4.2: Median weekly temporal tracking coverage across the population as a function of time. A significant drop in coverage occurs in August and September 2021.

To identify unique locations visited by individuals, we aggregate each of the POIs visited by each individual into geographical locations based on their spatial proximity. This is particularly useful considering that detected spatial coordinates of visited locations can often be noisy (Alessandretti, Sapiezynski, et al. 2018). We use the DBSCAN algorithm (Ester et al. 1996) to cluster the check-ins for each individual using a maximal distance ε. We use a maximum distance $\varepsilon = \mathbf{50}$ meters and **min_samples** $= \mathbf{1}$, to produce places of the approximate size of a building, consistent with previous literature (Alessandretti, Sapiezynski, et al. 2018; Cuttone et al. 2018; Hong et al. 2023). The result of this preprocessing clustering is an assignment of location label to each inferred POI check-in, where the label refers to a geographical place of the POI check-in record. We combine these obtained labels with the location classification to further identify unique maintenance and discretionary locations visited by each of the study participants, consistent with classifications proposed in the time use literature (C. Chen et al. 2006) and presented in Table 3.2.

Table 4.2: Classification of out-of-home non-work locations, as defined by C. Chen et al. 2006

Maintenance locations	**Discretionary locations**
Essential retail (Groceries, fuel, home goods, etc.)	Non-essential retail (Clothing, cosmetics, jewelry, bookstore, etc.)
Personal services (Financial, automative, legal, etc.)	Dining and drinking (Restaurants, cafes, bars, etc.)
Medical services (Doctor, pharmacy, etc.)	Entertainment (Movie theater, museums, night-life, etc.)
	Exercise and recreation (Gym,)
	Religious/civic services

We compute our outcomes of interest (i.e.: daily and weekly time use at out-of-home non-work locations, number of weekly unique out-of-home non-work locations visited) using this preprocessed data for each individual participant. Further, we compute these outcomes for both maintenance and discretionary locations, as defined by the processed data.

3.3 Sample summary

We present key demographic characteristics of our sample in Table 3.3 and compare them to national statistics as reported by the U.S. Census Bureau. This comparison focuses on full-time employees, our study's main group of interest. Our sample is overrepresentative of females compared to the U.S. population, with females being 52% of our sample compared to 47% in the U.S. population. Additionally, our sample is overrepresentative of low income households (47.8% in our sample vs. 22.7% in the U.S. population for annual household incomes less than 50,000 USD) and under-representative of high income households (14.5% in our sample vs 43.8% in the U.S. population for annual household incomes greater than 100,000 USD). This oversampling is a result of the characteristics of the SimilarWeb panel, which is geographically representative of US smartphone users, but is not fully representative of the US population across several demographic characteristics. It is possible that lower income individuals are more likely to be part of an online panel to earn income from survey incentives.

Our sample underrepresents Caucasians (50.7% in our sample vs 72.1% in the U.S. population) and is overrepresentative of racial minorities. In terms of educational attainment, our sample over-represents individuals with at least a college degree (60.2% in our sample compared to 44.8% across the U.S. population) and underrepresents individuals with only a high school degree or less. Finally, in terms of vehicle ownership, even though our distribution is not exactly match that across the U.S. population, our statistics closely track those across the population at large. Finally, Figure 4.3 presents the geographical distribution of our study participants. The map highlights a diverse representation across the United States. Participants come from a diverse set of states, including those in the Midwest, Northeast, South, and West. This broad distribution ensures that our study captures a rich variety of regional characteristics, ensuring our analysis are not just representative of local trends.

Table 4.3: Sociodemographic characteristics of full-time employee study participants

Category	**Sample (%)**	**U.S. Pop. (%)**
Gender		
Male	47.5	52.7
Female	52.5	47.3
Age		
19 and under	0.9	3.4
20-24	6.4	9.4
25-34	27.3	22.6
35-44	30.8	21.0
45-54	22.6*	20.7
55-59	5.7	9.7
60-64	4.0	7.3
65 and over	1.4	5.9
Household Income (USD)		
0 - 24,999	13.3	7.2
25,000 - 49,999	34.5	15.5
50,000 - 99,999	37.7	33.5
100,000 - 149,999	10.3	21.6
150,000 - 199,999	1.9	10.7
200,000 or more	2.3	11.5
Race/Ethnicity		
White	50.7	72.1
Black	19.3	11.6
Native American	2.2	0.7
Asian/Pacific Isl.	11.0	6.2
Other	6.6*	5.7
Mixed race	7.3	4.3
Hispanic Status		
Hispanic	20.0*	17.3
Not Hispanic	76.0	82.7
Education		
< High School	1.5	8.9
High School	38.3	46.3
College	51.2	31.6
Postgraduate	9.0	13.3
Household Vehicles		
0	7.3	8.6
1	38.2	32.7
2	33.5	37.2
3 or More	20.7*	21.4

[*] $p < 0.05$

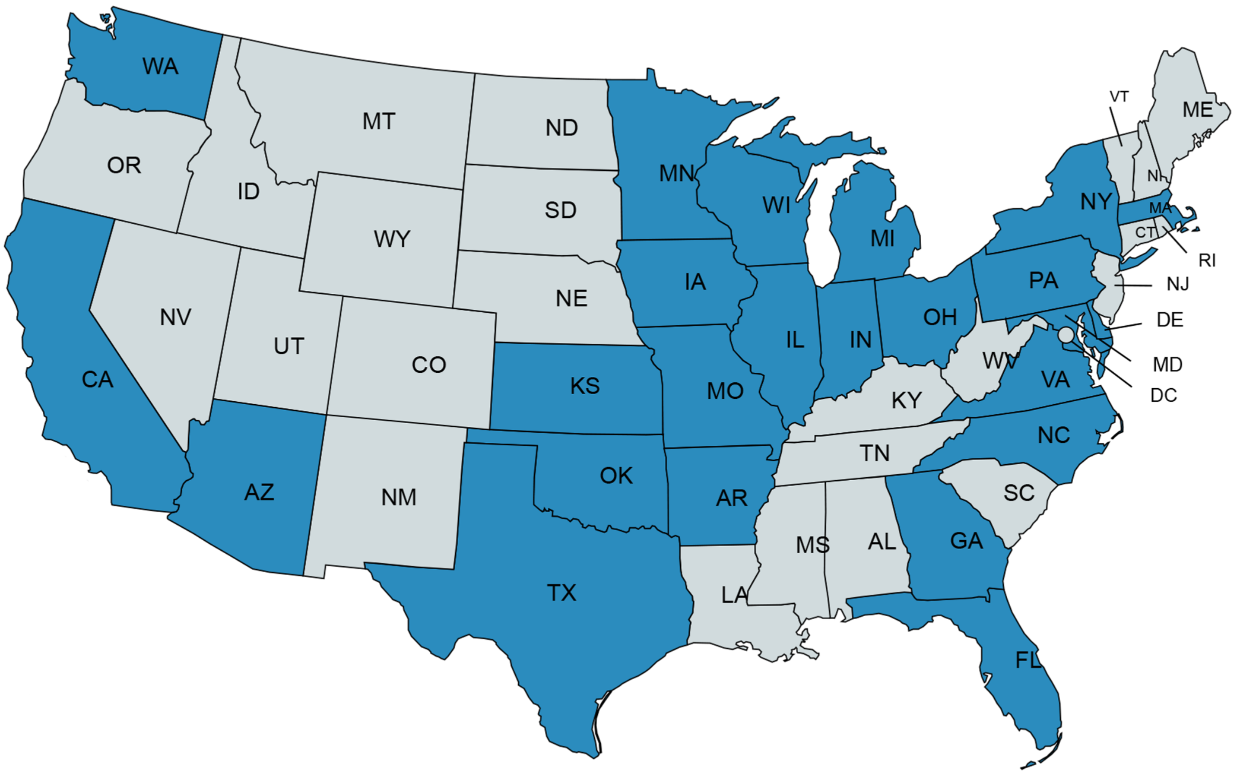

Figure 4.3: Geographical Distribution of Study Participants

3.4 Modeling framework

In this research, we consider three key questions. First, we want to determine the time use of workers on telecommute days relative to commute days. The second question is to determine whether such difference is substitutional or additive. Third, we want to understand to what degree the number of telecommuting days impact the out-of-home non-work activity set size.

To achieve our research objectives, we implemented quasi-experimental research designs using our longitudinal dataset described in Section 3.1. We use the repeated individual observations within fixed effects and first-differences designs to control for any unobserved time-invariant individual characteristics that impact both individuals' likelihood to telecommute and their travel behavior, notably time use and number of unique locations visited. This approach allows us to overcome unobserved confounding problems reported in previous telecommuting literature, and documented in the literature review section of this manuscript and in Obeid, M. L. Anderson, et al. (2024).

In contrast to previous works, which focus on different subsegments of the workforce (Wight et al. 2009; Giménez-Nadal et al. 2020; Restrepo et al. 2020; Restrepo et al. 2022), our results indicate the effects of telecommuting for all full-time workers. This, in addition to the high telecommuting rates across all sectors of the workforce in the U.S., allows for our results to be generalizable. In the rest of this section, we provide more details on the model specifications used to answer each of our three research questions.

To determine the effect of telecommuting on out-of-home non-work time use on telecommuting days relative to commute days, we estimate the following fixed effects model:

$$Y_{it} = \alpha + \beta \times WFH_{it} + \delta_i + \eta_t + \epsilon_{it} \tag{4.1}$$

Where Y_{it} indicates our outcome of interest, the total time use in out-of-home non-work locations for individual i on day t, in minutes. We model this outcome as a function of a constant α, an indicator variable WFH_{it} indicating individual i's telecommuting status on day t, as well as individual fixed effects (δ_i), and time fixed effects η_t. WFH_{it} is a dummy variable equal to one if individual i telecommutes on day t, and zero otherwise, as inferred from the passively collected POI data. Individual fixed effects δ_i are included as a vector of individual dummy variables equal to one if the observation is from individual i and zero otherwise, and control for any unobserved individual time-invariant characteristics that impact time use such as individuals habits and preferences. Time fixed effects η_t are introduced in the model as a set of year and week of year indicator variables that control for factors that impact the outcome of interest on a given time of year, and are common across all individuals, such as seasonality factors, or the COVID-19 pandemic context at any point in time. ϵ_{it} is the error term. The parameter of interest, β, measures the average effect of telecommuting on time use (in minutes) in out-of-home non-work locations on telecommuting days relative to commute days. This effect is identified under the assumption that telecommuting is as good as random after controlling for time-invariant individual characteristics and time specific trends. In addition to estimating the effect of telecommuting on total time use at out-of-home non-work locations, we estimate the effect of telecommuting on total time use in maintenance and discretionary activities. We estimate our model for different time periods informed by the pandemic's context in the United States (See section 4.2 for more details on the different analysis periods) to evaluate how our model estimates evolved since the pandemic's onset.

To verify whether these findings indicate the total or direct effects of telecommuting on time use on telecommuting days, we estimate an additional model, shown in Equation 4.2, by controlling for the effect of telecommuting on induced non-work travel, through the inclusion of the number of non-commute trips (NWT_{it}) taken by individual i on day t. We summarize findings of this analysis in the results section but only include the detailed findings in

Appendix 3.

$$Y_{it} = \alpha + \beta \times WFH_{it} + \gamma \times NWT_{it} + \delta_i + \eta_t + \epsilon_{it} \tag{4.2}$$

To evaluate whether the impact, if any, of telecommuting on the daily time use at out-of-home non-work locations is the result of shifting time use between telecommute and commute days, we investigate the impact of one additional day of telecommuting on the weekly time use at out-of-home non-work locations. Unlike the daily analysis, we rely on survey responses to identify the number of telecommute days in the week preceding each survey wave, which helps overcome limitations posed by possibly incorrect inferences using only passively collected POI data, allowing us to distinguish telecommuting days from other non-commute days, such as sick days or days off. The downside of this approach, however, is that we have asked participants about their telecommuting behavior for a single week per individual in each survey wave, resulting in a considerably smaller sample size compared to that used in daily analysis.

