

**Preparing urban mobility for the future of work:
impacts and adaptation**

by

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Abstract

The unexpectedly rapid rise of remote work in recent years has upended longstanding travel patterns. Commuting to work is no longer a routine trip with a fixed destination; millions of people have suddenly been granted the flexibility to choose their own work location and travel schedule when working remotely. Urban transportation systems designed and operated to serve regular commuters are struggling to meet the evolving mobility needs of their communities and are facing substantial demand shortfalls as a result. Moreover, there is evidence of a latent desire for new mobility services and land use policies that allow remote workers to take full advantage of the flexibility offered by remote work.

This dissertation takes a three-step approach to addressing the issues presented by remote work through transportation policy. First, it creates the conceptual infrastructure needed to support interdisciplinary remote work research that can be translated into evidence-based policy. This infrastructure includes a common taxonomy of remote work stakeholders and arrangements, a map of the relationships between stakeholders, and a conceptual framework for describing and classifying individual remote work studies. Several examples demonstrate how the taxonomy and framework can be used to develop comprehensive research findings that facilitate the design of remote work policy.

The second step is collecting and analyzing extensive primary data related to remote work arrangements and associated travel behavior. New questions were added to a monthly national survey, allowing the identification of unanticipated aggregate and disaggregate trends. One of the most important findings is that approximately

one-third of all remote work takes place outside of the home, at other work-friendly third places such as coffee shops and libraries. Many personal factors are found to be predictive of the choice of work location, including household characteristics such as the presence of roommates, employer remote work policies, and attitudes towards colleagues. An extended example of modeling the commuting frequency, mode choice, departure time, and destination of commutes to third places demonstrates how this rich source of data can be used to inform travel demand modeling for remote workers. These new models, which leverage zero-one inflated beta regression and mobile phone records to predict individual commuting patterns, are then applied to the City of Chicago to estimate the impact of remote work on carbon emissions from commuting. The study finds that overall carbon emissions are reduced by 31% relative to a 2019 baseline, and that commutes to third places are responsible for 16% of all commuting-related emissions.

The third step is applying the insights and predictive models generated from the previously collected data to optimize urban mobility systems for remote work. The studies in this section of the dissertation tackle challenges faced by different remote work stakeholders: shared mobility platforms, public transit agencies, and shared workplace providers. For shared mobility platforms, a new type of ride-pooling service that leverages the destination flexibility of remote workers and other customers is shown to lead to more efficient passenger-vehicle matching and thus the total reduce vehicle distance traveled. A case study using ride-hailing data from Manhattan estimates that when a quarter of passengers have flexible destinations, overall travel can be reduced by 4.8%. The matching algorithm also allows shared mobility platforms to cooperate with employers and shared workplace providers to offer an all-inclusive mobility and workplace service. Employer incentives for employees to work at the same location as their team members are found to reduce the efficiency of passenger-vehicle matching and lead to longer trips.

To help public transit agencies respond to remote work, a new transit capacity flexibility model is developed. It allows agencies to evaluate the capacity of the network under different levels of passenger flexibility and changing destination preferences. The capacity flexibility model, which is the first such model that is tractable for network-sized problems, is then solved for the Boston rapid transit system. It demonstrates that the Boston network can accommodate 13% fewer passengers when commuting demand partially shifts from the downtown core to neighborhood centers as a consequence of remote work.

Many governments are exploring opportunities to build new shared workplaces due to substantial interest in working at third places among remote workers. Shared workplaces can also address some of the social issues presented by remote work, such

as social isolation and fewer interaction opportunities. The third study in this section proposes an integer programming model for selecting optimal shared workplace sites under social objectives. It finds that the distribution of shared workplaces varies significantly depending on the objective, and proposes a multi-objective framework for generating solutions with a balanced set of social benefits.

To conclude, the potential applications of this research are discussed and an extensive agenda for future remote work and urban mobility research is presented.

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Chapter 1

Introduction

1.1 Background and motivation

In 2018, about 4.8% of all worked hours in the United States were conducted remotely [1]. Consequently, the destination of nearly every work trip in the country was pre-determined and routine. There had been a gradual rise in remote work over the preceding years, inadequate communication technology, employer expectations, social pressure, unproductive home working environments, and the simple behavioral inertia resulting from decades of in-person work collectively presented a formidable barrier to widespread adoption [2]. Then, in 2020, the COVID-19 pandemic forced anyone who could potentially work at home to overcome these barriers in the space of days or weeks. Remote work suddenly represented more than 60% of all worked hours in the United States [3]. As the public health threat of the pandemic subsided over the next two years, so did the share of remote work. Yet remote workers and their employers, having internalized the benefits of remote work and developed new habits, are almost certainly not returning to old in-person working norms. As of

July 2023, about 30% of all worked hours occur remotely, a sixfold increase in the remote work share relative to just five years earlier. The trends in remote work over the past six decades are summarized in Figure 1-1.

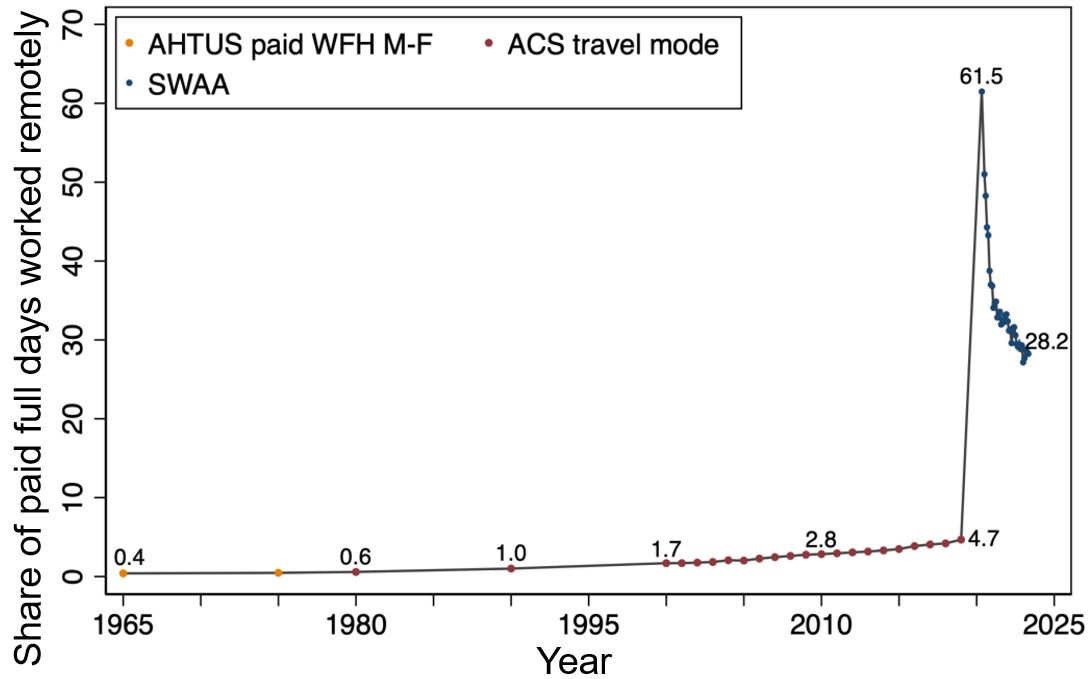


Figure 1-1: Remote work as a percentage of all worked days from 1965 to 2023. Adapted from Barrero et al. [4]. Note: 1965 to 1975 data is from the American Historical Time Use Survey, 1980 to 2019 data is from the American Community Survey, and 2020 to 2023 data is from the Survey of Workplace Arrangements and Attitudes.

The result of the rise in remote work is that a major portion of work trips no longer have a fixed destination or schedule. Remote workers may choose to work at home, thus eliminating the need to travel entirely, or they may decide to travel to a coffee shop for a change of scenery in the afternoon. As a result, the aggregate demand for certain transportation modes has been dramatically curtailed; total public transit ridership in the United States is 30% less than it was in 2019 [5]. Origin-destination

patterns have also shifted, moving away from suburb-to-downtown trips and towards trips within and between neighborhoods [6, 7]. Urban transportation systems funded by user fees and tax revenue are now facing severe budgetary shortfalls, thus having to reduce the services that they offer [8]. For example, Toronto Transit Commission has recently announced a new wave of service cuts [9] due to a lack of operating funds.

Remote work is more than a simple demand shock for urban transportation systems, like the suburbanization of U.S. jobs in the late 20th century that shifted demand patterns between locations. It is a transformation of how individual travel decisions are made. Every remote work day is an opportunity for people to choose a different work location, the timing of their trip to that location, and the mode they use to get there. Should I walk to the library in the morning to work on a high-focus task in the morning? What about accepting an invitation to work at a friend's house in the afternoon to avoid yet another week of working at home alone? The possibilities are endless, with many different and possibly competing considerations, creating a significant cognitive burden for remote workers. Rather than basing errands or social gatherings around work trips, work trips can now be chosen to make running errands or social gatherings more convenient. Existing urban transportation and land use systems must adapt to the new remote work demand patterns and the new decision-making processes in order to remain viable and provide convenient, affordable, and sustainable mobility services.

The relationship between transportation systems and society has also become more complex. While transportation has always determined the set of feasible destinations for any trip, people would make the necessary arrangements to travel to and from their primary work location. Employees did not have the agency to choose a new location to improve their productivity, or well-being, or change the people

they encountered on their way to and from work. When working remotely, however, individuals are generally responsible for their choice of workplace, which has many secondary effects when aggregated at the societal level.

The decline of spontaneous in-person interactions between colleagues and strangers due to working at home is thought to be inhibiting labor productivity [10]. The diversity of social encounters has declined as people are less likely to leave their neighborhoods when working remotely [11]. Finally, a looming commercial real estate “apocalypse” [12], caused the rise of remote work threatens to empty downtown cores of economic activity and vibrancy. By reshaping their operating and strategic plans to meet the new demand for remote work at non-home locations, urban mobility providers may help to mitigate some of these concerns raised by remote work.

Fundamentally, remote work introduces a new dimension of flexibility into people’s lives. They are take full advantage that flexibility to make new decisions about where, when and with whom to work. That flexibility presents a complexity challenge for travel demand modelers and transportation planners, who previously leveraged the fixity of routine work trips to simplify their tools and decision-making. Yet the flexibility afforded by remote work also means people have more discretion to adjust their travel behavior in response to new transportation policies and service designs.

Up to this point, the development of evidence-based remote work policy has been impeded by three major issues. First, recent research into the effect of remote work on urban systems is often narrowly focused on the outcomes for a single stakeholder or discipline. Studies typically do not consider effects outside of their discipline, despite the impact of remote work on nearly every aspect of urban life. For example, studies evaluating the decrease in commuting-related carbon emissions from remote work [13, 14, 15] typically ignore the associated increases in carbon emissions from residential

buildings, not to mention the effects on productivity or worker well-being. It is also difficult to compare findings from multiple studies due to their discipline-specific terminology and standards for describing the problem settings. As a result, few review papers explore the conflicting findings between similar remote work studies.

Second, there remains insufficient empirical evidence of the impacts of remote work on travel behavior at a broad temporal and spatial scale, hindering efforts to predict policy outcomes. As Jane Jacobs wrote, "City processes in real life are too complex to be routine, too particularized for application as abstractions. They are always made up of interactions among unique combinations of particulars, and there is no substitute for knowing the particulars" [16]. The dynamics of remote work are no different. Surveys with a broad geographic reach are expensive to distribute, and synthesizing the results of multiple smaller surveys can be challenging or impossible when the questionnaires and samples vary. Moreover, attitudes and policies towards remote work have fluctuated substantially over time, preventing the comparison of surveys issued mere months apart. Repeated surveys covering many different locales are needed to understand how remote work practices are changing over time and how they may evolve in the future.

Finally, remote work introduces complex behavioral dynamics that are not captured in existing models for designing and operating mobility systems. Decisions about where and when to work are now made on a daily basis, resulting in a merging of travel behavior with considerations related to productivity, fears of exposure to illness, and family life. Old models of travel demand and land use allocation that assume fixed work destinations are no longer reliable. There is also unmet demand for mobility services that recognize and leverage the destination flexibility of remote workers.

Resolving these three critical issues is necessary to support the development of ur-

ban transportation and land use policies for sustainable and economically productive cities in the remote work era.

1.2 General literature review

Each of the chapters of this dissertation contains a separate summary of the literature that is relevant to the specific problem addressed in the chapter. Nevertheless, the intersection of remote work and urban mobility has been studied in some form for many decades, and reviewing the history and broad scope of this body of research in detail provides greater context for the overall motivation of this dissertation and the gap that it is intended to address. This general literature review section is therefore included to review remote work trends and summarize the state of the art from four disciplines as they relate to remote work: travel behavior, transportation science, land use and real estate, and organizational behavior. First, Section 1.2.1 (Remote Work Trends) describes in detail the literature relating to aggregate remote work adoption over time. Section 1.2.2 (Travel Behavior) includes the micro-level decision-making processes and associated psychological factors that contribute to travel choices regarding remote work. Section 1.2.3 (Transportation Science) focuses on measuring the aggregate impacts of remote work on travel demand, and analytical models of transportation systems that explicitly incorporate remote work travel behavior. There has been considerable speculation about the effects of remote work on cities; these studies are summarized in Section 1.2.4 (Land Use and Real Estate). Finally, Section 1.2.5 (Organizational Behavior) includes research related to individual and organizational attitudes towards remote work and how such arrangements affect organizational outcomes.

1.2.1 Context: the rise of remote work

Remote work has been proposed at least as far back as the 1950s, [17] and became sufficiently popular by the 1980s to become the subject of several economic and organizational behavior studies [18, 19]. Surveys of remote workers conducted around this time imply some participation, but the phenomenon remained fairly uncommon and difficult to measure [20]. Several social trends later contributed to the growth of remote work. Advances in digital and communication technology enabled the first truly remote workers; personal computers, the Internet, email, and eventually video conferencing have progressively improved remote collaboration [21].

The number of people who worked at least one day per month at home in the United States rose from 4 million in 1990 to 23.6 million in 2001 [22] as technology continued to improve. New societal factors, such as increased globalization, the rise of the “gig economy”, and online sales platforms, have made it easier to substitute freelancing and self-employment for full-time salary work [23]. However, even in 2018, remote work represented only 5% of all worked days in the United States [3].

Then, in early 2020, the COVID-19 pandemic forced most workplaces to close due to the risk of spreading the virus. By May 2020 over 60% of worked days in the U.S. were taking place at home [3], a twelve-fold increase compared to the pre-pandemic norm. Throughout the pandemic, employers began to reconsider their long-term remote work policies. Much like the inertia that kept traditional in-person work the dominant arrangement long after technology was sufficient to permit remote work, the inertia of pandemic-related remote work has begun to increase the desire for permanent full-time remote work. Many large employers, including Salesforce, Facebook, and Google, have announced remote work policies that include full-time remote options [24].

The degree to which remote work will remain after the public health threat of COVID-19 has subsided has been the subject of a lot of speculation and survey efforts. Chapter 3 presents a comprehensive breakdown of current and future remote work trends based on primary survey data collected for this dissertation. Other surveys vary in methodology and timing, making the results difficult to compare. Barrero et al. [3] conducted a comprehensive longitudinal survey of 22,500 working-age Americans between May 2020 and November 2020. The survey found that employers intend for 26.6% of all worked days to take place remotely going forward (see Figure 1-2), while the average worker would prefer remote work 47% of the time. A PwC survey of 1,200 U.S. workers around the same time found that, on average, workers would prefer 56% of their workdays to be flexible after COVID-19 has passed [25]. The employer intention results from [3] are similar to a survey of HR professionals and hiring managers conducted in April 2020 [2]. The results are heterogeneous across job sectors, income levels, and gender, suggesting that the benefits and impacts of remote work will not be shared evenly. Surveys have also found a racial difference in the desire to return to the office full-time [26].

Surveys issued in 2021 and later have often found a greater preference for remote work than those issued early in the pandemic. A Harvard Business School survey of 1,500 U.S. professionals in March 2021 [27] found that 88% would prefer at least 2 days per week of remote work. In their longitudinal survey from May 2020 to March 2021, Barrero et al. [3] has found that the number of people who want only remote work has increased over time. Preferences for remote work may be growing as a return to the office becomes more realistic and workers begin to consider the downsides (commuting, etc.) more closely. People may also have become more comfortable with remote work and virtual communication over time. Finally, it may be that people began to enjoy the additional location choices provided by remote

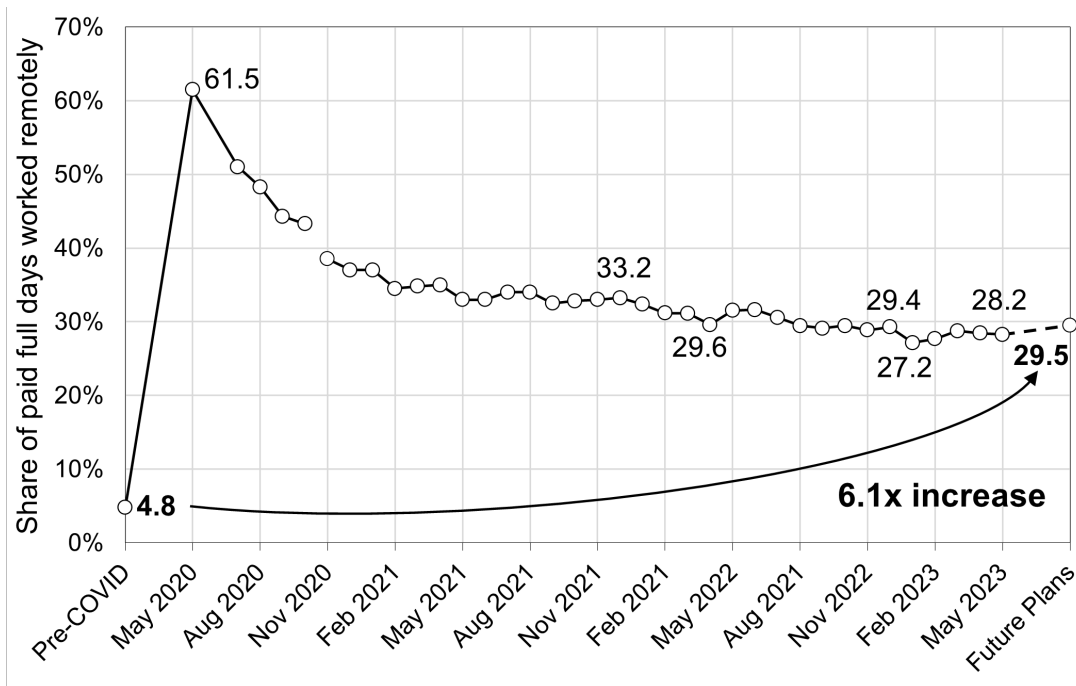


Figure 1-2: Remote work as a percentage of all worked days from 2018 to 2023. Adapted from Barrero et al. [3]. Note: Pre-COVID share is based on the 2017-2018 American Time Use Survey; post-COVID share is the share anticipated by employers. The break in the series in November 2020 reflects a change in the survey question.

work as pandemic-related restrictions on travel, retail outlets, and social gatherings were lifted.

Employees in certain sectors of the economy, typically service and knowledge work sectors, appear to value remote work more than the average worker. Surveys of staff at higher education institutions have found a significant preference for remote work; in December 2020 Duke University found that staff would prefer remote work for 70% of working days, with 91% of respondents preferring more than 1 day of remote work [28]. Boston University [29] and the University of Michigan [30] found similar trends for their workforces. Technology company executives surveyed in September

2020 indicated that, on average, 34% of their employees will have entirely remote work after the pandemic [31].

Global surveys have been less common than US-based surveys, but there have been several notable examples. Boston Consulting Group collected responses from 209,000 people across 190 countries in October and November 2020 [32]. The study finds that, like many of the US studies, approximately 9 in 10 workers would prefer remote work at least 2 days per week. The higher preference for remote work among knowledge and office workers is also observed globally. Interestingly, the study finds that workers in less developed countries are most interested in remote work and hypothesize that this could be due to differences in relative transportation costs. A December 2020 - January 2021 international survey by McKinsey found that, on average, corporate and government workers preferred 52% of their days to be flexible. Workers in Latin America and Australia favored remote work the most, while workers in Asia and Europe were least interested [33]. A survey of approximately 200 workers in India found that the share of people with at least one day of remote work is expected to double as a result of the pandemic, from 34% to 76% [34].

In the most comprehensive effort to compare national trends in remote work, Aksoy et al. [35] surveyed between 700 and 2,500 respondents in 34 different countries in the Spring of 2023. The results are visualized in Figure 1-3. They find that English-speaking countries have adopted the greatest share of remote work, with Canada and the United Kingdom leading the way among sampled countries. Asian countries average about one-half of the amount of remote work of their English-speaking counterparts, while Europe, Latin America, and South Africa are somewhere in between. Even the countries in this survey with the lowest remote work uptake, such as Greece and South Korea, are now working remotely more than twice as much (as a share total worked days) than the United States did in 2018.

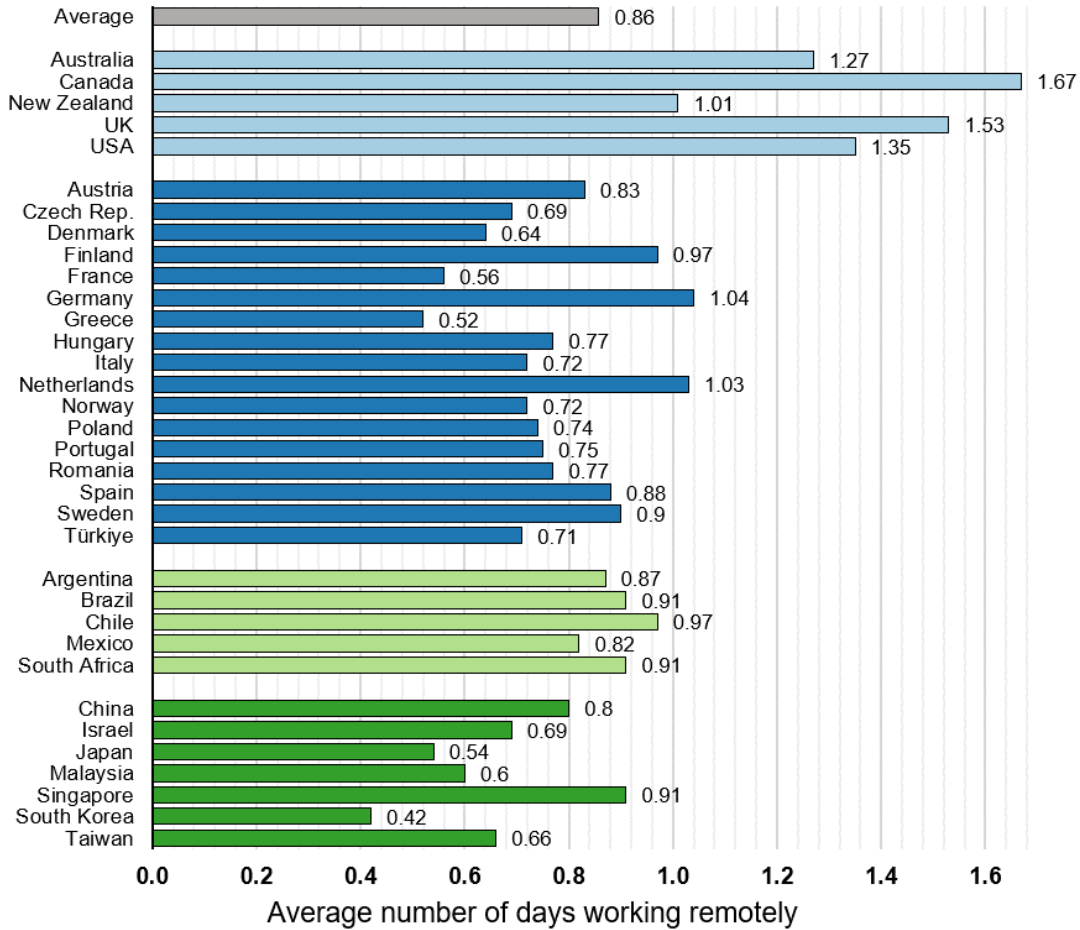


Figure 1-3: Comparing national averages of remote work as a percentage of all worked days

Adapted from Aksoy et al. [35].

1.2.2 Travel behavior

Remote work was a popular research topic in the 1990s and several discrete choice models were estimated based on survey responses. Bagley and Mokhtarian [36] and Stanek and Mokhtarian [37] conducted surveys of California workers to obtain preferences for working from home and a remote work center. Mokhtarian and Salomon

[38] found that attitudes towards work, family, and commuting are more important than sociodemographic factors in determining preferences toward remote work. This is similar to the results from Vana et al. [39]. In addition to estimating a discrete choice model, Yeraguntla and Bhat [40] offers a taxonomy of remote work arrangements. Given that telecommunication technology was not very mobile at the time, the authors only considered two remote work locations: home and a regional teleworking center.

Pouri and Bhat [41] includes several occupational factors in a remote work choice model, finding that part-time workers and employees of private companies are more likely to choose remote work, while those requiring daily face-to-face interactions are less likely to choose remote work. Sener and Bhat [42] also included work characteristics in estimating a copula-based sample selection model using household travel survey data from Chicago. Tang et al. [43] and Singh et al. [44] review the impact of the built environment on the propensity to work from home, and confirms the existence of several nuanced effects, such as greater perceived regional accessibility leading to less frequent remote work. Arabikhan [45] demonstrates that a fuzzy rule-based network, rather than the traditional discrete choice framework, can improve the modeling of remote work adoption.

While these discrete choice studies were being conducted, there was also an effort to develop a behavioral theory to explain the rationale behind the observed decisions. In a remarkable series of papers, Mokhtarian and Salomon create a conceptual model to explain the desire for remote work in terms of constraints, attitudes, personal satisfaction, and utility [46, 47, 48]. van Wee and Witlox [49] point out that many traditional travel behavior concepts (utility theory, social practice theory, time geography, and theory of planned behavior) would predict a significant increase in remote work after COVID-19 due to increased familiarity with virtual communica-

tion tools and lasting changes in social norms. The authors recommend research into policy responses for long-term changes in activity and travel behavior as a result of the COVID-19 pandemic.

Much of the effort in modeling remote work decisions has focused on the frequency and duration of remote work, rather than the location and the choice to co-locate with others [50, 51]. This is partly due to implicit assumptions that remote workers are making a binary choice: work at an office or work from home. Even recent comprehensive frameworks that include the duration of remote work do not consider location choice or the impact of personal relationships [52, 53, 54]. While anecdotal, recent interviews with remote workers in the New York City area found that many enjoy working from non-home, non-work locations for increased productivity and "a change of scenery" [55]. This suggests a latent demand for alternative work locations that may become more prevalent as the COVID-19 related restrictions on travel and group activities begin to ease.

1.2.3 Transportation science

Even when remote work (known at the time as “telework”) was in its infancy, Harkness [56] hypothesized that the adoption of remote work could have significant impacts on transportation systems. Remote work has long been of interest to transportation researchers, but most of the literature is focused on empirical studies rather than analytical models that connect remote work and transportation.

A seminal report by Mokhtarian [57] and a review by Nilles [58] provide a good summary of early empirical research. Mokhtarian is a pioneer in this field of study, publishing dozens of influential papers over several decades [60, 61, 62, 63, 64, 51, 59]. From the very beginning, they identified the need for remote work to be incorporated

into travel demand models [65]. More recent empirical research includes studies of how remote work has affected road congestion in Australia [66], Norway [67], Iran [68], and Sweden [69].

In addition to the aggregate impact on travel, researchers have also investigated differences in travel patterns between flexible and traditional workers. Interestingly, Hong [70] finds that home-based remote workers are less likely to travel during the morning rush hour, but often travel during the evening rush hour. A more recent paper found similar trends for knowledge workers in the United States [71]. This suggests that remote workers are generally sticking to typical work schedules, and are eager to pursue non-work activities after they have finished work. These results could have a significant impact on transportation providers, as the effect of remote work on peak demand may not be symmetric. Handy and Mokhtarian [63] notes that the popularity of remote work and its effect on travel demand is related to many other travel demand management policies, including congestion pricing, office parking subsidies, and zoning.

The impact of remote work on non-work travel behavior has long been debated. Early research finds that the average number of trips on remote work days increases, but the distance traveled decreases [72]. A Ph.D. thesis analyzing U.S. travel behavior data from 1995 confirms these results and finds that remote workers and their families have a greater average annual travel distance [70]. Recent articles have found that there is more daily travel overall for remote workers in the United States [73, 74, 75]. On the other hand, Choo et al. [76] finds that remote work has little-to-no impact on overall vehicle-miles traveled in the United States; de Abreu e Silva and Melo [77] encounters a similar result for single-household workers in the United Kingdom. Kim et al. [78] finds that non-work travel is higher for Korean families whose primary breadwinners can work remotely, but only if there are fewer vehicles than employed

adults in the household.

de Abreu e Silva and Melo [73] finds that part-time remote workers have a longer average commute and are more likely to commute by private car, leading to more travel overall and less sustainable travel choices. Ory and Mokhtarian [79], however, suggests that the decision to move further from work tends to precede the start of any part-time remote work, while those who move after beginning part-time remote work actually move closer to their workplace. Salomon and Mokhtarian [80] argues that the differences in results are often due to heterogeneity among remote workers, as well as a lack of consistency in defining remote work and in survey methodology.

The opposite effect, whether discretionary trips affect the decision to choose remote work, has also been investigated [81]. The authors find that people with the option for remote work are more likely to do so on days when they plan a discretionary activity, and the length of the discretionary activity is predictive of the decision to engage in a full day of remote work.

Despite the evidence of different travel patterns, relatively few models that incorporate the effects of remote work on urban transportation systems have been developed. Two seminal papers in modeling the transportation impacts of remote work, Nagurney et al. [82, 83], provide an equilibrium traffic flow model formulation and solution method that includes the option of teleworking from multiple alternative destinations. The authors introduce virtual links to the network to represent the teleworking alternatives. Pawlak et al. [84] also allows for teleworking in their comprehensive econometric model of the joint choice of activity, duration, mode, and route. Similarly, De Graaff and Rietveld [85] incorporates the preference for working at home or out of home directly into the utility function to estimate the trade-off between the two working arrangements.

One paper was found that includes the simulation of a transportation system

with remote work locations [86]. The authors use an agent-based regional travel demand model to evaluate the effect of remote workplaces on commuting distances. Interestingly, they find that requiring the co-location of teams can lead to worse outcomes than the status quo under certain conditions. The study does not include any mathematical modeling or productivity considerations, however.

Finally, there have been some efforts among transportation researchers to develop analytical models for the *long-term* impacts of the COVID-19 pandemic on transportation demand. Zhang and Zhang [87] uses an urban equilibrium model to predict the effect of various post-pandemic policies on long-term mobility in China. The authors find that while remote work produces more sustainable mobility outcomes, these effects are largely negated if shared mobility (public transit and car sharing) becomes less popular. Habib and Anik [88] use an integrated land use model to estimate that car ownership and commuting distance could be expected to increase as a result of the pandemic.

1.2.4 Land use and real estate

Transportation and land use are intrinsically linked, so it is important to consider how changes in mobility patterns due to remote work can impact the built environment, and vice versa. The US Department of Transportation has been interested in remote work as a travel demand management strategy for some time; in the 1990s, the department funded the establishment of Residential Area-Based Offices (RABO), a precursor to co-working spaces, to reduce the air pollution associated with commuting [89]. Mokhtarian has been arguing for land-use policies that encourage co-working centers in residential and mixed-use developments since the 1990s to reduce commutes [51].

Saxena and Mokhtarian [90], in an early pilot study, found that remote workers visit destinations that are both closer to home and more even distributed geographically on days that they work from home compared to days that they commute to an office. These results were confirmed by Asgari et al. [91] for the New York City area. This suggests a re-alignment of demand away from commuting corridors and commercial districts towards residential areas and neighborhood centers. A recent paper also found similar results using the National Household Travel Survey, noting that remote workers have more complex and varied schedules and that they visit more locations than regular commuters [75]. The authors note that remote workers remain at home on only 20% of work days, and often chose to work in a location outside the home.

Another related area of research is modeling job accessibility in a partially flexible environment. Muhammad et al. [92] introduces virtual spaces into the accessibility modeling framework and finds that remote work increases job accessibility overall, with greater benefits in rural areas. Several subsequent papers by many of the same authors explore this area in greater detail [93, 94, 95].

Theoretical models of urban economies generally suggest that increased remote work will lead to decentralization, with areas located at a medium distance from urban centers experiencing the greatest increase in demand [96, 92]. Helling and Mokhtarian [97] argues that this is because remote work makes accessibility less important in choosing a housing location. Decentralization has not been borne out thus far; urbanization has generally continued in developed and developing countries, even as the share of remote work has risen in recent decades. It could be that other factors have emerged that exert a stronger pull towards urban life, or perhaps remote work as a share of the economy has yet to reach the activation energy required for the decentralization effect to take hold.

remote work may reduce the demand for traditional offices and the demand for travel during peak hours, freeing up commercial space and transportation infrastructure for alternative uses [98]. A survey of workers in Montreal, Canada found that those working in the central business district pre-COVID expect the highest degree of remote work in the future, suggesting that demand for prime urban office space could be reduced [99]. Rosenthal et al. [100] finds similar effects by studying U.S. commercial real estate prices, noting a decline in the premium for centrally-located office space. The authors also point out that the effects are larger in dense, transit-oriented cities than in car-oriented cities. On the infrastructure side, experts have argued for prioritizing safe and sustainable modes such as cycling and public transport rather than returning to the pre-pandemic status quo of private vehicle dominance [101].

A shift in working arrangements towards co-working spaces could provide new benefits, especially in smaller communities. Mariotti et al. [102] surveys co-working space users in Italy and finds that 85% believe the co-working space has a positive impact on their community by hosting cultural events, purchasing from local services, and improving security. These impressions were stronger for co-working spaces located outside of major metropolitan areas. Policymakers in certain European countries had begun to promote co-working spaces in peripheral areas in order to boost economic development and reduce commutes [103].

1.2.5 Organizational behavior

Organizational behavior is a critical component of remote work. As stated by Brewer and Hensher [104], “Individual work arrangements are influenced by the internal constraints of organizations such as organizational structure and managerial policies,

including human resource management, work organization, and external constraints such as union policies and agreements.” The authors go on to provide an excellent overview of how organizational behavior affects travel behavior and offer a call to action for additional research into the links between the two fields. Their work builds on previous work by Brewer [105], who notes that remote work requires both *willingness* and *capacity* from employers. Technological advances since the publication of that research may have increased the capacity of employers to facilitate remote work, but willingness remains mixed. A 2001 study of employers in Belgium found that the barriers to remote work adoption were largely institutional rather than technological [106].