To quantify the effect of an additional telecommuting day on time-use at out-of-home non-work locations, we estimate a first-differences regression model describe by the following equation:

$$\begin{aligned} \Delta Y_{it} =& \beta_e \times \Delta WFH_{it} \\ &+ \beta_{12} \times I(W_1 < t < W_2) \\ &+ \beta_{23} \times I(W_2 < t < W_3) \\ &+ \beta_{34} \times I(W_3 < t < W_4) \\ &+ \beta_{45} \times I(W_4 < t < W_5) \end{aligned} \tag{4.3}$$

Where ΔY_{it} is the difference in weekly time use at out-of-home non-work location by an individual between weeks corresponding to two successive survey waves. The parameters β_{12} through β_{45} capture the time effects, corresponding to the first differences between successive survey waves. In this formulation, we assume that the individual fixed effects only remain constant between successive survey waves, a less stringent assumption than that made by a fixed effects design, where individual fixed effects remain constant throughout the study period. However, making this assumption comes at the expense of reducing our sample size, as it limits our analysis to only those individuals who participated in at least two consecutive survey waves across all our survey waves. Similarly to the daily analysis, we also estimate the effect of telecommuting on weekly time use at both discretionary and maintenance locations.

Lastly, to investigate the impact of telecommuting on the number of the number of unique out-of-home non-work locations visited, we use the same first-differences design presented in Equation 4.3 by computing ΔY_{it} as the difference in the number of unique out-of-home non-work locations visited by individual i between two consecutive survey waves.

All of our model parameters are estimated using ordinary least squares. We cluster the standard errors at the individuals to capture the correlation in the structure of residual errors for the same individual across several observations in our dataset.

4 Results

This section presents the results of analysis of the impact of telecommuting on out-of-home non-work time use and unique locations visited. We begin with a descriptive analysis to establish an understanding of how our outcomes of interest evolved throughout the study period in 4.1. Next, in section 4.2 we present the analysis of the impact of telecommuting on daily time use at out-of-home non-work locations, distinguishing between maintenance and discretionary activities. We extend this analysis in Section 4.3 to determine if the daily impacts of telecommuting on time-use, if any, are additive or substitutional at the weekly level. We then assess how telecommuting affects the number of weekly unique locations visited in Section 4.4. We conclude by presenting a summary of all our results in Section 4.5.

4.1 Descriptive Analysis

Our POI data can be processed to compute various mobility metrics (e.g., number of trips, time use, radius of gyration, etc...) at various time scales (e.g., daily, weekly, etc.). In this section, we present the two key outcomes derived from our POI data that are directly related to our research objectives and linked to well-being in prior research: 1) the total time spent at out-of-home nonwork locations daily/weekly, and 2) the number of unique out-of-home non-work locations visited weekly. However, we present descriptive statistics of several additional travel behavior metrics commonly studied in transportation research in 2. This appendix includes the evolution of these metrics throughout the pandemic period, offering context for our main analysis while keeping the focus of the main text on our primary outcomes of interest.

Figure 4.4 illustrates the daily time spent at all out-of-home non-work locations. With the onset of the COVID-19 pandemic, there was a substantial decline in the time spent at these locations, decreasing from approximately 142 minutes per day to about 90 minutes. This reduction was largely driven by the widespread and high concerns of contracting the COVID-19 virus or in compliance with the implemented mobility restrictions. As governments started opening in early summer 2020, people exhibited an increasing tendency to spend more time at out-of-home non-work locations. Despite this initial recovery, the time spent at out-of-home non-work locations has experienced continuous fluctuations accompanying the pandemic's evolution, including the emergence of new variants and the progress of vaccination efforts, but has shown a recovery since the initial onset of the pandemic. A similar pattern was observed at the weekly level (Figure 4.5), where the total weekly time spent at out-of-home non-work locations decreased in the early phases of the pandemic from approximately 875 minutes to 550 minutes per week (approximately 40% decrease), but recovered to its pre-pandemic levels ever since.

In terms of number of unique out-of-home locations visited, our data presents similar insights to those of time use at the onset of the pandemic. The average number of unique out-of-home non-work locations visited dropped from approximately 6.5 to about 5 unique locations per week at the initial onset of the pandemic. However, since the initial stage of the pandemic, we observe a continuous recovery in the number of unique out-of-home non-work locations visited.

In the following section, we present our results on the impact of telecommuting on both the time spent at out-of-home locations and weekly locations visited.

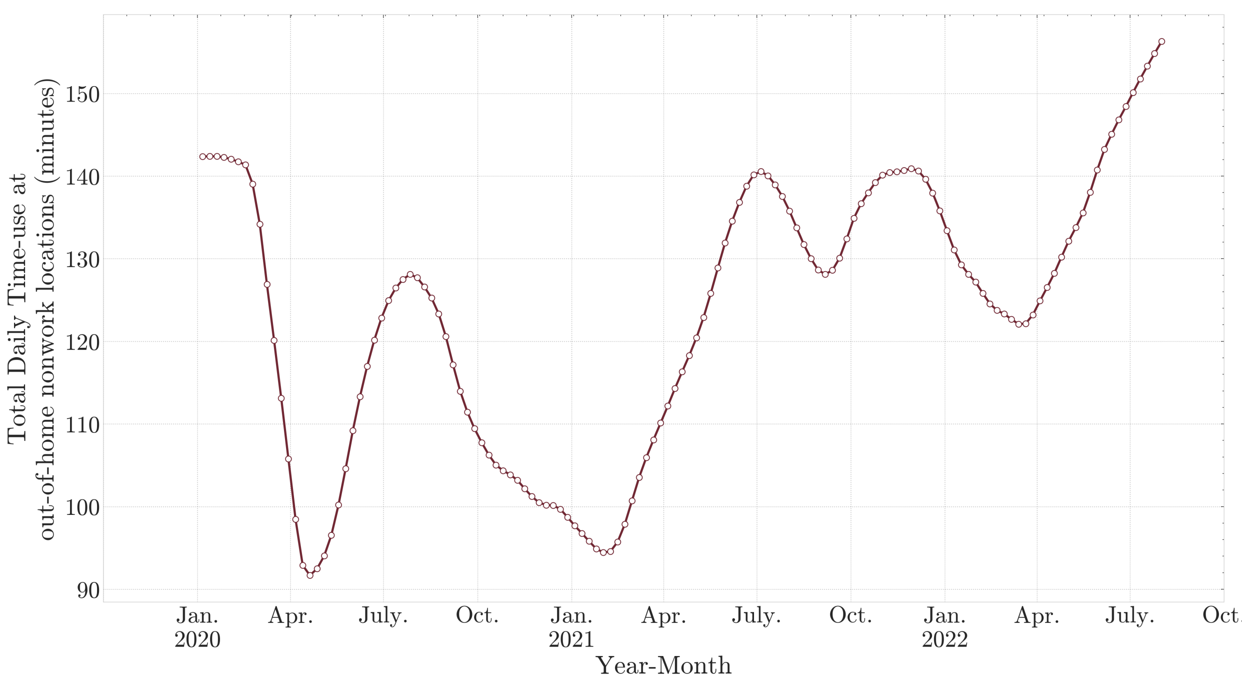

Figure 4.4: Average daily time use at out-of-home non-work locations by study participants throughout the COVID-19 pandemic (January 2020 - August 2022). ($N = 809$ individuals)

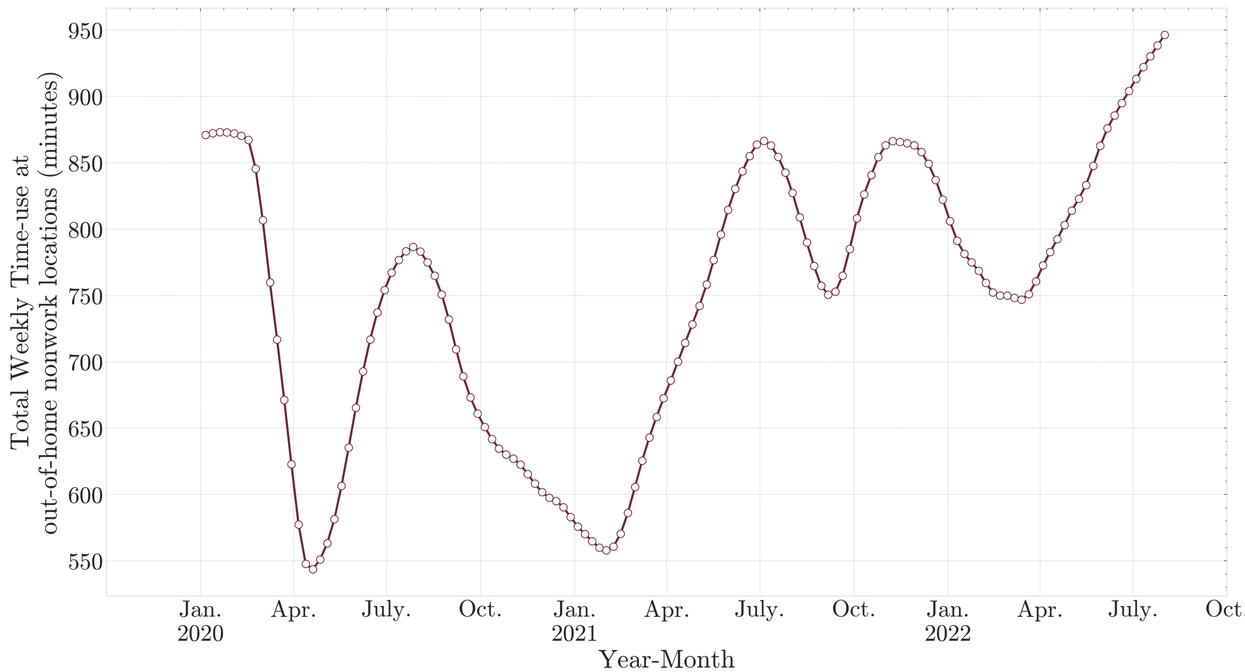

Figure 4.5: Total weekly time use at out-of-home non-work locations by study participants throughout the COVID-19 pandemic (January 2020 - August 2022). ($N = 809$ individuals)

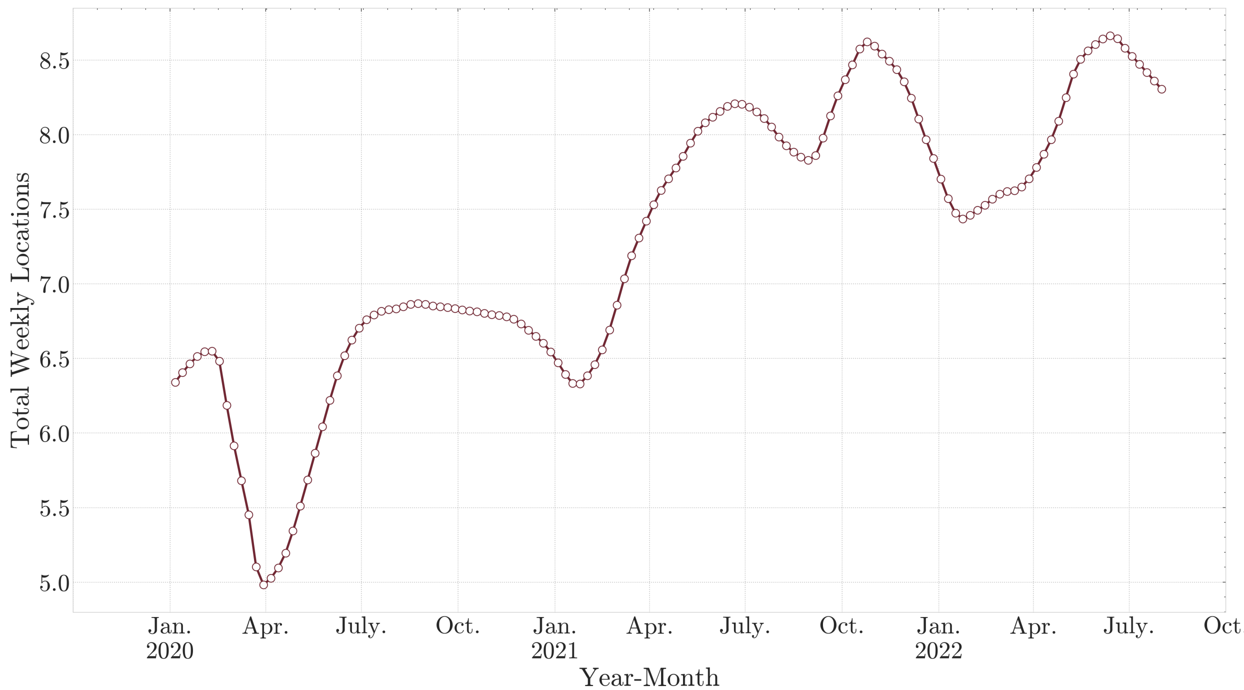

Figure 4.6: Number of unique weekly out-of-home non-work locations visited by study participants throughout the COVID-19 pandemic (January 2020 - August 2022). (N = 809 individuals)

4.2 Effect of telecommuting on daily time use

In this section, we examine the effect of telecommuting on time use in out-of-home non-work locations. This analysis is further provided for maintenance and discretionary locations, in line with the location classification presented in Section 3. To understand how telecommuting's effect on time use was impacted by the COVID-19 context, if at all, we conduct our model estimations separately for different phases of the pandemic. These phases reflect the pandemic's evolution in the U.S. and are outlined as follows:

- Pre-pandemic: January 2020 - March 2020
- Early Lockdowns: March 2020 - May 2020
- Pre-vaccination: June 2020 - December 2020
- Early vaccination: January 2021 - May 2021
- Post vaccine availability: June 2021 - December 2021

- Post COVID-19: January 2022 - September 2022

According to the COVID-19 state policies database compiled by Raifman et al. (2020), the latest mobility restrictions in the U.S. were lifted on January 25, 2021, which falls between the third and fourth waves of our survey, and during the early vaccination period outlined above. As such, any findings from the last two periods should not be affected by any mobility restrictions.

In Table 4.2, we provide estimates from the fixed effects model in equation 4.1, detailing the effect of telecommuting on time use at out-of-home non-work locations on telecommuting days for all defined time periods. Our results show that, regardless of the analysis time period, telecommuting results in individuals spending more time at out-of-home non-work locations on telecommute days compared to commute days, with all of our results being statistically significant at the 1% level. However, the extent of such impacts has not been constant throughout the pandemic. Before the pandemic (January and February 2020), telecommuting results in workers spending an additional 114 minutes on average in out-of-home non-work locations, relative to commuting days. This impact decreased to approximately 64 minutes during the early phases of the pandemic, a 45% decline from the pre-pandemic estimate and reflecting the initial public response to the pandemic involving fear of contracting the virus and compliance with implemented mobility restrictions. As the pandemic progressed and conditions ameliorated, marked by easing of restrictions, expansion of reopenings, and increased vaccination rates, the effect of telecommuting on out-of home time use gradually recovered to levels similar to those before the pandemic, with telecommuting resulting in people spending approximately an additional 118 minutes in out-of-home non-work locations on telecommute days, relative to commute days.

Table 4.4: Estimates of the fixed effects regression of the effect of telecommuting on total time use at out-of-home non-work locations. Regression results are shown for different phases of the COVID-19 pandemic.

	Total out-of-home non-work time use (min)					
	Pre-pandemic	Lockdown	Pre-vaccine	Early vacc.	Post vacc.	Post covid
WFH	114.35***	63.96***	90.93***	84.31***	119.02***	117.92***
	(6.38)	(6.53)	(4.65)	(6.13)	(7.84)	(8.75)
Observations (person-days)	18901	15948	85360	41673	29595	24494
Time FE	YES	YES	YES	YES	YES	YES
Person FE	YES	YES	YES	YES	YES	YES

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the person level.

Table 4.2 and Table 4.2 detail our findings on how telecommuting impacts time use at discretionary and maintenance locations, as classified in Table 3.2. In line with our findings on the effect of telecommuting on total out-of-home non-work time use, we find that telecommuting shows a positive effect on time use at both discretionary and maintenance locations, albeit to different degrees. In the pre-pandemic phase (January and February 2020), people spent an additional 98 minutes at discretionary locations and approximately 16 minutes at maintenance locations on telecommute days. This effect diminished during the early lockdown phases for both categories, albeit to different extents, 9.8 minutes for maintenance locations and 54.1 minutes for discretionary locations. The effect of telecommuting on time use at maintenance locations returned to its pre-pandemic levels by late 2020 (16.01 minutes). This could be because maintenance activities, such as grocery shopping, healthcare visits, and running errands, are necessary for personal and household upkeep, in contrast to discretionary activities. In contrast, the effect of telecommuting on daily discretionary time use did not revert to its pre-pandemic levels until the post-vaccination phase, beginning in the second half of 2021. These results suggest that when people do not leave their home for work, they compensate for the additional time spent at home with more time spent at out-of-home non-work locations.

Table 4.5: Estimates of the fixed effects regression of the effect of telecommuting on time use at maintenance activity locations. Regression results are shown for different phases of the COVID-19 pandemic.

	Total out-of-home non-work time use (min)					
	Pre-pandemic	Lockdown	Pre-vaccine	Early vacc.	Post vacc.	Post covid
WFH	15.91***	9.88***	16.01***	13.56***	21.92***	18.74***
	(2.17)	(2.21)	(1.76)	(1.81)	(3.38)	(4.40)
Observations (person-days)	18901	15948	85360	41673	29595	24494
Time FE	YES	YES	YES	YES	YES	YES
Person FE	YES	YES	YES	YES	YES	YES

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the person level.

We test the hypothesis that the number of telecommuting induced trips induces the relationship between telecommuting and time use to identify whether this estimated impact of telecommuting are the total or direct effects of telecommuting on time use at out-of-home non-work locations. We estimate the model described in Equation 4.2 and find that the telecommuting exhibits a direct effect on time use at out-of-home non-work locations, the magnitude of which is statistically equivalent to the effects shown in Table 4.2, since the estimates are close in value and the confidence intervals display large overlap. These conclusions persist when breaking down the analysis by discretionary and maintenance locations. Appendix 3 presents our estimation results in more detail.

Table 4.6: Estimates of the fixed effects regression of the effect of telecommuting on time use at discretionary activity locations. Regression results are shown for different phases of the COVID-19 pandemic.

	Total out-of-home non-work time use (min)					
	Pre-pandemic	Lockdown	Pre-vaccine	Early vacc.	Post vacc.	Post covid
WFH	98.44***	54.09***	74.92***	70.75***	97.10***	99.18***
	(6.02)	(5.88)	(4.12)	(5.34)	(7.18)	(7.87)
Observations (person-days)	18901	15948	85360	41673	29595	24494
Time FE	YES	YES	YES	YES	YES	YES
Person FE	YES	YES	YES	YES	YES	YES

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the person level.

4.3 Effect of telecommuting on weekly time use

The analysis presented in the previous section suggests that telecommuting leads to an increase in the time spent by workers at out-of-home non-work locations. To evaluate whether this effect accumulates over the week, we investigate the effect of one extra day of telecommuting on the weekly time use at out-of-home non-work locations. Drawing on previous research by Obeid, M. L. Anderson, et al. (2024), which found that an additional telecommuting day induces an additional weekly non-commute trip, rather than shifting it from other days of the week, we hypothesize that an additional telecommuting day results would result in an overall increase in weekly time use at out-of-home non-work locations. Under this hypothesis, our estimate of the parameter of interest β_e in the model described in Equation 4.3 should be strictly positive, and statistically significant.

Table 4.3 presents the results of our estimates. Similarly to our daily analysis, we present the results on the effect of telecommuting on the total weekly out-of-home non-work time use and further break this effect for maintenance and discretionary locations. Contrary to our initial hypothesis, we find that an additional day of telecommuting reduces the weekly time spent at all out-of-home non-work locations, with an average reduction of 9.6 minutes across all out-of-home non-work locations, split into a reduction of 7.25 minutes for discretionary locations and 2.41 minutes for maintenance locations. However, the magnitude of these results is small and the figures are not statistically significant, as indicated by the high p-values (and wide confidence intervals) of all three evaluated outcomes.

These results suggest that while telecommuting induces newly generated non-commute trips at the weekly level (Obeid, M. L. Anderson, et al. 2024), we find no evidence that it changes the total time spent at such locations. To reconcile these two seemingly contradictory conclusions, we investigate the impact of an additional day of telecommuting on the average time spent per visit at out-of-home non-work locations using the same design as the one presented in equation 4.3, and find that an additional day of telecommuting reduces the dwell-time per visit at out-of-home non-work locations by approximately 15 minutes. We include the results of this regression in Appendix 4.

Table 4.7: Estimates of first differences design of the effect of one additional telecommuting day on time use at out-of-home non-work locations. Results are provided for all out-of-home non-work locations and broken down for Maintenance and Discretionary locations.

	Out-of-home non-work time use (min)		
	Total	Maintenance	Discretionary
WFH	-9.66	-7.25	-2.41
	(46.09)	(43.92)	(11.17)
Observations	524	524	524

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the person level.

4.4 Effect of telecommuting on the number of unique locations visited

Next, we present the results of the impact of telecommuting on the number of weekly out-of-home non-work locations visited. Similarly to the weekly analysis of the impact of telecommuting on out-of-home non-work time use, we also break down our analysis results for maintenance and discretionary locations. The model's null hypothesis is that an additional day of telecommuting has no effect on the weekly number of out-of-home non-work locations visited. Under this hypothesis, the estimated coefficient β_f would be statistically equivalent to zero.

Table 4.4 summarizes our first-differences model results. For brevity, we only show estimates of our parameter of interest β_e. The results show that an additional day of telecommuting results in an average decrease of 0.35 in the activity set size. This estimate is statistically significant, ruling out the possibility that telecommuting has no effect on the activity set size of noncommute locations. This decrease is significant for both discretionary and maintenance locations, albeit to different degrees. Notably, 36% of the total decrease (0.13) in the activity set size of noncommute locations is associated with maintenance locations and 64% of the decrease towards discretionary locations.

Our results also suggest that the magnitude of this decrease is slim; fully remote workers visit on average only 1.75 fewer locations, compared with their counterparts who commute every day.

Table 4.8: Estimates of first differences design of the effect of one additional telecommuting day on number of weekly unique out-of-home nonwork locations visited. Results are provided for all out-of-home non-work locations and broken down for Maintenance and Discretionary locations.

	Number of weekly unique places		
	Total	Maintenance	Discretionary
WFH	-0.35***	-0.13**	-0.23**
	(0.124)	(0.05)	(0.11)
Observations	524	524	524
Adjusted R^2			

Notes: * p < 0.10, ** p < 0.05 , *** p < 0.01. Standard errors are clustered at the person level.

4.5 Results Summary

In synthesizing our research findings within the broader context of telecommuting literature, we find that our results on the impact of telecommuting on daily time use at out-of-home non-work locations complement existing studies, with our estimates being within the range presented in the literature; previous research finds that telecommuting is related to workers spending upwards of an additional 174 minutes in non-work locations (see Table 1). Figure 8 summarizes our daily analysis results, broken down by COVID-19 period and by discretionary and maintenance locations. Specifically, we found that on telecommuting days, workers spend significantly more time at out-of-home non-work locations, relative to commute days. This effect decreased from 114 minutes (98 minutes at discretionary locations and 15 minutes at maintenance locations) in the pre-pandemic period to 64 minutes (54 minutes at discretionary locations and 10 minutes at maintenance locations) in the early lockdown period of the pandemic, and slowly recovers to its pre-pandemic levels of 117 minutes (99 minutes at discretionary locations and 18 minutes at maintenance locations).