Handy and Mokhtarian [65] provides a good summary of early corporate resistance to remote work, which includes concerns about productivity, supervision, and morale loss due to “officelessness”. In an interesting reversal of the remote work choice models described earlier, Yen et al. [107] use a survey to elicit the factors that contribute to *employers’* decision to approve remote work. The study finds that employers desire a smaller amount of remote work than their employees prefer, much like the post-pandemic surveys issued nearly 30 years later. The primary concerns from employers were employee productivity, morale, and communication.

Empirical studies of remote worker attitudes have shown several interesting relationships. Koh et al. [108] find that remote workers generally perceive higher support for work-life balance from their employer. A meta-analysis of studies on remote work [109] and organizational outcomes found that remote work is perceived to “increase productivity, secure retention, strengthen organizational commitment, and to improve performance within the organization.” Coenen and Kok [110] confirmed these results in a subsequent study. Girit [111] surveyed flexible and traditional workers to compare personality traits, attitudes, and performance. The survey found that

remote workers had higher performance scores and job satisfaction than those who worked in an office full-time. Surprisingly, remote workers considered themselves to be more extroverted than office-based workers, despite preferring a working arrangement with less face-to-face interaction. Studies conducted during the COVID-19 pandemic find that the relative productivity of remote workers is dependent on job characteristics and the suitability of the home environment for work [112, 113].

On the employee choice side, Mokhtarian and Bagley [114] find that personal benefits and work effectiveness were two significant motivating factors in the decision to choose a workplace between home, a remote work center, and a primary office. Similarly, Laumer and Maier [115] shows that household characteristics, including the suitability of the home for work activities, are an important determinant in the decision to work from home or elsewhere. Shafizadeh et al. [116] examines the conditions under which remote work is advantageous for the employee, the employer, and society writ large. The authors find that remote work is a net positive for employers when employee productivity does not diminish due to remote work and when employers can translate remote work policies into real estate savings. Bernardino and Ben-Akiva [117] uses a comprehensive model of both employer and employee considerations to determine that remote work has the potential to improve employee lifestyle and productivity, but less potential to reduce employer costs. Choudhury et al. [118] finds that workers with the flexibility to relocate (“work from anywhere”) are more productive than remote workers who visit a central office semi-regularly.

In an extremely comprehensive review of the literature related to “virtual work”, Raghuram et al. [119] identifies a tremendous number of research gaps related to remote work arrangements, teamwork, and technology. The authors create a citation map of existing literature in these areas, finding that “telecommuting” research is a distinct cluster containing very few co-citations with other organizational behavior

articles (see Figure1-4). Studies related to the effects of remote work on employees and their employers are summarized; employees with remote work arrangements generally feel more empowered and less stressed, but also more isolated from their colleagues and less self-identification with their organization. A case study of Microsoft employees working remotely before and after the onset of the COVID-19 pandemic found that collaboration became more static and sharing information became more difficult after the switch to remote work [120].

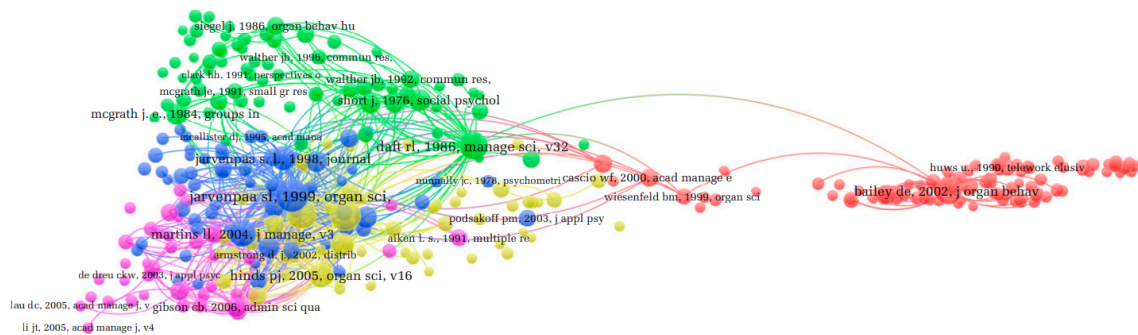


Figure 1-4: Co-citation map for articles on virtual work

From [119]. Red: Telecommuting; Green: Computer-mediated work; Blue: Virtual teams; Yellow: Distributed teams; and Pink: Team dynamics. Each node is an article and the size of the node indicates the frequency with which the article has been co-cited with another article in the map. The distance between the nodes shows the strength of the relationship between two co-cited articles.

Co-working spaces have recently become a flexible option for employers who are growing rapidly or who prefer not to sign a long-term lease. As opposed to working at home, co-working spaces do not require investment in a home office, avoid the potential distractions of home-based work and allow interaction with colleagues or people from other organizations. Ross and Ressia [121] and Gandini [122] review the literature on co-working from an organizational behavior perspective, including the positive externalities of idea flow between co-located firms.

One of the key limitations of the state of the art is understanding how and why people choose between alternative locations for remote work (i.e. at home, a co-working space, a café). Furthermore, preferences for remote work associates are not well studied. It has been shown that social relationships developed at work can affect commuting patterns [123], so it is likely that these relationships would also affect location choices if multiple alternatives are available.

1.3 Research questions and objectives

This dissertation addresses three broad and consequential research questions, motivated by the urgent need for policy to adapt urban mobility systems to the recent rise of remote work.

Question 1: How will the recent rise in remote work affect current and future travel demand patterns in urban areas? While several recent studies have investigated elements of this question, there remains considerable uncertainty regarding key travel behavior elements. One notable gap is destination choice for remote workers; most previous studies assume that all remote work takes place at home and therefore do not explore the alternative work locations that have proven popular thus far. Understanding how travel behavior such as mode choice and departure time change when traveling to different types of work locations will be critical in determining the set of optimal adaptation strategies. Connecting remote travel patterns to different personal factors such as household characteristics, employer policies, and attitudes will also be necessary to model policy effectiveness across a range of possible future scenarios.

Question 2: How can remote work stakeholders use this information to design an efficient and environmentally sustainable transportation system

that enables an economically productive urban future? This is perhaps the most important of the research questions; the information collected in response to the previous question has little value if it cannot be used to inform decisions. Translating knowledge into action requires new models of transportation and land use systems. The models must accurately represent the dynamics of the system involved, including a realistic set of design, operating, or policy decisions on the part of the stakeholders. Finally, the model must be tractable when applied to realistic problems.

Question 3: How can academic research help to build a consensus approach to remote work policy across jurisdictions? Despite three years of evidence and experience, there is still little agreement from public officials about whether remote work should be encouraged, tolerated, or banned entirely. The first step in resolving this research question will be to identify the barriers that make it difficult to translate existing research into policy. Then, a new approach to remote work research must be developed to create the conditions for future evidence-based remote work policy.

The overall objective of this dissertation is to provide new evidence and tools for urban transportation policy design in the remote work era. Seven concrete research objectives were developed to answer the research questions above and therefore guide the dissertation toward the larger goal:

1. Determine how remote work has affected the spatial and temporal distribution of demand for transportation in urban areas.
2. Given the uncertainty surrounding the future of remote work, evaluate the travel demand impact of different scenarios.
3. Create the analytical tools to adapt the design and operation of urban trans-

portation systems to the new demand dynamics introduced by widespread remote work.

4. Identify opportunities for transportation-related policies that leverage remote work to foster sustainable and economically productive cities.
5. Illustrate the application and benefits of specific policies through the use of realistic case studies with historical data.
6. Design conceptual tools for connecting remote work research to policymaking.
7. Set a direction for future remote work research.

The first two research objectives seek to answer Research Question 1 by providing evidence of changes in travel patterns and predicting future behavior based on historical data. Research objectives 3, 4, and 5 are related to the second research question. Collectively, these three specific objectives design innovative new methods for adapting urban mobility systems to remote work, then evaluate their societal outcomes. The final two research objectives are intended to resolve the problem posed by the third research question.

1.4 Methodology and dissertation structure

This section describes the approach that the remaining chapters of this dissertation take in order to achieve the stated research objectives. In general, the chapters of this dissertation are organized by their contribution to preparing urban mobility for the future of work. Chapter 2 is aimed at laying a theoretical foundation for the subsequent chapters. It clarifies the terminology used to describe remote work and prepares a consistent framework for describing remote work studies. Chapters 3-5

provide empirical evidence for the rise of remote work and the resulting impacts on urban systems, and use the data to predict future travel patterns. Finally, Chapters 6-8 incorporate the travel behavior prediction models to develop new optimization methods that can inform the design and operation of urban transportation and land use systems. Chapter 9 offers conclusions, discusses the broader policy implications of this research, and provides possible directions for future research in this area.

Each of the empirical and methodological chapters (i.e. Chapters 3 to 8) fits into a classification structure for remote work studies based on the primary stakeholders involved and the purpose of the research. The purpose of the research could be 1) “descriptive”, intending to describe an existing remote work phenomenon, 2) “predictive”, using data and modeling to predict future trends and outcomes, or 3) “prescriptive”, offering recommendations for action by one or more remote work stakeholders. Figure 1-5 illustrates this structure using a table where the rows represent the research purpose and the columns represent different stakeholders.

The six chapters are mapped to the appropriate cell within the table. Several chapters have implications for multiple stakeholder groups. For example, Chapter 8, which presents an optimization model for locating shared workplaces, provides tools that can help cities adapt to remote work, but the spatial distribution of remote working hubs also affects remote workers, employers and mobility providers. For clarity, each chapter is classified under the “primary” stakeholder in Figure 1-5.

The breadth of this dissertation is evidenced by the fact that there is at least one chapter dedicated to each of the four stakeholders and each of the three research purposes. They do not cover all of the possible study types; the empty cells are likely to be promising directions for future research. Chapter 2 is more conceptual in nature and spans all stakeholders, therefore it does not fit neatly into this classification structure.

		Primary Stakeholder Group			
		Workers	Employers	City	Services
Research Purpose	Descriptive		Chapter 3: The impacts of remote work on travel	Chapter 5: The potential of remote work for reducing carbon emissions	Chapter 7: Evaluating transit capacity flexibility
	Predictive	Chapter 4: Enhancing travel behavior models for remote work			
	Prescriptive			Chapter 8: Optimal location of shared workplaces	Chapter 6: Designing a shared mobility system for remote workers

Figure 1-5: Classifying six of the chapters in this dissertation by stakeholder and research purpose

1.4.1 Chapter 2: Motivation and theory

Chapter 2 is informed by a need for holistic, interdisciplinary remote work research. It postulates that two major issues that prevent recent remote work studies from being translated into public policy: the narrow, discipline-specific scope, and a lack of structure for describing the research context. To encourage interdisciplinary collaboration, a common taxonomy for remote work stakeholders, arrangements, and policies is proposed. Then, it presents a new conceptual framework for classifying and describing general remote work studies.

This chapter was inspired in part by Powell [124], in which a unified framework is

developed for a wide range of sequential decision problems. Any unified framework for an entire subfield of research (i.e. remote work) would necessarily be too general to be used in practice. However, many of the components, such as a common terminology, a map of relevant stakeholders, and a structure for describing research problems, are needed to facilitate cross-disciplinary collaboration. Such tools are especially important given the relatively recent explosion of interest in the field, and the lack of consensus around terminology. The first step uses conceptual diagrams, as shown in Figures 2-3 and 2-2, to identify relationships and group related elements of the framework together. Both the taxonomy and framework are referred to throughout the remainder of the dissertation. Together, these contributions will help to mitigate ongoing issues with remote work studies and lead to a more holistic body of research.

1.4.2 Chapters 3-5: Empirical evidence

Chapter 3 presents a comprehensive analysis of descriptive statistics about remote work and travel behavior from the monthly U.S. Survey of Working Arrangements and Attitudes (SWAA). The SWAA provides an extremely rich, ongoing source of data on remote work trends and associated travel behavior. The survey's travel questions were introduced specifically for this dissertation research. The results demonstrate the variation in mode choice, departure time, commute travel time, and frequency of travel in socioeconomic, geographic, and employment groups. The use of third places by remote workers and the key differences between third place commuting and traditional commuting are discussed in detail.

When this research began, there was considerable uncertainty about the future of remote work; it was not clear if remote work was a transitory fad or a long-term realignment of work arrangements. As a result, it would not have been appropriate to

base adaptation strategies on revealed preference data, as those preferences may have been constrained by pandemic-related activity restrictions, employer policies, and so on. Stated preference surveys were, therefore, the best opportunity to collect data on the future preferences, personal characteristics, and attitudes of remote workers every month. Distributing the survey online through an existing platform was deemed the most efficient method for collecting the data and this research ultimately benefited from collaboration with the research team behind the original survey.

There are some limitations to online data collection that were addressed to the extent possible. The first is that the survey sample is unlikely to be representative of the population. The samples are therefore weighted to match the United States population based on age, sex, education, and income. In addition, the responses cannot be independently verified. Several attention-check questions were used to filter out poor-quality responses. The questions were designed very carefully with the help of experts to limit any misinterpretation by the respondents. Finally, the aggregate remote work trends elicited from the survey were validated through comparison against the results of similar surveys. Detailed information on the survey methods is available in Section 3.3.

Moving from data collection to prediction, the next two empirical chapters rely on many traditional travel behavior modeling techniques. Methodological and practical advances for applying these techniques to the travel behavior of remote workers are summarized in Chapter 4. The advances are then applied to several case studies in Chapters 5 (as well as the methodological chapters 6 - 8). Discrete choice methods are used in this dissertation to model the following travel behavior decisions:

- Travel mode
- Work location

- Departure time
- Commute frequency

The classical multinomial logit (MNL) model [125] is applied for each of these choices. The ordered version is used in the special case of commuting frequency, which is an ordinal variable. Although other, more advanced discrete choice models have been developed for travel behavior analysis in recent years, methodological innovation in discrete choice modeling is not the emphasis of this dissertation. The simplicity and interpretability of the MNL model allow the methods and case studies to focus on the central topic of this dissertation: the unique travel behavior dynamics of remote work. The methods proposed in each case study were intentionally designed to permit more complex discrete choice model structures if desired.

Using the survey data described in Chapter 3, Chapter 4 shows how to address the complexities introduced by remote work when designing travel behavior models. The first complexity is the mixed discrete-continuous nature of remote work preferences, which is resolved through the use of ZOIB regression. The second is the influence of employer policies, working arrangements, and household variables on travel decisions. The final complexity is the need to model flexible destinations for work trips. Chapter 4 demonstrates how model design and large-scale mobility data can be used to overcome these issues. An extended case study, focused on estimating the characteristics of work trips to third places, is used to illustrate the benefits of the methods described in this chapter.

Chapter 5 builds on both previous empirical chapters to determine how changes in individual travel behavior due to remote work have affected overall carbon emissions from commuting. ZOIB regression, k-means clustering, and a data-driven destination choice estimation model are used to predict changes in commuting travel patterns

after the rise in remote work. The results of a Chicago-based case study highlight how commuting to third places has become a major component of carbon emissions from commuting. The disaggregate nature of the model also produces estimates of changes in commuting trips to each census tract and how commuting patterns might evolve in the future.

1.4.3 Chapters 6-8: Methodological innovations

The final three research chapters apply operations research methods to optimize urban mobility systems given predicted travel patterns. This is where the major methodological contributions of the paper occur; the emerging behavioral dynamics of remote work require new model designs and solution methods. More specifically, the methodological advances in Chapters 6 through 8 focus on integer linear programming problems. Each chapter solves the issue of linearizing non-linear travel behavior functions, such as the MNL model, using different approaches. The behavior functions can then be introduced into the larger system optimization problem without sacrificing overall tractability.

Chapter 6 addresses the needs of one type of urban mobility service: ride-hailing platforms. Unlike traditional work trips, remote workers have the flexibility to choose from a set of possible work locations. This chapter imagines a new ride-hailing service that takes advantage of the flexibility of remote work trips to improve the efficiency of matching in ride-pooling trips. It introduces a new optimal passenger-vehicle matching model that incorporates flexible destinations, as well as the constraints and incentives that remote workers may face concerning destination choice. A case study of ride-hailing demand in Manhattan, New York is used to evaluate the overall performance of the ride-hailing service with flexible destinations.

Chapter 7 pivots to another urban mobility service: public transport operators. Remote work has had a tremendous impact on public transit ridership patterns by eliminating or shifting many traditional commuting trips. The capacity for public transit systems to adapt to shifting travel patterns has historically been difficult to estimate at the network scale. This chapter develops a new mixed-integer programming model and solution algorithm for the “transit capacity flexibility” problem that incorporates more realistic passenger dynamics than the status quo and is sufficiently tractable to solve network-scale problems for the first time in literature. The transit network in Boston, Massachusetts is used in a numerical experiment to test the model. It is determined that the hub-and-spoke network topology of the network is effective in handling traditional transit ridership patterns to and from the downtown core, but the capacity of the network is reduced if passengers begin to favor destinations outside of downtown.

The final methodological chapter, Chapter 8, addresses land use adaptation for remote work. As noted in Chapter 3, many remote workers are choosing to work at third places. However, land use has not yet evolved to make third place trips more convenient. As a result, many governments are beginning to consider policies to encourage new shared workplaces in the era of remote work. Chapter 8 designs an innovative new facility location model for shared workplaces with objectives that capture the social externalities of remote work. Using Boston as a case study, optimal locations are selected for a variety of goals including minimizing travel, maximizing workplace usage, and minimizing social isolation.

The case studies in these chapters make heavy use of the SWAA data and other data sources such as mobile phone visitation data, census demographic and population data, and public transit network schedule data as necessary. The data sources are cited and described in appropriate detail in their respective chapters.

1.5 Related publications

Each of the original research chapters of this dissertation has been adapted for publication as a journal article. Due to the recent nature of many of the papers and the duration of the peer review process, most of the articles remain under review during the submission of this dissertation. Chapters 2, 3, 4 and 5 are the foundations for Caros and Zhao [126], Caros et al. [127], Caros and Zhao [128] and Caros et al. [129], respectively, all of which are currently under review. Chapter 6 is the basis for Caros and Zhao [130], which has been published in *Transportation Research Part D: Transport and Environment*. Chapter 7 is the basis for Caros and Zhao [131], which is under review, and Chapter 8 is the basis for Caros and Zhao [132], which is also under review.

Chapter 2

An interdisciplinary approach to remote work and urban policy

2.1 Introduction

The newfound freedom for millions of remote workers to choose whether and where to commute has created the need for essential connections between academic disciplines, such as urban planning and organizational behavior, that have historically had little overlap. The studies that do exist often focus on a particular topic of interest (e.g. travel demand) and ignore the implications for another (e.g. labor productivity). Smart public policies, corporate strategies, and infrastructure investments informed by academic research will be necessary to enable human flourishing and liveable, sustainable cities in the era of widespread remote work. By identifying new trends, proposing a new taxonomy and common framework for describing remote work settings and stakeholders, and identifying promising opportunities for future cross-disciplinary research, this article is intended to be the first of many steps

toward evidence-based remote work policy.

Widespread remote work has disrupted many features of urban life: traffic congestion, corporate workflow design, city center retail, and real estate markets, to name a few. American employers are planning for the share of remote work hours in 2023 and beyond to increase by a factor of six compared to 2018 levels [3]. Disruptions to historical behavioral patterns are not inherently problematic. Remote work, when conducted at home, eliminates the need for what is often a long private vehicle trip during the periods with the greatest traffic congestion. As a result, many cities have experienced a reduction in transportation-related carbon emissions [133] and a flattening of peak travel demand [134]. Employees benefit as well; less time spent commuting has allowed remote workers to spend more time on leisure activities, childcare, and household maintenance [3]. Remote work does present major challenges for many urban systems, however. Public transportation revenue and retail activity remain well below their 2019 levels as a result of fewer commutes to the downtown core [135, 136]. Office vacancy rates have more than doubled in many large cities as people choose to work from home or third places more frequently, leading to sharp drops in urban commercial real estate valuations [137]. In the absence of new policies to sustain and adapt these systems for the remote work era, cities are likely to continue to face severe financial challenges and the possibility of cuts to social services.

Recent studies investigating the impact of remote work on social and economic outcomes have shown mixed results. On one hand, Bloom et al. [138] found that hybrid work resulted in a small improvement in both observed productivity (measured by lines of code written) and self-reported productivity. Gibbs et al. [139], on the other hand, found that a shift from in-person to fully remote work resulted in longer hours and lower individual productivity. The results appear to be quite

sensitive to specific organizational contexts and work arrangements. In addition, the holistic impacts of remote work can be overlooked due to the narrowly defined scopes of studies within a single discipline. For example, several recent articles on the potential for remote work to reduce commuting-related carbon emissions (e.g. [13, 14, 15]) do not address the difference in building-related carbon emissions from working at home rather than a central office.

Despite the emerging evidence, or perhaps because of isolated and mixed findings, there remains a troubling lack of consensus about whether urban policy should encourage, discourage, or remain agnostic towards remote work. The national governments of Ireland, Australia, and Portugal have begun providing grants and building infrastructure to facilitate remote work from rural areas [140]. Leaders in the United States, the United Kingdom, and Canada have taken the opposite approach, pushing for public and private workers to return to the office to boost downtown spending [141]. Many city governments are also resistant to remote work; New York City has banned hybrid work for city employees and criticized private employers who allow remote work [142]. This variance in policy prescriptions might be a result of differing societal goals but is also likely to be fueled by uncertainty around the externalities of remote work related to social welfare, social equity, and public finances.

One reason for the uncertainty around remote work externalities is the narrow focus of existing studies. When researchers from different domains study a similar remote work issue, ordinary variations in terminology and methods make it difficult to synthesize the results to generate broader insights. These ongoing issues both present barriers to translating new research findings into policy design.

This article offers an in-depth review of available literature on the impacts of remote work on urban systems as a motivation for new urban policies. A clear and comprehensive taxonomy of remote work settings and stakeholders is then proposed

to enable comparison between studies, reproduction of findings, and collaboration across the many academic disciplines whose expertise is essential for creating holistic remote work policy. Finally, an agenda for future interdisciplinary remote work research to inform evidence-based urban policy is presented.

2.2 A new era for remote work

While there is much uncertainty around remote work, there is evidence that a steady rise in the share of remote work over many years was dramatically accelerated by the COVID-19 pandemic and that elevated levels of remote work will persist over time. U.S. employers across all sectors are planning for remote work to exceed 31% of all worked hours in the long term, compared to just 4% in 2018 [3]. Planned remote work has risen steadily since mid-2020 as employers have become more comfortable with remote work technology and business practices. Employees, on average, would prefer about 40% of worked hours to be remote. These preferences are heterogeneous across industries, regions, incomes, and genders. The magnitude of remote work plans and preferences in other countries and regions varies, but the overall trend of a persistent increase following the COVID-19 pandemic has been observed across the globe [33].

An emerging area of complexity is the fact that new remote workers are not just working at home. Remote working at non-work, non-home locations such as libraries, cafés, and co-working spaces make up about a third of all remote working hours, as shown in Figure 2-1. Conducting work at each of these locations influences productivity, well-being, and travel behavior. For example, Caulfield and Charly [14] find that workers who used remote work hubs near Dublin, Ireland reduced their travel by 60 kilometers per day and chose sustainable travel modes more often than when working at the office. These workers were also more likely to experience feelings

of isolation and lack of privacy during work.

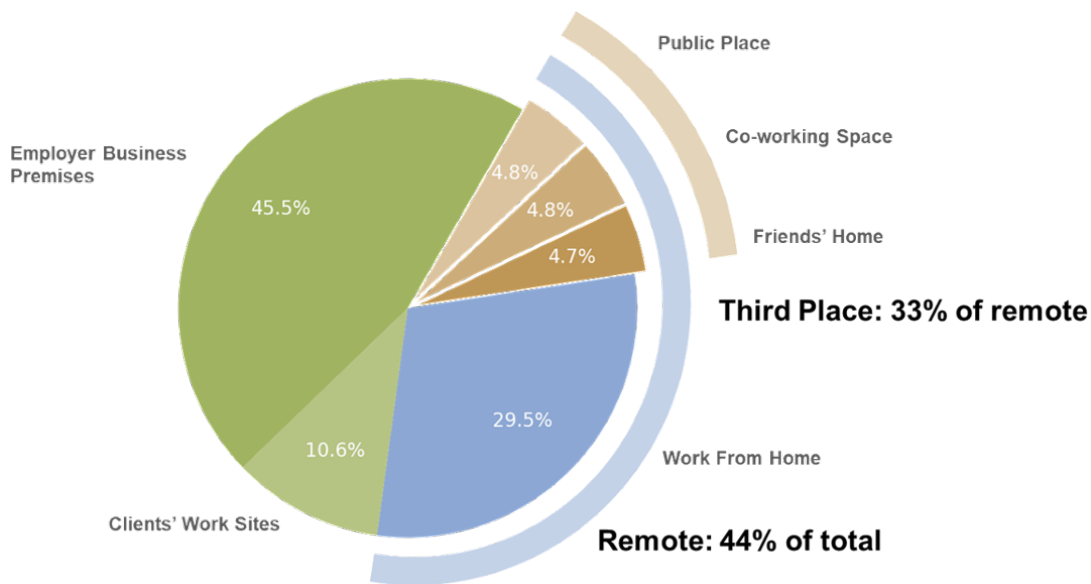


Figure 2-1: Distribution of remote work hours by location

Data source: Barrero et al. [3]

The shift in the distribution of work locations from a single employer-provided workplace to a broader spectrum of possible locations has had tremendous secondary impacts on urban systems. Urban transportation systems were significantly impacted by the reduction in commuting travel, as they typically rely on user fees for funding. Public transit networks, many of which are designed to facilitate routine commuting trips between outlying residential areas and downtown business districts, are one example. Transit agencies have experienced a sudden fall in ridership and most do not expect ridership recovery to occur in the short or medium term [136]. As of the end of 2022, overall transit ridership in the U.S. remains at about 70% of 2019 levels [143]. Other urban transportation systems have seen a more robust recovery of demand. Private vehicle travel has rebounded to near 2019 levels in the U.S. [144], China [145], and the United Kingdom [146]. Global bookings for large ride-hailing

platforms such as Uber now exceed pre-pandemic levels, although demand recovery varies by region [147]. Ridership of urban bike-sharing systems recovered very quickly and has continued to grow in popularity across the world [148].

These shifts in demand for different transportation modes have contributed to changes in CO₂ emissions in urban areas relative to 2019. Emissions from the ground transportation sector declined significantly during pandemic-related lockdowns, but at a global level, emissions from residential and commercial buildings were very similar from 2019 to 2020 [149]. This result is consistent with previous findings that the decrease in ground transportation emissions due to remote work exceeds overall increases in building-related emissions incurred from working at home [150], although the dynamics are very context-dependent and much more research is needed on this topic.

Beyond transportation and emissions, the rise of remote work has also had a dramatic impact on urban land use and real estate. Remote work inherently reduces the demand for centralized office space, thus exerting downward pressure on the value of commercial real estate. Office vacancy rates have risen tremendously since 2019 in cities such as New York City (11% to 22%), San Francisco (5% to 23%), and London [151, 137]. Gupta et al. [12] estimate that, if elevated levels of remote work persist over time, office valuations in 2029 will be 45% lower than in 2019, representing a \$USD 450 billion destruction of value. In addition to concerns about tax revenue from office buildings, cities face a sharp decline in revenues from retail spending within commercial districts. Overall activity during 2022 urban cores remained below 50% relative to 2019 in many large North American cities, including San Francisco, Philadelphia, Vancouver, and Montreal [135]. Ensuring long-term urban vitality and local tax revenues may require retrofitting or replacing vacant office buildings, a process that would benefit from smart urban policy and incentives guided by research

into the future of remote work arrangements. Finally, remote work has affected social and economic networks within cities. Increases in remote work after 2020 have been found to predict greater feelings of isolation and loneliness among Finnish workers [152]. When people do interact in urban areas, recent research has shown that the income diversity of urban encounters has declined [11]. Within organizations, the rapid rise in remote work and loss of spatial proximity has generally been found to reduce communication between those who do not work closely together [153, 154, 120].

These secondary disruptions created by widespread remote work are the product of responses to remote work by four broad groups of urban stakeholders. The first stakeholder group is the subset of urban residents who engage in remote work. The sudden flexibility with regard to work location has encouraged many remote workers to reconsider where they live, how they commute, and who they work for. These individual decisions drive the demand for urban transportation, retail stores, and real estate.

The responses of remote workers are heavily influenced by the policies set forth by the second stakeholder group: employers. Corporate policies around remote work constrain or enable the decisions made by their employees. For example, a company-wide hybrid work policy forces employees to maintain physical proximity to their office, while allowing fully remote work enables employees to relocate as they choose.

The third stakeholder group is that of work-related service providers, such as commercial real estate firms and mobility services. These companies have already launched unique services aimed at remote workers, including private teleworking booths in train stations [155] and daily rentals of residential homes for remote work [156]. The increasing variety of potential remote work arrangements and services may create a greater demand for remote work, compounding the uncertainty currently

faced by corporations and policymakers.

The final stakeholder group is urban policymakers. Their response to remote work, if well-designed, could have a strong influence on the decisions of the other stakeholders. Zoning for remote work hubs near transit stations could help to reduce carbon emissions by encouraging remote workers to choose public transit. Tax incentives for employers who offer co-working memberships to remote staff may address the isolation of working from home. Effective remote work policies to manage the externalities of remote work will first require a deep understanding of the motivations of the other stakeholder groups and how they can be expected to respond to policy changes.

2.3 Challenges in connecting remote work research to policy

Evidently, the rapid rise in remote work has attracted considerable attention from across academic disciplines. Individually, recent studies provide valuable insights into overall remote work trends and the secondary impacts of remote work on employers, employees, cities, and business services. Yet two major barriers limit the applicability of this research in designing comprehensive public policies. The first is the narrow, discipline-specific scope of existing studies. When the larger context of remote work is not considered, research findings might support a policy prescription with unintended externalities. For example, transportation scholars may argue that the best solution to congestion and carbon emissions from commuting is to incentivize remote work whenever possible, ignoring the potential downsides related to social segregation and isolation that are more likely to be studied by a different discipline. The second

concern is that, without a common taxonomy and classification system, it can be difficult to identify the factors that lead to different outcomes between two seemingly similar remote work studies.

Sutton-Parker [13], [14] and [15] are all excellent studies of the impact of remote work on carbon emissions from commuting, but none consider how the choice of workplace also impacts emissions from buildings. As a result, there is no consensus about whether policies to promote remote work could support a mandate to reduce or eliminate citywide carbon emissions. Similarly, Choudhury et al. [118] focus their impressive study on the productivity impact of a “work from anywhere” policy introduced by the United States Patent and Trademark Office, finding that patent examiner productivity increased by 4.4% for those who adopted the policy. While qualitative interviews suggest a generally positive attitude towards the policy, the impact on overall employee well-being, hours worked, and loneliness were not quantified in the study. Employers enticed by the productivity benefits of such a policy cannot know whether to expect pushback from their staff, or whether additional complementary measures will be needed to support employee well-being in a work-from-anywhere environment.

There is certainly a limit on the overall scope of any research project, and no individual project should be expected to cover every conceivable secondary effect of remote work in extensive detail. Nevertheless, two simple steps can help to make future remote work research more germane to public policy. First, anticipate the policy implications of the proposed research project and consider whether the study design will provide sufficient information to inform policy development. Second, involve researchers from multiple disciplines in the study design process to identify and address significant gaps in the study. Even if certain research questions are considered to be beyond the scope of the initial study (e.g. employee well-being),

the data collection process could be adjusted to capture important information for future studies by others. Adding one or two questions about energy use while working at home to an existing survey is much easier and less expensive than conducting an entirely new survey months or years later.

Robust meta-analyses, such as the one conducted by O'Brien and Aliabadi [150] on the energy impacts of remote work, are often helpful in synthesizing the results of distinct studies on the topic. Comparing results from differing periods and geographic settings is no substitute, however, for multidisciplinary teams collaborating on the same project to understand the holistic impacts of remote work in a single context. Moreover, meta-analyses and review papers are difficult to organize without a common framework and terminology for describing each study's setting and actors.

Recent studies of the productivity impacts of remote work are an illustrative example of the need for a common descriptive framework. As mentioned above, Choudhury et al. [118] reported a productivity increase for patent examiners who adopt a fully remote working arrangement. Gibbs et al. [139], conversely, found a marked decline in productivity among IT professionals who adopted fully remote work in response to the COVID-19 pandemic. These contrasting results are not entirely surprising given the myriad differences between the settings of the two studies: geographic location, industry, occupation, time period, local culture, voluntary vs. mandatory policies, and so on. Yet without a shared framework describing each setting, these important differences are difficult or even impossible to identify. Future researchers intent on uncovering the causal factors that contribute to diverging results between two remote studies may overlook important differences due to inconsistencies in the information provided.

2.4 Towards interdisciplinary research

Advancing evidence-based urban remote work policies will require extensive collaboration across academic disciplines and a commitment to communicating research findings with policymakers and the public. To that end, two new tools are proposed. The first, a taxonomy of remote work stakeholders, their relationships, and their decisions, encourages engagement between groups of researchers, but also between researchers and policymakers, by providing accessible alternatives to discipline-specific jargon. The second tool, a conceptual framework for classifying remote work studies according to the actors and setting involved, makes it much easier for researchers to identify connections between their work and the work of others. It also creates a formal structure for describing remote work studies that can be used to identify the subtle differences between study designs that can produce contrasting outcomes. Furthermore, both tools expand the context of remote work beyond traditional disciplinary silos, prompting scholars to consider the extended impact of their research.

2.4.1 Stakeholder taxonomy

There are four primary stakeholders involved in remote work: 1) employers, 2) employees, 3) local policymakers (cities), and 4) services, such as real estate firms and mobility providers. Each stakeholder has their own set of incentives, remote work-related decisions, and their own functional relationships with the other stakeholders. Note that cities and service providers are also employers, which can often lead to conflict between their internal and external positions on remote work. For example, Apple has marketed its products to people who want to “escape from the office” while requiring their own employees to return to the office full-time [157]. For cities and service providers, it is therefore important to carefully consider their exact role in any

given remote work research project. The full set of stakeholders and the relationships between them are summarized in Figure 2-2.