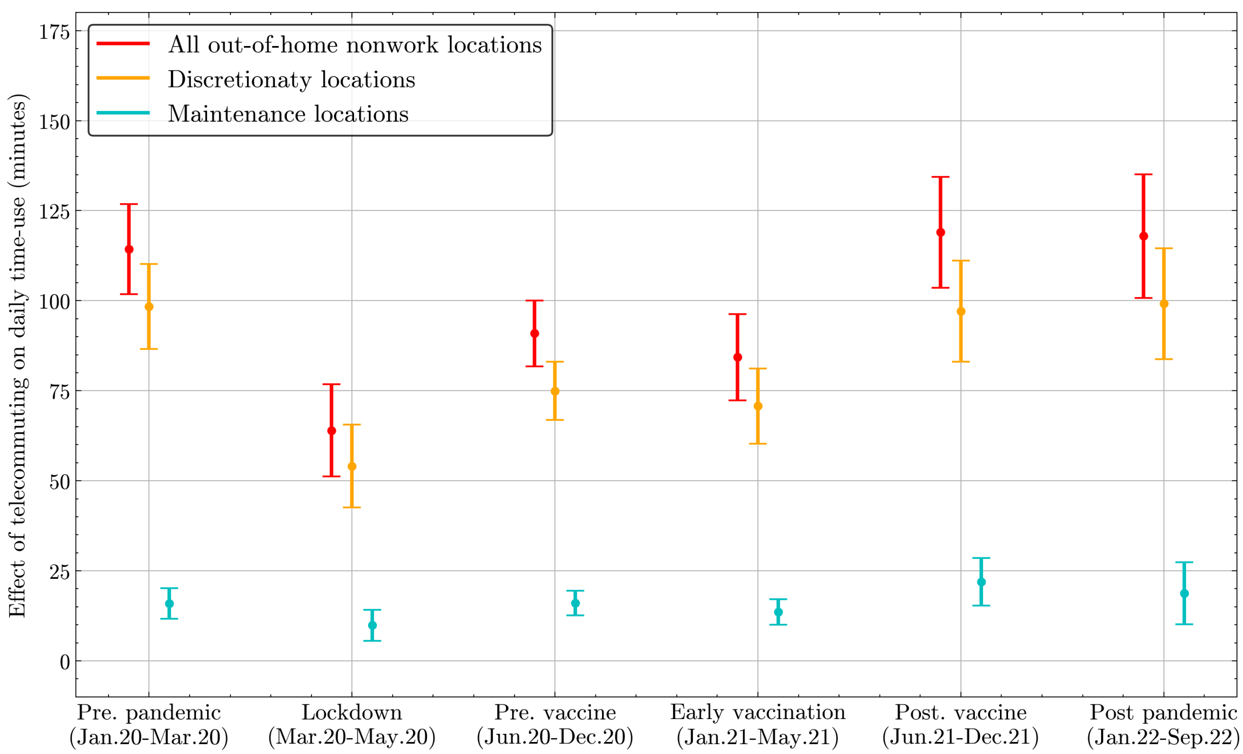

Figure 4.7: Results Summary of the impact of telecommuting on daily time-use at out-of-home non-work locations. Results are shown for different periods throughout the study duration (shown on x-axis) and broken down by discretionary and maintenance locations (different colors). Sample size: 18901-85360 person-days, depending on the analysis period.

Moreover, our findings extend the current understanding of telecommuting's impact by providing novel insights into the impact of telecommuting on weekly time use at out-of-home non-work locations and the number of unique out-of-home non-work locations visited. Figure 9 illustrates our weekly analysis results for both time-use (left axis) and number of unique locations visited (right axis). We find that the effects of each additional telecommuting day on weekly time use at out-of-home non-work locations to be null, indicating that telecommuting's impact on time use at out-of-home non-work locations are substitutional at the weekly level, as individuals shift their time use at out-of-home non-work locations from commute days to telecommute days, across both discretionary and maintenance out-of-home non-work locations. While the confidence intervals might seem wide, they range between -13% and +10% of total time spent at all out-of-home non-work locations (765 minutes), between -15% and +12.5% of weekly time spent at discretionary locations (631 minutes), and between -18% and 15% of weekly time spent at maintenance locations. In contrast, our analysis reveals a more definitive impact on the diversity of locations visited. Each additional telecommuting day is associated with a reduction ranging from 0.11 to 0.60 unique out-of-home non-work locations visited per week, with an average effect of 0.35 locations. This represents a 1.5% to 8.3% decrease from the average of 7.2 unique weekly out-of-home non-work locations. For discretionary locations, the effect ranges from a negligible 0.002 to a more substantial 0.46 fewer locations per week, averaging 0.23 locations. Given the typical 5.6 discretionary locations visited weekly, this could reduce variety by up to 8.2Maintenance locations show a range of 0.02 to 0.25 fewer locations per week, averaging 0.13 locations. With individuals visiting an average of 1.6 maintenance locations weekly, this effect represents a 1.3% to 15.6% reduction.

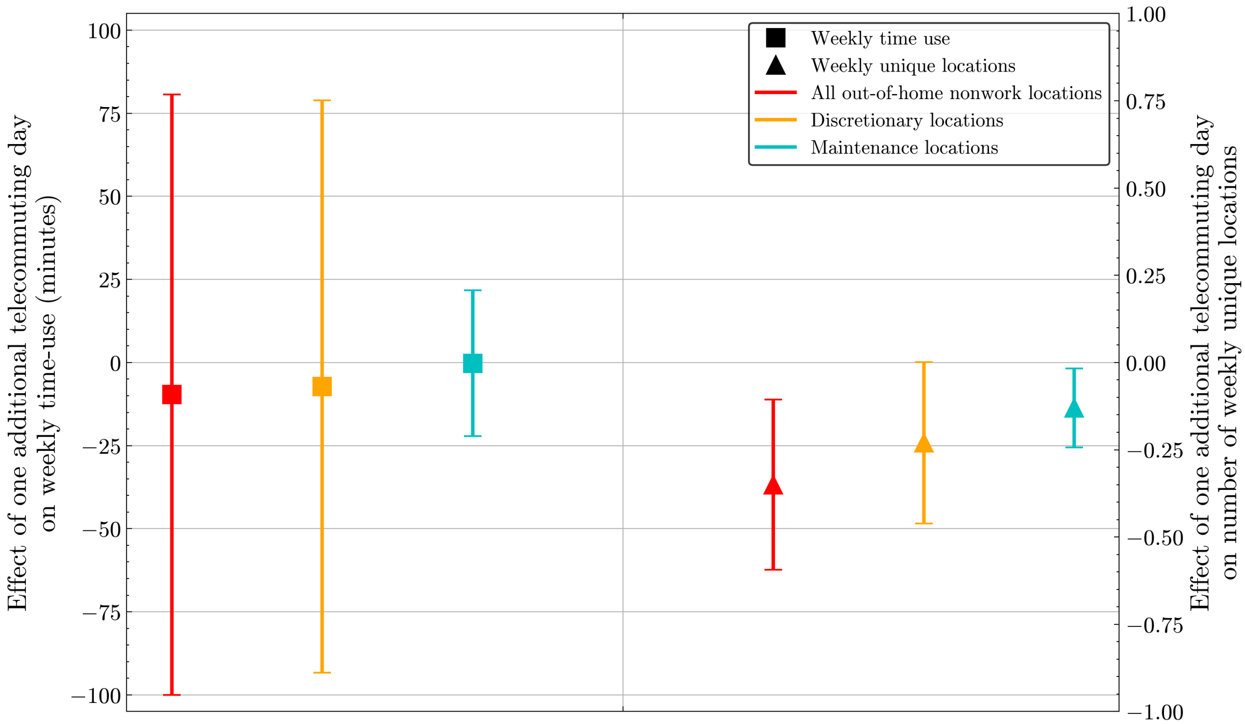

Figure 4.8: Results summary of the impact of one additional telecommuting day on weekly time-use at out-of-home non-work locations (left y axis) and the unique locations visited (right y axis). Error bars are the 95% confidence intervals of our parameter estimate. Sample size: 524 First-Differences.

5 Conclusions

In this study, we investigate the impact of telecommuting on time use at out-of-home non-work locations and the number of unique visited locations, contributing to the large body literature on the impact of telecommuting on travel behavior. We use a unique longitudinal dataset, combining both passively tracked travel behavior data and survey responses from a panel of U.S. smartphone users over the course of the COVID-19 pandemic, and aim at quantifying the impact of telecommuting on out-of-home non-work time use (i.e.: discretionary and maintenance) as well as the number of unique out-of-home non-work locations visited. In contrast to previous studies, we employ quasi-experimental designs to control for unobserved confounding, providing more robust estimates of the causal impact of telecommuting on our outcomes of interest.

We find that workers spend more time at out-of-home non-work locations when they telecommute, with this increase occurring for both maintenance and discretionary locations.

However, our weekly analysis indicates that the difference in time use at the daily level does accumulate over the week, indicating that workers only shift their time use in out-of-home non-work locations to telecommute days, both for discretionary and maintenance locations, rather than an overall increase or decrease. Our results also indicate how the impact of telecommuting on time-use evolved throughout the COVID-19 pandemic.

In terms of weekly unique out-of-home non-work locations visited, we find that the effect of an additional day of telecommuting results in the reduction of the activity set by an average of 0.35 locations, indicating that full-telecommuters visit 1.75 fewer out-of-home non-work locations compared to full-commuters.

Our study has some notable limitations. While our quasi-experimental designs help control for unobserved confounding, our study period could limit the generalizability of our findings beyond the pandemic context. Travel behaviors were significantly influenced by mobility restrictions and concerns about contracting the virus, particularly in the early stages of the pandemic, likely affecting the estimated impact of telecommuting on time-use and diversity of locations visited. At the same time, we hypothesize that the pandemic's context has attenuated our estimates, with the effect of telecommuting on non-commute travel being larger in a "new normal". Our findings support this hypothesis, as we see that the effect of telecommuting on out-of-home non-work time use was at its lowest in the early stages of the pandemic, and that it constantly increased as we moved away from the initial pandemic wave (Table 4.2, Table 4.2, Table 4.2). Additionally, although the high rates of telecommuting during the pandemic help mitigate self-selection bias to some extent, they do not completely address it. The pandemic induces other types of selection issues. For example, individuals who were not laid off during the pandemic and those who chose or were able to telecommute are not random samples of the workforce. Employment status and the ability to telecommute during the pandemic are likely influenced by factors such as job security, industry, and individual circumstances, which could affect both the likelihood of telecommuting and related outcomes. These selection biases limit the broader applicability of our findings.

While passive data helps overcome many of the limitations of cross-sectional survey data, it has its own set of limitations. Passive data may not accurately capture short trips or specific locations visited, leading to an underestimation or overestimation of time spent at different locations. For example, brief stops at locations might be missed, while extended stays in large areas (e.g., parks or shopping centers) might be inaccurately recorded as single events. Additionally, passive data collection heavily depends on the participants' devices (e.g., smartphones). Variability in device accuracy, battery life, and user behavior (e.g., turning off location services) can lead to incomplete or inaccurate data. Poor GPS signal quality, particularly in indoor locations, can result in erroneous location data, significantly impacting the precision of the inferred activities. Finally, inferring the activities in our data relied on proprietary algorithms, making it more difficult to have a complete understanding of how inference was done. Future work should also replicate the findings of this research using other datasets from the same time period and investigate whether our results hold way beyond the pandemic. Moreover, it will be valuable for future investigations to examine our research question with a broader spectrum of datasets, including those that are publicly available, to validate and enrich the conclusions drawn from this research. Our study relied on proprietary third-party data collected through their proprietary methods, and while we performed several data quality checks and verification procedures, examining the research question through alternative data sources will enhance reproducibility and provide stronger evidence on the validity of our findings.

Given the historically documented relationship between time use and well-being, and between human mobility and the degree of social connectedness, our results might indicate that telecommuting has impacts on the well-being of individuals and the number of social contacts. Future work should investigate these causal relationship directly, using outcomes of well-being from well-established psychology literature and social network size from prior literature. Future work should also investigate the reasons why telecommuters might shift their time-use at out-of-home non-work locations between commute and non-commute days, reasons why they visit a smaller number of locations.

6 Acknowledgements

The authors are grateful to SimilarWeb for providing access to the passive data used in this research. The authors of this paper would like to thank the University of California Center for Information Technology Research in the Interest of Society (CITRIS) for funding support. The opportunity to undertake this research was also made possible by the Dwight D. Eisenhower Transportation Graduate Program, which is administered by the Federal Highway Administration. Any omissions are unintentional.