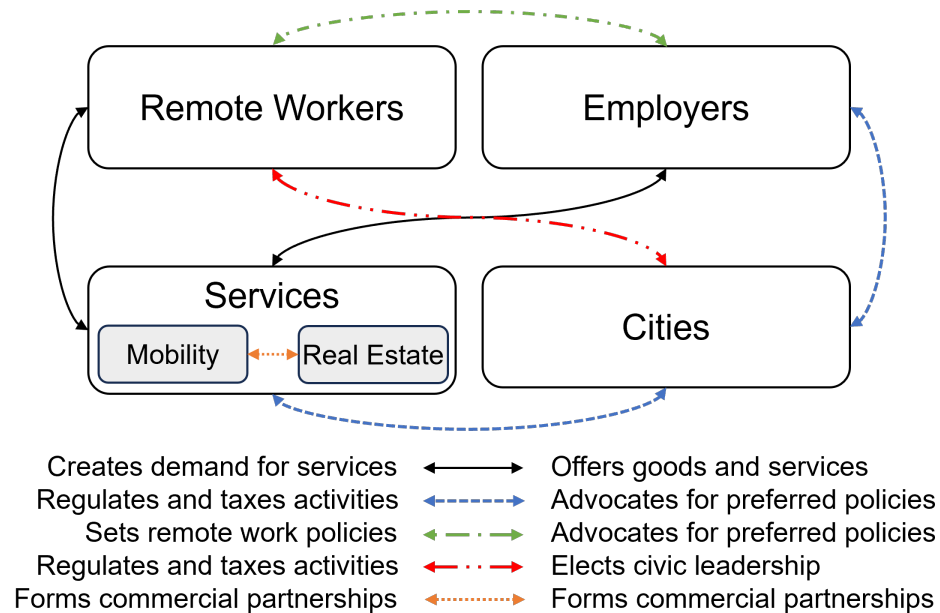


Figure 2-2: Remote work stakeholders and their relationships

Within the context of remote work, the role of the worker is to choose a preferred remote working arrangement, which may include engaging with a range of service providers, subject to the constraints of their employer’s remote work policy. They may exert influence on the decisions of the other stakeholders by advocating for changes to their employer’s remote work policy (or changing employers altogether), soliciting services from competing service providers, and pressuring local officials to amend public policy. Remote workers make these decisions based on a complex set of considerations, such as income, status, psychological well-being, desire for social connection, and so on.

Employers define the set of available arrangements through their remote work policies and may seek to influence the worker’s choice of arrangement through incen-

tives. They interact with service providers such as commercial real estate holders as needed and are subject to regulation by the city government. Like remote workers, they can seek to influence policy changes through advocacy. Employers could have many motivations related to remote work, including employee performance, employee morale, and limiting business expenses associated with office space.

Service providers are the third remote work stakeholder. This broad group involves any business that serves the needs of commuters or employers: real estate providers, retail businesses in business districts, and transportation services. Specific examples include co-working platforms, lunch restaurants catering to office workers, and public transit agencies. Service providers sell their products to workers and employers, competing based on cost, quality, and convenience. Like employers, they are affected by the regulations set forth by local governments. Mobility and real estate providers are specifically highlighted as examples of services in Figure 2-2 to illustrate that services may also interact with one another by forming commercial partnerships to offer integrated services to remote workers or their employers.

Lastly, cities (i.e. local policymakers) may become involved in remote work by encouraging the other stakeholders to change their behavior through incentives or regulation. One example is public subsidies for new co-working spaces, a policy that affects the behavior of co-working platforms (service providers) and ultimately influences the options available to remote workers. Such a policy has been adopted by the City of New York and others [158]. Cities, of course, have a special relationship with workers, who make up a significant portion of the electorate that chooses civic leadership.

Beyond enumerating the stakeholders, there are two additional terms related to remote work that would benefit from a clear definition. A “remote work policy”, set forth by an employer, defines the flexibility afforded to each remote worker. Remote

work policies might allow for fully remote work, no remote work, or some combination of in-person and remote work (often referred to as a “hybrid” remote work policy). Hybrid policies can involve several restrictions that also lack common terminology. It is proposed that restrictions that require a minimum number of remote work days per week, but not specific days, are referred to as a “flexible hybrid schedule” policy, and that requirements to work in the office on specific days of the week as a “fixed hybrid schedule” policy.

Remote work policies are different from remote work “arrangements”, which are the setting where work takes place, involving a combination of a workplace and co-located associates. Most remote work research to date focuses on the two most common workplaces: the employer’s business premises and the home. As noted above, there are many other workplace options, some designed specifically for work (e.g. co-working spaces) and others that have a separate primary purpose but facilitate work (e.g. cafés). Co-located associates are an important component of a remote work arrangement. While many people would choose an arrangement involving colleagues or other work-related associates, it is also conceivable to choose associates in order to socialize or for some non-work benefit. For example, many remote workers are choosing to work remotely in the company of friends [159]. Future research will be needed to understand the individual and societal effects of different working arrangements under different conditions.

Not all arrangements will be available to all remote workers at any given time. The considerations that restrict remote work arrangement choice shall be referred to as “dependencies”. There are three general categories of dependencies. A facility dependency is a requirement for a location with specific features or equipment, such as a 3D printer, to complete a design prototype. Geographic dependencies are related to the location of a workplace. An example of a geographic dependency is someone

who chooses a workplace in a certain neighborhood to facilitate picking up children after school. Associate dependencies are related to the need for co-location with specific individuals, perhaps two colleagues who desire face-to-face collaboration in order to finish a brainstorming task. Dependencies can be either hard constraints or simply desirable, and enforced from the top-down by employers through remote work policies or bottom-up by individuals. Identifying any active dependencies can help to explain why remote workers choose certain arrangements.

Carefully considering each stakeholder in the research design stage can help in identifying gaps that undermine the policy relevance of the findings. For example, a study of the commuting behavior of remote workers might start with the implicit assumption that decisions are made at the individual level. Reviewing the remote work stakeholders, however, could uncover the influence of employers (e.g. offering incentives for in-person work), service providers (e.g. introducing new flexible transit passes for hybrid remote workers), and city policies (e.g. taxes on employee parking) on decisions about where, when, and how frequently to commute. Overall, the stakeholders-policies-arrangements-dependencies taxonomy provides researchers with a common vocabulary for communicating with potential collaborators and interpreting remote work studies in other disciplines.

2.4.2 Conceptual framework

Comprehensive, policy-relevant research to address the existing uncertainty around remote work will require deep collaboration across disciplines. Decisions by remote workers might be studied by travel behavior experts and sociologists; decisions by corporations, on the other hand, fall into the domains of organizational behavior and labor economics. City and service provider decisions would benefit from the

perspectives of city planners, public policy scholars, transportation scientists, and urban economists, among others.

To facilitate such collaboration, a conceptual framework for mapping and categorizing remote work research is proposed. The overall framework is presented in Figure 2-3. At the most basic level, a remote work study has a decision environment, or “setting”, and a decision maker, or “actor”. While this framework is sufficiently general to apply to many other areas of research, the benefit of this structure for remote work studies in particular is that it enforces a careful description of all features that are relevant to remote work, rather than only discipline-specific features, thus ensuring that future scholars will be able to reproduce and build upon new findings.

The setting has five types of features: 1) place and time, 2) people, 3) task characteristics, 4) employment policies, and 5) exogenous conditions. Place and time relate to the location and schedule at which work takes place: office vs. home, the amenities available, the cost of using the space, and so on. People other than the agent are important to consider for remote work settings because co-location with colleagues, friends, or strangers affects the flow of information and ideas. Tasks might require collaboration or be highly stressful, impacting decisions by the actor. Employment policies create constraints on the decision space; workers subject to a strict in-office work policy cannot choose to work from a café twice a week. Finally, exogenous conditions such as weather or macroeconomic crises are beyond the immediate control of any remote work actor, but might affect decisions.

An actor is defined along four feature categories: their role with respect to remote work, their objectives, the decision they face, and their institutional or personal characteristics. The possible roles match the four remote work stakeholders described in the previous section: workers, employers, cities, and service providers. Each role has a set of possible objectives. Service providers might decide to increase

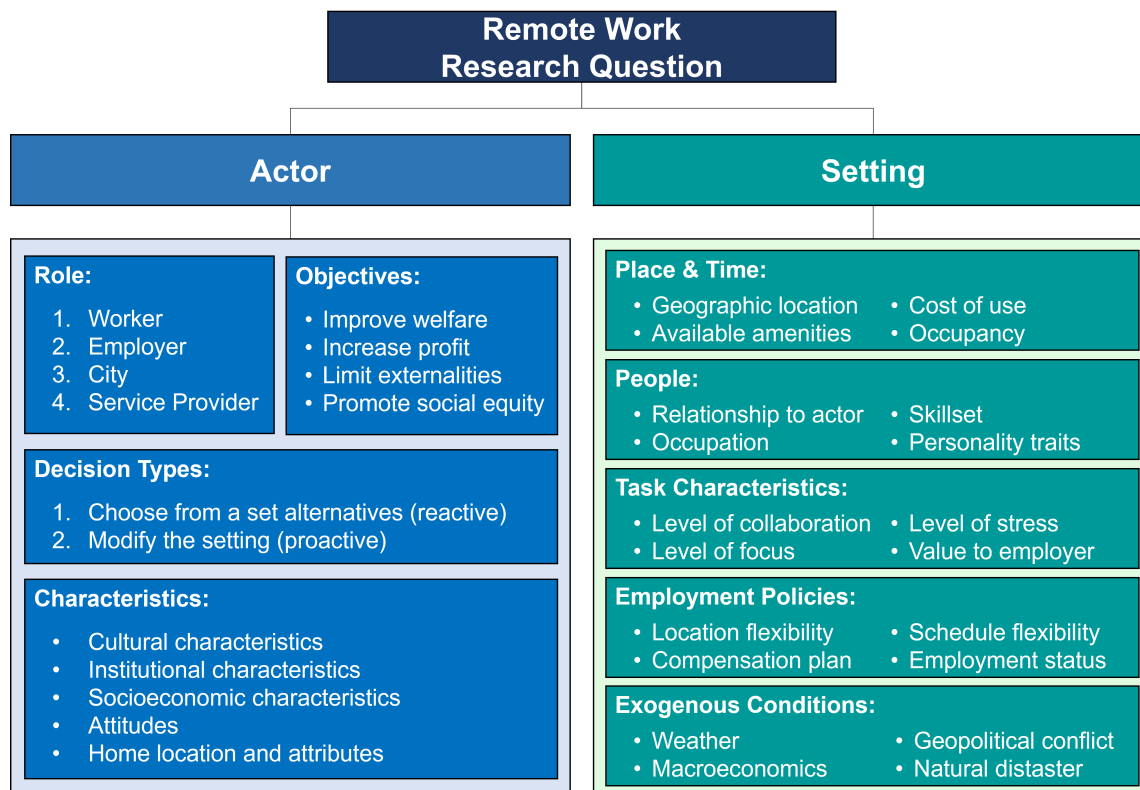


Figure 2-3: Conceptual actor-setting framework for classifying and describing remote work research

revenue or minimize expenses. Cities, on the other hand, may make decisions to limit externalities or improve public finances. These decisions fall into one of two categories. The first is a reactive decision to choose from alternatives subject to the constraints of the setting. An example would be a worker choosing a remote work location from a set of possible alternatives. The second decision type is to proactively modify the parameters of the setting. This might involve an employer who leases new satellite offices, thus changing the “place” component of the setting. This creates feedback between the two: one actor’s decision affects another agent’s setting. Actors also have personal or institutional characteristics that impact their

decision-making processes and outcomes.

The proposed actor-setting framework is sufficiently flexible for application to remote work problems across a wide range of disciplines. Labor economists might be interested in how the choice of work location is affected by a remote workers' compensation plan (Agent: Worker; Objective: Maximize compensation; Decision: Choose from alternatives). An urban planner may take the resulting choice model to estimate how carbon emissions from transport would change if co-working spaces were introduced within residential neighborhoods (Agent: City; Objective: Reduce externalities; Decision: Modify the setting). A sociologist might compare the initial survey results to a survey from another country to understand how cultural values shape the importance of compensation to remote workers (Objective and Decision same as initial project; Agent: New cultural values). The conceptual framework gives these disparate disciplines the capacity and language to build upon each others' findings, producing holistic research to inform urban and employment policies.

Another benefit to this structured framework is that it provides clarity to the reader and reproducibility for other researchers. When two remote work studies have conflicting findings, the framework can be used to easily identify the differences between the settings or actors that may have contributed to the variation in results. For example, if this rigorous framework were adopted by the two studies finding opposite impacts of fully remote work on productivity [118, 139], it would permit future researchers to identify whether the setting, task, employment policies, exogenous factors, or other contextual differences are responsible for the divergent outcomes. Over time, such comparisons between studies could unlock new insights into the dynamics of remote work that would be difficult to extract from individual studies.

2.5 Outlook

There are notable ongoing efforts within the academic community to understand the broader impacts of remote work on society and make policy recommendations. The SWAA is a continuous monthly survey of U.S. adults with questions about remote work, well-being, productivity, and travel behavior [3]. The entire set of responses is publicly available online for further research. The Downtown Recovery Project provides a different perspective, examining the relationship between remote work, urban demographics, public policy, and activity levels across dozens of cities in North America [135]. Lastly, a remarkable data collection effort by Huo et al. [133] published near-real-time estimates of carbon emissions by sector from 1500 cities worldwide, which can be used to evaluate the impacts of efforts to improve urban sustainability through remote work policy. There are almost certainly other, yet-to-be-published remote work projects that should follow the lead of these pioneering studies and make their data available to the broader research community.

There remain many underexplored and policy-relevant remote work topics that would benefit from new interdisciplinary research. Evidence-based remote work policy requires both a robust source of empirical data and new methods that can incorporate emerging work dynamics. A detailed agenda for future research is presented in Section 9.4

The rise of new technology and global events have often precipitated large-scale shifts in social behavior. We are living through a period where both are occurring simultaneously. Old assumptions about stable commuting patterns and large, centralized workplaces are no longer valid. The shift towards remote work is not simply a series of challenges to overcome, however. Through effective, evidence-based policy leadership informed by thoughtful, coordinated research, we might finally take

advantage of a liminal moment to shape a more sustainable and equitable future.

Chapter 3

The impacts of remote work on travel: insights from three years of monthly surveys

3.1 Introduction

In 2020, a slow and steady rise in remote working over decades was dramatically and irreversibly accelerated by the onset of the COVID-19 pandemic. In the United States, employers are planning for about 32% of all worked hours to take place remotely in the long term, a nearly seven-fold increase in remote work shares relative to 2018 [3]. The average employee would prefer even higher levels of remote work than their employers are planning, suggesting that there is room for remote work to grow if business practices, technology, and infrastructure evolve to ease existing remote work constraints.

This sudden rise in remote work has resulted in the biggest shock to urban travel

patterns in generations. The primary effect of increased remote work is that many commuting trips can now be replaced by working at home or close to home. The substitution of some commuting trips for remote work also has narrow secondary effects on travel behavior, including changes to mode choice, departure time choice, home location choice, and destinations for non-work travel. New survey data is needed to inform future travel demand forecasting models that accurately reflect these primary and secondary effects of widespread remote work. Yet there has also been a more fundamental change to how travel decisions are made. Remote work offers the freedom to choose a work location, whether that is at home, at the employer's workplace, or somewhere else entirely. Moreover, it forces employees and employers to consider coordination with colleagues in their decisions about where and when to work remotely. The outcomes of these decisions have implications for travel demand, but also productivity, personal well-being, and local retail spending. In the past, when the vast majority of the workforce commuted to the same location on a regular schedule, the connections between travel behavior and employment attributes could be largely ignored as employees did not have the agency to act on their preferences. In the remote work era, however, these connections can no longer be neglected. It is now essential to understand how employment attributes and inter-organizational coordination impact travel choices for remote workers.

To quantify emerging trends in remote work travel behavior, including connections between travel and employment, this chapter first introduces an important source of remote work data: the monthly SWAA [3]. Initially designed to understand experiences and attitudes towards remote work from early 2020 onward, the SWAA was updated in 2021 to include questions about the travel behavior of remote workers. This chapter presents the results of each travel behavior-related question and explores how choices differ based on demographic status, lifestyle choices, geography,

and critically, job type, employer attributes, and employer policies. Policy-relevant insights for remote workers, employers, transportation services, and urban planners are highlighted. Lastly, new open-source tools for conducting further analysis of the SWAA data are presented.

The primary contribution of this chapter is to explore the factors that contribute to the choice of work location for remote work, and the secondary effects of work location choices on mode choice, travel time, and departure time. For the first time in literature, these choices are disaggregated by employment-related factors, thus demonstrating how travel behavior has become highly correlated with employer decisions, job types, and attitudes towards work and collaboration. While previous surveys have investigated changes in travel behavior since the rapid rise of remote work in 2020, the SWAA is unique in its scope, duration, and level of detail. The analyses presented herein are based on comprehensive monthly surveys of 5,000 or more respondents spanning nearly three years. Over 400 unique questions have been presented to respondents across the dozens of survey waves, enabling the identification of several unexpected trends and travel behavior patterns with relevance for urban transportation and land use policy.

3.2 Literature review

Transportation scholars have been interested in the topic of remote work (often referred to as “teleworking”) since well before the boom occurred in 2020. Much of the effort in modeling remote work decisions has focused on the frequency and duration of flexible work, rather than the location and the choice to co-locate with others [50, 51]. This is partly due to implicit assumptions that flexible workers are making a binary choice: work at an office or work from home. Bagley and Mokhtarian [36]

and Stanek and Mokhtarian [37] conducted surveys of workers in California to elicit preferences for working from home and from a remote work center. Mokhtarian and Salomon [38] and Vana et al. [39] found that attitudes towards work, family, and commuting are more important than sociodemographic factors in determining preferences towards flexible work. Pouri and Bhat [41] includes several occupational factors in a remote work choice model, finding that part-time workers and employees of private companies are more likely to choose flexible work, while those requiring daily face-to-face interactions are less likely to choose flexible work. Sener and Bhat [42] also included work characteristics in estimating a copula-based sample selection model using household travel survey data from Chicago. Even recent comprehensive frameworks that include the duration of remote work do not consider location choice or the impact of employer policies [52, 53, 54]. In a very interesting study, Stiles and Smart [160] reviews the travel patterns of remote workers from 2003 to 2017 based on their choice of work location using data from the American Time Use Survey. Leading up to 2020, remote work remained a niche working arrangement in the United States, restricted to specific industries and occupations. As a result, surveys were limited to small panels and often focused on employees within a single firm or employment sector.

Several new travel and remote work surveys were issued in 2020 and early 2021 to capture new behavioral patterns resulting from pandemic-related restrictions on mobility and social activities. This was a period of very high remote work (over 60% of worked hours in the United States in May 2020) and considerable uncertainty about working arrangements in the medium and long term. Beck and Hensher [161] and Echaniz et al. [162] used surveys during the early days of the pandemic to identify significant shifts in travel behavior due to mobility restrictions in Australia and Spain, respectively. Dianat et al. [163] surveyed 1,000 travelers in the Toronto, Canada area

about changes to their activity scheduling and mode choice during and immediately after the lifting of pandemic-related restrictions. Currie et al. [164] and Jain et al. [165] use a survey distributed in Melbourne, Australia during the summer of 2020 to estimate the total impact of remote work on future travel demand and identify contributing factors, respectively. They find that access to remote work technology and employer support were significant factors in determining the likelihood of continuing remote work, and that attitudes were not a significant driver of long-term remote work preferences. Balbontin et al. [166] compared differences across countries with respect to remote work preferences in late 2020, also finding that employer support has a strong positive effect. In a widely cited paper, Salon et al. [167] explored potential changes to a wide range of travel behavior among remote workers, including shopping, restaurant patronage, air travel, and home relocation. The number of published studies investigating remote work trends in this period is substantial and continues to grow.

After restrictions were lifted and the perceived public health threat subsided, working arrangements slowly began to stabilize. New survey instruments were introduced to gain an understanding of the future of remote work and travel behavior. Nayak and Pandit [168] uses logistic regression to estimate preferences for remote work among a small sample of Indian commuters in March 2021. The authors find that several household characteristics, including poor internet connectivity and distractions caused by other household members, are predictive of preferences for less remote work. Asmussen et al. [169] moves beyond the home-office paradigm in a stated preference survey of hypothetical work location choices for Texas residents in early 2022. The study finds that workplace environment is at least as important as geographic location when choosing from working at home, at the employer’s business premises, or at a “third place” (e.g. café, library, or community center). Using a

longitudinal survey from December 2020 to March 2022, Tahlyan et al. [170] tracks changes in attitudes towards remote work, shopping and travel for the same group of respondents over time.

Remote work was not only a topic of interest to transportation scholars. Many social scientists, including the SWAA founders, conducted surveys to explore the economic and psychological impacts of widespread remote work. Barrero et al. [3] is the original working paper exploring the responses to non-travel questions on the SWAA, finding significant differences in preferences for remote work across demographic and employment categories. Other large online surveys investigating remote work trends were conducted by Bick et al. [171] and Brynjolfsson et al. [172] around the same period, with similar results. Using a small sample of U.S. residents, Tahlyan et al. [173] find that middle-aged workers experienced greater remote work satisfaction than young and older workers. Similarly, Shi et al. [174] explores the factors that contributed to greater productivity while working at home among employees in the Seattle, United States area. These surveys are not intended to elicit travel preferences and therefore do not provide a substantive travel behavior component. To the author's knowledge, this is the first detailed analysis of survey results that connect remote work location choice, travel behavior, and employment characteristics during the widespread remote work era.

3.3 Survey methodology

The insights in this chapter are generated from the SWAA. It is a comprehensive monthly survey designed and administered by the WFH Research team. The entire catalog of past survey questions and the cumulative response data are available online at <https://wfhresearch.com>.

The author of this dissertation began to collaborate with the WFH Research team in 2021 to add over 20 travel-related questions to the survey during different survey waves. The travel-related questions cover many different aspects of travel behavior: destination choice, mode choice, travel time, departure time, non-work trips, and more. The responses to the travel-related questions are the basis of the insights presented in Section 3.4. The travel-related questions are cross-tabulated with the comprehensive set of existing SWAA questions on demographics, geography, household characteristics, work characteristics, and attitudes to provide new insights into the factors that impact travel behavior during the remote work era.

The first wave of the survey was distributed in May 2020, shortly after the onset of the COVID-19 pandemic in the United States. The survey was continued in July 2020 and has been distributed monthly ever since. All survey waves are restricted to U.S. residents over the age of 19. Minor changes to the sample size and sampling methodology have been made since the survey began. The first travel-related questions were added in November 2021. At that time, the monthly sample was 5,000 respondents and restricted to people who had earned at least USD \$10,000 in 2019. In early 2022, the sample was increased to 10,000 respondents per month who had earned at least USD \$10,000 in the previous full calendar year.

The SWAA is a panel survey distributed online by commercial survey providers who recruit respondents through a variety of sources. Respondents are not recruited for the SWAA specifically, rather they are recruited for online surveys and then provided with a link to the SWAA questionnaire. Each questionnaire includes approximately 40 to 60 questions, with a typical response time of 8 to 10 minutes. No identifying information is provided, and the survey administrators do not interact directly with the respondents.

Attention check questions are used to filter out a small number of low-quality

responses from each survey wave. Then, individual survey responses are then re-weighted to match the United States Current Population Survey (CPS) shares with respect to age, sex, education, and income. The re-weighted sample is also very similar to the CPS shares for census division (region of the country) and industry. The sample is not weighted by race, therefore race is not used as an independent variable for the analyses in this chapter. All results are drawn from the re-weighted sample. The aggregate results of the SWAA are consistent with the results of other similar remote work surveys [175].

After survey administration, data cleaning, and scaling, the result is a high-quality, representative sample of thousands of working-age U.S. residents per month across three years and a total sample size of more than 148,000 responses. Questions have been added and removed over time, with over 400 different questions included in at least one survey wave. This rich dataset can then be used to generate new insights that connect remote work, travel behavior, and organizational behavior. The findings are presented in the next section and the implications are discussed in Section 3.5.

3.4 Survey findings

This section presents the travel-related findings from the SWAA survey, cross-tabulated with other variables of interest. The wide-ranging findings are organized into five subsections:

1. Work location choice
2. Mode choice
3. Departure time

4. Productivity and travel

Each subsection is further divided among different topics of interest, such as non-work trips, trip duration, and so on. The abundance of data and questions collected over three years makes it impossible to fit an exhaustive analysis within this chapter. Therefore, only a selection of the most interesting and policy-relevant findings is provided herein. To encourage further analysis by interested readers, tools for data cleaning, organization, and visualization have been shared in a public GitHub repository: <https://github.com/jtl-transit/swaa>. These tools can also be used to replicate the results and charts below using the public survey data.

The variation in responses to travel-related questions across standard demographic, household, employment, and attitudinal groups are analyzed below. The standard demographic variables are age, gender, income, and education. The standard household characteristic variables are the number of children, internet quality, home office availability, and population density of the home ZIP code. The standard work characteristics include industry, occupation, company size, the population density of the work ZIP code, percentage of tasks requiring a computer, employment type, and percentage of tasks that can be done remotely. Standard attitudinal variables include attitudes towards commuting, socializing at work, efficiency at home, and risk of infection on certain travel modes. All independent variables are categorical unless otherwise noted.

The travel-related questions were added to the SWAA questionnaire in November 2021, after COVID-19 vaccines were widely available in the United States and most pandemic-related restrictions on social gatherings and public activities were lifted. As context for the results in this section, it is worth noting that the Omicron variant of COVID-19 emerged in November 2021 leading to a dramatic increase in the number

of reported COVID-19 cases in the United States from December 2021 to March 2022. Survey responses from that period may therefore reflect greater concerns about the public health risks of in-person work and shared transportation than responses from subsequent survey waves. Attitudes towards managing the risks of the COVID-19 pandemic varied significantly across the United States, however, so it is difficult to make generalizations about the country as a whole.

Note that not all questions were asked on all survey waves nor presented to all respondents on the same survey wave due to survey logic, so the number of respondents and timing varies by question. In particular, certain questions about attitudes and behaviors related to remote work were only presented to respondents who were participating in some amount of remote work. Sample sizes and time periods are indicated below each figure.

3.4.1 Work location choice

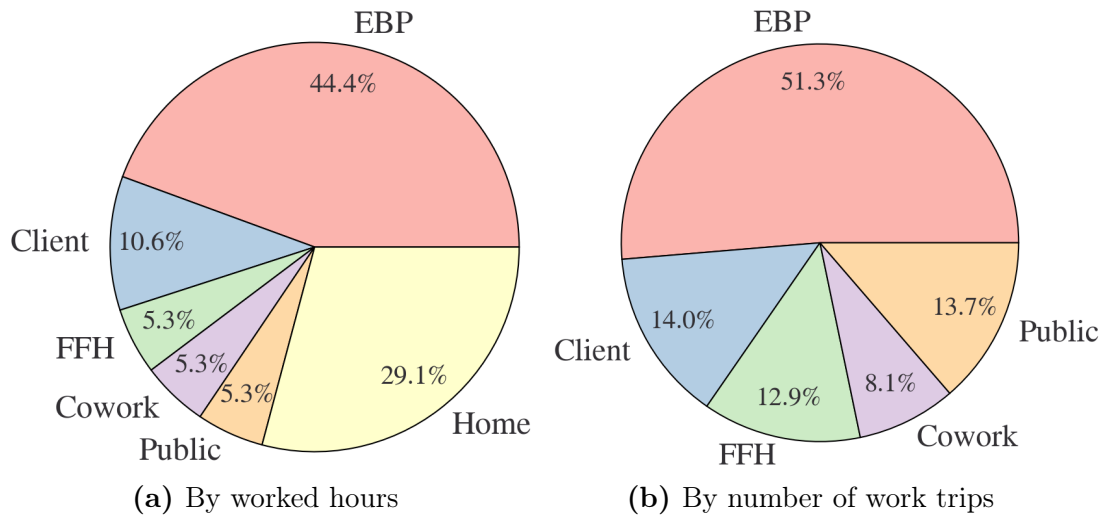
Despite the common misconception that remote work is synonymous with “working from home”, remote work is actually the flexibility to choose a work location from a set of possible alternatives. These alternatives typically include the traditional workplace and home, but, as shown in the subsections that follow, often include third places or client’s workplaces as well. The rapid rise in flexibility with regard to work location choice across much of the workforce is a major disruption to urban transportation systems, which have largely been designed and operated to serve stable commuting patterns for decades. It is also a significant concern for commercial real estate providers, downtown retail businesses, and employers, who are navigating these changes with very little information. This section briefly describes aggregate preferences for remote work, the evolution of remote work preferences over time, and

some of the constraints that prevent additional remote work. Then, the focus of this section is describing the dynamics of work location choice between home, the employer’s business premises, and other possible locations, which has a profound impact on the demand for transportation. The impact of work location choice on trip duration and total commuting time is also investigated in detail.

Work location trends

One of the primary contributions of this research is the extended investigation into the use of third places for remote work. The SWAA considers three types of “third places”: public spaces (e.g. cafés, libraries, community centers), co-working spaces (that are not provided by the employer), and the homes of friends and family members (FFH). Breaking down all worked hours by location, it is shown that about one-third of all remote work takes place outside the home, with a relatively even split between public spaces, co-working spaces, and the homes of friends and family members. The remaining remote work hours take place at home, while in-person work is split unevenly between the employer’s business premises (EBP) and a client’s workplace. The results are shown in Figure 3-1(a). After weighting by respondent earnings, it is determined that 17.3% of all income in the United States is earned while working at a non-home, non-work location.

Using responses to a question about work trips rather than worked hours, it can be shown that 34.7% of all work-related trips are to public spaces (13.7%), co-working spaces (8.1%), and FFH (12.9%), as shown in Figure 3-1(b). The higher share of third place trips relative to hours is because working at home does not induce a work trip. These results have remarkable implications; overlooking third places as a possible work location for remote workers results in over a third of all work trips



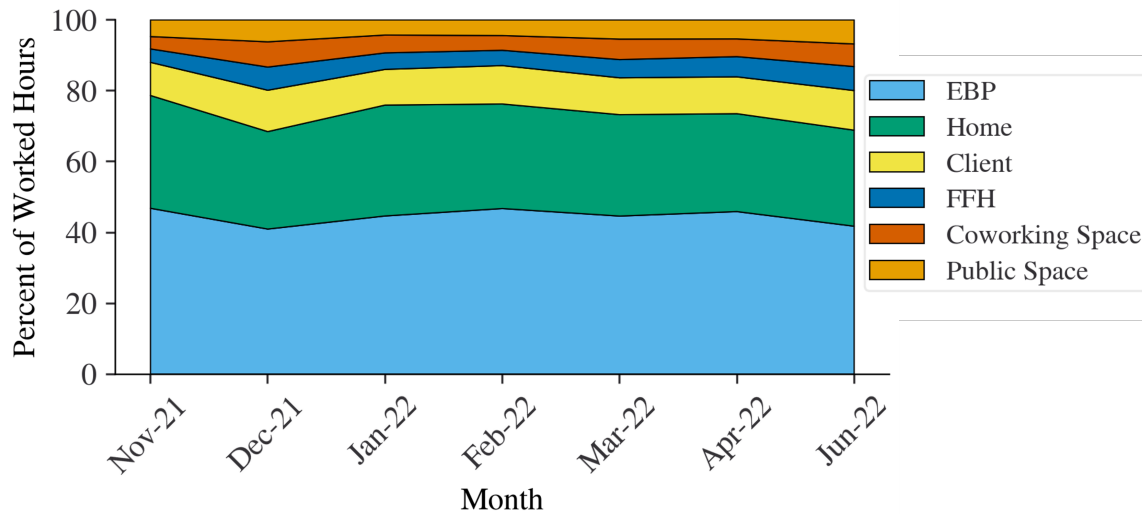
(a): Nov 2021 - Jun 2022, N = 27,364; (b): Nov 2022 - Jan 2023, N = 13,091.

Figure 3-1: Work location split by worked hours (a) and number of work trips (b)

being ignored. Third place trips are different from traditional commute trips to the employer’s business premises (EBP). Over 43% of respondents in the November 2021 survey had spent at least some time working at a third place during the previous week.

The repeated nature of the SWAA also allows tracking of the use of third places over time, as shown in Figure 3-2. Third place use was lowest during January and February 2022, presumably due to the sharp rise in COVID cases across the United States during the same timeframe. By May and June 2022, working at EBP was on the decline and working from FFH and co-working spaces was rising.

One of the advantages of the SWAA relative to other remote work and travel surveys is the breadth of questions relating to employment and attitudes. Use of third places can be compared across demographic groups, household characteristics, employer characteristics, job characteristics, attitudes towards coordinating with colleagues, and general attitudes towards remote work. Figure Those who are younger,

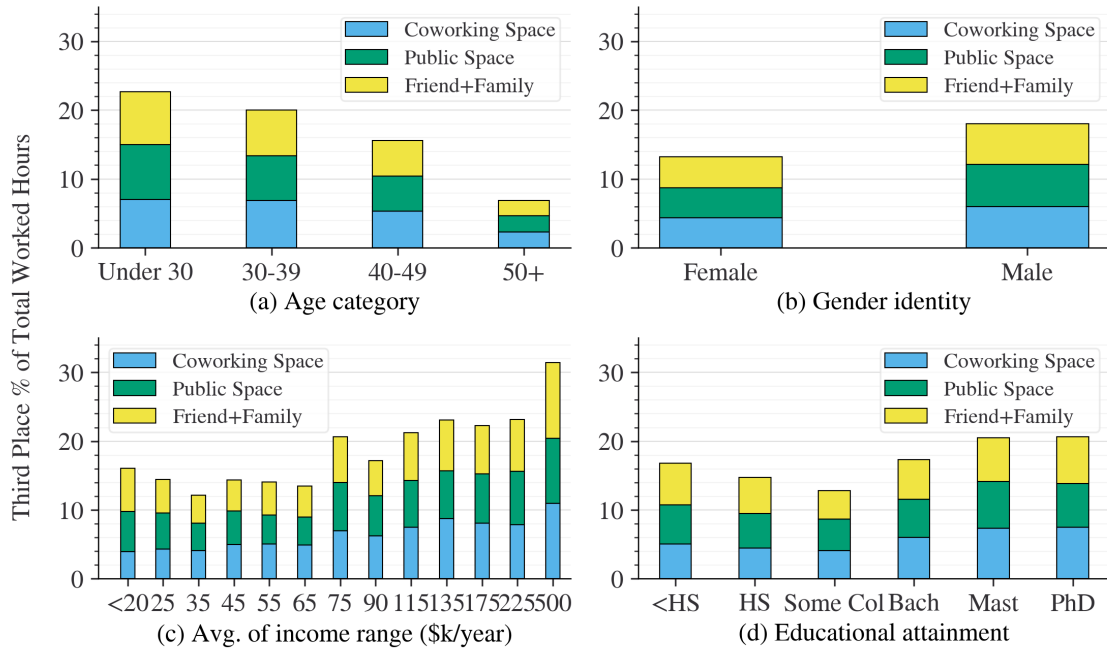


Nov 2021 - Jun 2022, N = 27,364.

Figure 3-2: Third place use over time

male and have higher educational attainment are much more likely to make trips to third places for remote work. The gender identity and age associations are particularly strong; people under 30 are three times more likely to be using third places for remote work than those 50 and over.

The analysis for different household characteristics is shown in Figure 3-4. People living or working in an urban area, those with roommates, those with a poor internet connections and people living in the Mid-Atlantic (MA) or Pacific (Pac) census divisions are much more likely to work from third places. This is in contrast with the results for remote work preferences, which found little association between having roommates and preferences for remote work. This suggests that people who live with roommates have similar remote work preferences as others, but are more likely to conduct that remote work outside the home. Urban dwellers are more likely to have third places near their home, so it would seem reasonable that they are more

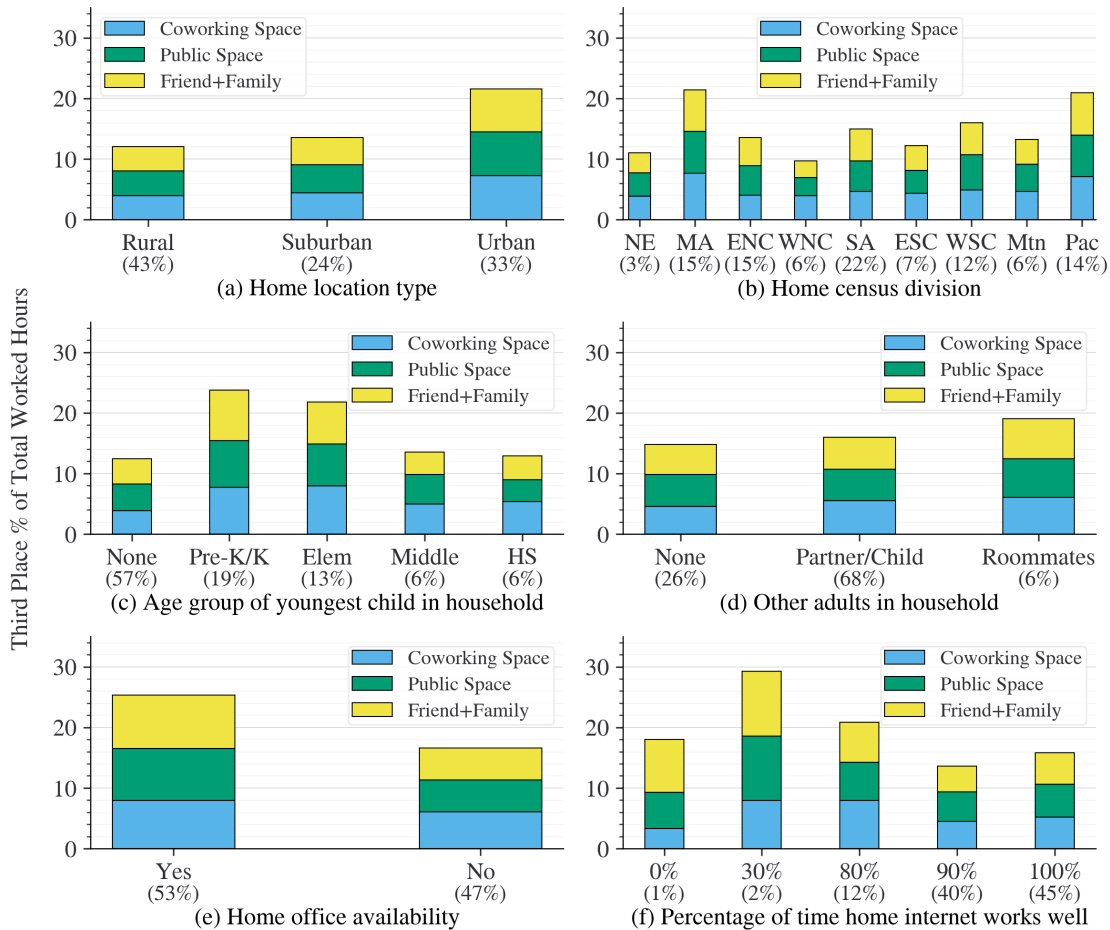


All: Nov 2021 - Jun 2022, N = 27,364.

Figure 3-3: Third place use by demographic group

likely to use third places. Poor internet quality was found to be predictive of more third place hours, but not necessarily more third place *trips*, suggesting that people with poor internet travel to third places at similar rates to others but stay longer during each visit. The New England (NE) and West North Central (WNC) census divisions were the least likely to make trips to third places, which may be a result of colder weather in those regions during the winter months when this question was included in the questionnaire.

Third place use also has strong associations with employment characteristics, as shown in Figure 3-5. People who work fewer than 40 hours per week are much more likely to do that work at a third place (FFH in particular), as are people who work 2 or more part-time (PT) jobs. Employees of medium-sized companies are also much



(a)-(d): Nov 2021 - Jun 2022, N = 27,364; (e)-(f): Nov 2021 - Dec 2021, N = 7,585.
 NE = New England, MA = Mid-Atlantic, ENC=East North Central, WNC = West North Central, SA = South Atlantic, ESC = East South Central, WSC = West South Central (WSC), Mtn = Mountain and Pac = Pacific.

Figure 3-4: Third place use by household characteristics

more likely than those working for very large or small companies to use third places. The type of remote work (RW) schedule does not have a strong bearing on third place use. These results underscore the need to include employment factors in travel demand models to capture commutes to third places.

Figure 3-6 shows that types of tasks that a person does at work are also strongly

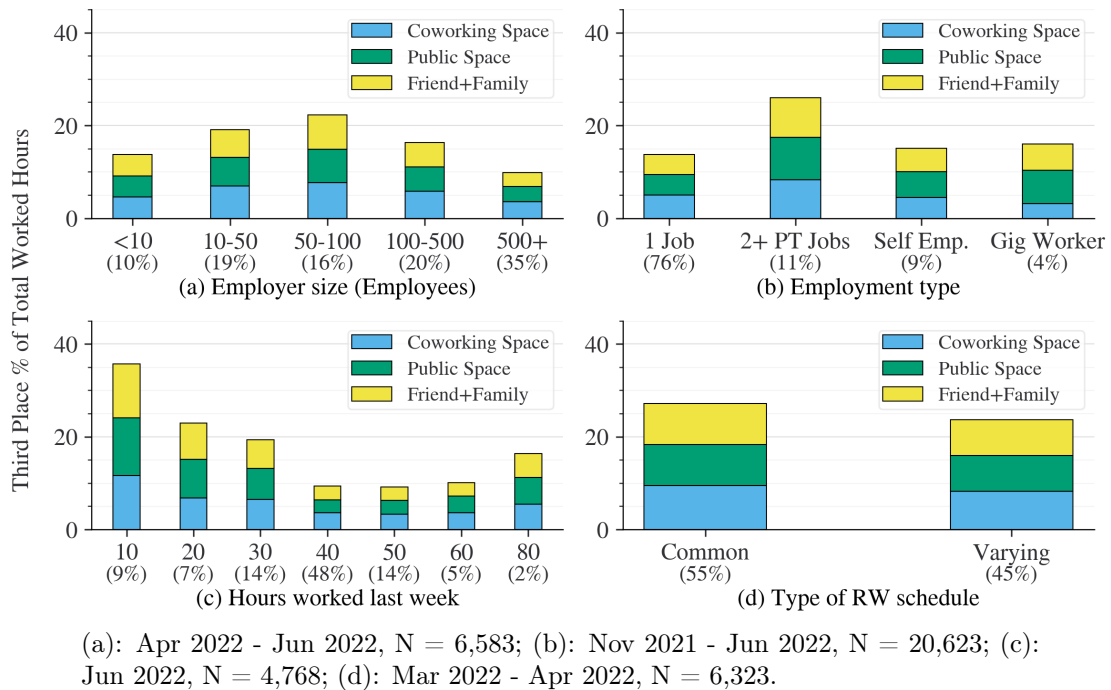


Figure 3-5: Third place use by employment characteristics

correlated with third place use. People who spend between 20 and 70 percent of their day meeting with others, and between 40 and 70 percent of their time using a computer, are the most frequent third place users. Interestingly, people who find themselves to be more effective during remote work are also more likely to use third places. This effect could be bidirectional, which would suggest that using third places can make people feel more effective during remote work. Lastly, people who can do some but not all of their tasks remotely are most likely to use third places.

Connecting third place use to attitudes around coordination with colleagues is also important, as shown in Figure 3-7. People who rarely or sometimes prefer to be co-located with colleagues are more likely to use third places than those who always prefer co-location. It can be inferred that people who always co-locate with colleagues

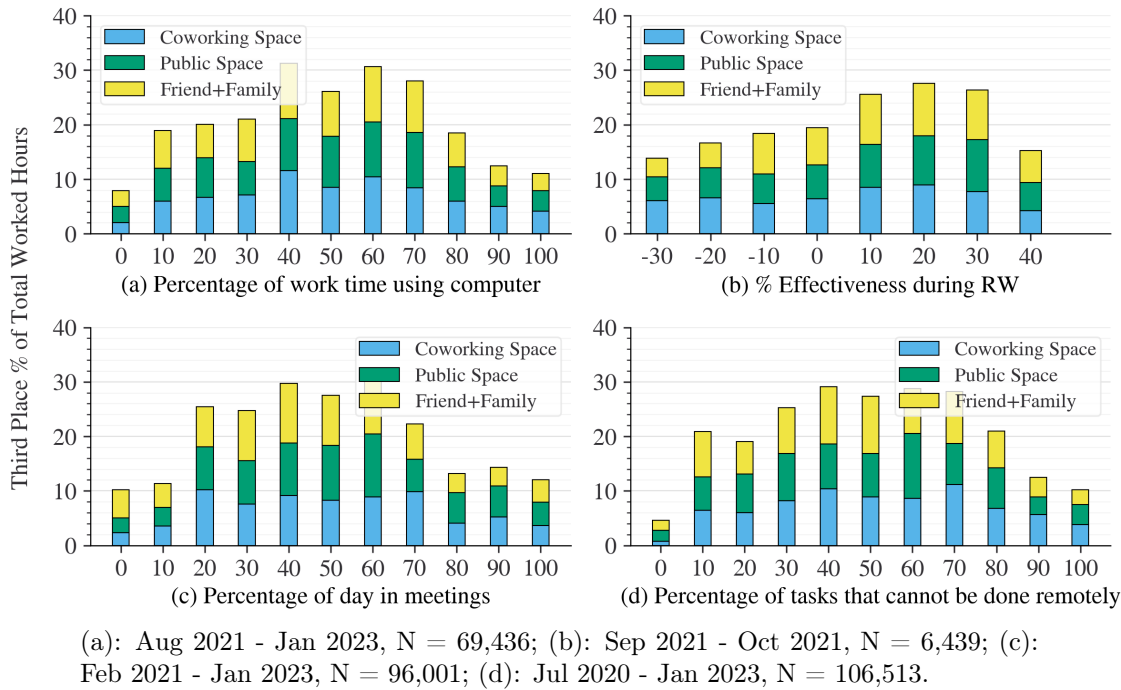


Figure 3-6: Third place use by task characteristics

are more likely to work at their employer’s business premises. People who claim that collaborating with colleagues is the primary barrier preventing them from additional remote work are also most likely to work at third places, possibly implying that third places are perceived as suitable for collaborative work between colleagues. illustrates the need to include employment and task-related factors into travel demand models. People who need to interact with specialized equipment use third places for remote work for only about 5% of their total working hours on average. Those who are able to coordinate in-person days with their boss also feel more comfortable using third places than those who do not.

Unsurprisingly, people who consider commuting time savings as a top benefit of remote work spend about 60% less time at third places than those who are less

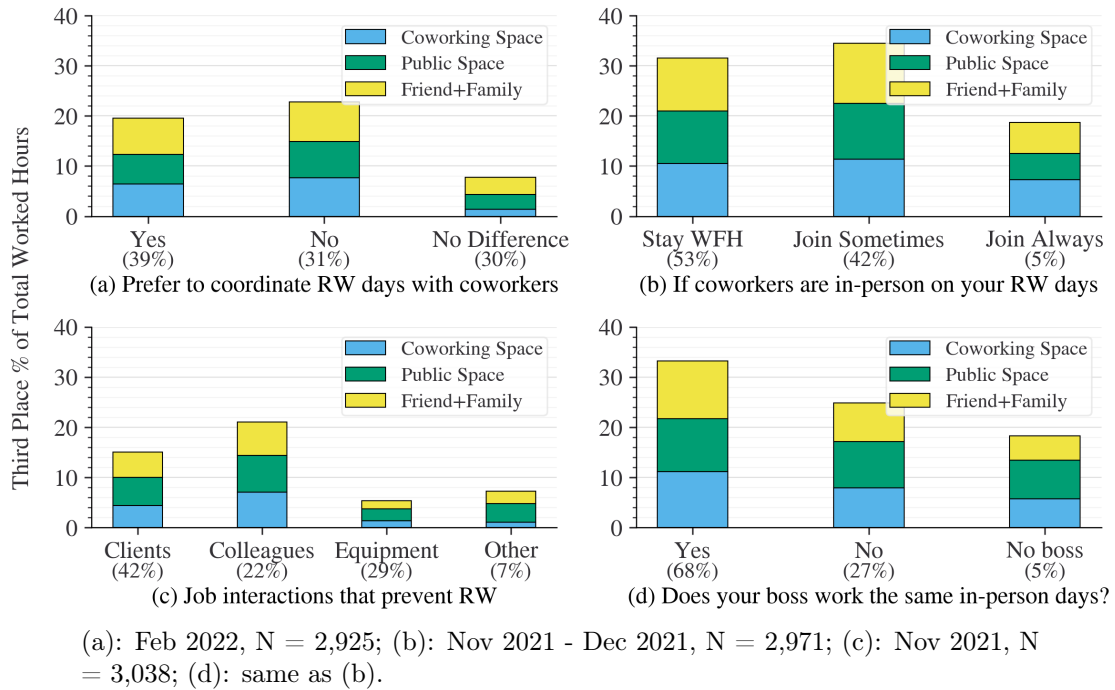
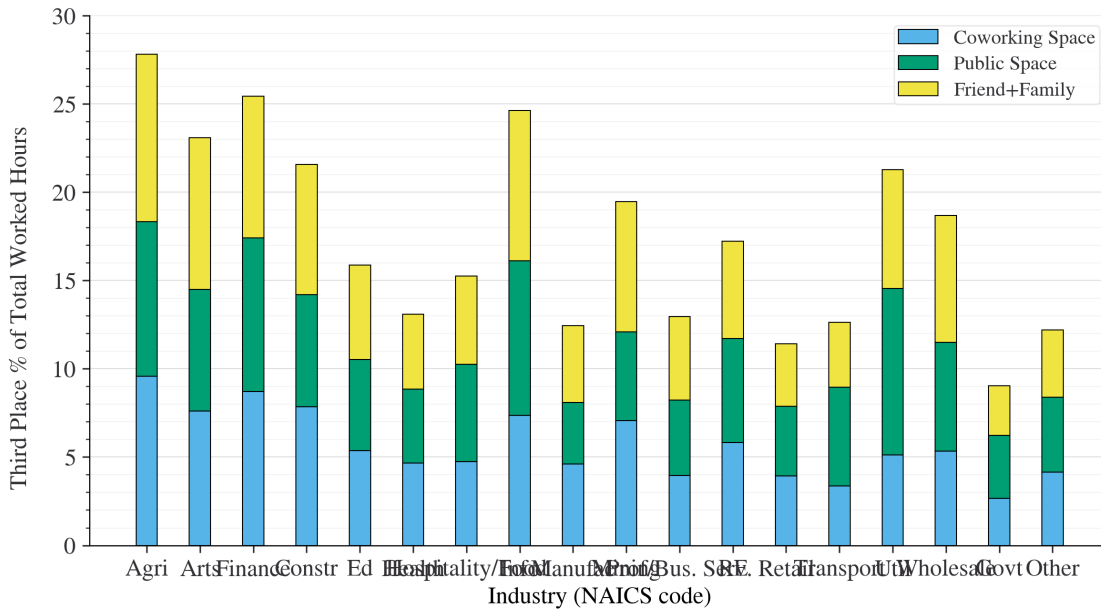


Figure 3-7: Third place use by attitudes towards coordinating with colleagues

concerned about commuting. Figure 3-8 presents the results for third place use by different perceived benefits of remote work. Another interesting finding is that people who enjoy socializing during in-person work are about 7 percentage points more likely to work at third places, suggesting that third places are perceived as social environments.

Third place trip duration

Because the SWAA includes questions about time spent at workplaces and the number of trips to different workplaces, the length of time spent at each work location type can be inferred by comparing the two. Trips to the employer’s business premises, a client’s workplace and co-working spaces have the longest average duration, as shown



All: Feb 2022 - Jun 2022, N = 11,307.

Figure 3-8: Third place use by perceived benefits of remote work

in Figure 3-9. This indicates that trips to co-working places follow a similar activity schedule as traditional work trips and might anchor the daily schedule in the same way. Trips to work at FFH and public spaces, on the other hand, typically last for less than two hours, implying that these are often secondary work locations used for a specific task or for a temporary change of environment rather than for a full work day.

Third place travel times

Respondents who used third places were also asked to provide the travel time needed to reach the third place that they visited most recently. This is an important concern for travel demand forecasting, given the popularity of working remotely from third places. The initial expectation that third place commutes would be shorter than

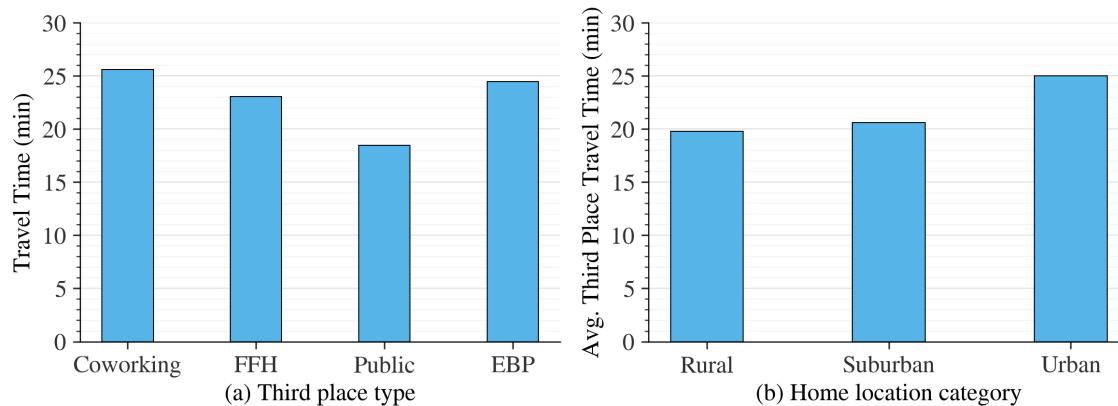


November 2022 - January 2023, N = 13,091.

Figure 3-9: Trip duration by work location

commutes to the employer’s primary place were confirmed, as shown in Figure 3-10. The average one-way commuting times to co-working spaces and FFH are 26 and 22 minutes, respectively. Public space trips are shorter, at 18 minutes on average. Note that these are average travel times across all modes, and third place commutes are more likely to involve slower modes such as walking or cycling, as discussed in Section 3.4.2.

Travel times to third places were also found to vary depending on the home location of the respondent, as shown in Figure 3-10(b). Those living in urban areas were likely to travel for longer than those in suburban and rural areas, which is somewhat counter-intuitive given that there is typically a greater density of third places in urban areas. However, urban dwellers are more likely to use modes with low average travel speeds, such as walking and public transport, and are more likely to encounter congestion.



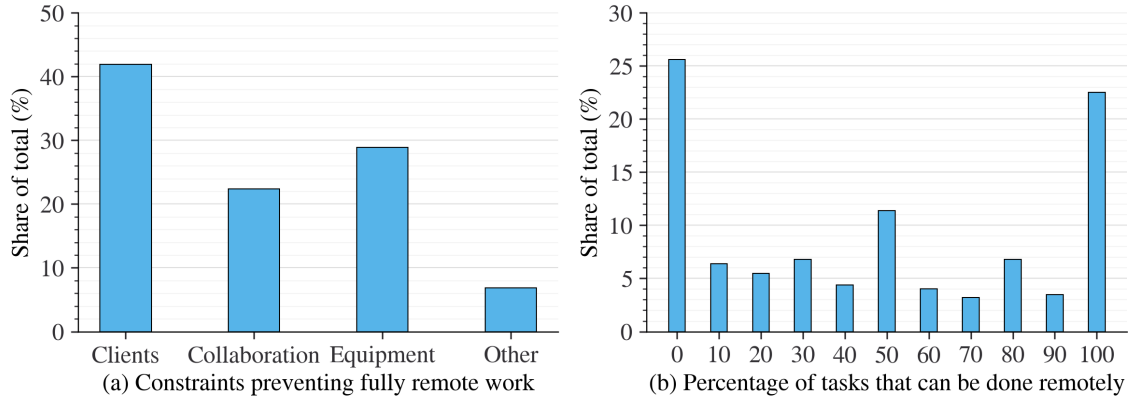
November 2022 - January 2023, N = 13,091.

Figure 3-10: Average travel times by third place type (a) and home location (b)

Remote work constraints

Another new question added to the SWAA in late 2021 relates to the task-related constraints that prevent additional remote work. The purpose of the question is to understand the potential for additional remote work in the future if some constraints are eased through improvements in communication technology. The results, shown in Figure 3-11, indicate that interaction with clients and equipment make up about 70% of all constraints preventing additional remote work. People who interact with clients in person would be those involved in retail sales, auto maintenance, and other customer-facing roles which could be difficult to do remotely. Interaction with specialized equipment is similarly challenging to do remotely, although automation and virtual reality technology may improve remote control of equipment in the future. Collaborative interactions with colleagues might be done remotely, however, given appropriate digital tools and technology. This would open up a further 22% of roles to fully remote work.

From the results in Figure 3-11(b), about a quarter of the workforce could be



(a) Nov 2021, N = 3,038; (b): Nov 2021 - Feb 2022, N = 16,273.

Figure 3-11: Constraints preventing additional remote work (a) and percentage of tasks that can be done remotely (b)

working a fully remote job, and another 23% cannot work remotely at all. The remaining 52% have a job that would support hybrid work. Put differently, about three quarters of the workforce require some amount of in-person work in order to do their job, suggesting that a large majority of people will still need to base their home location around access to their primary work location going forward unless tasks are re-allocated between jobs.

Remote work preferences

The SWAA survey includes three different questions about remote work: the share of remote work as a percentage of total work, the respondent’s preferred share of remote work in the future, and employer plans for remote work in the future. This allows the establishment of an upper and lower bound on future levels of remote work in the near term, assuming that preferences and plans remain stable. The breakdown of remote work shares by demographic and employment groups is the primary focus of other literature (e.g. [3]) and is therefore not included here. Results for actual, planned

and desired amount of remote work from the SWAA, broken down by factors related to demographics, household characteristics, employment, job tasks, remote work policies, remote work attitudes, perceived remote work benefits, attitudes towards coordination with colleagues and overall life priorities are provided in Appendix A for interested readers.

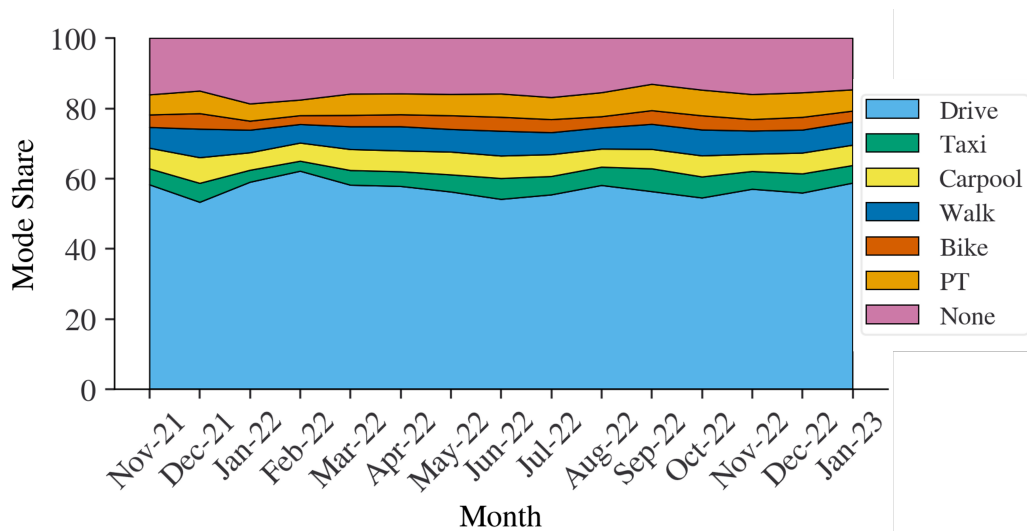
Important findings include the fact that people who work for larger employers, those who work fewer hours, and gig workers are more likely to prefer additional remote work. From a task breakdown perspective, people whose work is primarily done on a computer, people who spend less time in meetings and people who spend less time collaborating are also more likely to prefer additional remote work. People who are interested in coordinating remote work days with their boss and colleagues prefer less remote work overall, as do people who feel less stressed and more effective on remote work days. Interestingly, people who want to work hard to ensure their organization's success and those who consider work to be the most important priority in life anticipate that their employer will plan for a higher share of remote work than those who are less enthusiastic about their work.

3.4.2 Mode choice

The choice of work location interacts with other travel decisions such as mode choice, departure time and even household location. This section investigates the choice of travel mode for commutes to the employer's business premises, commutes to third places and for non-work trips. The responses indicate how remote workers are traveling when they choose to conduct remote work outside the home, and how non-work trips differ from commuting trips.

Commuting mode choice

Questions about mode choice for commuting in general have been included in the SWAA questionnaire since November 2021. These questions ask about current mode choices and mode choices in 2019, enabling quantification of the effects of remote work on mode choice and whether the trend has changed over time. The time series results are shown in Figure 3-12. Commuting modes have been relatively constant over time, with public transit and walking increasing somewhat in the summer of 2022. The response “None” indicates that the respondent did not commute during the week prior to responding to the survey.

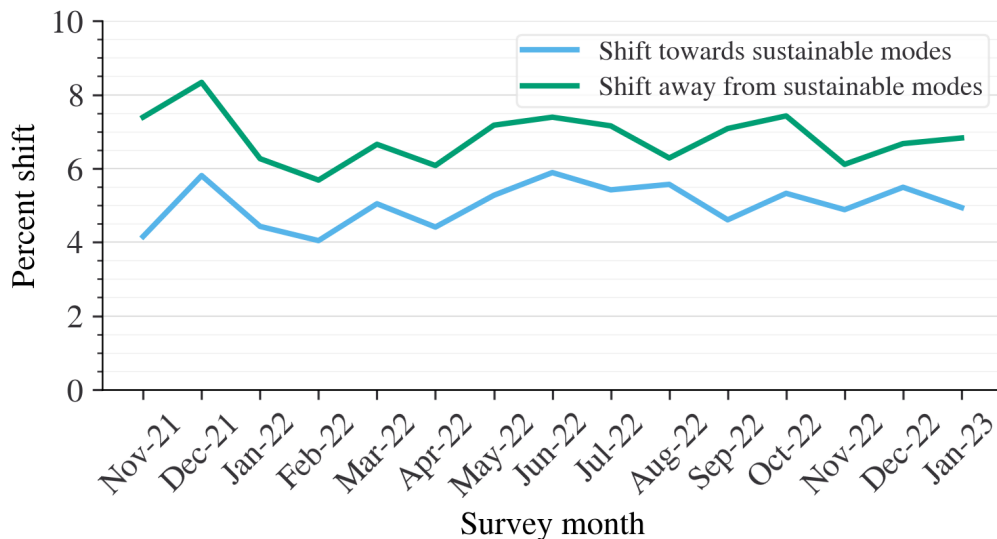


Nov 2021 - Jan 2023, N=70,029.

Figure 3-12: Commuting mode shares from November 2021 to January 2023

The survey data permits investigation into whether people have changed commuting modes over time. Of particular interest is the transition to and from “sustainable” travel modes. For the purpose of this analysis, public transit, walking, cycling, and carpooling will be considered sustainable modes. Every survey wave has found that

a greater share of people have transitioned *away* from sustainable commuting modes since 2019 than have transitioned *towards* sustainable commuting modes, as shown in Figure 3-13. The average across survey waves is that 6.8% of people have switched from sustainable modes in 2019 to driving or using a taxi, while only 5.0% have done the opposite. These high-level results suggest that even if commuting frequency has decreased as a result of remote work, the carbon intensity of each commuting mile travelled is likely to have risen, although it should be noted that these questions do not capture important factors such as vehicle occupancy or fuel efficiency.



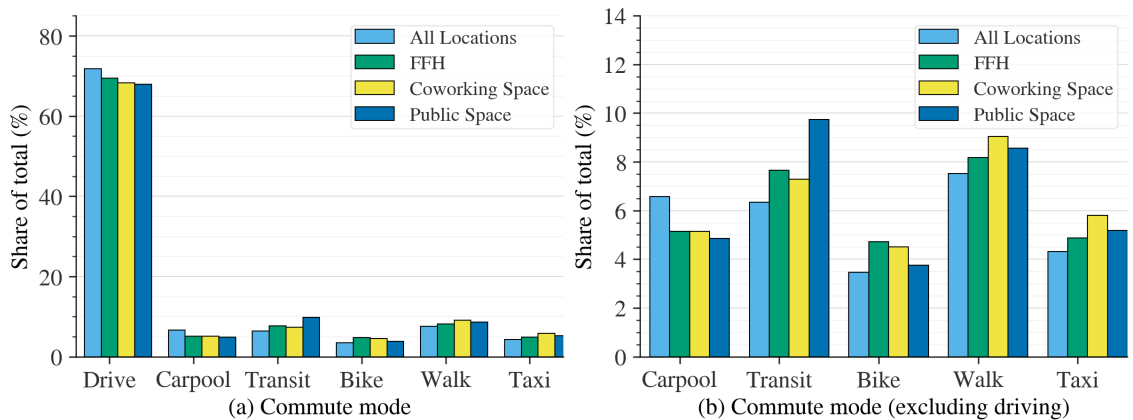
Nov 2021 - Jan 2023, N=70,029.

Figure 3-13: Reported transitions to and from sustainable commuting modes since 2019, by survey wave

Third place commutes

Mode choice distributions also differ for third places relative to overall commute mode shares and mode shares for trips to the employer’s business premises. Figure 3-14(a)

shows the breakdown of mode choice by work location, while Figure 3-14(b) shows the same data with driving excluded. The results for third place mode choices are quite remarkable, despite appearing similar to the average commuting mode in Figure 3-14(a). Looking at Figure 3-14(b), it is evident that at a national level, the mode shares for cycling, walking and transit are all higher than average commuting mode shares. Transit mode shares are much higher for remote work trips to third places, especially public spaces (54% greater than the average mode share) suggesting that third place use is associated with greater patronage of public transit systems.



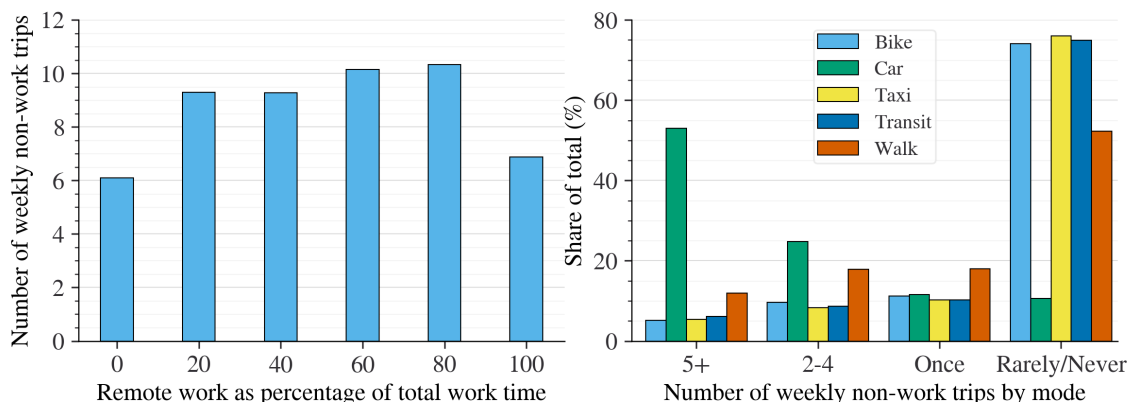
Jan 2022 - Apr 2022, N = 2,235.

Figure 3-14: Mode choice by work location, including (a) and excluding (b) driving

Non-work trips

As remote work has grown, non-work trips have become an increasingly important contributor to overall travel demand. Respondents were asked to provide their frequency of trips by mode for non-work trips during consecutive survey waves in the spring of 2021. By plotting the number of weekly trips against remote work share in Figure 3-15, three separate groups emerge: those who work entirely remote, those

with hybrid work arrangements, and those who do not work remotely at all. Interestingly, hybrid workers conduct the most non-work trips, and the balance of remote and non-remote work within the hybrid schedule does not appear to be strongly associated with the number of non-work trips. Fully remote workers make somewhat fewer non-work trips, while fully in-person workers make the fewest non-work trips of all. This may be due to their ability to go shopping, run errands or conduct social activities during work breaks or on the return trip from work. Looking at non-work trips by third place use also indicates that people who spend more time at third places also make more non-work trips.



Mar 2022 - Apr 2022, N = 5,681.

Figure 3-15: Non-work trips by remote work share (a) and frequency of non-work trips by mode (b)

With respect to mode choice, the overall trends are similar to the commuting trips, although the two are not directly comparable due to the different question formats. More than 50% of the population drives to conduct non-work trips at least five times per week, while more than 75% of the population rarely or never choose transit, walking or biking for non-work trips. These shares are somewhat different depending on the home location; urban residents are more likely to use non-car modes

for non-work trips than those who live in rural areas.

3.4.3 Departure time

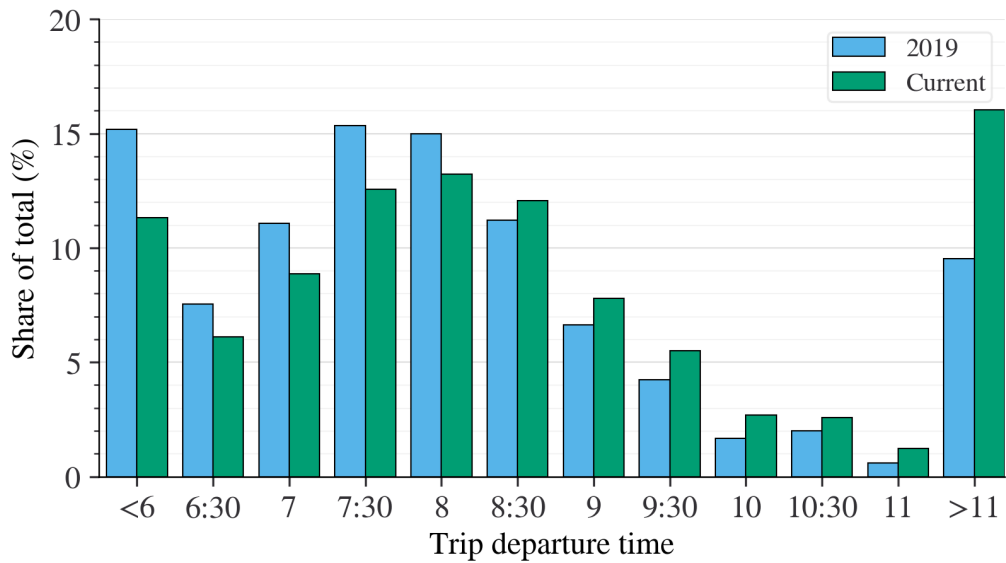
Flexibility related to the physical location of work has also translated into flexibility regarding the temporal aspect of work. The freedom to work at home allows remote workers to start working in the morning, then leave travel to the office or a third place after peak congestion has subsided. This section reviews the distribution of work trip departure times, how those departure times have changed since 2019, and how they vary by work location including third places.