Chapter 5

Final Remarks

As I conclude this dissertation, I find it necessary to circle back to the heart of what propelled me down my research journey: my own lived experience through the COVID-19 pandemic. The pandemic reshaped my doctoral journey, introducing a landscape marked by lockdowns, virtual interactions, and isolation. Yet, it was this shift, this "new normal", that sparked the questions driving my work. Yet, it was within this context of change and uncertainty that the motivation for this dissertation was born. My experiences, alongside those of millions worldwide, led me to question how the pandemic-induced shift towards greater flexibility push for greater flexibility affected our ways of living, working, and connecting in profound, and possibly enduring ways. This dissertation, therefore, aimed to gauge the impact of pandemic-induced flexibility on activity patterns, spatial habits, and schedule habits, exploring whether the changes observed during the COVID-19 pandemic represent permanent shifts or only temporary adjustments.

In Chapter 2, I presented the design and the implementation of a nationwide, large-scale, longitudinal smartphone-based study to track the behaviors and state of people throughout the COVID-19 pandemic. I, with other collaborators, collected a rich panel dataset combining both active and passive data collection methods from U.S. participants throughout the COVID-19 pandemic, overcoming limitations of active or passive data when used individually, in addition to limitations of cross-sectional datasets. Despite the richness of our passive data, it still has some limitations. First, mode use information is not available for each of the identified trips, preventing any investigation of mode use behavior or the relationship of mode use with other aspects of travel behavior. This lack of mode use information is what prompted us to include questions mode use in the survey. Second, our data lack contextual information on type of activities undertaken different locations. Second, our data do not allow us to identify joint travel decisions, i.e. whether each of the trips are taken individually or with other individuals, preventing any analysis of joint travel behavior decisions. This dataset represents the foundation of the other two studies in this dissertation and has supported other works by other researchers. The development of this data infrastructure can be key in bridging the gap between the “mobility science” and transportation researchers, as they have historically used passive data and surveys in their analyses, respectively.

Recognizing that the pandemic spurred the relaxation of spatio-temporal activity constraints, primarily through the adoption of telecommuting and e-commerce services, in Chapter 3 I propose a framework to investigate impacts of the relaxed spatio-temporal constraints on activity patterns, spatial habits, and schedule habits using metrics from both the “mobility science” and traditional transportation literature. Further, I propose a metric capturing intrapersonal schedule regularity across weeks, accounting for day-of-week differences. Using data from Chapter 2, I find that while the number of weekly trips, radius of gyration, peak period demand, and exploration rate of new places have returned to their pre-pandemic baselines, the total time spent at home and location entropy are different in post-pandemic. Most importantly, I find that despite the documented large-scale shift towards flexible work arrangements, schedule habits have strengthened rather than relaxed, defying our initial hypotheses. Finally, I observe a negative relationship between spatial entropy and schedule regularity, showing that people with higher spatial diversity are likely to exhibit less regular day-of-week schedules across weeks.

Chapter 4 aims to quantify the impact of telecommuting on non-commute travel, specifically time-use at out-of-home nonwork locations and the diversity of these locations, in light of the well-documented relationship between these metrics and and well-being. Previous research covers the impact of telecommuting on time-use, they have only analyzed daily impacts and have largely overlooked the diversity of locations visited. Using data from Chapter 2 and employing quasi-experimental designs, I find strong evidence that on telecommuting days, workers spend significantly more time at out-of-home nonwork locations, estimated to be between 63 minutes and 120 minutes, depending on the analyzed time period during the pandemic, a finding aligned with previous literature. Notably, this increase is unevenly distributed between maintenance and discretionary locations. A novel finding of this research is the identification of substitutional effects on a weekly basis, meaning increases in time spent at out-of-home nonwork locations is a shift of time use from other days of the week. On location diversity, I find that at the weekly level, an additional day of telecommuting results in a decrease of 0.35 in the number of unique locations visited, also unevenly distributed across maintenance (36%) and discretionary (64%) locations, suggesting that telecommuting may lead to fewer social interactions due to the limited variety of locations visited.

1 Future Directions

In Chapter 3, we evaluated how the relaxation of spatio-temporal constraints of key activities such as work and shopping during the COVID-19 pandemic impacted activity patterns, spatial habits, and schedule habits. We present first evidence on activity patterns, spatial habits, and schedule habits are reshaping beyond the pandemic. Future research should validate our results using other datasets, both from within the U.S. and in other regions to strengthen our findings or deny them. A natural follow-up extension is to investigate the degree of such impacts across different groups, given the documented disparities in the impact of the pandemic across socio-demographic groups. Additionally, my proposed metric measures the degree of intrapersonal schedule regularity across weeks considers a schedule as the time allocation across different geographical areas, and does not take into consideration: 1) the semantic context of type of locations, 2) activities taken in such locations, 3) or order in which such activities are taken. Future work should expand on this metric to account for these omitted characteristics, especially given that the relaxation of spatio-temporal constraints is likely to impact decisions such as location, timing and order of activities.

On the topic of telecommuting, researchers can extend our work in many ways. In Chapter 4, we build on previous literature on the impacts of telecommuting on daily time-use. In this research, we provide novel evidence of the substitutional impacts of telecommuting on time-use at the weekly level and evidence showing that telecommuting reduces the diversity of locations visited. Future research should try to replicate our weekly analyses to help deepen our understanding of the impacts of telecommuting. Second, researchers can extend our work by investigating the impact of telecommuting adoption on residential location choices, especially since telecommuting frees workers from the necessity of living closer to work. The COVID-19 pandemic presents an opportunity to deal with endogeneity between telecommuting choices and residential location choices. This extension is important, as its findings can have significant implications on land use patterns. Within the same realm, evaluating modal and trip timing differences between commuters and telecommuters is also critical in evaluating the environmental impact of telecommuting. Second, given the relationship between activity participation, time-use, and well-being, a future extension to our work is to investigate the impact of telecommuting on the well-being of workers, using various scales of subjective well-being presented in the literature, and comparing/contrasting findings from these different scales.

Finally, the impact of telecommuting extends far beyond the transportation realm. While there is considerable research on understanding the impacts of telecommuting on travel outcomes, little attention has been given to how telecommuting impacts our social life. Future work should expand on the link between social and spatial behavior by investigating the impacts of telecommuting adoption on the quantity, diversity, and strength of human connections. Researchers should strive to derive causal conclusions from this line of work, rather than simply limiting any investigations to simple correlations. This is especially critical as this research direction is key to understand the social impacts of telecommuting, and would give us critical insights on how telecommuting is to shape the fabric of our society.

2 Conclusion

To conclude, this dissertation set out to investigate how the pandemic induced relaxation of spatio-temporal constraints has impacted activity patterns, spatial habits, and schedule habits. In trying to achieve this goal, this dissertation relied on metric methods from traditional travel behavior, mobility science, and causal inference. While this dissertation has revealed some new findings, the true extent of the pandemic's impact on our societal fabric, our spatial habits, and our daily routines remains a fertile ground for exploration. I look forward to future insights and discoveries, that a deeper understanding of our mobility patterns can unlock significant insights that could help shape resilient and vibrant communities, better prepared for future disasters or pandemics.

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Appendix A

Tracking the state and behavior of people in response to COVID-19 through the fusion of multiple longitudinal data streams: Supplementary Material

1 First Wave Survey Questionnaire

Q1.2 If you agree to participate in this research, please click on "I accept", and screenshot or save a copy of this page to keep for future reference. If you do not wish to take part, please close this window.

- I Accept

Start of Block: Safety Measures

Q2.1 Thank you for choosing to take this survey! We'll be asking you a variety of questions related to your life during the Covid-19 pandemic.

Our first questions will help us learn about some of your recent habits.

Q2.2 In the **past seven days**, how many times a day have you been washing your hands with soap and water or using hand sanitizer?

- 0 times

- 1-3 times
- 4-6 times
- More than 6 times
- I prefer not to answer

Q2.3 Relative to before the Covid-19 pandemic began (March 2020), how has your hand-washing frequency changed?

- Decreased
- No change
- Increased
- I prefer not to answer

Q2.4 In the **past seven days**, how often have you worn a mask or face covering in the following situations?

- Not applicable
- Never
- Sometimes
- Frequently
- Always
- I prefer not to answer

Options: While inside your home, While indoors outside your home (e.g. grocery store, gym, etc.), While walking or exercising on your own outside, While socializing with other people outside, While traveling in public (not in your own car)

Q2.5 Which type(s) of mask or face covering have you worn?

- I don't wear a mask

- Cloth mask
- Surgical mask
- N95 or similar
- Scarf, bandana or other cloth face covering
- A mesh mask that intentionally doesn't provide protection
- Other
- I prefer not to answer

Q2.6 In the **last two weeks**, what is the largest group gathering you have been to outside of your household?

- I haven't been to a group gathering outside my household
- Fewer than 5 people
- Between 5 and 10 people
- Between 10 and 20 people
- Between 20 and 50 people
- Between 50 and 100 people
- More than 100 people
- I don't know
- I prefer not to answer

Q2.7 In the **last two weeks**, which of the following actions did you take because of the Covid-19 pandemic?

- Cancelled or changed travel plans
- Did not go to religious or other community events
- Held no in-person gatherings with friends

- Sanitized groceries or other purchases
- Stayed at least 6ft away from other people in public
- Avoided shaking hands or hugging others not in my household
- Other [Specify]
- None of the above
- I prefer not to answer

End of Block: Safety Measures

Start of Block: Modal questions

Q3.1 These next few questions are about how you travel on a daily basis.

Q3.2 Have you been employed at all in the **last 12 months?**

- Yes
- No
- I prefer not to answer

Q3.3 Please indicate how many days you worked in the **last seven days**

- 0
- 1
- 2
- 3
- 4
- 5
- 6
- 7

- I prefer not to answer

Q3.4 Please indicate how many days you worked **from home** in the **last seven days**

- 0
- 1
- 2
- 3
- 4
- 5
- 6
- 7
- I prefer not to answer

Q3.5 Relative to before the Covid-19 pandemic began (March 2020), how has the number of days you travel to work changed?

- Significantly decreased
- Somewhat decreased
- No change
- Somewhat increased
- Significantly increased
- I prefer not to answer

Q3.6 If you worked in the **last seven days**, which was the primary means of transportation you used to get to work?

- I did not leave my home for work

- Driving alone or with household members
- Carpooling with people outside my household
- Carsharing (e.g. Zipcar, Gig, etc.)
- Ridehail (e.g. Uber/Lyft) or Taxi
- Transit (e.g. bus, subway, train, etc.)
- Bicycle
- Walking
- Other
- I prefer not to answer

Q3.7 In the **last seven days**, on how many days did you use the following for transportation (not including walks around your neighborhood for exercise, etc.)?

Options: 0 days, 1-2 days, 3 or more days, I prefer not to answer

- Driving alone or with household members
- Carpooling with people outside my household
- Carsharing (e.g. Zipcar, Gig, etc.)
- Ridehail (e.g. Uber/Lyft) or Taxi
- Transit (e.g. bus, subway, train, etc.)
- Bicycle
- Walking

Q3.8 Is this more, less, or about the same as your use of each before Covid-19?

Options: Less, About the same, More, I prefer not to answer

- Driving alone or with household members
- Carpooling with people outside my household

- Carsharing (e.g. Zipcar, Gig, etc.)
- Ridehail (e.g. Uber/Lyft) or Taxi
- Transit (e.g. bus, subway, train, etc.)
- Bicycle
- Walking

Q3.9 In the **last seven days**, for which purposes did you use each of the following for transportation?

Options: Work/school, Healthcare, Errands (e.g. groceries), Leisure, Other, I prefer not to answer

- Driving alone or with household members
- Carpooling with people outside my household
- Carsharing (e.g. Zipcar, Gig, etc.)
- Ridehail (e.g. Uber/Lyft) or Taxi
- Transit (e.g. bus, subway, train, etc.)
- Bicycle
- Walking

Q3.10 Have cuts in transit service since the Covid-19 pandemic began (March 2020) been an issue for you?

- Yes, a significant issue
- Yes, a minor issue
- No, they haven't been an issue
- There have not been any service cuts
- I do not use transit
- I prefer not to answer

Q3.11 Which of the following measures would increase your use of transit (including bus, subway, train, etc.)?