Commuting departure times

Typical departure times have shifted later in the day relative to 2019, as shown in Figure 3-16. All departure times from 8:30 AM onward have become more popular, while all earlier departure times have become less popular. Notably, the portion of the population reporting departure times after 11:00AM has increased from 9.5% to 16%, likely reflecting an increase in the use of third places for remote work.

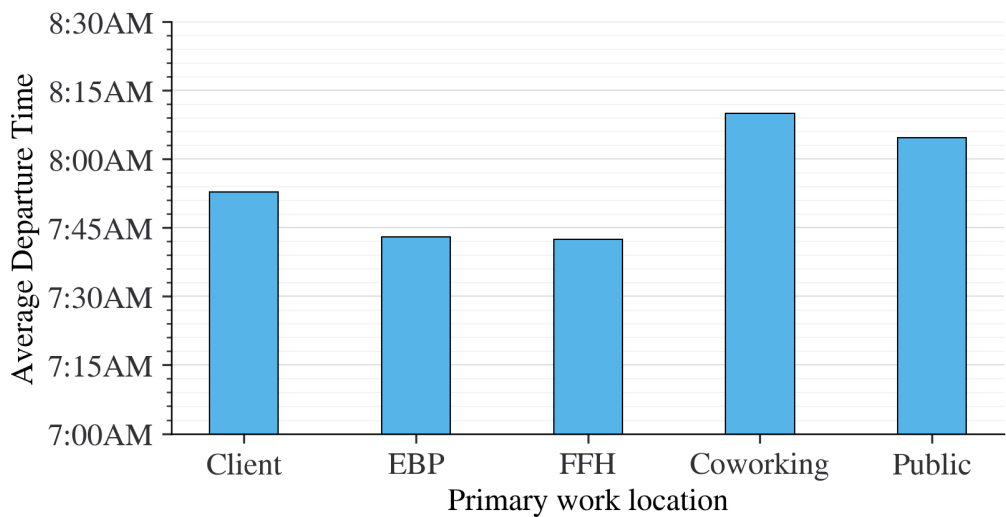
Third places

Departure times can also be differentiated based on the respondent's primary work location. As shown in Figure 3-17, departure times by work location reflect a similar trend to third place trip duration. Departure times for trips to co-working spaces specifically are similar to departure times for traditional commutes. Departure times for trips to public spaces and FFH, conversely, occur much later in the day on average.



Nov 2021 - Feb 2022, N = 16,723.

Figure 3-16: Work trip departure time changes from 2019 to current



Nov 2021 - Feb 2022, N = 16,723.

Figure 3-17: Departure times by primary work location

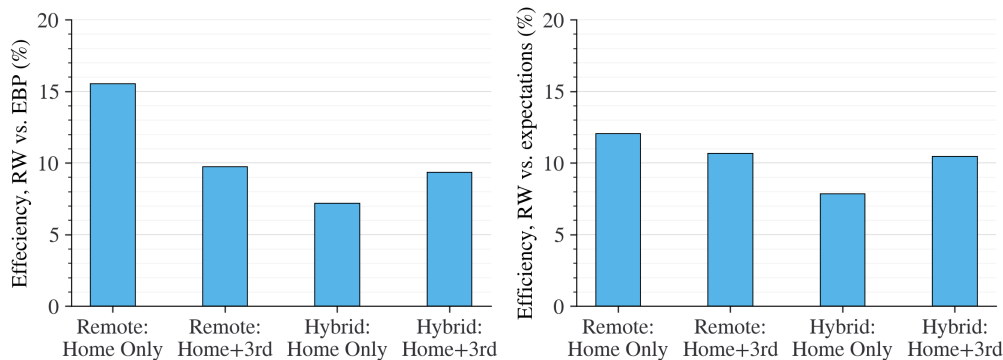
3.4.4 Productivity and travel

One of the unique benefits of the SWAA questionnaire is that it includes a comprehensive set of questions related to employment and productivity in addition to the travel questions. This section reviews how the travel choices described above are related to perceptions of productivity. These results connect the often disconnected fields of organizational behavior and transportation planning, demonstrating how remote work is inherently an interdisciplinary topic with complex trade-offs.

Figure 3-18 shows how perceptions of personal efficiency during remote work is closely associated with the choice of work location. In Figure 3-18(a), it can be observed that people who work fully remote and spend all of their remote work time at home (“Remote: Home Only”) have the highest self-reported efficiency relative to working at their employer’s business premises. People who work 100% remotely but choose to spend at least some of their remote work hours working at a third place (“Remote: Home+3rd”) still have positive perceptions of their remote work productivity, but less than that of people who work entirely at home. This may be because the choice to work at a third place is associated with a somewhat unproductive home work environment, meaning that third place work is not necessarily the cause of lower perceived efficiency. This trend may also be a result of people making work location choices based on factors other than maximizing productivity; third places can offer a more social environment, new networking opportunities or more comfortable surroundings.

The opposite trend is can be observed for remote workers with a hybrid remote work schedule where some of their time is spent working at their employer’s business premises. Hybrid workers who do not use third places for remote work perceive themselves to be less productive than people who split their working time between

their employer’s business premises, home and third places. This suggests that providing easily accessible third places for hybrid workers, who are the largest cohort of workers in the economy, could be associated with a small rise in work efficiency. Similar trends can be observed for efficiency relative to expectations in 2019, albeit with less variation.



Nov 2021 - Apr 2022, N = 9,012.

Figure 3-18: Perceived change in efficiency during remote work relative to working at EBP (a) and relative to expectations (b)

3.5 Discussion

The future of working arrangements and work-related travel patterns remains uncertain. Demand for remote work rose very quickly and appears durable in the medium term. New infrastructure, technology and services to support remote work are only just beginning to emerge and may increase the demand by making remote work more accessible and convenient for a wider range of tasks. Alternatively, a future economic downturn may shift the balance of power to employers, who typically favor less remote work than their employees would want. What is clear, however, is that remote work has a strong influence on travel behavior, including destination choice, mode

choice, and departure time. Furthermore, widespread remote work, by providing flexibility about where and when to work, connects travel demand with employment characteristics and attitudes to a much greater degree than ever before.

The SWAA results demonstrate a number of notable findings relative to the travel behavior of remote workers. Conducting remote work at a third place has become relatively popular and now accounts for over a third of all commuting trips. The characteristics of these trips depends on the type of third place; trips to co-working spaces are fairly similar to traditional commutes with respect to travel time, duration and departure time, but trips to FFH and public spaces are altogether different. Sustainable travel modes including walking, carpooling, public transit and cycling have lost mode share since 2019, but third place commuting trips are more likely to use these modes than the average commuting trip. Departure times for commuting trips have shifted later in the day overall, and the total number of non-work trips is likely to have grown, given that hybrid and fully remote workers conduct more non-work trips than people who do not work remotely.

This research has many important policy implications. The first is that it is essential to consider third place commutes when estimating overall travel demand. Many people assume that “working from home” and “remote work” are synonymous, but this research shows that remote work often happens outside the home, inducing a commuting trip with social externalities that differ from traditional commutes. Preferences for third places vary considerably, not just by the typical demographic and household characteristics that are often included in household travel surveys, but also by employer characteristics, task characteristics, employer remote work policies, coordination between colleagues, and attitudes towards remote work. Policymakers must consider these factors and how they might change over time when making investments in transportation infrastructure. Public transit agencies can also use

these insights to identify where third place trips are occurring and offer new services to make third places more accessible.

The SWAA findings also show that third place commutes are generally shorter, are less likely to take place during peak hours, and have a more sustainable mode share than typical commutes. Moreover, perceptions of work efficiency are greater among hybrid workers who use third places relative to those who only conduct remote work from home. These trends are despite the fact that land use, transportation systems and third place operators have not fully adapted to the rapid and unexpected rise in remote work. As shown in Figure 3-10, the average commuting trip to a third place remains relatively long. By making third places more accessible and evenly distributed across urban areas, policymakers can make third place commutes even shorter and thus more accessible by walking and cycling in the future. This could be especially beneficial for suburban areas, rural areas, and communities where the existing housing stock might not be conducive to working at home.

Third place trips are also more likely to take place during off-peak hours. Moreover, remote workers are leveraging the schedule flexibility provided by remote work to make other home-based trips during the workday. Public transit agencies should consider whether the rise of remote work in their service areas warrants a more even distribution of transit resources throughout the day, rather than focusing on peak hours. This would not just benefit remote workers and attract third place commuters to public transit, but also improve the overall transit experience for anyone working irregular or atypical hours. A more even distribution of service would also benefit those who conduct care, household maintenance, or leisure trips throughout the day.

This chapter explores an ongoing source of comprehensive data on travel, remote work, and employment. There are many future directions for this research. Developing statistical models to quantify the effects of different independent vari-

ables on travel behavior would be helpful in calibrating travel demand forecasting tools. Supplementing this aggregate longitudinal survey with travel diaries could also help to provide detailed information about third place trips, such as travel distance and carbon emissions. Further research is also needed into the factors that affect the choice of a specific third place for remote work. These are likely to include traditional factors such as travel time and accessibility by various modes, but also the types of amenities available, the work task to be accomplished, and the average occupancy. The data and code used for this analysis are freely available at <https://github.com/nick-caros/swaa-travel-analysis> for anyone interested in pursuing future research in this area.

Chapter 4

Enhancing travel behavior models to address the complexities of remote work

4.1 Introduction

The tremendous increase in remote work, catalyzed by the COVID-19 pandemic, has been widely reported in the literature. New mobility patterns have emerged as remote workers have been freed from the need to commute to their employer's business premises to conduct their work. Remote workers are frequently choosing to work outside of their homes, at libraries, co-working spaces, and cafés (known as “third places”), shifting demand from the downtown core to regional sub-centers. Over a third of all work trips in the United States in 2022 were trips to third places by remote workers. What has received less attention, however, is how the spatial and temporal flexibility afforded by remote work has upended traditional decision-

making processes and introduced new factors into the choice of commuting frequency and, importantly, commuting destination.

The traditional modeling framework for travel demand estimation needs several enhancements to capture the third place commuting behavior of remote workers. First, it must be able to capture the differences in behavior between people with fully remote work, hybrid work (some remote and some in-person), and fully in-person working arrangements. There is a tendency to estimate preferences for remote work as a linear or logistic dependent variable, but these three arrangements represent very different lifestyles. Second, travel demand models need to incorporate employment and attitudinal factors when estimating choices. Two people in the same role at the same firm might make very different decisions regarding work location based on their attitudes towards collaborating with colleagues, their self-perceived productivity at home, or their managers' policy towards remote work. Lastly, travel demand models would benefit from new approaches to modeling the destination choice for commuting trips to third places, a trip category that, until recently, was very rare and received no attention in the literature.

This chapter addresses these critical issues through the novel application of existing demand modeling methods to enhance existing travel demand models for the remote work era. Specifically, the benefits of three model enhancements are demonstrated:

1. Zero-one-inflated beta regression to improve the modeling of preferences for fully remote, hybrid, and fully in-person working arrangements;
2. Introducing exogenous variables representing remote work arrangements, employer remote work policies, employer characteristics, and personal attitudes towards remote work when modeling classical travel choices, and;

3. Theory-driven approaches complemented with location visitation data for predicting third place destination choices by remote workers.

These three steps are then integrated into a holistic framework for estimating third place commuting by remote workers. An extended example demonstrates how the framework can be applied in practice using data from a large national survey of remote work travel behavior in the U.S. that includes a wide range of questions about remote work and employment. Categories of remote work variables that influence third place commuting are summarized, and example questions are provided to facilitate future travel survey design. Models of remote work arrangement preferences, trip frequency, mode choice, and departure time for discretionary third place trips are all estimated using the techniques developed in this chapter. Implications of the model estimation results for practitioners and policymakers are discussed.

The models developed in this chapter address a significant and growing problem in travel demand modeling: how to provide an accurate estimate of the travel demand for discretionary commuting trips to third places. To the author's knowledge, this is the first comprehensive framework for estimating trip frequency, departure time, mode choice, and destination choice for third place trips by remote workers. In addition, it provides practical survey design considerations to improve data collection and model accuracy for the travel behavior of remote workers. Lastly, it is the first research effort to differentiate the third place commuting patterns of hybrid workers and fully remote workers, capturing important differences in behavior.

4.2 Literature review

Remote work was limited but steadily growing in popularity prior to the COVID-19 pandemic. Scholars have been interested in the travel choices of remote workers for

several decades, although most focused on the choice to work either at home or at the employer's business premises. Collectively, Shafizadeh et al. [176] and Shafizadeh et al. [177] provide an excellent overview of early empirical research on the topic. From the very beginning, Mokhtarian and Salomon have argued that attitudes and work-related constraints must be included in remote work choice models [46, 178, 48, 38, 179]. Peters et al. [180] explores preferences for remote work among a small sample of Dutch workers who used computers to conduct their work. The authors find that some work-related factors (e.g. amount of computer use) have a significant effect, but household and personal factors are less influential. Haddad et al. [181] use regression models to determine that personal factors and attitudes towards work and traffic are predictive of desires for part-day and full-day remote work. Tang et al. [43] finds that neighborhood built environment characteristics such as the density of restaurants play a role in the choice to work at home. Pouri and Bhat [41], Sener and Bhat [42], and Singh et al. [44] use different methodological approaches and data to model remote work desires and frequency, but neither considers the location choice for remote work. In an early exploration of preferences for different remote working arrangements a discrete choice, Mokhtarian and Ory [182] estimates a nested logit model that combines work schedule (full-time, part-time, unemployed) with remote work schedule (none, hybrid or full).

Other early surveys sought to understand differences in travel patterns between remote and non-remote workers. To evaluate non-work travel by remote workers, Su et al. [75] estimates a binary logit model for whether someone does or does not conduct remote work. The study finds significant differences in travel times and non-work travel patterns, although it does not differentiate between hybrid and fully remote workers. Asgari et al. [183] differentiates between full-day, regular part-day, and irregular part-day remote workers, finding that full-day remote workers travel

furthest for discretionary trips. Using a longitudinal panel survey, Mokhtarian and Meenakshisundaram [184] finds that frequency of remote work is correlated with the likelihood of continuing to engage in remote work over time. While these studies occurred when remote work was relatively rare, the early evidence indicates that remote workers exhibit heterogeneous travel behavior and that different remote working arrangements should be considered separately.

The studies described above assume that all remote work is conducted at home, and as a result, none were concerned with the location of remote work. However, some pre-2020 studies did consider the choice of remote work at “telecommuting centers”, shared office spaces for remote workers that are the predecessors of what are now called co-working spaces. Henderson and Mokhtarian [185] find that telecommuting centers can help to reduce travel relative to working at an employer’s business premises. Working at telecommuting centers was also found to be a relatively transient behavior, as workers were often called back to the office by their employers Varma et al. [186]. Preferences for telecommuting centers were explored by both Bagley and Mokhtarian [36] and Mokhtarian and Bagley [114] using different sets of data. The studies found that at the time, remote workers were relatively indifferent towards remote working at home or at a telecommuting center. Taking a more holistic approach, Vana et al. [39] develops a comprehensive joint model of work schedule, remote work frequency, and remote work destination choice between home and a telecommuting center. While it was published in 2020, Stiles and Smart [160] uses a large national dataset to investigate remote working at third places (cafés and libraries) between 2003 and 2017. Third place use was found to be limited overall, but also to have an observable effect on departure time and total daily travel.

Since 2020, there has been considerable interest in emerging preferences for remote work and the travel behavior of remote workers. Large surveys have been used

to identify trends in behavior in the United States [171, 3, 167, 170], Canada [163], Australia, [164], India [168], Spain [162], and elsewhere. Many studies have estimated choice models for remote preferences [166, 187, 165] and satisfaction Tahlyan et al. [173]. In an interesting paper, Asmussen et al. [169] estimates preferences for different hypothetical workplaces using survey data from workers in Texas. The home environment is found to have a strong influence on whether working at home or at a third place is preferred by remote workers. The study does not include an estimation of third place commuting frequency or destination choice. Using qualitative methods, Reuschke et al. [159] investigates the use of both co-working spaces and private homes as collective workplaces for remote work and the factors that contribute to location selection.

Finally, the last methodological section of this chapter provides an overview of possible approaches to disaggregate destination choice modeling for trips to third places by remote workers. Typical travel demand models estimate destination choice aggregated to pre-defined zones of an urban area (e.g. 188, 189). Destination choice estimation in the literature has often relied on o gravity-based models or utility theory-based models [190]. Vitins et al. [191] provides a comprehensive overview of both approaches. The competing destination model is another popular approach [192, 193, 194]. Bhat et al. [192] demonstrates how home-based work trips can be incorporated into a zonal competing destination choice model, but only considers the density of employment at the destination zone as an attractive factor. Rietveld and van Woudenberg [195] shows how destination utility for work trips can be estimated theoretically if strong assumptions are made about the distribution of possible work locations within a symmetrical urban area.

There has been little research into destination choice for work trips, given that work trips were almost always fixed. Many destination choice models have been

estimated in the past for tourism [196, 197] and for non-work discretionary trips [198, 199, 200]. These choices have many of the same principles as work trips, but they are fundamentally different they do not involve considerations around productivity, focus, or collaboration on work tasks. A few interesting papers have sought to improve the accuracy of work trip destination choice modeling. Vitins et al. [191] adds capacity limits to destination zones for general work trips, which is very relevant for work trips to third places. Clifton et al. [201] includes measures of pedestrian comfort in a utility-based destination choice model, finding that supportive pedestrian infrastructure has a significant and positive effect on the likelihood of a particular zone being chosen for home-based work trips.

Some work has gone into estimating values for the utility of destinations, a key component of utility-based destination choice models, using revealed preference data and simulation. Molloy and Moeckel [189] estimates destination utility at the zonal level for long-distance tourism trips using location-based services data. Taking a similar approach, Zhu and Diao [202] uses crowdsourced location visitation data to estimate destination utility for shopping and leisure trips. Yan and Zhou [203] model destination choice in a congested transportation network using a game theoretic approach, finding that it performs well at replicated observed intra-city flows between mobile phone coverage areas. Exploring the use of different workplace types, Shearman [204] shows how a “work location probability space” can be constructed from survey data, although the method is developed and applied for types of workplaces rather than specific geographic locations.

This chapter updates and extends the work of early remote work scholars by developing a model of remote work preferences and commuting frequency for several categories of third places rather than “telecommuting centers”. Unlike the previous research, it applies these methods to data from the widespread remote work era (2020

onward) to generate new insights that have immediate policy relevance. Lastly, it presents approaches to estimating destination choice for discretionary third place work trips at the disaggregate level, an area that has not been explored in the previous literature summarized above.

4.3 Methodology

This three-part section describes the overall modeling framework for estimating the frequency and destination of third place commutes. The first section develops a model for estimating working arrangement preferences using zero-one-inflated beta (ZOIB) regression to capture the lifestyle differences between fully remote work, hybrid work, and fully in-person work arrangements. The second section estimates three separate discrete choice models for the frequency, mode, and departure time of discretionary trips to third places. These models demonstrate how including remote work arrangements, employer remote work policies, employer characteristics, household characteristics, and personal attitudes improves prediction accuracy for third places travel behavior. The final section shows how theory and data can be combined to develop and calibrate a model for third place destination choice. The flowchart presented in Figure 4-1 illustrates the overall procedure and the role of each section.

The first two sections estimate models based on data from the SWAA. An extended description of the SWAA methods and data is included in Section 3.3; relevant details for this chapter are included here. It is a national survey, issued monthly since July 2020 to U.S. respondents over the age of 19 who earned at least USD \$10,000 in the previous year. The initial survey waves had 5,000 respondents per month, with more recent waves issued to 10,000 respondents. The result of the monthly SWAA is a pool of over 140,000 individual survey responses to a wide range of questions

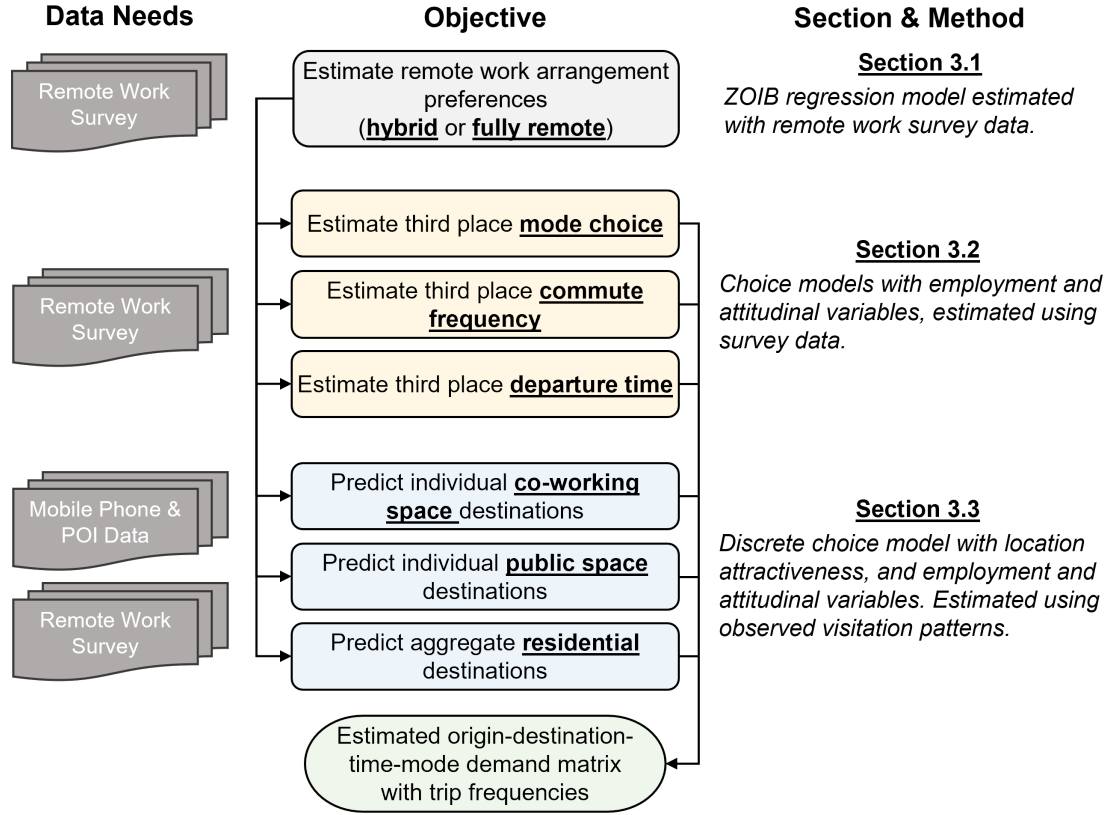


Figure 4-1: Flowchart illustrating the overall procedure for estimating third place travel behavior

about employment, remote work, and travel behavior. The results of the SWAA are consistent with other similar remote work surveys [175]. The entire catalog of past survey questions and the cumulative response data are available to the public online at <https://wfhresearch.com>. To ensure only quality responses are included in the dataset, attention check questions are used to filter out low-quality responses. The time range and sample size of the responses used to estimate the models in this chapter are indicated in the appropriate section below.

The specific details of the inputs for the models estimated in the following sec-

tions, including the survey questions and sample means, are available in Appendix B.

4.3.1 Mixed discrete-continuous remote work preferences

The first modeling enhancement proposed in this chapter is the use of ZOIB regression to determine the factors that contribute to preferences for different remote work arrangements. There are three possible arrangements: fully remote work, fully in-person work, and hybrid work (a scheduled or flexible mix of remote and in-person work). Remote work arrangement preferences, if realized, have a direct influence on daily travel patterns and overall demand as in-person work provides a spatial and temporal anchor for daily activity schedules.

Each of these arrangements is associated with important lifestyle and household considerations. Fully remote work frees the worker from the need to live within a reasonable commuting distance from a fixed workplace, allowing them to choose a home location based on non-work factors. They must also ensure that their home environment is suitable for remote work, or find an alternative third place work location. A fully in-person worker does not need a productive remote work environment, but is more sensitive to commuting distance. Hybrid workers need both a suitable work environment near home and relatively convenient access to their workplace, but may choose to accept a longer commute than a fully in-person worker or a standard remote work environment in order to satisfy other home location preferences. These lifestyle differences are reflected in the distribution of preferences for remote work (as a percentage of total worked hours) collected from the SWAA survey. The distribution of observed remote work, employee preferences for remote work, and employer plans for remote work all exhibit inflation at the zero and one levels, as shown in Figure 4-2.



Survey waves: November 2021 - December 2021, N = 7,407.

Figure 4-2: Distribution of observed remote work share, employee preferences for remote work, and employer plans for remote work as a percentage of total worked hours

Surveys of remote work preferences often ask respondents the percentage of days that they would prefer to work remotely (e.g. 3). In model design, this can be treated as a continuous dependent variable or as a discrete choice between three options (fully remote, fully in-person, and hybrid). As noted earlier, there are significant lifestyle differences between 0% remote work, 1 - 99% remote work, and 100% remote work. Discontinuities would be expected at the extreme ends of the distribution. Traditional linear and logistic regression models for continuous dependent variables are therefore not appropriate for this problem. Similarly, a discrete choice model would not capture the relationships between the input variables and preferences for different remote work splits within the hybrid work arrangement (e.g. 1 day per week vs. 4 days per week). These splits define the number of commuting days and therefore must be captured in the travel demand modeling process.

The ZOIB regression model was recently developed to handle mixed continuous-

discrete distributions that have a probability mass at both the zero and one levels. Despite its evident usefulness for modeling this type of data, it has rarely been applied to remote work preferences or any travel demand modeling topics in the literature [205, 206, 207]. The general class of zero-or-one inflated beta regression models and estimation methods are described in Ospina and Ferrari [208]. The ZOIB model is a mixture of three models estimated simultaneously. The first is a logistic regression model to predict whether an outcome y_i takes an extreme value, $y_i \in \{0, 1\}$, represented by $p_{0,1}$. There is another logistic regression model to predict whether the value is 1, conditional upon the outcome being an extreme value, represented by p_1 . Finally, there is the beta regression model that estimates the parameters of the beta distribution (mean μ and precision ϕ) for the non-extreme outcomes. The density function of the beta distribution is represented by $f_{\text{Beta}}(y_i)$, with mean μ . The estimated ZOIB parameters can therefore be used to determine the probability that an outcome is zero (p_0), the probability that an outcome is one (p_1), and the probability density of outcomes between zero and one. The probability density function $f(y_i)$ is then given by the expression:

$$f(y_i) = \begin{cases} p_{0,1}(1 - p_1) & \text{if } y_i = 0 \\ p_{0,1}p_1 & \text{if } y_i = 1 \\ (1 - p_{0,1})f_{\text{Beta}}(y_i) & 0 \leq y_i \leq 1 \end{cases} \quad (4.1)$$

Applied to remote work preference data, ZOIB allows estimation of, with a single model, the effect of any independent variables on preferences for fully remote work, fully in-person work, and hybrid work, as well as the effect on the remote work split preferences within hybrid work.

A sample SWAA responses from May 2022 (N=2,128) are used to demonstrate

how ZOIB regression can be used to generate insights about remote work preferences. The May 2022 time period was chosen for analysis as it represents a time when attitudes towards remote work (RW) and the public health threat posed by COVID-19 had begun to stabilize. The May 2022 SWAA questionnaire also includes an interesting set of questions that can be tested as potential explanatory variables in the ZOIB model. The model parameters were estimated with Bayesian estimation methods using the `brms` package for R [209].

Explanatory variables including demographic factors, household location, job task characteristics, and attitudes towards remote work were tested for their impact on remote work preferences. For parsimony, insignificant variables were gradually removed from the model. The final continuous and categorical explanatory variables, including their distributions across the sample, are described in Table B.3. The results and significant parameters for the ZOIB model are shown in Table 4.1. The reference category for the categorical independent variables are 1) rural home location, 2) no children under 5, and 3) remote work (RW) perceptions are better among almost all acquaintances.

In order to provide a baseline for comparison, the “Reference” row shows the results for a hypothetical respondent that falls within each of the reference categories and has the sample mean values for each of the continuous variables. The expected preferences distribution of someone with an urban home location and one more year of education than the mean can be calculated by taking the sum of the first three numerical rows in the table. The mean values for each variable are reported in Table B.3.

Interpreting the various model parameters illustrates the value of ZOIB regression. The first column, $P(x = 0)$, is the effect of the independent variable on the probability that someone will choose a fully in-person arrangement. The directions

Table 4.1: Summary of ZOIB regression results for remote work arrangement preferences

Variable	$P(x = 0)$	$P(x = 1)$	$P(0 < x < 1)$	μ	$\mathbb{E}[x]$
	<i>No Remote</i>	<i>Fully Remote</i>	<i>Hybrid Work</i>	<i>Hybrid Remote %</i>	<i>Combined Effect</i>
Reference	35.33%	41.33%	23.34%	57.98%	51.72%
Education (years)	-2.58%**	1.29%**	1.29%**	0.89%**	1.89%**
Urban home location	-7.11%*	4.59%*	2.52%*	-	5.53%*
Child under 5	-10.57%*	5.72%*	4.34%*	-	7.34%*
Employer size (per 100)	-0.04%*	0.56%*	-0.52%*	0.00%*	0.37%*
Computer task % of work	-0.10%***	0.14%***	-0.03%***	0.06%***	0.13%***
All meeting %	0.17%*	-0.13%*	-0.04%*	-	-0.14%*
Coworker meeting %	-0.17%***	0.11%***	0.06%***	0.09%***	0.14%***
RW better for most	2.65%***	-6.62%***	3.97%***	-5.81%***	-5.77%***
RW better for some	5.42%*	-8.38%*	2.96%*	-6.45%*	-7.91%*
RW no change	13.49%*	-10.27%*	-3.22%*	-4.88%*	-11.65%*
RW worse for some	-	-	-	-7.29%*	-0.51%*
RW worse for almost all	16.78%*	-11.82%*	-4.96%*	-	-13.67%*

* denotes a 95% confidence level, ** a 99% confidence level, *** a 99.9% confidence level. The symbol - replaces parameters below a 95% confidence level

of the coefficients are not entirely surprising. Higher education, urban home location, having a young child at home, working for a large company, and spending more time on a computer all lead to a greater desire for remote work. Every additional year of education is predictive of a preference for 2% more remote work on average, so someone with a four-year college degree would prefer about 7.5% more remote work than someone with the exact same lifestyle but who did not go to college. The same variables also increase the likelihood that someone will prefer fully remote work. Interestingly, they have opposing effects on preferences for hybrid work. Working for a large company and spending time on a computer decrease preferences for remote work, although the effect is relatively weak. Education, urban living, and young children increase preferences for hybrid work, however. The overall magnitude of the young child effect is greater than the urban home location effect, indicating that par-

ents of young children in rural areas would like to work remotely more than childless adults in urban areas.

Perceptions of remote work among one's social group also play a strong role in determining preferences for remote work. Relative to the reference (perceptions of remote work increased among almost all), all other responses have a strong negative effect on preferences for fully remote work. If perceptions of remote work have still improved overall, just not among the entire social group, people are likely to replace preferences for fully remote work with preferences for hybrid work. If perceptions of remote work have worsened, people are likely to replace preferences for fully remote work with preferences for fully in-person work. These attitudes also have a strong negative effect on the amount of remote work preferred by hybrid workers. By contrast, more education increases the percentage of remote work preferred by hybrid workers. These nuances, which have a substantial impact on travel demand, are lost when treating remote work preferences as either a continuous or categorical variable.

4.3.2 The influence of employment, household, and attitudinal variables

The second model design step that is essential for estimating remote work travel behavior, especially discretionary third place trips, is the inclusion of individual-specific variables related to remote work arrangements, employer remote work policies, employment characteristics, household characteristics, and personal attitudes towards remote work. Before remote work became widespread, these questions were largely irrelevant for modeling work travel, as workplaces and work schedules were fixed for the vast majority of travelers. Now that remote work represents a substantial share of all work hours, many people have the flexibility to choose complex daily activity

patterns involving work trips. How, when, and where people choose to make discretionary work trips can ultimately affect the overall demand for travel. This section shows how different remote work-related exogenous variables, in addition to traditional demographic and geographic variables, can improve the modeling accuracy for three entirely different components of third place travel: trip frequency, departure time choice, and mode choice. In addition, it recommends a specific language to use for common survey questions to allow for comparison between surveys with different samples or sampling periods.

Five categories of remote work-related exogenous variables are incorporated into the travel behavior models in this section. Examples within each category are presented in Table 4.2. Each of the 24 questions is recommended for inclusion in future travel surveys; future surveys may adopt the detailed language and response options presented in Tables 4.2 and B.4 - B.6 to facilitate the reproduction and comparison of results across future surveys. Many of these questions are typical for broad economic surveys (in fact many are extracted directly from the SWAA survey) but they are rarely if ever included in travel surveys.

The categories are assigned letters so that individual questions may be identified using the category and the question number (e.g. A1 for the first question in the remote work arrangements category). The first category of remote work variables is remote work arrangements. As discussed in the previous section, hybrid, and fully remote arrangements reflect very different lifestyles, and could therefore be expected to influence travel behavior for third places. Fully remote workers may prefer to use third places more frequently, as they have fewer face-to-face interactions with colleagues than regular hybrid workers. Unlike fully remote workers, hybrid workers who endure severe congestion during commutes to their employers' business premises may be discouraged from driving when they travel to third places. Remote work

arrangements are incorporated into all four of the travel behavior models estimated below.

Table 4.2: Categories and recommended language for remote work-related questions that affect travel behavior

Category	Recommended question language
Remote work arrangements (A)	<ol style="list-style-type: none"> 1. Last week, how many hours did you work: a) at your employer’s primary business premises or a client site; b) remotely. 2. How many hours per week would you prefer to work: a) at your employer’s primary business premises or a client site; b) remotely. 3. Do the days of the week that you work remotely change by week?
Employer remote work policies (B)	<ol style="list-style-type: none"> 1. Does your employer require you to work the same in-person days as your direct manager? As your team members? 2. Who sets your remote work schedule? a) you, b) your manager, c) senior management. 3. Does your employer monitor compliance with remote work policies? 4. Does your employer offer incentives or subsidies for working at third places (e.g. pays for a co-working subscription)? 5. Would your supervisor prefer to end remote working in the future?
Employment characteristics (C)	<ol style="list-style-type: none"> 1. How many employees work for your current employer? 2. How many people belong to your main work team? 3. Do you directly manage or supervise other employees? 4. Which of the following best describes your employment status? a) Full-time job; b) One or more part-time jobs; c) Self-employed; d) Freelancer or gig worker. 5. What percentage of your time is spent on tasks that cannot be done remotely? 6. What percentage of your time is spent collaborating with colleagues?
Household characteristics (D)	<ol style="list-style-type: none"> 1. How would you rate your home internet quality? 2. At home, do you have your own room (not bedroom) to work in? 3. Do you live with your partner and/or children? 4. Do you currently live with one or more roommates?
Remote work attitudes (E)	<ol style="list-style-type: none"> 1. How does your efficiency working remotely compare to your efficiency working at your employer’s business premises? 2. How have perceptions of remote work changed among people you know? 3. How would working one more day of remote work than your co-workers affect your chance of promotion? 4. How much of a pay raise would you value one additional day of remote work (hybrid workers)? 5. How much of a pay cut would you value the same as one additional day of in-person work (fully remote workers)? 6. Do you continue to practice social distancing at work or in social settings (e.g. on public transit)?

The second and third types of questions are about employer remote work policies and employment characteristics. Employer remote work policies could include requirements to coordinate in-person work days with a supervisor or colleagues, or a supervisor who discourages remote work. Such policies could be expected to influence the frequency of third place trips and the types of third place chosen for remote work. Employment characteristics, such as the size of the company or whether someone directly manages others, could have a similar effect. Large companies may invest more in digital communications tools, making it easier for their employees to work from third places. Managers might be more inclined to mentor others by coordinating in-person working days or organizing collaborative remote working days at a third place. However, all else being equal, employment characteristics and policies are not expected to affect mode choice and are therefore not included in the mode choice model.

Household characteristics could certainly influence the choice of when and where to conduct remote work. Having a young child at home or living with roommates does not impact a traditional commute, but may make remote workers more or less inclined to visit third places. Departure times for third place trips could be affected by a child's school or daycare schedule. Similarly, personal attitudes towards remote work, perceptions of personal efficiency during remote work, and attitudes towards the risk of COVID-19 may influence the frequency, timing, and destination of third place trips. Like employment variables, these additional household and attitudinal variables are not expected to have an independent effect on mode choice and are therefore excluded from the mode choice model.

Logistic regression (logit) models are used for mode choice, departure time choice, and trip frequency. As is common in the literature, mode and departure time are modeled using multinomial logit (MNL), while trip frequency, which is an ordered

discrete dependent variable, is modeled using an ordered logit (OL) model structure. The MNL model assumes that the utility of each alternative has both deterministic and random components. The deterministic component is a weighted combination of the independent variables. Let x_i^n be the n^{th} independent variable for alternative i with coefficient β_i^n , and x_i the vector of all such independent variables. The random utility deviate ε_i , is then added to the deterministic utility term to get the random utility. The random utility for alternative i , represented by U_i , is given by:

$$U_i(x_i^n) = \sum_n \beta_i^n x_i^n + \varepsilon_i \quad (4.2)$$

In the MNL model, ε_i is assumed to be independent and identically distributed across the alternatives with an extreme value distribution. The probability of choosing alternative i is then given by:

$$P(y = i|x_i) = \frac{e^{\sum_n \beta_i^n x_i^n}}{\sum_i e^{\sum_n \beta_i^n x_i^n}} \quad (4.3)$$

The OL model, used for to estimate the choice of trip frequency, is an extension of the MNL model that accounts for the ordinal nature of the available alternatives. The observed ordinal choice variable y is a function of a different continuous latent variable denoted by y^* that has various thresholds τ_i . The value of y^* is computed using a similar expression as the utility function in the MNL model:

$$y = \sum_n \beta^n x^n + \varepsilon \quad (4.4)$$

Then, the observed variable y depends on the value of y^* relative to the thresholds. Let there be M alternative discrete values for y . The value of y is determined

according to the following expression:

$$y = \begin{cases} 0 & \text{if } y^* \leq \tau_1 \\ i & \text{if } \tau_i \leq y^* \leq \tau_{i-1} \\ M & \text{if } y^* \geq \tau_{M-1} \end{cases} \quad (4.5)$$

Then the probability $P(y = i)$ is the probability that y^* is in the i^{th} range. When ε has a standard logistic distribution, the probability calculation reduces to:

$$P(y = i) = \frac{1}{1 + e^{\tau_i + \sum_n \beta^n x^n}} - \frac{1}{1 + e^{\tau_{i-1} + \sum_n \beta^n x^n}} \quad (4.6)$$

Additional details of the derivation of these commonly used models are omitted here for brevity; Small [210] provides extensive discussion of each model with application examples. Each of the logit models is implemented using Biogeme 3.2.11 for Python [211]. The unknown parameters are estimated. The models are summarized in B. Exogenous variables and their descriptive statistics are also described for each model.

Responses from the November 2022 - January 2023 waves SWAA survey, the most recent data available, are used to estimate the models for trip frequency and departure time. Due to changes in the survey design, mode choice for third place is estimated from earlier waves of the survey, January 2022 to April 2022. Only responses by employed respondents with hybrid or fully remote schedules were included. In addition to the remote work-related variables described above, each model includes demographic variables (income, gender, age, education), commute time, and home location category (rural, suburban, or urban). Baseline models are also estimated without including the new remote work variables for comparison.

Third place departure time

The model estimation results for the third place departure time MNL model are presented in Table 4.3. The alternative specific constant for <7:00 is set to 1 for scaling. The columns of the table represent the departure time categories (in 24-hour clock format). Many of the remote work and employment-related variables are found to be statistically significant predictors of certain departure times. Moreover, the model fit is improved relative to the baseline model where only demographic, geographic, and household variables are included. The improvement in model fit relative to the baseline is found to be statistically significant at a 99.9% confidence interval using the Wilks likelihood-ratio test [212].

The model estimation results provide interesting insights into the impact of remote work characteristics on departure time. Having a hybrid remote work arrangement is associated with a greater likelihood of departing during the traditional morning peak hours relative to those who work entirely remotely. Those who work at both very large and very small employers are more likely to depart during the traditional lunch hour, perhaps as part of splitting their work day into working from home in the morning and working at a third place in the afternoon. Remote workers who manage others are much less likely to depart for a third place in the middle and late afternoon. Meanwhile, people whose boss is planning to end remote work in the future are much more likely to visit third places late in the day when meetings are more likely to have wrapped up for the day. Remote workers who prefer to continue social distancing are more likely to avoid congested commuting times, while those who report higher efficiency during remote work are most likely to depart for third places very early or at lunchtime.

Table 4.3: Model estimation results for third place departure time

Variable	<7:00	8-9	10-12	12-14	14-16	>16:00
Constant		3.303***	1.934**	3.102***	2.166***	1.783*
Female	0.471*	-0.424**				
Age (years)	0.041**					0.037**
Education (years)			0.108***			
Urban home						-0.611*
Suburban home		-0.394*				
Live with partner/child (D3)						-0.572*
Live with roommates (D4)	2.069***		1.111**			
Hybrid arrangement (A1)		0.337*				
Large employer (C1)				0.516**		
Small employer (C1)				0.527**		
Manage others (C3)					-0.627**	-0.695**
Boss prefers no RW (B5)						0.844**
Keep social distancing (E6)					0.537*	
Remote work efficiency (E1)	0.018**			0.012*		
Log-likelihood				-2891.06		
Log-likelihood of baseline model				-2919.96		
Likelihood ratio				57.80		
Difference in number of estimated parameters				10		
Likelihood ratio test				Reject null hypothesis***		

Note: columns for **7-8** and **9-10** are omitted as only the constants were found to be significant (**7-8**: 3.136***, **9-10**: 3.373***)

* denotes a 95% confidence level, ** a 99% confidence level, and *** a 99.9% confidence level.

Third place trip frequency

Next, the estimation results for the third place trip frequency ordinal logit model are shown in Table 4.4. The model of third place trip frequency, like the model of third place departure time, includes several significant employment-related variables, and the model fit is improved relative to the baseline model where remote work and employment variables are excluded.

Fewer of the employer variables were found to be significant in the trip frequency

Table 4.4: Model estimation results for third place trip frequency

Variable	Coefficient
Threshold 1	0.300***
Threshold 2	0.603***
Threshold 3	1.126***
Threshold 4	1.478***
Female	-0.411***
Age (years)	-0.047***
Education (years)	0.069**
Urban home	0.392***
Live with partner/child (D3)	0.298**
Large employer (C1)	-0.411***
Small employer (C1)	-0.426**
Manage others (C3)	0.764***
Log-likelihood	-2524.64
Log-likelihood of baseline model	-2568.64
Likelihood ratio	88.00
Difference in number of estimated parameters	3
Likelihood ratio test	Reject null hypothesis***

* denotes a 95% confidence level, ** a 99% confidence level, and *** a 99.9% confidence level.

model relative to the departure time model. Yet the estimation results do find that people working for either large or small employers make fewer trips to third places relative to those working for moderately-sized employers (50 - 499 staff). This may reflect that small firms, especially those founded recently, are less likely to have a dedicated office and might offer co-working subscriptions as an alternative. Large firms, on the other hand, may have more resources to address concerns about company culture and employee well-being by subsidizing occasional in-person meetings and team-building days at third places. Moreover, people in management positions are found to make more trips to third places. This result might be indicative of managers choosing to meet with their subordinates at third places on occasion, or it may be that those in management positions generally have more flexibility and

disposable income relative to those who have no direct reports.

Third place mode choice

While the choice of travel mode when visiting third places is unlikely to be influenced by employer size or a manager’s attitude towards remote work, the model results in Table 4.5 show that it is influenced by the type of remote work arrangement. An MNL model was estimated for mode choice when visiting third places, with remote work arrangement as an exogenous variable. Remote work arrangement was found to be statistically significant in the choice of public transit and taxi for third place trips, and including these variables was found to improve the model fit with a 99.9% confidence level.

Table 4.5: Model estimation results for third place mode choice

Variable	Drive	Carpool	Transit	Bike	Walk	TNC
Constant						- 1.672***
Female		0.445**	0.229*		0.323*	
Age (years)	0.018***	-0.032***				
Education (years)	0.106***			-0.060***		0.098***
Commute time (min)			0.004*			
Urban home	-0.569***				-0.627***	
Suburban home		0.641**		0.456*		
Hybrid arrangement (A1)			-0.220*			-0.266*
Log-likelihood				-4073.11		
Log-likelihood of baseline model				-4076.80		
Likelihood ratio				7.37		
Difference in number of estimated parameters				2		
Likelihood ratio test				Reject null hypothesis***		

* denotes a 95% confidence level, ** a 99% confidence level, and *** a 99.9% confidence level.

The alternative specific constant for the drive mode is set to 1 for scaling. Relative

to a fully remote arrangement, hybrid workers are less likely to use transit and taxis or Transportation Network Companies (TNCs) such as Uber to access third places. The key lifestyle difference between hybrid and fully remote workers is that hybrid workers must maintain convenient access to their employer’s primary business premises. Fully remote workers who do not commute on a routine basis might be more likely to allocate their travel budget towards relatively high-cost taxis or TNCs for occasional third place trips. It is not entirely obvious why hybrid workers would have a lower likelihood of using transit to access third places, although Table 4.3 shows that hybrid workers are more likely to travel to third places during the AM peak hour. The possibility of crowding on transit vehicles during that time might make transit a less desirable mode.

4.3.3 Predicting discretionary work trip destinations

The two previous subsections have shown how new model types and modeling variables can be used to improve estimates of travel behavior associated with third trips, but did not address destination choice for third place trips. Previously, travel behavior models relied on the stability and mandatory nature of the commute or school trip destination to anchor daily and weekly activity schedules. A single question on a travel survey asking the respondent to enter the ZIP or address of their work location provided sufficient information to model the impact of commuting on carbon emissions and congestion. With the rise of remote work, however, a large fraction of commuters have the flexibility to choose their work location from many possible alternatives on a daily basis. As a result, work trips have become similar to discretionary trips, where even the set of alternative destinations under consideration is difficult to estimate. Third place destinations recorded within a travel diary may change entirely

the week or month after the survey is completed, making survey-based methods for modeling work trips insufficient for third place trips.

Traditional models of discretionary trips involve a measure of “attractiveness” for individual destinations or spatial clusters of destinations (e.g. 201). The attractiveness of a third place is influenced by the same factors as other discretionary trip destinations, such as familiarity and proximity to complementary destinations. Unlike typical discretionary trips, however, third place destination attractiveness is also influenced by work-related amenities (e.g. Wi-Fi quality). This subsection reviews the unique considerations associated with destination choice modeling for third place trips: the attractiveness of third place types, the influence of employers and attitudes towards remote work, and challenges in collecting data for calibration. As in the previous subsection, the importance of accounting for remote work and employer-related factors when estimating third place travel behavior is emphasized. It also demonstrates how revealed preference mobility patterns and Point of Interest (POI) data can be leveraged to inform and calibrate choice models for third place trips. The methods described in this subsection are applied to practical problems as part of the case studies in Chapters 5 through 8.

Developing a utility-based discrete choice model for third place trip destinations involves three important steps: determining the attractiveness of a destination, adding individual-specific variables, and finally, estimating the model using observed or stated behavior. These components are illustrated in Figure 4-3.

Functions of the attractiveness of third places, unlike those for other discretionary trips, should include remote work amenities in addition to the factors related to travel such as accessibility and travel cost. Remote workers are likely to consider the availability of laptop chargers and a strong Wi-Fi connection, noise levels, and the explicit (e.g. subscription fee for a co-working desk) or implicit (e.g. cup of

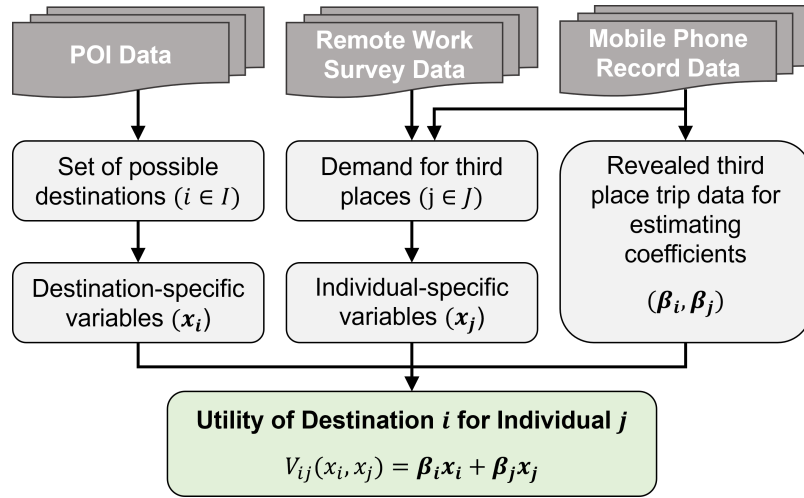
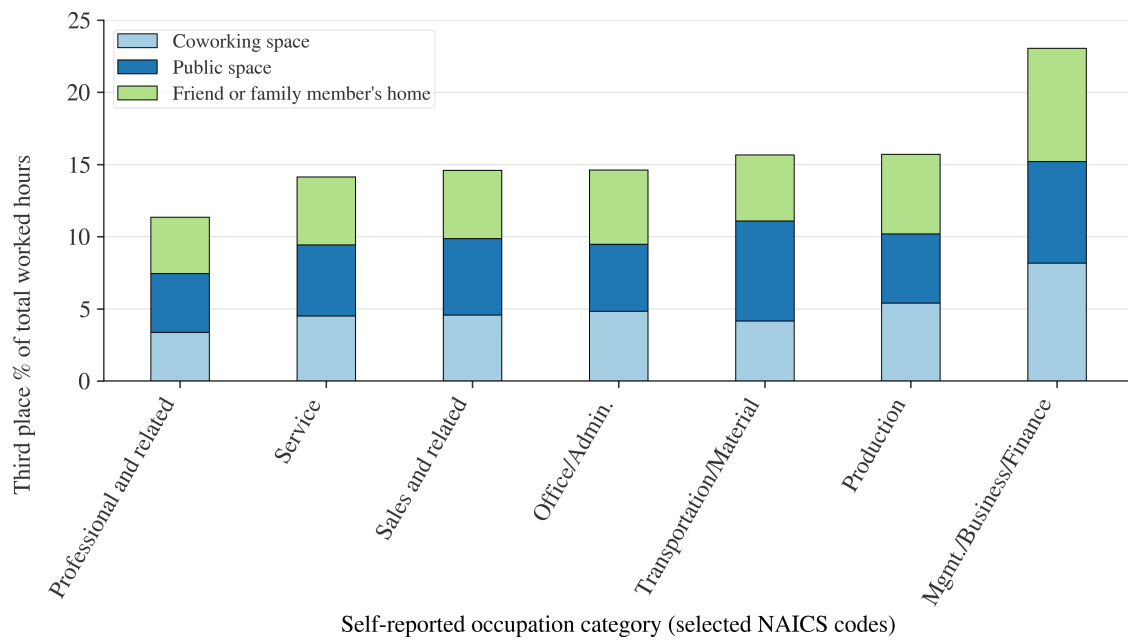


Figure 4-3: Flowchart illustrating the different components and data sources proposed for estimating third place destination choices

coffee) cost of admission as part of the attractiveness of a third place. Information about third place amenities can be difficult to obtain and verify, but crowdsourced and commercial POI data are potential sources that are increasingly being used to collect location amenities for destination choice modeling [213, 214]. In the absence of location-specific data, the presence of typical amenities could also be inferred from the type of third place; libraries are quieter than cafés, co-working spaces are more expensive but almost certain to have Wi-Fi, etc. An attractiveness measure for each location type is likely to provide additional accuracy relative to a single attractiveness measure for all location types while avoiding the data requirements and computational complexity associated with location-specific attractiveness variables.

The individual-specific variables needed for an accurate third place choice model are different from those needed for other trip purposes. For example, survey data shows a strong variation in third place type choice across occupations, as shown in Figure 4-4. The employment variables described in Section 4.3.2 should therefore be

included whenever available. Details about job tasks are also likely to influence destination choice. A remote worker whose job consists primarily of high-focus individual tasks might prefer quiet libraries over bustling cafés. Job characteristics also affect location choice through the decision to work at third places with others. Someone whose role involves developing creative ideas with their colleagues could be expected to choose third places that are amenable to group collaboration. They may also be less sensitive to travel time when choosing a third place if the destination choice for group collaboration is negotiated between group members. Lastly, employer policies, such as reimbursement for remote work equipment or co-working subscriptions would certainly influence third place location choice.



Survey waves: November 2021 - June 2022, N = 27,364.

Figure 4-4: Differences in third place use by occupation category

The final challenge in modeling third place destination choice is estimating models using ground truth data. Travel diaries and other household travel surveys are

certainly helpful and should be updated to include third place work as a trip purpose. These surveys can be expensive to administer, however, and it is not feasible to collect them on a continuous basis. Like other discretionary trips, third place trips may not be part of a routine and therefore may not be captured by a single day or week of travel patterns.

Mobile phone records and other location visitation data can be used as a source of spatio-temporal information about trips to third places, however. These datasets often cover longer time periods, allowing them to capture routine and exploratory visits to third places. Extracting third place trips from the set of all trips in a mobile phone record database is the primary challenge. Location type and the duration of visits can be used to isolate third place trips, however.

Third place trips to co-working spaces are relatively straightforward to identify, as co-working spaces do not have an alternative purpose. Trips to co-working spaces that occur frequently at the same time and same day of the week over a certain period could be filtered out as they are likely to be indicative of someone for whom the co-working space is their employer's primary business premises or an employee of the co-working space operator.

Third place trips to public spaces are more difficult to isolate from other trips to the same location. Coffee shops, restaurants, and libraries may be visited by remote workers seeking a third place, but they are also visited by many other customers whose primary purpose is not work. Applying a minimum trip duration threshold for third place trips to public spaces is recommended. Additionally, a travel distance threshold can be helpful. People visiting coffee shops several hours' drive from their homes are much more likely to be tourists stopping for a break than remote workers electing for an extreme commute to a third place. Finally, time-of-day and day-of-week filters are a useful tool; a three-hour trip to a restaurant on a Saturday evening

is not likely to be a third place trip, but a visit from 1 PM - 4 PM on a Tuesday could be related to work. Filtering characteristics are summarized in Table 4.6.

Table 4.6: Characteristics that can be used to isolate third place trips

Third place type	Trip characteristic
Co-working space	Time of day
	Day of week
	Consistent weekly pattern
Public space	Time of day
	Day of week
	Trip duration
	Travel time

The final third place type is the homes of friends and family members. Trips between residential locations are less likely to be included in mobile phone records for privacy purposes, making them difficult to elicit from widely available data sources. In addition, they are challenging to differentiate from other trip purposes using temporal characteristics. A visit to a friend’s home to work remotely together could have the same duration, time of day, and day of the week as a purely social trip to the same location. Trips during traditional work hours are somewhat more likely to be work-related, but not all remote workers are working full-time jobs that take place during traditional work hours. To overcome this issue, it is recommended that future travel surveys include a differentiation of trip purposes between social trips and trips to conduct remote work with friends and family. In the meantime, the travel demand for third place trips to the homes of friends and family can be approximated through the distributions of stated preference data for trip distance, mode choice, departure time, and trip duration.

To summarize, the utility functions for destination choice models for third place trips should include a measure of destination attractiveness, determined by the third

place type and possibly the characteristics of individual third places if available, as well as employer and job task-related individual-specific variables. The model can be estimated for co-working and public space trips using revealed preference data from mobile phone records, offered by commercial providers such as SafeGraph. Third place trips can be isolated from other trip types using destination characteristics as well as the time of day, day of the week, and duration of the visit. Third place trips to the homes of friends and family members cannot yet be identified through surveys or available mobile phone records, and should be estimated at an aggregate level.

Applications of this approach to destination choice modeling for discretionary work trips are demonstrated in the next four chapters of this dissertation. In Chapter 5, mobile phone-based visitation data is used to create a probability distribution for the destinations of co-working and public space trips. Then, in the absence of a dedicated travel survey for third place trips, the destinations of general “socializing” trips from a previous travel survey are considered as possible destinations for discretionary work trips to the homes of friends and family members. Additional details are provided in Section 5.2.

In order to model the ride-pooling service for trips with flexible destinations (which includes discretionary work trips) in Chapter 6, an “attractiveness” measure is generated for each potential trip destination. The case study involves a pool of remote workers seeking to travel to a co-working place. Given that this is a hypothetical future scenario for destinations with no observed demand data available, the attractiveness of each destination is drawn from a uniform random distribution. In the future, either revealed demand data for each destination or survey data could be used to inform a quantitative measure of the attractiveness of individual co-working places for each customer.

In Chapter 7, the capacity of a public transit network is evaluated assuming

that some portion of the riders have flexible destinations. Again, an attractiveness measure is needed for each destination station to ensure that the destination model approximates existing demand patterns. In this case, origin-destination flow data is available for the entire network. The attractiveness of each destination is calibrated using an iterative method to minimize the root-mean-squared error between the observed visits to each destination and the estimated visits to each destination. Finally, the case study in Chapter 8 involves estimating the demand for future shared workplaces among remote workers. As the destinations do not currently exist, there is no observed data that can be used to calibrate the attractiveness value for each destination. The hypothetical scenario assumes that the shared workplaces will be functionally identical with the same amenities, so the attractiveness measure is constant across destinations.

4.4 Conclusions and policy implications

In recent years, remote work has shifted from a niche working arrangement to one that is practiced by a broad swath of employees across many sectors of the economy. This large cohort of remote workers generally has the freedom to decide where (and to a lesser degree, when) to conduct their remote work, whether that is at home, at their employer's business premises, or somewhere else altogether. As a result, work trips on remote work days have begun to resemble other discretionary trips, but with an important difference: the travel choices associated with these trips are strongly influenced by work considerations. Addressing the behavioral complexities of discretionary remote work trips requires changes to the methods, theories, and data used in travel demand modeling.

This chapter describes three steps to improving the capacity of travel demand

models to capture third place travel behavior. First, introducing ZOIB regression for estimating remote work preferences is proposed due to the mixed continuous-discrete distribution. ZOIB regression is shown to provide behavioral insights into the effect of different individual factors on preferences for fully remote work, hybrid work, and fully in-person work arrangements that cannot be elicited by purely discrete or continuous models. Then, a new set of remote-work related survey questions is proposed for future travel surveys. Through the estimation of discrete choice models for third place trip frequency, departure time, and mode choice, these new variables are shown to influence the travel behavior of remote workers and improve modeling accuracy. Finally, the actual destinations of third place trips have a strong impact on transportation networks, but also on retail spending in neighborhoods and the diversity of social interactions, among other social externalities. A data-driven method for constructing and estimating a destination choice model for third place trips is presented. Taken as a whole, these three model improvements provide a holistic framework for estimating the overall travel demand created by third place trips.

The theoretical and empirical results of this work have several insights for policymakers. First, it is crucial to add remote-work related questions to future travel surveys in order to capture individual-specific factors that affect the demand for, and characteristics of, third place trips. Recommended questions in each of the five categories are presented in Table 4.2. Policymakers would benefit from the inclusion of these variables in travel demand models, as they are likely to provide insights into the effectiveness of policy tools for managing third place travel demand (e.g. tax treatment of employer subsidies for co-working memberships). Second, surveys must have new trip purpose categories for third place trips. Current practice in survey question design is likely to result in mixing discretionary third place trips with gen-

eral work trips or even social trips if the third place is a friend's home. This could be applied to general household travel surveys, but also user surveys of specific transportation services such as public transit. Transit agencies could adjust service to attract the emerging demand for third place travel, but only if they understand how and when people are using their service to visit third places. Finally, the empirical results show that driving remains the dominant mode for third place trips, but that driving is less popular among urban residents. This effect is likely due to the greater density of third places in urban areas, and the availability of alternative modes such as public transit. Policymakers should explore methods for increasing the density of third places and improving sustainable mobility options in suburban and rural areas to encourage a sustainable mode shift for third place trips.

There are some limitations to this work and several opportunities for additional research. The focus of this chapter was not on using complex, state-of-the-art models for travel behavior, but rather to provide clear and concise evidence of the need for different exogenous variables when modeling third place travel choices. Focusing on a single third place travel decision (e.g. trip frequency) and incorporating remote-work related exogenous variables into advanced choice models such as the integrated choice and latent variable model (ICLV) is a promising area of research that is likely to provide additional insights into the travel behavior of remote workers. In addition, Section 4.3.3 proposes a method for estimating third place destination choices using discrete choice theory and large-scale mobile phone data. However, due to a lack of reliable ground truth data for third place trips, especially those to friends' and family members' homes, no model can be estimated at this stage. This area of research would greatly benefit from future empirical work to collect revealed preference data specifically for third place trips.

Chapter 5

The benefits and limitations of remote work for reducing carbon emissions

5.1 Introduction

Since the beginning of the COVID-19 pandemic, there has been considerable attention paid to the dramatic rise in working from home and the broader implications for society going forward. However, the simple term “working from home” belies the fact that many workers have been spending their remote work hours in a wide range of places: coffee shops, libraries, co-working spaces, and friends’ living rooms. In this study, the binary “home-or-office as work locations” paradigm is demonstrated to be insufficient to capture the true dynamics of remote work, and can lead to an overestimation of the benefits of remote work on two critical urban transportation indicators: total demand for travel and travel-related carbon emissions. Furthermore,

it is shown that mobile phone data can be used to estimate commuting patterns for trips to non-home, non-work locations at a disaggregate level to facilitate long-term transportation planning. Finally, the implications of these findings for urban land use and transportation policy in the U.S. context are discussed.

From the beginning of the COVID-19 pandemic, there has been a strong research interest in the sudden increase in remote work adoption. In a working paper titled “Why working from home will stick”, Barrero et al. show that remote work represented more than half of all worked hours in the United States during the height of the pandemic (see Figure 1-2) [3]. The authors also find that remote work is expected to represent more than 31 percent of all worked hours after the pandemic subsides, a six-fold increase from 2018.

There has been a tremendous effort to understand the impact of remote work on travel demand since the outset of the COVID-19 pandemic. Many studies have used survey instruments to elicit preferences for remote work across demographic groups during the pandemic’s various stages [215, 216, 217, 164, 218, 219, 220]. These surveys, while valuable for a range of research questions, only consider two possible working locations: home and a fixed workplace. Another set of articles used survey data to estimate statistical models for future commuting patterns, predicting a significant decline in overall commuting demand [221, 166, 187, 222]. The models can be used for predicting travel modes and the number of commuting trips during non-remote working days, but each model assumes that remote work takes place entirely at home.

The narrow home vs. office framing of previous remote work studies can produce aggregate estimates of post-pandemic travel demand that ignore trips made to non-home remote work locations (e.g. 13, 14, 15). Even before the COVID-19 pandemic, it had been acknowledged that remote work was taking place in a variety of locations

[204]. In the post-COVID era, Hensher et al. [222] finds that many employers are beginning to embrace co-working spaces as an alternative to working from home, and Beck and Hensher [223] points out that “working close to home” could be an appealing work modality.

Past literature, adapting a term from Oldenburg and Brissett [224], has referred to alternative remote work locations collectively as “third places” to differentiate them from the home and traditional workplace [225, 226, 227]; for consistency that terminology is also used here. Understanding the use of third places is critical not only for travel behavior, but also for broad economic indicators such as employee satisfaction, firm productivity, and commercial real estate demand.

To study the current and future use of third places, several questions have been added to recent waves of the SWAA, a monthly survey of several thousand working-age U.S. residents [228]. It is found that, after scaling the results to the demographics of the country, 14.3% of total worked hours from November 2021 to March 2022 happened at a third place (see Figure 2-1). This represents 32.6% of all remote work hours in the United States. After weighting hours by income, it is found that 17.3% of wages in the United States are earned in non-work, non-home locations. The survey also shows that the distribution of employee preferences for third places is similar to their existing use of third places.

Reported working hours at third places are relatively evenly split between the three categories included in the survey: public spaces (e.g. coffee shops or libraries), co-working spaces, and the home of a friend or family member. Preferences for third places are not evenly distributed across the population, however. For example, the use of third places is more prevalent in urban areas than in suburban areas. Similarly, the use of third places varies considerably by income group. It is clear from the survey data that third places represent a significant proportion of remote

work, with complex preferences that differ between demographic and employment groups. Quantifying the contribution of these factors as they relate to remote work preferences is the first step towards estimating the overall share of remote work as well as the preferences for third places for a given population.

This chapter shows that assuming all remote work takes place at home results in a significant underestimation of future travel demand and transportation-related carbon emissions. Our survey results demonstrate that third places are the chosen destination for a meaningful proportion of remote work commutes, and that those additional trips are currently being ignored. Moreover, it is demonstrated that the false assumption leads to a skewed prediction of the spatial distribution of travel, as third place trips are typically shorter than a traditional commute and are more likely to take place within neighborhood centers. This mischaracterization of travel demand could lead to insufficient sustainable transportation infrastructure, such as public transit or micro-mobility, to accommodate third place commutes. Ignoring remote work trips to third places is also predicted to overestimate the benefits of remote work with respect to reducing carbon emissions from commuting.

In this study, a large, continuous nationwide survey is leveraged to estimate preferences for remote work and third place visits for different demographic and geographic groups using Zero-One-Inflated Beta (ZOIB) regression and k-means clustering models. Then, it is demonstrated that mobility trace data collected from a variety of sources can be used to estimate the characteristics of third place trips, including destination and distance. Finally, the carbon emissions related to traditional and third place commutes are computed. This procedure enables quantification of the effect of third places on aggregate travel demand, spatial demand patterns, and transportation-related carbon emissions across an urban area.

The future is inherently uncertain, so survey respondents were asked three dif-

ferent questions about third place use. The first question asks respondents to report their time spent working at a third place as a share of total work hours in order to estimate commuting patterns if there are no further changes in working arrangements. Then the survey asks about respondents' plans for working at third places in the medium-term future, assuming that the public health threat of the COVID-19 pandemic has subsided. This provides the basis for a second scenario with each respondent's best guess for the future, including any future changes that their employer may be planning with regard to their working arrangements. Finally, respondents are asked about their desired time spent working at third places in the future, regardless of existing constraints, informing the development of a third hypothetical scenario in which workers are given total freedom over workplace choice. For each of the three scenarios, the travel demand and carbon impacts with and without third place commutes are computed and compared against the pre-COVID baseline. This results in seven different possible commuting patterns that can be ranked against one another in terms of carbon emissions and total travel demand.

To the author's knowledge, this study is the first of its kind to examine the impact of third places on post-pandemic travel demand. It is also the first to develop a method for forecasting the specific travel patterns resulting from an increase in remote work at third places by merging various data sources including surveys and mobile data.

5.2 Methods

A four-step process was used to predict changes in travel patterns. The first is a ZOIB regression model estimated from the SWAA data to estimate individual shares of remote work. Next, a k-means clustering model is trained using the SWAA data

to determine how remote work is divided between the home and different third place categories. Different questions from the SWAA survey provide an estimate for three scenarios: current (2022) levels of remote work, employees' desired levels of remote work, and employers' planned levels of remote work. Then, mobile phone record data are used to create a model that predicts the distribution of third place commute destinations based on the home census tract. Finally, the results are aggregated for the entire urban area to generate multiple travel demand scenarios and calculate the carbon emissions associated with each scenario. To illustrate the importance of considering third places for remote work, a "Home Only (HO)" scenario is created where all remote work takes place at home, and a more realistic "Spectrum of Work Locations (SWL)" scenario where some remote work occurs at third places.

5.2.1 Data

There are three primary sources of data used in this analysis. The first is the SWAA which is administered by a consortium of academic institutions [228]. The SWAA is the source of information for future remote work location preferences and includes demographic and employment data for each respondent. The second is the My Daily Travel Survey conducted by the Chicago Metropolitan Agency for Planning (CMAP) between 2018 and 2019 [229]. The CMAP survey includes detailed travel and personal information for over 12,000 households in the Chicago area and is available to the public. This is the source of information for existing (pre-COVID) commuting patterns, which are then modified based on the mode and work location changes predicted by the SWAA to produce an estimate of post-COVID commuting patterns. Origin and destination locations for each trip are available at the census tract level.

The final source of information is SafeGraph, a data provider that aggregates anonymized location data from mobile applications to provide insights about travel and activity patterns. SafeGraph provides the locations of Points of Interest (POIs) and relative visitation frequencies for retail businesses [230]. SafeGraph information is used to determine the distribution of locations for trips by remote workers to third places such as coffee shops and co-working spaces. Home locations for visitors in the SafeGraph dataset are available at the census block group level.

Note that the CMAP survey is the only data source that is specific to the Chicago area (the SWAA and SafeGraph are both national in scope). Many state departments of transportation and Metropolitan Planning Organizations conduct similar surveys, so these results are largely generalizable to other U.S. metropolitan areas subject to data availability. The nationwide National Household Travel Survey could also be used to conduct a similar case study for the entire country, although doing so at the census tract or census block group level could present computational challenges. Chicago was chosen to illustrate the methods presented in this study, as it represents a very large urban area with high demographic and economic diversity.