- Widespread use of face masks
- Reduced crowding
- Reduction of Covid-19 rates in area
- Effective Covid-19 treatment or vaccine
- Increased sanitation/cleaning
- Return to regular service levels/schedule frequency
- I am already comfortable using transit
- None of the above
- Other: Please specify
- I prefer not to answer

Q3.12 Which of the following measures would increase your use of ride hailing or sharing services such as Uber, Lyft, Zipcar or Gig?

- Widespread use of face masks
- Reduction of Covid-19 rates in area
- Effective Covid-19 treatment or vaccine
- Increased sanitation/cleaning
- I am already comfortable using these modes
- None of the above
- Other:
- I prefer not to answer

Q3.13 If you are reading this question, please select “Somewhat increased” below

- Significantly decreased
- Somewhat decreased
- No change
- Somewhat increased
- Significantly increased
- I prefer not to answer

Q3.14 How many vehicles are available for regular use by the people who currently live in your household?

- 0
- 1
- 2
- 3+
- I prefer not to answer

Q3.15 As a result of the Covid-19 pandemic, have you made any of the following purchases? Please only select those that you wouldn't have made if it weren't for the pandemic.

- Purchases to improve your home/outdoor living space
- Purchases to improve your home working/school environment
- Purchases to improve your home or personal security
- Purchases to support your physical health
- Purchases to support a hobby
- Purchases to increase your motorized transportation options (car, RVs, etc.)
- Purchases to increase your active transportation options (bicycle, etc.)
- Other

- None
- I prefer not to answer

End of Block: Modal questions

Start of Block: Household dynamics

Q4.1 These next questions are about who you currently live with.

Q4.2 How many people (adults and children) currently live in your household, including yourself?

- 1 (I live alone)
- 2
- 3
- 4
- 5
- 6+
- I prefer not to answer

Q4.3 How does your relationship with your household members now compare to before Covid-19?

- Much worse
- Somewhat worse
- About the same
- Somewhat better
- Much better
- I don't know
- I prefer not to answer

Q4.4 Does conflict within your household affect your ability to spend longer periods of time at home?

- Yes
- Somewhat
- No
- I don't know
- I prefer not to answer

End of Block: Household dynamics

Start of Block: Economic Factors

Q5.1 These next questions are about how your employment is changing with Covid-19.

Q5.2 Were you working before the Covid-19 pandemic started?

- Yes, full-time
- Yes, part-time
- No
- I prefer not to answer

Q5.3 Since the beginning of the Covid-19 pandemic (March 2020), have you experienced any of the following changes to your working situation?

- Been laid off or lost a job
- Reduced pay or income
- Put on temporary leave from job
- Increased hours worked per week
- Got a new job

- Job did not change
- Other
- I prefer not to answer

Q5.4 Since the beginning of the Covid-19 pandemic (March 2020), have you received any form of financial government assistance?

- Yes
- No
- I prefer not to answer

Q5.5 Do you believe your change in employment was a result of the Covid-19 pandemic?

- Yes
- No
- I don't know
- I prefer not to answer

Q5.6 Relative to before the Covid-19 pandemic began (March 2020), how has your household income changed?

- Significantly decreased
- Somewhat decreased
- No change
- Somewhat increased
- Significantly increased
- I prefer not to answer

Q5.7 How confident are you that your household will be able to pay your next rent or mortgage payment on time?

- Not confident
- Somewhat confident
- Very confident
- Payment is/will be deferred
- Not applicable
- I prefer not to answer

Q5.8 How would a 400 emergency expense that you may have to pay impact your ability to pay your other bills this month?

- I would not be able to pay all of my bills
- I could still pay all of my bills
- I don't know
- I prefer not to answer

Q5.9 How much longer do you think you can endure the **economic** impact of Covid-19?

- I can't endure it anymore
- A few more weeks
- A few more months
- A year
- Indefinitely
- I don't know
- I prefer not to answer

Q5.10 How much longer do you think you can endure the **emotional** impact of Covid-19?

- I can't endure it anymore
- A few more weeks
- A few more months
- A year
- Indefinitely
- I don't know
- I prefer not to answer

End of Block: Economic Factors

Start of Block: Political

Q6.1 The next questions relate to your views and activities.

Q6.2 How closely do you follow the news?

- Not at all closely
- Not too closely
- Fairly closely
- Very closely
- I prefer not to answer

Q6.3 Which of the following are your **main** sources of Covid-19 news?

- National cable news outlets, e.g. Fox News, CNN, MSNBC
- Nationally broadcast television news, e.g. ABC, CBS, NBC, PBS
- Local news outlets

- Radio and/or podcasts
- National newspapers (printed or online)
- Social Media, e.g. Facebook, Twitter, Instagram
- State/local officials
- Public health organizations and officials
- The White House and the Coronavirus Task Force
- Family and friends
- Other
- I prefer not to answer

Q6.4 Which of the following Covid-19 related guidelines are currently in effect in your local area?

- No indoor dining
- No outdoor dining
- Some businesses are not allowed to open (e.g. gyms, salons, bars, movie theaters, etc.)
- Face coverings required indoors outside your home (e.g. grocery store)
- Face coverings required on public transportation (e.g. bus, subway, train, etc.)
- Face coverings required when outdoors in public spaces
- Restrictions on in-person gatherings (e.g. community, religious, entertainment, social, etc.)
- Quarantine and/or testing required for out-of-state visitors
- Restrictions on residential evictions
- None
- Other
- I don't know
- I prefer not to answer

Q6.5 What do you think about Covid-19 related restrictions imposed on your local area?

- Far too lenient
- Too lenient
- About right
- Too strict
- Far too strict
- I don't know
- I prefer not to answer

Q6.6 What do most of your family members and friends think about social distancing and stay-at-home directives imposed on your local area?

- Far too lenient
- Too lenient
- About right
- Too strict
- Far too strict
- I don't know
- I prefer not to answer

Q6.7 Do you feel people in your local area are complying with the imposed Covid-19 related restrictions?

- No, almost all are not complying
- No, many are not complying
- Yes, many are complying
- Yes, almost all are complying

- I don't know
- Not applicable
- I prefer not to answer

Q6.8 Since the COVID-19 pandemic began (March 2020), which of these activities did you leave your house for?

- Eating outdoors at a restaurant/bar
- Eating indoors at a restaurant/bar
- Grocery shopping
- Attending a large sports or concert event
- Attending a protest
- Going to the gym
- Medical/healthcare
- Caring for a relative or friend
- Socializing with friends in person
- Attending religious services
- Flying on an airplane
- Staying at a hotel/airbnb
- Other
- I prefer not to answer

Q6.9 Which of the following form(s) of protests have you attended since the Covid-19 pandemic began?

- Against police brutality/systemic racism
- Against current business/work/school closures and in support of reopening areas

- Against vaccines
- Other
- I prefer not to answer

Q6.10 What do you think about the following statements?

Options: Strongly disagree, Disagree, Agree, Strongly agree, I prefer not to answer

- Small businesses (e.g., local restaurants and bars) **could not** survive if people keep social distancing
- Young adults **do not** need to practice social distancing
- Social distancing stops Covid-19 from spreading around
- Older adults should stay at home because they are more vulnerable
- Not being able to hang out makes me upset
- Social distancing decreases the burden on medical resources, so people in need can use them
- Social distancing makes people lose their jobs
- The government **should not** mandate wearing masks/face coverings
- Wearing masks reduces the spread of Covid-19
- I practice social distancing because people around me do so
- Federal government assistance, **in the form of stimulus checks to individuals**, is the right thing to do
- Federal government assistance, **in the form of aid to businesses**, is the right thing to do

Q6.11 Are you registered to vote?

- Yes
- No

- I don't know
- Not eligible
- I prefer not to answer

Q6.12 How often have you voted since you became eligible?

- Every election
- Almost every election
- Some elections
- Rarely
- There hasn't been an election since I became eligible
- I dont vote
- Not Eligible
- I prefer not to answer

Q6.13 Generally speaking, would you describe your political views as ...?

- Very conservative
- Somewhat conservative
- Moderate
- Somewhat liberal
- Very liberal
- I prefer not to answer

Q6.14 How important is your religious community in your life?

- Not at all important

- Not too important
- Fairly important
- Very important
- Not applicable
- I prefer not to answer

Q6.15 Would you get a Covid-19 vaccine if/when one becomes available?

- Definitely not
- Probably not
- Probably
- Definitely
- I don’t know
- I prefer not to answer

Q6.16 What would be a reason(s) not to get a Covid-19 vaccine?

- I would be concerned about side effects or getting infected from the vaccine
- Im not concerned about getting seriously ill from Covid-19
- I don’t think vaccines work very well
- I won’t have time to get vaccinated
- Other
- I prefer not to answer

End of Block: Political

Start of Block: Personality

Q7.1 The next few questions ask about how you think of yourself.

Q7.2 How well do the following statements describe your personality?

Options: Strongly disagree, Disagree, Neither agree nor disagree, Agree, Strongly agree, I prefer not to answer

I see myself as someone who...

- Is reserved
- Is generally trusting
- Tends to be lazy
- Is relaxed, handles stress well
- Has few artistic interests
- Is outgoing, sociable
- Tends to find fault with others
- Does a thorough job
- Gets nervous easily
- Has an active imagination
- If you're reading this, please select Disagree
- Is willing to take risks
- Is influenced by people I am close to

End of Block: Personality

Start of Block: Physical Health

Q8.1 Thanks for sticking with us! These next questions ask about your health.

Q8.2 How would you rate your physical health?

- Poor

- Fair
- Good
- Very good
- Excellent
- I Don't know
- I prefer not to answer

Q8.3 Which of the following is your **main** source of healthcare coverage?

- Employer sponsored (yourself, spouse, or parents)
- Personally purchased
- Student health care plan
- Medicare/Medicaid/Other government healthcare plan
- Do not have insurance
- Other Source
- I don't know
- I prefer not to answer

Q8.4 Does anyone in your household **not** have health insurance or some other kind of healthcare plan?

- Yes
- No
- I don't know
- I prefer not to answer

Q8.5 Do you suspect you have ever been infected with Covid-19?

- Yes
- No
- I don't know
- I prefer not to answer

Q8.6 Have you been tested for Covid-19 or the antibodies to it?

- No, not tested
- Yes, tested positive
- Yes, tested negative
- Yes, prefer not to specify result
- I prefer not to answer

Q8.7 Do you think someone in your household has had Covid-19?

- Yes
- No
- I don't know
- I prefer not to answer

Q8.8 Do you personally know someone else outside of your household (relative, coworker, friend, etc.) who has had Covid-19?

- Yes
- No
- I don't know
- I prefer not to answer

Q8.9 Have you been hospitalized due to Covid-19, or do you personally know someone who has been hospitalized or died due to Covid-19?

- Yes
- No
- I don't know
- I prefer not to answer

Q8.10 In the **last seven days**, did you experience the following symptoms?

Option: Yes, No, I prefer not to answer

- Severe or significant persistent cough
- Shortness of breath
- Fever higher than 100°F
- New loss of smell and/or taste
- Sore throat
- Severe fatigue
- Skipped meals

Q8.11 How worried are you that you or someone in your family will get Covid-19?

- Very worried
- Somewhat worried
- Not too worried
- Not at all worried
- I/they already have
- I don't know

- I prefer not to answer

End of Block: Physical health

Start of Block: Psychological Factors

Q9.1 Here are a few more questions that ask about how you're doing.

Q9.2 Relative to before the Covid-19 pandemic began (March 2020), how has your ability to get things done for work changed?

- Significantly decreased
- Somewhat decreased
- No change
- Somewhat increased
- Significantly increased
- Not applicable
- I prefer not to answer

Q9.3 Since the Covid-19 pandemic began (March 2020), how often do you feel isolated or lacking companionship?

- Never
- Rarely
- Sometimes
- Often
- Always
- I prefer not to answer

Q9.4 Is this more, less, or about the same as before Covid-19?

- Less
- About the same
- More
- I prefer not to answer

Q9.5 Over the **last two weeks**, how often have you been bothered by the following problems?

Options: Not at all, Several days, More than half the days, Nearly every day, I prefer not to answer

- Feeling nervous, anxious, or on edge
- Not being able to stop or control worrying
- Little interest or pleasure in doing things
- Feeling down, depressed, or hopeless

End of Block: Psychological Factors

Start of Block: Demographics Q10.1 Finally, these last few questions ask about your current living situation.