5.2.2 Work location distribution and carbon impact

This study uses a four-step procedure to evaluate the impact of third places on the demand for urban mobility at a disaggregate level. It begins with a baseline household travel survey and seeks to update that survey to reflect changes in travel behavior. In this case, the primary changes in travel behavior are the substitution of traditional commuting trips with working at home or trips to third places. Specific data sources and methods are used to estimate how the travel behavior of each respondent in the baseline household travel survey change. Then, the results are

aggregated to provide an estimate of the overall impact of these travel behavior changes across the region.

The overall procedure is summarized in Figure 5-1. Each of the steps is explained in detail in the subsections that follow.

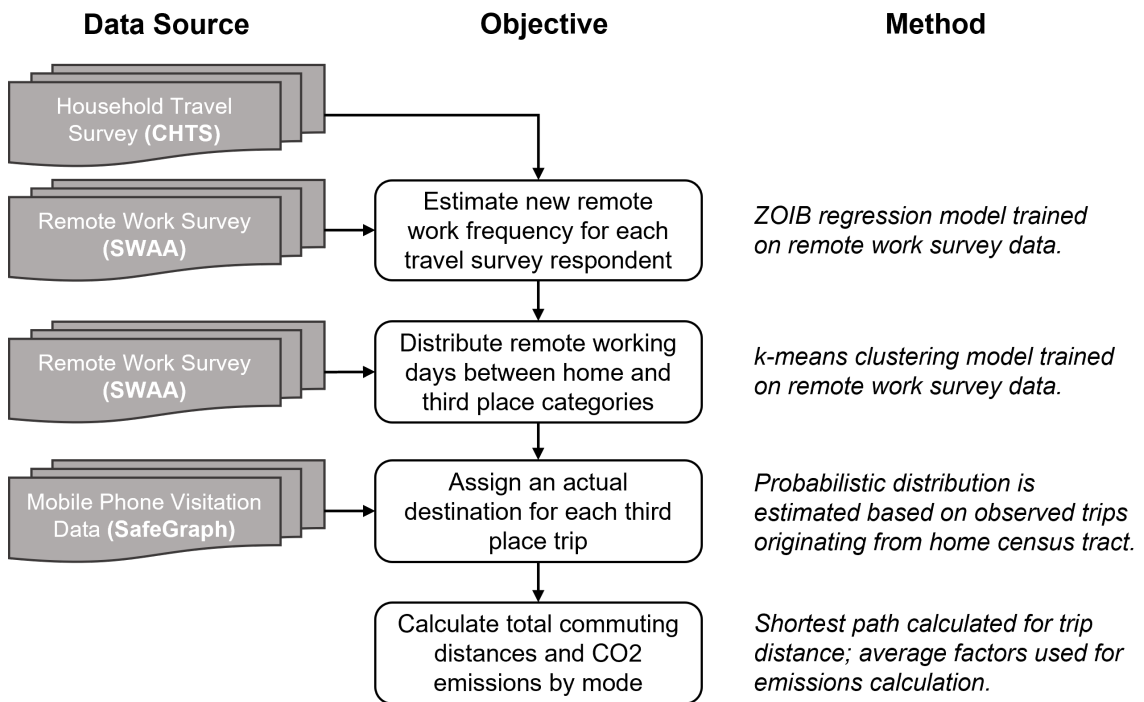


Figure 5-1: Flowchart demonstrating the emissions estimation process.

This procedure is similar to the canonical four-step model for travel demand forecasting [231]. First, the number of total in-person and third place commuting trips for each individual is estimated, which is analogous to the “trip generation” step. Then, the third place trips are assigned to specific destinations, much like the “trip distribution” step of a traditional model. Mode choice is extracted directly from the household survey data. Route choice information is not available, so the shortest path with respect to travel time is assumed.

Work location choice prediction (trip generation)

To estimate how commuting patterns and carbon emissions could change as a result of working from third places, first the distribution of location choices for remote work must be predicted. As discussed earlier, opportunities for remote work and preferences for third places are highly heterogeneous. For that reason, a disaggregate approach is applied wherein work location choices are predicted for each individual using employment and demographic information. A model is developed to predict, given a commuter with a specified set of demographic and employment variables, the fraction of pre-COVID commuting trips that fall into the following categories: A) eliminated due to working at home, B) have a modified destination due to working at a third place, and C) unchanged due to working at the employer's work site. The trips within Category B) are further distributed among the different types of third places: public spaces, friends' homes, and co-working spaces.

The scaled SWAA responses are scaled to match the Current Population Survey (CPS) based on age, sex, education, and earnings. An extended description of the SWAA methods and data is included in Section 3.3; relevant details for this chapter are included here. SWAA responses from November and December 2021 (N=7,950) are used as training data for the prediction model. The full list of SWAA employment and demographic variables used in the model are presented in Table 5.1. Home ZIP Population density was split into three categories: Urban (> 3000 residents per square mile), Suburban (1000 – 3000 residents per square mile), and Rural (< 1000 residents per square mile).

A ZOIB regression model was estimated using the SWAA data in order to predict the current, desired, and planned percentages of remote work for each CHTS respondent. ZOIB regression is a mixture model typically used to model proportion data

Table 5.1: Input variables for work location choice model

Variable	Variable Type
Sex	Categorical
Age	Continuous
Education	Continuous
Household Income	Continuous
Home ZIP Population Density	Categorical

where a qualitative difference between the populations with a 0% response, a 100% response, and a response between 0% and 100% is expected. This condition exists for the distribution of remote work preferences. The population with 0% remote hours may represent a much different population than those working 1% or more of their hours remotely. As an example, the 0% population may work in a role where remote work is not possible (e.g. grocery store clerk, butcher, automotive mechanic), making it qualitatively different from the rest of the population. Additionally, 100% remote work enables a much different lifestyle than 90% remote work by untethering the worker from the need to live near an office. As expected, the SWAA preference data is inflated at 0% and 100% of remote work hours, as shown in Figure 4-2. The parameters of the three ZOIB model processes are estimated using Bayesian inference and presented in Table 5.2.

While only one step in the aggregate travel demand process, the estimation of the ZOIB model provides several interesting insights into the dynamics of remote work. The estimated parameters can be used to determine the effect of the independent socioeconomic variables on the probability of choosing 0% remote work, 100% remote work, and the mean of the Beta distribution (denoted by μ) if the proportion is neither 0% nor 100%. The results are shown for current, employee-desired, and employer-planned levels of remote work in Table 5.2. Note that the categorical variables “sex” and “population density” were set to Male and Urban for the reference

Table 5.2: ZOIB regression results for the proportion of remote work

Variable	$P(x = 0)$	$P(x = 1)$	$P(0 < x < 1)$	μ	$E[x]$
	<i>No Remote</i>	<i>Fully Remote</i>	<i>Hybrid Work</i>	<i>Hybrid Remote %</i>	<i>Combined Effect</i>
Current Remote Work Share					
Median	20.19%	18.83%	60.99%	55.38%	54.00%
Female	4.27%	6.95 %	-11.22%	-	0.23%
Suburban	17.75%	-2.46%	-15.29%	-2.28%	-7.75%
Rural	17.75%	-2.46%	-15.29%	-2.21%	-12.28%
Age (years)	1.00%	0.13%	-1.14%	-0.12%	-0.60%
Education (years)	-3.11%	0.11%	3.22%	-	1.82%
Income (\$10k)	-2.86%	0.06%	2.80%	0.16%	1.81%
Employee Desired Remote Work Share					
Median	18.08%	21.96%	59.96%	60.73%	58.95%
Female	-0.61%	6.67 %	-6.06%	-	2.72%
Suburban	-	-	-	-1.70%	-0.44%
Rural	8.87%	-0.83%	-8.04%	-3.75%	-6.74%
Age (years)	0.57%	0.02%	-0.60%	-0.13%	-0.40%
Education (years)	-3.37%	0.20%	3.17%	-	2.27%
Income (\$10k)	-1.59%	-0.09%	1.68%	0.21%	1.06%
Employer Planned Remote Work Share					
Median	28.41%	15.85%	55.74%	60.89%	49.94%
Female	-	-	-	-	-
Suburban	-	-	-	-2.30%	-0.54%
Rural	10.74%	-3.17%	-7.57%	-4.05%	-8.73%
Age (years)	0.59%	0.01%	-0.60%	-0.10%	-0.40%
Education (years)	-2.65%	0.10%	2.76%	-	1.69%
Income (\$10k)	-1.89%	0.02%	1.86%	0.15%	1.27%

Note: the - symbol represents a parameter that is not statistically significant at a 95% confidence level.

group, respectively, and the median results are not scaled to the US population average.

For the current remote work model, the negative coefficients for the Education continuous variable with respect to “No Remote” and “Fully Remote” suggest that people with more education are more likely to work a hybrid work schedule. This

model also indicates that women are more likely to be working either fully remotely or fully in person than men. Insignificant parameters in the employee preference model and employer plan model also have interesting implications. The insignificance of the Suburban categorical variable implies that, unlike high and low-density areas, living in a moderate-density area does not have a statistical effect on preferences for different working arrangements. Similarly, in the employer plan model, the insignificance of the Female categorical variable suggests that gender does not play a statistically significant role in employers' plans for remote work.

A k-means clustering approach is also trained on SWAA data to distribute this remote work share among different locations, including home, public spaces, friends' homes, and co-working spaces. The remote work location choice probability distributions for each of the clusters are shown in Figure 5-2. The k-means clustering approach resulted in clusters that were largely differentiated by the home ZIP population density categories, with corresponding variations in the remaining socioeconomic and employment variables. Remote workers in the "urban" cluster are much more likely to work at a third place than those in the "suburban" and "rural" clusters. These results seem sensible; low-density land uses in rural and suburban areas make it more difficult for residents to access third places for remote work.

Assigning third place destinations (trip distribution)

Creating new trips to third locations for future commuting patterns requires strong assumptions, but actual data were used wherever possible. There are three categories of third places in the SWAA questionnaire: public spaces, co-working spaces, and the home of a friend or family member. As the specific locations were not included in the survey, it is not possible to compute the distribution of travel distances for each

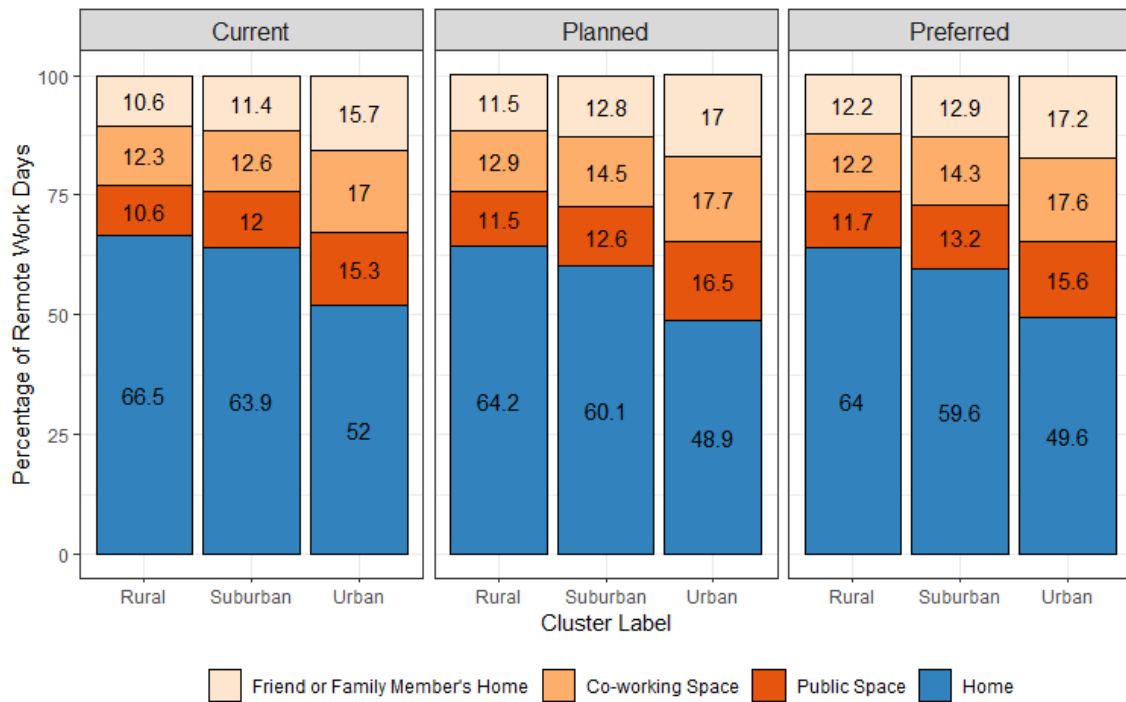


Figure 5-2: Current, employee desired, and employer planned remote work location distributions by cluster

of these location types directly. An alternative means of estimating trip distances is therefore needed.

SafeGraph data uses mobile phone records to estimate the home locations of visitors to an extensive list of retail establishments. Establishment type is also included, so the distribution of visits from a given home location (at the census block group spatial resolution) to different establishment types can be determined. This method is used to create a distribution of public space and co-working space visit probabilities and the associated travel distances for every home census tract in the Chicago Metropolitan Area. The expected value of public space and co-working space trip distance for each home census tract can then be estimated.

An initial investigation found that third place trips were longer than expected due to noise in the SafeGraph data. Unlike co-working spaces, visits to public spaces may be conducted for a variety of non-work reasons. Visitors from distant suburbs may stop at a cafe as part of a shopping trip, for example. Since the SafeGraph visitation data cannot be differentiated by trip purpose, a heuristic filter was applied to ensure that the estimated travel distances for remote work at public spaces reflect reasonable commuting behavior. The filter removed any public space trips that exceed the length of the traditional commute to the employers' workplace by more than 1 kilometer, as it is unlikely remote workers would choose to travel further than their typical commute to work remotely from a public space.

SafeGraph data does not contain information about visits to residential locations, so an alternative method is needed to estimate trip distances to the homes of friends and family members. Rather than SafeGraph data, the CMAP survey was used as it contains information related to the purpose of each trip. Trips with the purpose of "socializing with friends" and "socializing with relatives" were used as a proxy for visits to the homes of friends and family. While socializing can take place in non-home locations, the inclusion of other trip purposes such as "dining out", "shopping", "recreation" and "special event" is assumed to reduce the number of non-home-based social events in the chosen trip categories. Aggregating the CMAP survey social trip distances for each home location census tract therefore provides a reasonable estimate of the distribution of travel distances for trips to friends' and family members' homes.

The results for one-way trip distance by location type shown in Table 5.3 demonstrate that third place commutes are typically much shorter than commutes to an employer's workplace. The reduction in commuting distances for third places and the elimination of commutes altogether for at-home working days are the two primary drivers of commuting-related carbon emissions reduction under widespread remote

work. If third place commuting distances were reduced further, then future carbon emissions from commuting would be even lower.

Table 5.3: Average one-way commuting trip distance by work location

Location type	Distance (km)
Employer workplace	10.3
Public space	3.5
Co-working space	10.8
Friend or family member's home	6.5

The average commuting distances to co-working spaces remain relatively high due to the concentration of available co-working spaces in the central business district of Chicago. The average commuting distance to public spaces, while the shortest of any location category, remains beyond a comfortable walking distance for most people. Policies to reduce the average travel distances to third places would include zoning and incentives for locating new remote work-friendly public spaces and co-working spaces within residential areas. Figure 5-4(a) shows how census tracts to the west and south of downtown Chicago are not estimated to receive many third place commuting trips due to a lack of available destinations. Introducing new third places in such neighborhoods could be expected to have a disproportionately high impact on carbon emissions by offering a nearby destination for local third place commuters. Encouraging remote workers to use existing public spaces such as libraries and community centers would have a similar effect.

Travel demand impacts

Once the predicted change in commuting frequency and location distribution at the individual level is determined, the aggregate effects on travel demand can be calculated. The 2018-2019 observed commuting distances are used as a baseline

against which the predicted distances are compared. Two scenario categories, HO and SWL, are compared to demonstrate the importance of including third place commutes in overall travel demand estimates. The overall change in aggregate travel distance and travel distance by mode is reported for both the HO and SWL scenarios. Furthermore, the overall change in trips by origin and destination is visualized by census tract for each scenario to identify spatial trends in third place commuting patterns.

Carbon emissions

Two primary factors contribute to the change in commute-related carbon emissions as a result of increased flexible work. The first and most critical is the anticipated reduction in commuting distance that results from working at home and third places rather than a fixed employer-specific workplace. When calculating distance, it is assumed that trips to third places follow the shortest possible route. This is a conservative assumption, as a small number of travelers may choose to deviate from the shortest path. The results presented in this chapter therefore represent an estimate of the lower bound of commuting-related carbon emissions when third place commutes are included.

The second factor that affects commuting-related carbon emissions is the change that arises from shifting from one commuting mode to another, as travel modes have significantly different emissions profiles. A targeted question was included in the January, February, and March 2022 waves of the SWAA to determine whether remote workers use different travel modes depending on their choice of work location. The survey found that individual remote workers almost always use the same travel mode, whether commuting to a traditional workplace or one of the third place categories.

The aggregate mode share for traditional workplaces and third places are nearly identical. As such, it is assumed that remote workers use the travel mode reported in the travel survey, regardless of work location choice. The changes in carbon emissions from commuting are therefore influenced only by commuting distance.

Using the difference in travel distance by mode from the previous section and multiplying by the average carbon emissions per unit distance by travel mode for the Chicago area, the total change in carbon emissions for both the HO and SWL scenarios is computed. The estimated CO₂ emissions per passenger-mile for each travel mode provided by U.S. Department of Transportation Federal Transit Administration [232] is utilized to compute the total carbon emissions.

5.3 Results

Results were generated using a systematic data-driven approach for estimating the new demand for travel under widespread remote work. First, the 2019 Chicago Household Travel Survey (CHTS) is used to examine commuting patterns before the pandemic. Then, to predict the individual levels of remote work and remote work location choices that affect commuting patterns, data from the longitudinal SWAA survey is incorporated. Finally, mobile phone records are combined with home location data to estimate the destinations of third place commuters.

Carbon emissions from commuting. As remote work arrangements have increased from 4.8% of worked hours pre-COVID to around 31.6% in 2022, there has been a significant decrease in carbon emissions related to commuting as more people are working from home or at third places near their homes. Table 5-3 presents the carbon emissions results for the six constructed scenarios and one pre-COVID baseline scenario. The pre-COVID baseline was computed directly from CHTS data.

The constructed scenarios include three HO scenarios where people work only from home for remote work, and three SWL scenarios that consider commutes for remote work at third places. Within the HO or SWL scenarios, travel patterns are estimated based on 1) current remote work rates and location choices, 2) employees' desired work-from-home rates and location choices, and 3) employers' planned work-from-home rates and location choices.

Before discussing the results, it should be noted that this study is concerned only with estimating the carbon impact of changes to the length and frequency of *commuting* trips to and from work as a result of the widespread increase in remote working. It does not consider other important components of the overall influence of remote work on carbon emissions, such as non-work travel and building emissions. The effect of remote work on the propensity for non-work travel has long been debated. Previous studies have found that under certain conditions, some remote workers conduct more non-work travel than those who work entirely in-person (e.g. de Abreu e Silva and Melo [73], Zhu et al. [74], Su et al. [75]), but other studies have found little-to-no effect under different conditions (e.g. Choo et al. [76], Kim et al. [78], de Abreu e Silva and Melo [77]). O'Brien and Aliabadi [150] provides an excellent summary of previous research on the various "rebound effects" of remote work, including changes to office and home energy consumption. Their literature review shows that, like non-work travel, the impact of remote work on energy consumption for buildings is mixed and highly dependent on context and assumptions. While our study generates new insights into possible changes in commuting-related travel in the post-COVID era, it is but one piece of a holistic investigation into the overall carbon emissions impacts of widespread remote work.

The model findings show that carbon emissions related to commuting have decreased by 31.1% from the pre-COVID level. When third places are considered,

people tend to work more at these locations and travel more while working remotely. For home-only scenarios, people generally prefer to work more flexibly from home rather than in the office. Employers are planning to have their employees work more frequently in the office, so scenarios based on employer plans produce fewer emissions relative to the employee preferences or current remote work scenarios. The results clearly demonstrate that it is important to consider third places when evaluating the impact of remote work on commuting, as not doing so can lead to an overestimation of the reduction in carbon emissions. In the current scenario, which assumes remote work arrangements remain constant going forward, ignoring third places results in an underestimation of carbon emissions by 16.6%.

Spatial travel patterns. By combining the actual work locations from the household travel survey with synthetic trips from mobile phone data, the model also estimates the disaggregate origin-destination patterns for each demand scenario. Figure 5-4(a) illustrates the change in the number of visits to each census tract from the pre-COVID baseline scenario to the current travel pattern (i.e. “Current with SWL” scenario). A “donut effect” can be observed, meaning that there is a decrease in visits to the city center and outskirts, but an increase in visits to near suburban areas. These spatial patterns are reminiscent of the donut effect observed by Ramani and Bloom [233] with respect to housing prices after COVID-19. These results suggest that people are traveling more often to third places located in dense residential areas, rather than commuting to offices located in the commercial core.

Figure 5-4(b) illustrates the difference in visits between the current scenario with SWL and the current scenario with HO. It’s clear that ignoring third places leads to the undercounting of many commuting trips, particularly in the densely-populated and amenity-rich northern part of Chicago.

Figure 5-4(c) shows the difference in visits between the current scenario and the

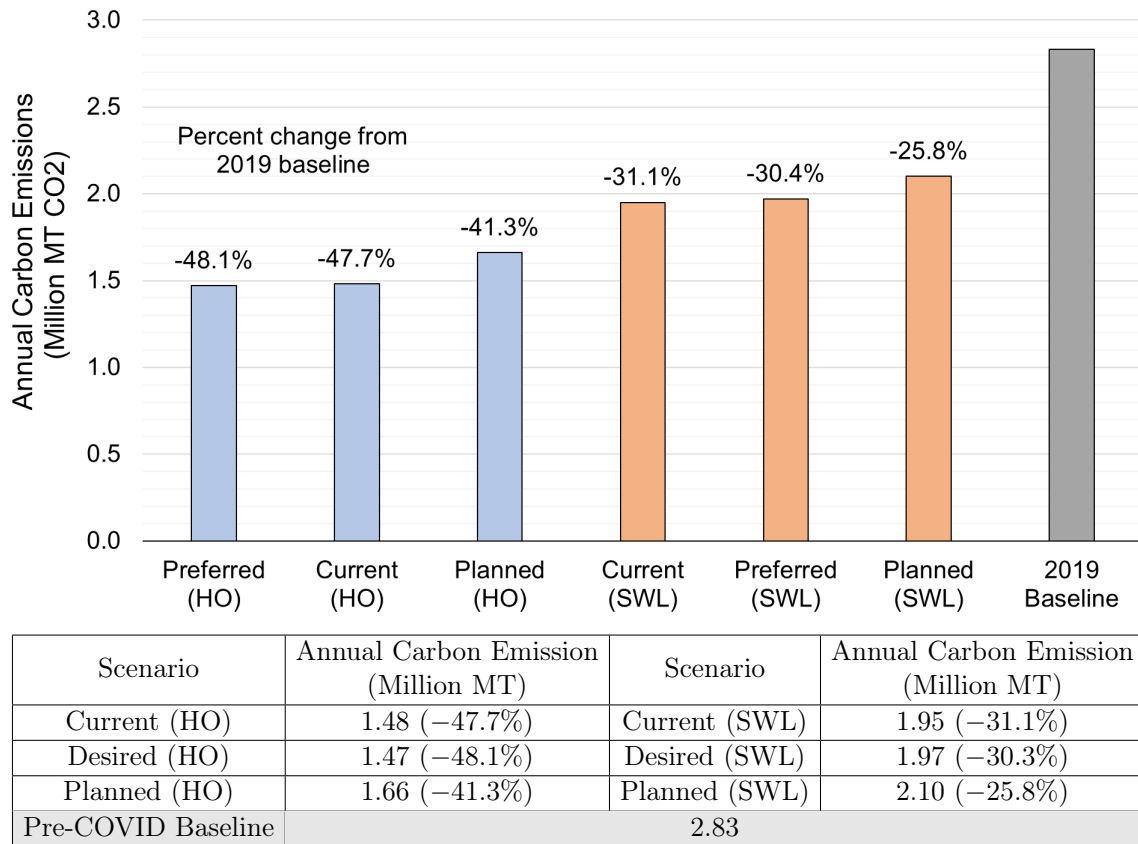


Figure 5-3: Carbon emissions for different commute-based travel demand scenarios

employer-planned scenario that takes third places into account. The employers in this scenario are planning to have their employees work in the office more frequently, resulting in more trips to the city center and outskirts and fewer trips to suburban areas. This is in contrast to the “donut effect” observed in Figure 5-4(a).

Figure 5-4(d) shows the difference in visits between the current scenario and the employee-desired scenario that takes third places into account. It is interesting that people prefer to work in the city center, outskirts, and certain suburban areas. These mixed results that in an ideal world, people would generally prefer to work slightly more at locations other than their homes, with some opting for the office and others

choosing third places.

5.4 Discussion

The results of this study demonstrate that third place commuting trips are an important component of overall travel demand within a region, and should not be ignored. While remote work does reduce commuting overall compared to the pre-pandemic baseline, the impacts of remote work on commuting travel are somewhat dampened by trips to third places. In addition, there is tension between employer plans and employee desires for remote work in the future. If the tension is resolved in favor of the employers, then future travel demand is expected to be somewhat higher than in a compromise or employee preference-driven scenario. Third place commuting affects not only the aggregate level of travel and emissions, but also the spatial distribution of each measure. These results have significant implications for transportation and land use planning going forward.

While this study demonstrates that there are some negative externalities related to third place commuting, the use of third places for remote work can have many positive effects on a community. First, there is a travel cost for the commuter associated with visiting a third place, and many third places charge a fee (e.g. co-working space) or require a purchase (e.g. café) by the user. The fact that people choose to conduct remote work at third places despite these costs suggests that third places have some positive utility for remote workers relative to working from home. The revealed utility could be related to productivity, such as a less distracting environment compared to home or a stronger Wi-Fi connection. It might also be related to the opportunity to socialize or network with other remote workers, which can lead to spillover effects that boost the productivity of those involved. Remote workers

who choose to work at third places also support the third places and surrounding neighborhoods through economic activity.

In a sense, the use of third places represents a compromise between working from home and working in a centralized employer-provided workplace. Remote workers benefit from a more social environment and avoid some of the negative aspects of working at home, while also limiting their travel costs and the impact of their travel on others through shorter commutes. The congestion and emission externalities of third place commutes can also be mitigated with intentional land use and transportation planning. This study found that suburban and rural residents are less likely to use third places and travel further when they do. Encouraging the development of third places outside of the city center would provide nearby options for remote workers in those areas, allowing them to reap the benefits of third places for remote work while reducing overall travel. The congestion externalities can be mitigated by providing sustainable transportation alternatives for third place trips to encourage the use of low-emissions modes. These alternatives could include better transit connections between residential areas and nearby town centers, or providing better micro-mobility, cycling, and walking infrastructure near third places. Third place commutes are also less likely to occur during peak hours compared to a traditional commute, so their impact on peak roadway and public transit congestion is of less concern.

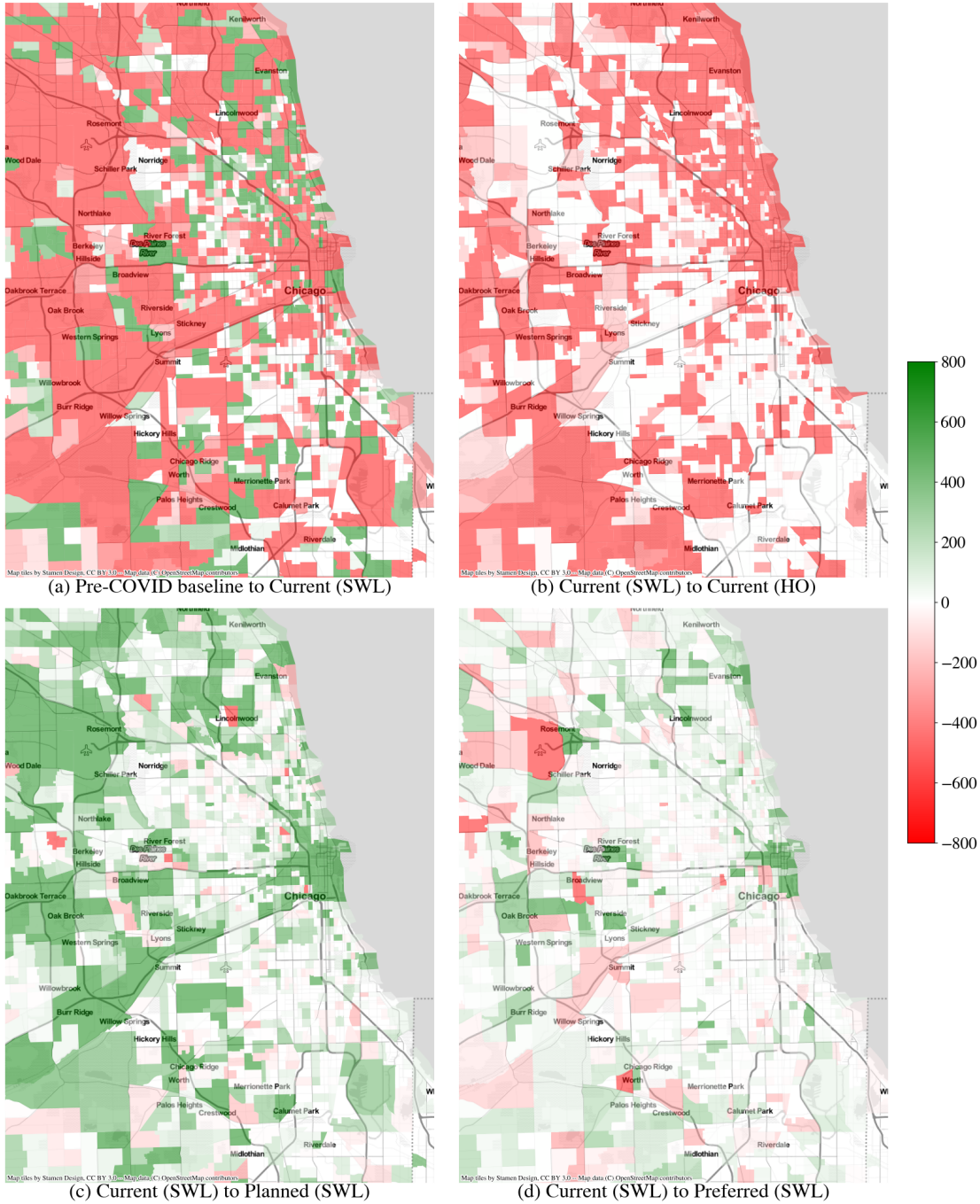


Figure 5-4: Changes in visits at census tract level between scenarios

From a more general perspective, this chapter proposes a rapid and inexpensive data-driven framework for revising travel demand estimates in the wake of sudden system-wide demand shocks. It leverages widely available, nationwide data sources that can be collected more quickly and with lower costs than a household travel survey. The author does not claim that the approach described herein is sufficient to replace household travel surveys altogether, as household surveys capture the granular data on individual trips needed to inform the data-driven approach. However, it provides a useful first-order estimate of demand pattern changes that may occur in the years between household survey waves.

Many of the limitations of this study are related to data availability. Mobile records are used to infer destinations for third place trips, but future studies could collect these destinations directly from the survey respondents for an improved understanding of preferences for third places. This area of research would also benefit from an exploration of alternative model structures for predicting remote work locations. The zero-one-inflated beta regression and clustering algorithms used in this study were selected for their accuracy, simplicity, and interpretability, but more complex models could be implemented in future research if suitable. Finally, future work could explore policy prescriptions for reducing the impact of third places by optimizing zoning for third places near residential areas or developing operating strategies for public transit systems to serve third place commuters.

Chapter 6

Evaluating the travel impacts of a shared mobility system for remote workers

6.1 Introduction

For the past century, individual commute patterns have typically involved a fixed destination that is stable over long periods. We are currently experiencing a profound shift in the nature of work, however. What was once a gradual trend towards increased remote work [234], driven by improvements in digital communication technology, the rise of the gig economy, and the emergence of co-working spaces was then suddenly and dramatically accelerated by the COVID-19 pandemic. A recent survey found that in 2023 and beyond, nearly a third of worked days in the United States are expected to be remote, a share that is more than six and a half times greater than the pre-pandemic average [3]. The same study finds that approximately one-third

of remote work in late 2021 and early 2022 was conducted outside the home. Beck and Hensher [101] refer to this arrangement as “Working Close to Home”. Figure 2-1 presents the distribution of full-time worked days in the United States by location; non-home remote locations include public spaces, co-working spaces, and friends’ homes.

Even before COVID-19, some employers allowed staff to choose among several work locations on a day-to-day basis, including co-working spaces [235]. This distributed office model is expected to become more popular in the future. A recent article [236] argues that employers should allow “hyper-local teams to choose a location based on their shared preference” to boost productivity and create “new relationships within and among organizations.” When multiple work locations are available, employees benefit from the opportunity to select a workplace that matches both their work and travel preferences. Innovative office solutions have quickly emerged to serve remote workers with flexible work locations; WeWork, a major co-working operator, has recently begun offering an all-access service where subscribers can choose to work from any location at any time [237]. There has been little innovation or research, however, regarding innovative mobility services that could serve remote workers with flexible work locations.

In this chapter, a new analytical framework is introduced to enable the simulation of a shared mobility system serving remote workers with multiple possible work locations. First, a novel matching algorithm is proposed that incorporates flexible destinations, location capacity constraints, and team member co-location constraints. The impacts of these remote work constraints and objectives on ride-pooling adoption, quality of service, and total travel demand are then explored for the first time in the literature through an experiment with real ride-hailing data from Manhattan. Finally, the implications of the results for future shared mobility providers, employer

remote work policies, and travel demand management are discussed.

Remote work locations represent an upending of the traditional travel demand modeling paradigm, wherein routine work trips are the anchor for daily travel patterns. In the past, urban mobility services such as public transit have been designed around serving stable commuting trips [238]. These designs may not fit the needs of commuters with remote work locations who will have many options for how, where, and when to travel. The benefits of remote work will only be realized if the mobility ecosystem can adapt to the new demands of remote work.

For example, one issue faced by remote workers with flexible work locations is coordinating the location of team members who are working on a collaborative task. Mobility services could respond by offering to arrange a location choice for multiple individuals that balances productivity considerations with travel costs. Other tasks, such as meeting a client or designing a product prototype, might need specialized amenities that are only available at certain work locations. A new terminology, “dependencies”, is proposed to refer to these remote work constraints that must be incorporated into travel decisions. Employers would benefit from a mobility platform that can accommodate dependencies while arranging efficient travel for employees. Moreover, these dependencies will impact the destination choices of remote workers, affecting aggregate travel demand.