Q10.2 What type of building do you currently live in?

- A mobile home
- A one-family house detached from any other house
- A one-family house attached to one or more houses
- A building with 2 to 5 apartments
- A building with 6 to 19 apartments
- A building with 20 or more apartments
- Other (boat, RV, van, tent, etc.)

- I prefer not to answer

Q10.3 Which of the following best describes your place of residence?

- Owned free and clear
- Owned with a mortgage or loan
- Rented
- Occupied without payment of rent
- I don't have a stable place of residence
- I prefer not to answer

Q10.4 How many children ages 0-6 currently live in your household?

- 0
- 1
- 2
- 3+
- I prefer not to answer

Q10.5 How many children ages 7-17 currently live in your household?

- 0
- 1
- 2
- 3+
- I prefer not to answer

Q10.6 Do you currently help care for an elderly or disabled person (family, relative, or friend)?

- Yes, at my home
- Yes, outside my home
- No
- I prefer not to answer

Q10.7 Do you currently help care for a child (family, relative, or friend)?

- Yes, at my home
- Yes, outside my home
- No
- I prefer not to answer

Q10.8 Are you an "essential worker"?

- No
- Yes, a healthcare worker
- Yes, a grocery store, pharmacy, or retail worker
- Yes, a food service worker
- Yes, a child care worker
- Yes, an essential government worker (e.g. firefighter, police officer)
- Other
- I prefer not to answer

Q10.9 Is anyone else in your household (excluding yourself) classified as an "essential worker"?

- No
- Yes, a healthcare worker
- Yes, a grocery store, pharmacy, or retail worker
- Yes, a food service worker
- Yes, a child care worker
- Yes, an essential government worker (e.g. firefighter, police officer)
- Other
- I prefer not to answer

Q10.10 How many **bedrooms** are in your home?

- 0
- 1
- 2
- 3
- 4
- 5
- 6+
- I prefer not to answer

Q10.11 How many **bathrooms** are in your home?

- 0
- 1
- 2
- 3
- 4

- 5
- 6+
- I prefer not to answer

Q10.12 How many **other rooms** are in your home? (exclude hallways, balconies, foyers and porches)

- 0
- 1
- 2
- 3
- 4
- 5
- 6+
- I prefer not to answer

End of Block: Demographics

Start of Block: Open Ended

Q11.1 Thank you for taking this survey! The final three questions give you an opportunity to tell us more about your experiences if you wish.

Q11.2 Is there anything else you would like to tell us about things that are particularly difficult for you during the pandemic?

Q11.3 Is there anything else you would like to tell us about positive aspects of your life during the pandemic?

Q11.4 Is there anything you would like to tell us about our survey?

End of Block: Open Ended

2 Survey Burden

Table A.1: Survey Burden According to point scheme by Axhausen et al. (2015)

Survey Section	Wave 1	Wave 2	Wave 3	Wave 4	Wave 5	Wave 6
Safety Measures	58	62	46	74	42	42
Modality	195	195	157	190	157	143
Household Dynamics	15	41	41	41	41	32
Economic Factors	50	49	46	49	46	32
Political Factors	162	159	156	167	189	137
Personality	52	52	N/A	52	N/A	N/A
Physical Health	70	70	70	70	70	42
Psychological Factors	30	30	26	30	26	26
Demographics	67	71	59	84	69	69
Open Ended Questions	18	18	18	18	18	18

3 Size of Survey Cohorts

Table A.2: Size of participant cohorts

Number of Waves	1	2	2R	3	4	4R	5	6	Cohort Size
1	X								347
			X						45
						X			134
								X	693
2	X							X	1
	X	X							183
	X			X					27
	X				X				19
	X						X		31
			X	X					58
			X		X				5
			X				X		6
						X	X		217
						X		X	4
3	X	X		X					163
	X	X			X				31
	X	X					X		25
	X	X						X	1
	X			X	X				9
	X			X			X		13
	X				X		X		14
	X						X	X	1
			X	X	X				12
			X	X			X		16
			X	X				X	1
			X		X		X		12
			X				X	X	1
						X	X	X	21
4	X	X		X	X				71
	X	X		X				X	1
	X	X		X			X		52
	X	X			X		X		39
	X	X			X			X	3
	X				X		X	X	1
	X			X	X			X	1
	X			X	X		X		23

			X	X			X	X	3
			X	X	X			X	1
			X	X	X		X		67
			X		X		X	X	2
	X	X		X	X			X	3
	X	X		X			X	X	4
5	X	X		X	X		X		212
	X	X			X		X	X	8
			X	X	X		X	X	24
6	X	X		X	X		X	X	50

4 Matrix Question Display on Smartphone

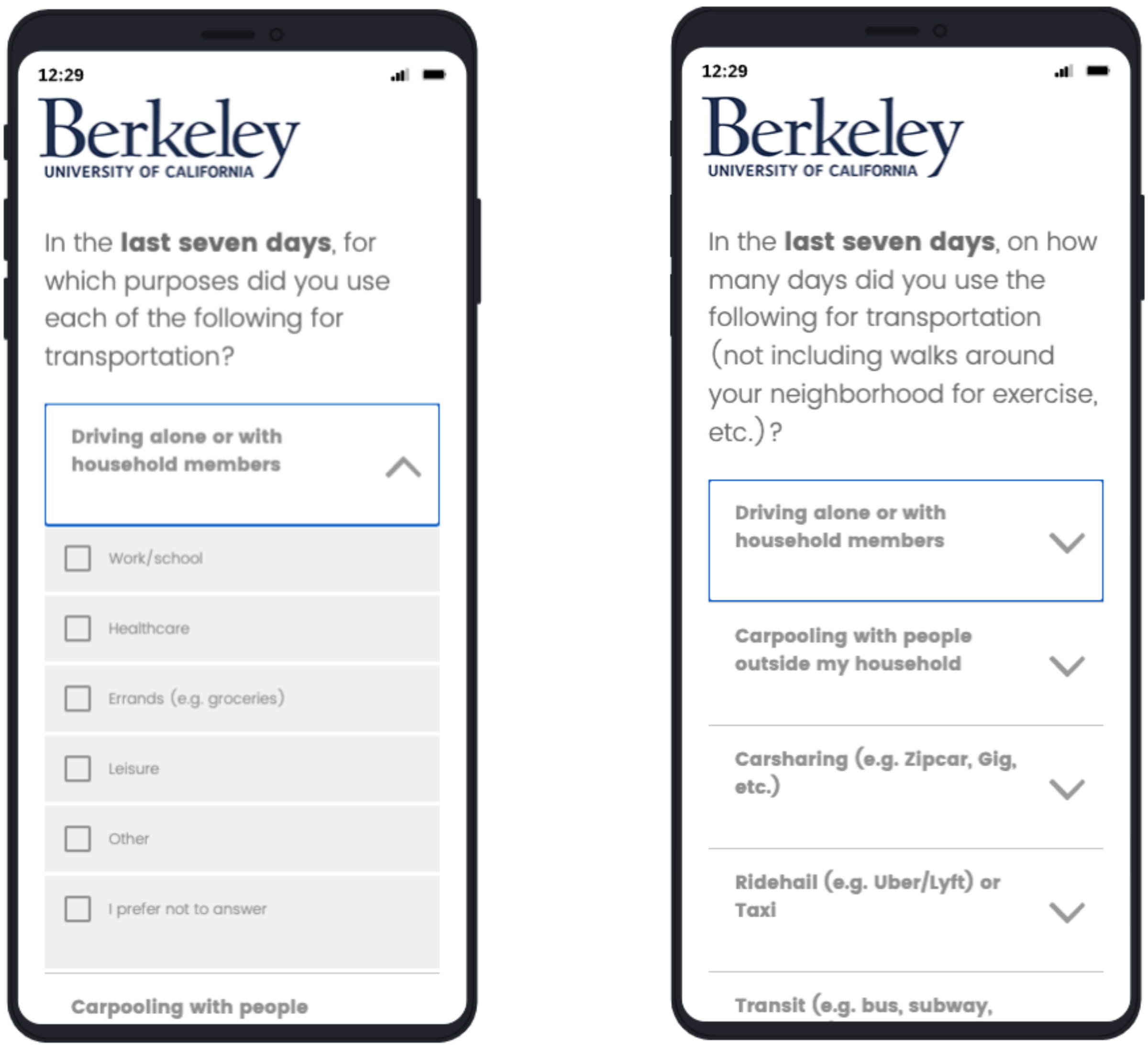

Figure A.1: Display of Matrix Questions on Smartphone

Appendix B

Human Mobility Reshaped? Deciphering the Impacts of the COVID-19 Pandemic on Activity Patterns, Spatial Habits, and Schedule Habits: Supplementary Material

1 Distribution of out-of-home dwell-time

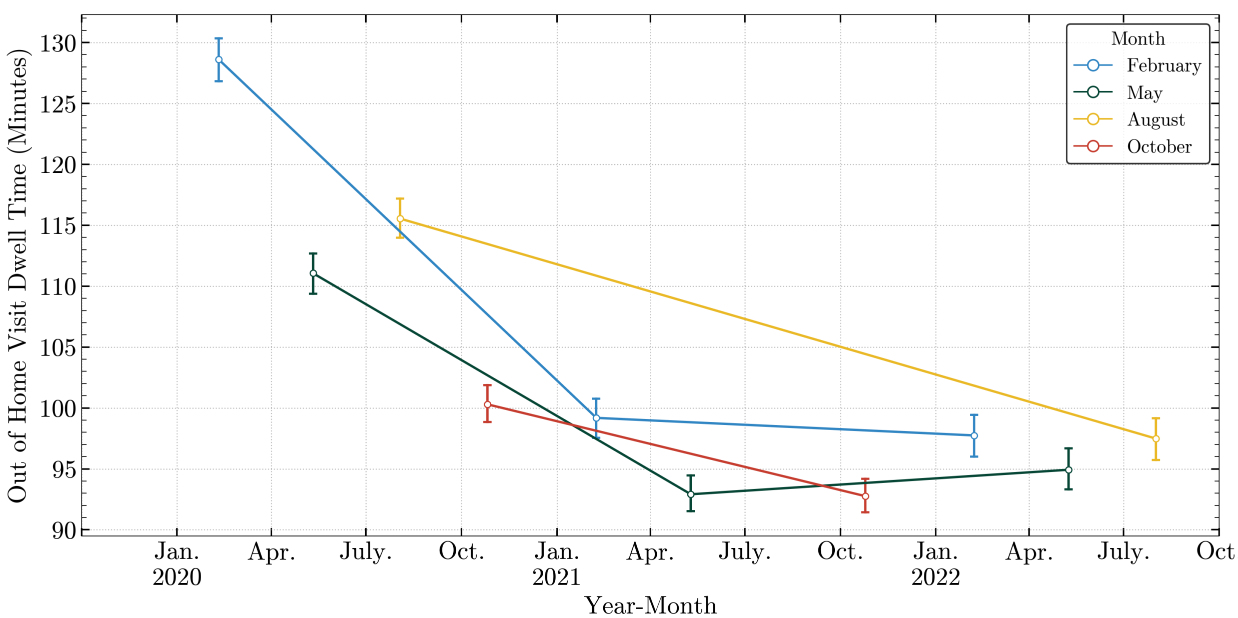

Figure B.1: Evolution of out-of-home dwell-time throughout the COVID-19 pandemic. The error bars represent the 95% confidence interval around the population mean. ($N \approx 21,700$ individuals)

Appendix C

Influence of telecommuting on out-of-home time use and diversity of locations visited: Evidence from the COVID-19 pandemic: Supplementary Material

1 Literature Summary – See next page

Table C.1: Literature findings on telecommuting impact on travel behavior

Study	Year	Population	Data	Outcome	Finding
Su et al. (2021)	2017	All workers	California Household Travel Survey	activity patterns	More diverse activity patterns
Mokhtarian, Handy, et al. (1995)	1992	16 years or older workers	Combined datasets	VMT and PMT	-38.3 PMT & - 27.9 VMT per telecommuting occasion
Choo et al. (2005)	1966-1999	All workers	Aggregate public data	VMT	- 37-102 VMT per telecommuting occasion
Zhu (2012)	2001 & 2009	All workers	National Household Travel Survey	PMT and trip frequency	Positively related to trip distance and frequency for all trips
Kim et al. (2015)	2017	All workers	California Household Travel Survey	PKT and VKT	-2.7 PKT & -0.9 VKT per telecommuting occasion
Silva et al. (2018)	2017	All workers	California Household Travel Survey	VMT	Increase weekly VMT
Obeid, M. L. Anderson, et al. (2024)	2017	All workers	Passively tracked POI data	PMT	Increase non-work travel by 1 trip and reduce distance traveled between 0.12 - 9.8 miles
Wang (2023)	2021	All workers	Online survey	VMT	Upwards of 320 VMT reduced, depending on telecommute frequency

2 POI Data Descriptive Statistics

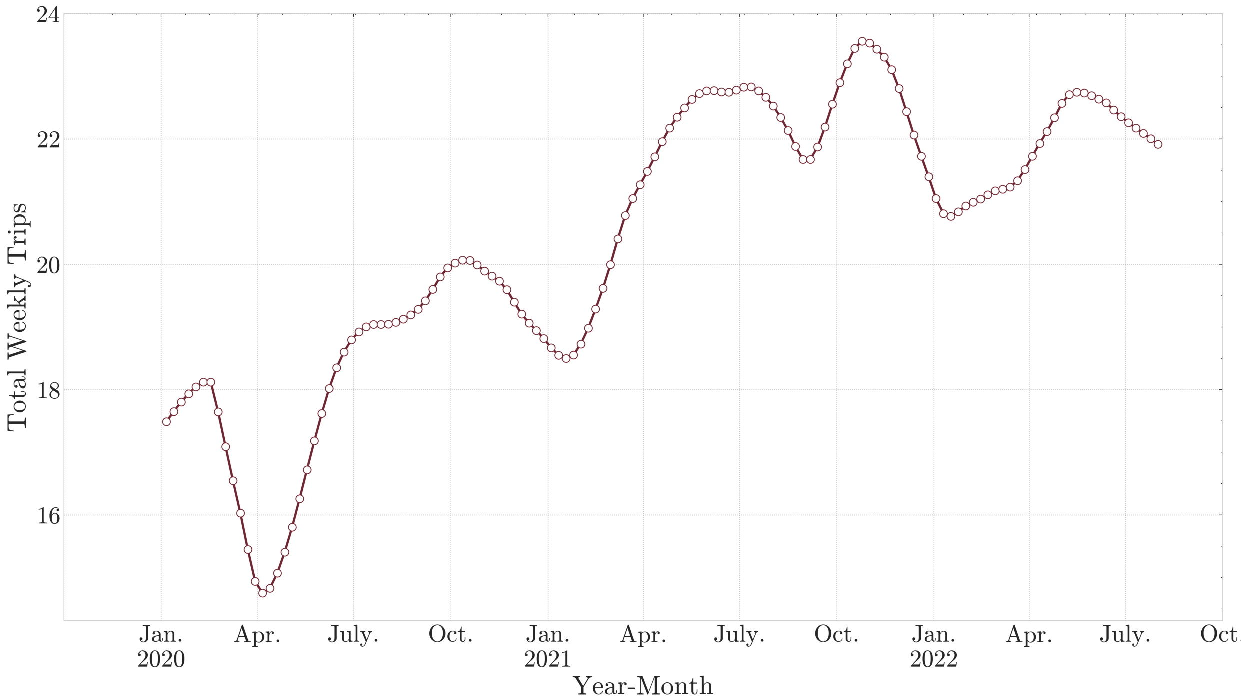

Figure C.1: Weekly number of trips by study participants throughout the COVID-19 pandemic (January 2020 - August 2022). ($N = 809$ individuals)

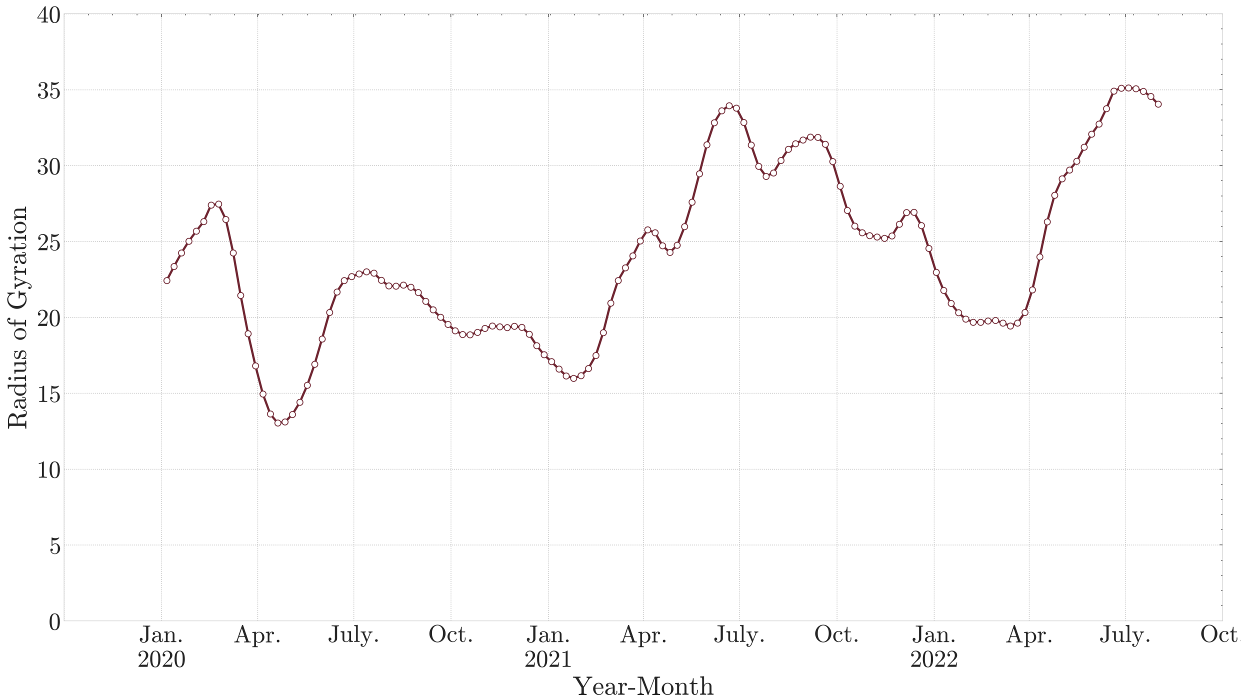

Figure C.2: Weekly radius of gyration by study participants throughout the COVID-19 pandemic (January 2020 - August 2022). ($N = 809$ individuals)

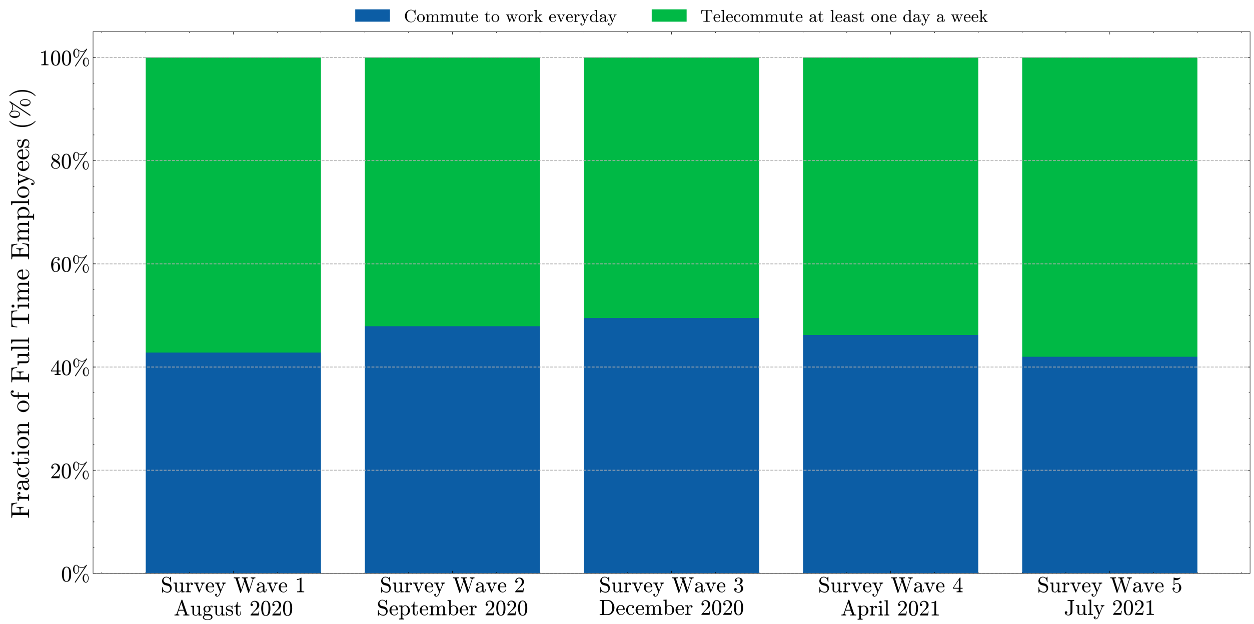

Figure C.3: The frequency of telecommuting and commuting across full-time employees. The sample size varies from 402 and 477 employees, depending on the survey wave, except for the third wave in December 2021, when the number drops to 328 (likely due to vacations related to end of year holidays)

3 Regression Results for Mediation Analysis

Table C.2: Estimates of the fixed effects regression of the effect of telecommuting on total time use at out-of-home non-work locations while controlling for the number of non-commute trips. Regression results are shown for different phases of the COVID-19 pandemic.

	Total out-of-home non-work time use (min)					
	Pre-pandemic	Lockdown	Pre-vaccine	Early vacc.	Post vacc.	Post covid
WFH	112.77***	61.63***	89.36***	83.46***	119.68***	116.98***
	(6.27)	(6.50)	(4.59)	(6.02)	(7.48)	(8.56)
Observations (person-days)	18901	15948	85360	41673	29595	24494
Time FE	YES	YES	YES	YES	YES	YES
Person FE	YES	YES	YES	YES	YES	YES

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the person level.

Table C.3: Estimates of the fixed effects regression of the effect of telecommuting on time use at maintenance activity locations while controlling for number of non-commute trips. Regression results are shown for different phases of the COVID-19 pandemic.

	Maintenance out-of-home non-work time use (min)					
	Pre-pandemic	Lockdown	Pre-vaccine	Early vacc.	Post vacc.	Post covid
WFH	15.91***	9.94***	15.94***	13.58***	21.96***	18.71***
	(2.16)	(2.19)	(1.74)	(1.81)	(3.37)	(4.38)
Observations (person-days)	18901	15948	85360	41673	29595	24494
Time FE	YES	YES	YES	YES	YES	YES
Person FE	YES	YES	YES	YES	YES	YES

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the person level.

Table C.4: Estimates of the fixed effects regression of the effect of telecommuting on time use at discretionary activity locations while controlling for number of non-commute trips. Regression results are shown for different phases of the COVID-19 pandemic.

	Discretionary out-of-home non-work time use (min)					
	Pre-pandemic	Lockdown	Pre-vaccine	Early vacc.	Post vacc.	Post covid
WFH	98.44***	54.09***	74.92***	70.75***	97.10***	99.18***
	(6.02)	(5.88)	(4.12)	(5.34)	(7.18)	(7.87)
Observations (person-days)	18901	15948	85360	41673	29595	24494
Time FE	YES	YES	YES	YES	YES	YES
Person FE	YES	YES	YES	YES	YES	YES

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the person level.

4 Estimation Results of Average Dwell-Time

Table C.5: Estimates of first differences design of the effect of one additional telecommuting day on average dwell time at out-of-home non-work locations. Results are provided for all out-of-home non-work locations. The first column show results for the model without controlling for number of non-commute trips, the second columns present results for the model controlling for the number of non-commute trips.

	Average Out-of-home dwell-time (min)	
	No control	Control
WFH	-15.49**	-16.22***
	(7.85)	(5.98)
Observations	524	524

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the person level.