Providing mobility services that can meet these new demands is very challenging due to the number of possible dependencies: relationships between individuals, the characteristics of available destinations, task-related constraints that change over time, and so on. Exploring how these complex relationships affect the spatial distribution of travel demand will require the design of new analytical tools. Furthermore, the factors that affect workplace location choice include both travel and work preferences, two areas of study that are not often linked. Bridging the gap between travel

behavior and organizational behavior is critical to preparing mobility systems for the future of work.

6.2 Literature review

Remote work has long been of interest to transportation researchers, but few analytical models connect remote work and transportation. The impacts of “teleworking” on urban travel were investigated as early as the 1970s; a report by Mokhtarian [57] and a review by Nilles [58] provide a good summary of early empirical research. Recent changes in commuting patterns are expected to have a significant impact on the demand for travel along two important dimensions. First, a reduction in the overall volume of peak hour travel. Beck and Hensher [101] predict a 20% reduction in urban core commuting post-pandemic. Second, a shift in the spatial distribution of demand away from commercial centers towards neighborhood centers, as remote workers have been shown to choose destinations that are closer to home than traditional commuters [75]. Additional empirical research includes studies of how remote work has affected road congestion in Iran [68] and Sweden [69]. A group of organizational behavior papers provides insight into the productivity considerations for remote work and co-working, but none include a transportation component [109, 110, 121]. There has also been research into the urban planning and real estate implications of flexible and remote work, with limited discussion of transportation [239, 240].

One paper was found that included a simulation of a transportation system with remote work locations [86]. The authors use an agent-based regional travel demand model to evaluate the effect of remote workplaces on commuting distances. Interestingly, they find that requiring the co-location of teams can lead to a worse outcome than the status quo under certain conditions. The study does not include any math-

emational modeling or productivity considerations, however.

Low occupancy ride-hailing trips represent a tremendous and problematic under-utilization of one of society’s most expensive and in-demand resources: the road network. Most ride-hailing vehicles have a capacity of four passengers or more, yet the average occupancy is just 1.3 passengers [241]. Ride-pooling is a ride-hailing service where multiple customers can be served by the same driver at the same time. This chapter uses the ride-pooling mode to study the effects of remote work on transportation.

The primary areas of ride-pooling research are developing algorithms to improve operations and exploring supply and demand dynamics. A recent paper provides an excellent overview of the dynamics of ride-hailing platforms and their interactions with other urban mobility systems [242]. Mourad et al. [243] survey research into optimization techniques for shared mobility, which includes ride-hailing, while Agatz et al. [244] review the literature in optimization for ride-hailing platforms specifically. Ke et al. [245] explores the relationship between fleet size, maximum detour constraints, fare price, and other variables in a ride-pooling market. Other ride-pooling research studies the social dynamics of sharing rides [246, 247].

In the past five years, a small number of papers have investigated the specific problem of ride-pooling with flexible destinations, suggesting a nascent but active subfield of research. Wang et al. [248] develops a matching algorithm that considers multiple destinations for each passenger but treats alternative destinations as equivalent from the traveler’s perspective. Such a framework is not consistent with ride-pooling research such as Wang et al. [249], which shows that perceived utility is the primary driver of decisions about pooled rides. Subsequent studies take a similar approach, where passenger utility is not considered during the destination assignment process. Mahin and Hashem [250] develop a pruning technique to

maximize ride-pooling, while de Lira et al. [251] test a new heuristic algorithm, finding that flexible destinations and activity schedules increase pooled rides by up to 55%. Khan et al. [252] develop a method of matching trips with flexible destinations using Steiner Trees to identify possible meeting points. Ride-pooling with flexible destinations based on a utility-maximization theory of travel behavior remains an unexplored research direction.

6.3 Remote work dependencies

First, a vocabulary is needed to categorize the relationships between people and places that affect work location choices. As proposed earlier, the term “dependency” will be used to refer to such relationships. Dependencies can exist between a person and workplace amenities (“location dependencies”), such as the requirement that a location includes a meeting room. Dependencies can also exist between a person and other people (“associate dependencies”). These associates might be coworkers needed for a face-to-face brainstorming activity, but also people with similar professions, people who work in the same industry, or even friends. Dependencies can be hard constraints or soft constraints (desirable but not necessary). They can be enforced by employers (top-down) or requested by individuals (bottom-up).

Second, it can be helpful to list common remote working arrangements, although any such list could never be considered exhaustive. Remote working arrangements can be considered a location-associates dyad. Working locations include spaces that are intended to be workplaces (corporate office, home office, co-working space) and those that facilitate work as a secondary purpose (café, library, community center). Associates could include co-workers, friends, family, people with a similar profession, and so on. The relationship between the individual and these groups can be im-

portant for productivity or personal utility. Arrangements are constructed from a combination of one location and any number of associates. For example, a traditional working arrangement is the corporate office + co-worker pair. During the pandemic, many people became familiar with the home + no associates arrangement. Industry meetups, an arrangement where professional groups organize a collective remote work and networking event in a rented workspace (i.e. co-working space + people with a similar industry) have been popular for some time [253]. There are many such combinations possible, each with different implications for mobility and productivity.

Finally, an analytical framework can now be established for transportation supply models that capture remote work dependencies. Each class of transportation mode has many models for optimizing service delivery, and each of these models interacts differently with the remote work dependencies. This framework can be represented as a conceptual table with supply models on the vertical axis and remote work dependencies on the horizontal axis, as shown in Table 6.1. Each of the cells represents a possible supply-demand model that includes the influence of remote work characteristics on a specific travel mode. The numbered cells are addressed in the case study that follows.

The capability of this structure to represent realistic scenarios is illustrated through a ride-pooling case study, which is just one element within the broader framework. The methods introduced in the case study apply to any mobility system where one or more passengers are matched with a vehicle in real-time (e.g. demand-responsive transit, car-pooling, shared autonomous vehicles). First, a variable demand model is introduced to capture the choice between pooled and exclusive rides. Then a new ride-pooling supply model that permits multiple destination options and facilitates the inclusion of remote work dependencies is developed. Finally, new constraints and objective function terms are proposed to capture the location and associate

Travel mode		Remote work characteristics			
		Flexible destinations	Location dependency	Associate dependency	Other
Public	Fixed route transit				
	Flexible transit				
Shared	TNCs and taxis				
	Ride-pooling	I	II	III	
	Shared AVs				
	Micromobility				
Private	Active travel				
	Private gas car				
	Private electric car				
	Private AV				

Table 6.1: Conceptual table for the mobility and remote work analytical framework dependencies.

6.4 Adding dependencies to shared mobility models

Now that a vocabulary for describing remote work dependencies and arrangements has been established, this section demonstrates how to incorporate them into a ride-pooling matching model in order to evaluate their impact on the transportation system. Dependencies affect demand, and because the supply is responsive to demand, they ultimately affect supply as well. This requires three substantial modifications to existing ride-pooling models, which are represented by Roman numerals in Table 6.1. The first set of modifications (Cell I) is simply to create a ride-pooling matching model that allows the passenger to choose between multiple alternative destinations. As discussed in the Literature Review section, previous models consider destinations to be fixed, or to be controlled by the platform.

The second modification (Cell II) is to add a location dependency to the supply

model. In this case, a scenario where remote workers would like to visit one of several co-working spaces, but there is a limited number of available workplaces at each location, is considered. The ride-pooling platform must incorporate these capacity constraints when finding an optimal ride-pooling matching arrangement for remote workers. This location dependency is used to explore the travel implications of co-working space capacity and geographic location within an urban area.

The third modification (Cell III) is to add two different associate dependencies: hard constraints and preferences. The hard constraint represents a requirement that different combinations of people (members of the same project team, for example) must work in the same location, but the choice of location is flexible. The preference dependency can be modeled by assuming that the ride-pooling platform receives a small premium for arranging rides such that certain combinations of employees work in the same location. This assumes that the employees perceive a benefit from being co-located with their team members and are willing to compensate the ride-pooling platform a small amount in exchange for that benefit. One could also imagine an employer bearing this additional cost through reimbursement to encourage face-to-face interactions between remote employees. The practice of reimbursing travel costs for remote workers to get together in person has recently been adopted by several large employers [254]. This dependency provides a connection between organizational behavior and transportation outcomes to demonstrate how remote work policies can impact travel patterns.

6.4.1 Adding flexible destinations (I)

There are two distinct components involved in adding flexible destinations to a shared mobility matching algorithm. Existing algorithms must be adapted to allow vehicle-

customer matching across several possible destinations. In addition, there must be a choice model to capture the customer’s choice of a single destination from a set of possible destinations once the trip characteristics are known.

Destination choice model

In the ride-pooling case study, total travel demand is fixed but individual customers (“agents”) can choose between a pooled ride and an exclusive ride. Consider a set of agents \mathcal{A} indexed by j and a set of all pooled and exclusive trips \mathcal{T} indexed by i . Note that in this chapter, the term “trip” is used to denote a supply-side variable: a *vehicle* trip that is either a pooled ride (multiple passengers) or exclusive ride. It should not be confused with a passenger journey between an origin and destination, which is also described as a “trip” in other contexts. All notation used in this chapter can be found in Tables 6.2 - 6.4.

Some agents have a fixed destination, while others indicate a willingness to consider multiple alternative destinations. These alternative destinations could represent several decentralized offices operated by the agent’s employer, a set of co-working spaces, or even nearby libraries or cafés. These alternative destinations could be served by either a pooled or exclusive ride. To model the choice between different ride types (pooled vs. exclusive) and different destinations, a mixed logit discrete choice model is introduced. The mixed logit discrete choice model has been found to provide a reasonably good fit for the mode choice between exclusive and pooled rides [255]. Our model differs from existing ride-pooling choice models by incorporating a destination utility term to represent the traveler’s varied preferences for alternative destinations. It also introduces a deterministic pricing model for the pooled ride discount.

Notation	Definition
\mathcal{A}	Set of all agents
j	Agent index
\mathcal{D}	Set of all destinations
d	Destination index
\mathcal{T}	Set of all trips
i	Trip index
\mathcal{V}	Set of all available vehicles
k	Vehicle index
\mathcal{E}_{AT}	Set of agent-trip pairs in the shareability graph
\mathcal{E}_i^V	Set of vehicles that can serve trip i

Table 6.2: Notation for sets and set indices

Notation	Definition
V_{ij}	Deterministic utility of trip i for agent j (utility)
v_{ij}	Destination utility derived from trip i for agent j (utility)
c_{ij}	Exclusive ride fare price for trip i charged to agent j (\$)
c_{ij}^s	Pooled ride discount of trip i for agent j (\$)
t_{ij}	Shortest path travel time for agent j on trip i (min)
δ_{ij}	Pooled ride detour of trip i for agent j (min)
ζ_i	Binary pooled ride indicator for trip i where $\zeta_i = 1$ if trip i is a pooled ride
β_1	Cost coefficient (utility/\$)
β_2	Time coefficient (utility/min)
β_3	Sharing penalty (utility)
U_{ij}	Total utility of trip i for agent j (utility)
ε	Random deviate, representing unobserved determinants of utility (utility)

Table 6.3: Notation for demand model

The utility function for the discrete choice model is shown in Eq. 6.1. The total utility of an exclusive ride trip i for an agent j , V_{ij} , is a linear function of the destination utility (v_{ij}), the exclusive ride fare price (c_{ij}) and the shortest path travel time (t_{ij}). Exclusive ride fare price is assumed to be a linear function of travel time

Notation	Definition
x_i	Binary trip served indicator where $x_i = 1$ if trip i is included in the optimal matching arrangement
y_{ij}	Binary agent-trip assignment indicator where $y_{ij} = 1$ if agent j is assigned to trip i
z_j	Binary unserved agent indicator where $z_j = 1$ if agent j is unserved
w_{ik}	Binary vehicle-trip assignment indicator where $w_{ik} = 1$ if trip i is served by vehicle k
q_{jd}	Binary agent-destination indicator where $q_{jd} = 1$ if agent j is assigned to destination d
p_i	Nominal operator profit associated with trip i (\$)
\bar{p}_i	Expected operator profit associated with trip i (\$)
λ_{ik}	Cost of assigning vehicle k to serve trip i (\$)
M	Operator penalty for one unserved agent (\$)
Q_{ijd}	Binary correspondence matrix defining correspondence between an agent-trip pair (i, j) and an agent-destination pair (j, d) , where $Q_{ijd} = 1$ if trip i results in agent j traveling to destination d
b_d	Maximum occupant capacity of location d (occupants)
μ_{jmd}	Binary agent co-location indicator, where if agents $\mu_{jmd} = 1$ if agent j and agent m are assigned to destination d
u_{jd}^{\max}	Maximum possible profit incurred from assigning agent j to destination d (\$)
I_{jmd}	Fraction of maximum benefit produced when agents $j, m \neq j$ are assigned to destination d (%)
u_{jd}	Total fraction of maximum benefit gained from assigning agent j to destination d (%)
α_{jd}	Substitution variable representing the realized fraction of additional profit from assigning passenger j to destination d (%)
g_{jd}	Binary auxiliary variable used to enforce the conditional relationship between $\alpha_{jd}, u_{jd}, q_{jd}$

Table 6.4: Notation for supply model

and distance. If the trip i is a pooled ride trip, there is also a pooled ride discount c_{ij}^s , a pooled ride detour time (δ_{ij}), and a binary pooled ride indicator (ζ_i) that models the inconvenience of sharing a vehicle with a stranger. Kang et al. [256] find that the

inconvenience of sharing is fixed with respect to travel time. Coefficients $\beta_1, \beta_2, \beta_3$ convert the cost, travel time, and sharing penalty terms into units of utility.

$$V_{ij}(v_{ij}, c_{ij}, c_{ij}^s, t_{ij}, \delta_{ij}, \zeta_i) = v_{ij} - [\beta_1(c_{ij} - c_{ij}^s) + \beta_2(t_{ij} + \delta_{ij}) + \beta_3\zeta_i] \quad (6.1)$$

The pricing algorithms used by ride-pooling platforms in practice are not available to the public, so a deterministic pooled-ride pricing algorithm is assumed. Pooled rides reduce operating costs by serving several passengers simultaneously, and a portion of these savings is passed on to customers as a fare discount. For a pooled ride to present an attractive alternative to an exclusive ride, $\beta_1 c_{ij}^s$ must be greater than $\beta_2 \delta_{ij} + \beta_3 \zeta_i$ for each passenger.

The profit for each trip is determined by taking the sum of the fare paid by all passengers and subtracting the operating costs, which are linear functions of the travel time and travel distance. To maximize profit, the operator would like to offer the minimum discount such that each passenger experiences an increase in utility over an exclusive ride and retain the remainder of the pooled ride savings as profit. The operator cannot know each agent's sensitivity to price, detour, and sharing, so instead it is assumed that the operator chooses some constant fraction of the operating cost savings to return as a discount to passengers. The total discount is then distributed among the passengers according to their relative excess disutility. As a result, if the total passenger discount is greater than the total excess disutility of sharing, it is guaranteed that all passengers will experience greater utility from the pooled ride relative to their exclusive ride option. If the total passenger discount is less than the total excess disutility of sharing, however, the passengers will experience greater utility from the exclusive ride.

The discrete choice model is incorporated by adding a new step in the matching process. The platform provides the characteristics of one pooled ride trip (fare discount, detour time) to each agent unless no feasible pooled ride trip exists for that agent. Then, the discrete choice model simulates the choice by each agent between the pooled ride offered by the platform or an exclusive ride. The agent chooses whichever ride maximizes their utility. The utility calculated in Eq. (6.1) is used as an input to determine each agent’s choice between alternative pooled rides and exclusive rides. It is common practice in travel demand modeling to include a random utility deviate, ε , to capture the unobserved determinants of utility between alternatives. There are many different distributions used for ε ; extreme value distributions are popular for their fit and tractability [125]. The total demand for exclusive and pooled ride trips, determined from the random utility discrete choice model, is then used to construct the shareability graph for the optimal matching model described in the next section.

Matching with flexible destinations

The parameters for each pooled ride can be determined by finding the optimal matching arrangement for a set of ride-pooling requests. The intuition for the matching algorithm is adopted from Alonso-Mora et al. [257], wherein a graph structure is created to identify possible vehicle-agent combinations, and then an optimization model is solved to select the optimal set of pooled rides. The procedure is generally tractable, even for the large vehicle capacities that would be needed for demand-responsive transit or van pooling, making it an attractive approach for this application. An entirely new shareability graph structure and generation procedure are developed to enable efficient matching despite the added complexity of flexible destinations.

Furthermore, a novel integer programming formulation with destination-specific decision variables is proposed for the optimal matching problem that permits remote work dependencies such as team co-location requirements. Together, these create a new passenger-vehicle-destination matching algorithm to evaluate the implications of remote work policies for shared mobility.

First, the set of shareable rides must be identified. Assume that during some fixed time interval, a certain number of agents make travel requests. Requests are shareable so long as constraints on waiting time, detour time, and vehicle passenger capacity are met. Another restriction is also added: the operating cost of a pooled ride cannot exceed the total operating cost of serving each agent with an exclusive ride. This ensures that only pooled rides that produce additional profit for the operator are considered. Any pooled rides that violate this restriction are not included in the shareability graph and therefore cannot be chosen by passengers. Additionally, agents whose trips are not shareable with another agent are served by an exclusive trip.

In the original algorithm, each request corresponds to a separate agent. Destination flexibility is modeled by including multiple requests from the same agent with different destinations. Two requests associated with the same agent are not shareable with each other. The new shareability graph involves 4 different node types: agents, requests, trips, and vehicles. The graph representation permits a new constraint to ensure that only one request per agent is assigned in the optimal solution.

A simple example is shown in Figure 6-1. The circular nodes represent requests (origin-destination pairs) associated with each agent. Each request node has an in-degree of 1, meaning that only one agent is associated with each request. In this case, Agent #2 has flexible destinations, represented by the 3 yellow request nodes connected to Agent #2. Requests by different agents are combined into possible

pooled ride “trips” served by a single vehicle. Note that the three requests from Agent #2 have no trips in common, as it would not be feasible for Agent #2 to be involved in multiple pooled rides at the same time. Finally, each of the potential trips can be served by one or more vehicles.

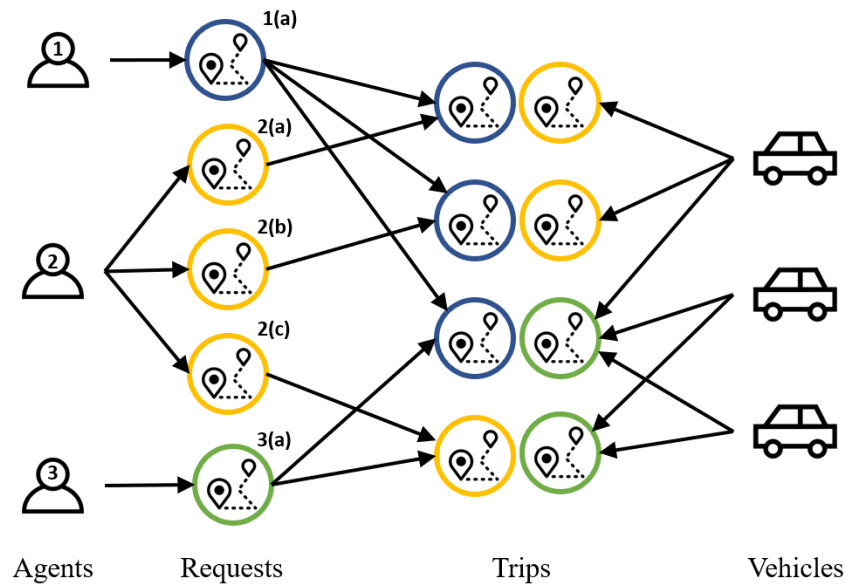


Figure 6-1: Example of the agent-request-trip-vehicle shareability graph

Once the shareability graph is constructed, an integer linear program (ILP) is solved to find the optimal assignment of agents and vehicles to trips. This assignment occurs twice: an initial assignment to provide pooled ride trip parameters to the agents before the actual demand is realized, and a final assignment for the agents who select pooled rides. The optimal initial assignment is used to find the set of feasible pooled rides that result in the greatest profit for the operator, which is then offered to the agents. Note that the operator only offers at most a single pooled ride to each agent. Depending on the demand, there could be many possible pooled rides involving each agent, but the agent does not have access to information about any

pooled rides beyond those offered by the operator. The operator, whose objective is to maximize their profit, has no incentive to increase the choice set of the agent by offering multiple pooled rides beyond those that maximize operator profit. For the final assignment, nodes corresponding to agents that choose an exclusive ride are pruned from the shareability graph, and the optimal matching arrangement is redetermined. The overall matching and passenger choice process is illustrated in Fig. 6-2. The final assignment occurs over a subgraph of the initial shareability graph and does not add significant computation time.

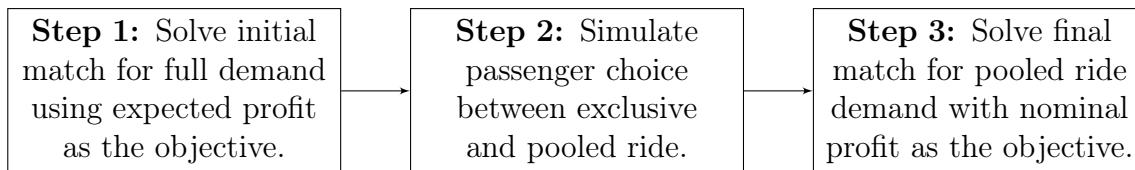


Figure 6-2: Flow chart demonstrating the matching and passenger choice process

The initial matching assignment is based on unrealized demand; ultimately, some of the pooled rides will not be feasible because the agents involved will choose an exclusive ride. Therefore, the matching should be weighted towards pooled trips that are most likely to be chosen by all agents involved. This can be accomplished by using *expected* profit in the objective function rather than the nominal profit. The probability that a pooled ride is chosen by all agents can be estimated in advance for each trip through simulation of the discrete model described in the previous section. In the final assignment, the demand is fixed and the nominal profit is used in the objective function. The two models are otherwise identical.

This process was designed to be similar to the actual ride-hailing customer experience. The user indicates their travel plans, the platform responds with a set of prices and travel times, then the user chooses from one of the alternatives. Note that the process is naïve in that it does not assume any learning of consumer preferences

over time. In reality, the platform may take advantage of its users' responses to design better recommendation algorithms or pricing strategies.

6.4.2 Location dependency (II)

The model developed in the previous section enables general ride-pooling matching with destination flexibility. To capture remote work dependencies, additional constraints and different objective functions can be formulated. For example, consider a ride-pooling platform and co-working service that each have a large market share. All co-working locations are available to the agents, but there are a limited number of seats at each location. The ride-pooling platform should be aware of facility capacities and therefore avoid routing numerous passengers to any single location regardless of centrality or travel convenience. The ride-pooling matching ILP described in Alonso-Mora et al. [257] does not contain any variables related to the destination, so a new model is created to allow for location dependencies. Additional indices are defined for the new ILP: $k \in \mathcal{V}$ for vehicles, and $d \in \mathcal{D}$ for destinations. The set of vehicles that can be assigned to a trip i is \mathcal{E}_i^V . Each trip produces a nominal profit p_i for the operator, while the expected profit is denoted by \bar{p}_i . The cost of assigning vehicle k to trip i due to vehicle relocation is represented by λ_{ik} .

The binary decision variables are chosen to permit constraints and objective terms dependent on destination choice, which are important for modeling the dynamics of remote work trips. Let $x_i \in \{0, 1\}$ indicate whether trip i is served, and $y_{ij} \in \{0, 1\}$ indicate whether agent j is assigned to trip i . Let $z_j \in \{0, 1\}$ indicate whether agent j is unserved and $w_{ik} \in \{0, 1\}$ indicate whether trip i is served by vehicle k . Finally, let $q_{jd} \in \{0, 1\}$ indicate whether an agent j is assigned to a trip with destination d . This destination-related decision variable is an important addition to enable associate

and location dependencies. Since each agent-trip pair (i, j) corresponds to exactly one destination, a correspondence matrix \mathbf{Q} can be created where $Q_{ijd} = 1$ if trip i results in an agent j visiting a destination d , and $Q_{ijd} = 0$ otherwise. The initial ILP can then be formulated as follows:

$$\max_{q,w,x,y,z} Z_0 = \sum_{i \in \mathcal{T}} (\bar{p}_i x_i - \sum_{k \in \mathcal{E}_i^V} \lambda_{ik} w_{ik}) - M \sum_{j \in \mathcal{A}} z_j \quad (6.2a)$$

$$\text{s.t. } x_i \leq y_{ij} \quad \forall (i, j) \in \mathcal{E}_{AT} \quad (6.2b)$$

$$Q_{ijd} y_{ij} = q_{jd} \quad \forall (i, j) \in \mathcal{E}_{AT}; d \in \mathcal{D} \quad (6.2c)$$

$$x_i \leq \sum_{k \in \mathcal{E}_i^V} w_{ik} \quad \forall i \in \mathcal{T} \quad (6.2d)$$

$$\sum_{i \in \mathcal{T}} w_{ik} \leq 1 \quad \forall k \in \mathcal{V} \quad (6.2e)$$

$$\sum_{i \in \mathcal{T}} y_{ij} - z_j = 0 \quad \forall j \in \mathcal{A} \quad (6.2f)$$

$$\mathbf{q}, \mathbf{w}, \mathbf{x}, \mathbf{y}, \mathbf{z} \in \{0, 1\} \quad (6.2g)$$

Function 6.2a maximizes total expected trip profit less the cost of vehicle assignments. A large penalty of M is applied for all unserved agents. For the final matching model, the \bar{p}_i term in 6.2a is replaced with p_i . Constraint 6.2b requires that the agents involved in a pooled trip are assigned to the trip if the trip is served. Constraint 6.2c defines the relationship between y_{ij} and q_{jd} such that $q_{jd} = 1$ if an agent j is assigned to a trip where the agent's destination is d ($y_{ij} = 1$ and $Q_{ijd} = 1$), and $q_{jd} = 0$ otherwise. Constraint 6.2d ensures that each served trip has an assigned vehicle. Constraint 6.2e requires each vehicle to serve one trip at most. Constraint 6.2f ensures that each agent is either assigned to one trip or unserved.

Finally, the location capacity limit is modeled by adding the following constraint on q_{jd} , where b_d is the number of available seats at the location d :

$$\sum_{j \in \mathcal{A}} q_{jd} \leq b_d \quad \forall d \in \mathcal{D} \quad (6.3)$$

6.4.3 Associate dependencies (III)

First, a hard associate dependency is added to the ILP to ensure certain individuals are assigned to the same location, perhaps team members who require face-to-face interaction to accomplish a task. The dependency is enforced by adding a constraint of the following form for two agents $j, m \neq j$:

$$\sum_{d \in \mathcal{D}} q_{jd} q_{md} = 1 \quad (6.4)$$

This is a non-linear constraint in the decision variables, however, which makes the model much harder to solve. The non-linearity can be overcome by introducing $|\mathcal{D}||\mathcal{A}|^2$ new binary decision variables, $\mu_{jmd} \in \{0, 1\}$ to represent the non-linear term $q_{jd} q_{md}$. Four linear constraints can be used to model the conditional relationship between μ_{jmd} and $q_{jd} q_{md}$, where $\mu_{jmd} = 1$ if $q_{jd} q_{md} = 1$ and 0 otherwise:

$$\mu_{jmd} \leq q_{jd} \quad \forall j, m \neq j \in \mathcal{A}, d \in \mathcal{D} \quad (6.5a)$$

$$\mu_{jmd} \leq q_{md} \quad \forall j, m \neq j \in \mathcal{A}, d \in \mathcal{D} \quad (6.5b)$$

$$\mu_{jmd} \geq q_{jd} + q_{md} - 1 \quad \forall j, m \neq j \in \mathcal{A}, d \in \mathcal{D} \quad (6.5c)$$

$$\mu \in \{0, 1\} \tag{6.5d}$$

Similar dependencies can be enforced using this linear formulation, such as a requirement that each employee works at the same location as at least one team member. The initial non-linear constraint in Eq. 6.4 is replaced by the following equation, and the same linearization techniques described above are applied:

$$\sum_{m \in \{\mathcal{A} \setminus j\}} \sum_{d \in \mathcal{D}} q_{jd} q_{md} \geq 1 \quad \forall j \in \mathcal{A} \tag{6.6}$$

The second associate dependency, which is a soft constraint, is introduced by changing the objective function. The model structure also allows for more complex objective functions that include remote work considerations. For example, imagine a version of the scenario described above where two people benefit from face-to-face interaction, but the interaction is simply preferred instead of required. Since the destination of each passenger is a decision variable in the ride-pooling matching model, it is not known in advance. Recall that in this scenario, the employer compensates the ride-pooling platform for the co-location of employees to encourage higher productivity. This provides an incentive for the ride-pooling platform to choose an otherwise suboptimal matching arrangement as long as it results in the co-location of certain employees. For simplicity, assume that each co-located pair of team members results in a constant payment, regardless of location. This framework can, however, include payments that vary by employee and location.

There is then some maximum amount of payment that can be obtained by locating agent j at location d , which occurs when all the team members of agent j are also located at d . This maximum payment is represented by a constant, u_{jd}^{\max} . A matrix

I of size $|\mathcal{A}| \times |\mathcal{A}| \times |\mathcal{D}|$ is defined, where $I_{jmd} \in [0, 1]$ is the fraction of u_{jd}^{\max} obtained when the agent m is co-located with the agent j at a destination d . In this simple case, I_{jmd} is equal to 1 over the size of the team, therefore $\sum_m I_{jmd} = 1$.

There are two conditions required for the payment to be realized. First, the team members must be co-located with the agent j . The auxiliary variable $u_{jd} \in [0, 1]$, is introduced to represent the fraction of u_{jd}^{\max} that could be accrued when the agent j visits a location d , given that some of the team members may not be co-located at d (i.e. $u_{jd} = \sum_{m \in \{\mathcal{A} \setminus j\}} I_{jmd} q_{md}$). Second, the agent j must be assigned to a destination d , which occurs when $q_{jd} = 1$. Multiplying decision variables u_{jd} and q_{jd} produces a non-linear term in the objective function, however. This binary-continuous product can be linearized through substitution. First, let $\alpha_{jd} \in [0, 1]$ represent $u_{jd} q_{jd}$. An auxiliary variable g_{jd} and constraints (6.8a) - (6.8f) are introduced to enforce $\alpha_{jd} = u_{jd}$ when $q_{jd} = 1$ and $\alpha_{jd} = 0$ otherwise. The objective function in Eq.(6.2a) is replaced by a new objective function:

$$\max_{q,w,x,y,z,u,\alpha,g} Z_1 = \sum_{i \in \mathcal{T}} (\bar{p}_i x_i - \sum_{k \in \mathcal{E}_i^V} \lambda_{ik} w_{ik}) - M \sum_{j \in \mathcal{A}} z_j + \sum_{j \in \mathcal{A}} \sum_{d \in \mathcal{D}} u_{jd}^{\max} \alpha_{jd} \quad (6.7)$$

The linear constraints are as follows:

$$u_{jd} = \sum_{m \in \{\mathcal{A} \setminus j\}} I_{jmd} q_{md} \quad \forall j \in \mathcal{A}, d \in \mathcal{D} \quad (6.8a)$$

$$-g_{jd} \leq q_{jd} \leq g_{jd} \quad \forall j \in \mathcal{A}, d \in \mathcal{D} \quad (6.8b)$$

$$1 - (1 - g_{jd}) \leq q_{jd} \leq 1 + (1 - g_{jd}) \quad \forall j \in \mathcal{A}, d \in \mathcal{D} \quad (6.8c)$$

$$-g_{jd} \leq \alpha_{jd} \leq g_{jd} \quad \forall j \in \mathcal{A}, d \in \mathcal{D} \quad (6.8d)$$

$$-(1 - g_{jd}) \leq (\alpha_{jd} - u_{jd}) \leq (1 - g_{jd}) \quad \forall j \in \mathcal{A}, d \in \mathcal{D} \quad (6.8e)$$

$$\mathbf{g} \in \{0, 1\} \quad \alpha \in [0, 1], \quad \mathbf{u} \in [0, 1] \quad (6.8f)$$

A total of $3|\mathcal{D}||\mathcal{A}|$ new decision variables, some continuous, are introduced to create a tractable mixed-integer program with a linear objective and linear constraints. This enables the ride-pooling matching problem to be solved efficiently for the co-working scenario. The objective is defined in Eq. (6.7), subject to constraints (6.2b) - (6.2f), (6.3) and (6.8a) - (6.8f).

6.5 Case Study

6.5.1 Experiment design

To demonstrate how the methods described in the previous section can be used to design ride-pooling services for remote work, an experiment was developed using real ride-hailing demand data from Manhattan. Exact origins, destinations, and pick-up times for each trip in June 2016 were collected from a public dataset provided by the New York City Taxi and Limousine Commission [258]. Time-dependent travel speeds for each street in Manhattan were used to determine travel times between pickup and drop-off locations [259]. Ride-pooling requests were grouped into 3-minute intervals during the morning rush hour (8 AM - 9 AM), a time period during which the vast majority of travelers are traveling to work. The interval starting at 8:00 AM was used for this experiment, which contained 840 requests. The vehicle fleet size was therefore chosen to be sufficient to satisfy the demand; initial vehicle locations were assigned uniformly at random from the set of street intersections. The values for all simulation parameters are presented in Table 6.5.

Parameter	Value
Cost coefficient mean (β_1)	1.59 [255]
Time coefficient (β_2)	0.318 [255]
Sharing coefficient (β_3)	0.693 [255]
Maximum wait time	10 minutes
Maximum detour time	25% of shortest path travel time
Fleet size	900 vehicles
Vehicle capacity	4 passengers
Base fare	\$2.65 [260]
Additional fare per mile	\$1.005 / mile [260]
Additional fare per minute	\$0.1125 / minute [260]
Exclusive ride profit margin	25% [260]
Pooled ride discount fraction	50% of operating cost savings
Total number of agents	840 agents
Agents with flexible destinations	168 agents (20% of total)
Available co-working locations	10 Manhattan WeWork locations
Optimality gap cut-off	0.5%

Table 6.5: Simulation Parameters

Values for β_1 , β_2 , and β_3 were adopted from the ride-pooling discrete choice model estimated by Alonso-González et al. [255]. The maximum pickup time was set to 10 minutes and the maximum detour was set to 25% of the shortest path travel time. Operating parameters for ride-pooling platforms are taken from a 2019 study of Uber and Lyft in Denver, CO [260]. Ten evenly spaced WeWork spaces in Manhattan are used as the representative remote work locations [261]. The destination utilities v_{ij} are unknown in practice, so a distribution is assumed. For each agent, the utility is sampled independently from a mixed distribution for each location such that the agents have similar but not identical utility for each destination. The mixed distribution is a normal distribution where the mean is drawn uniformly at random from the range (50, 60) for each destination, with a standard deviation of 3 units.

Three scenarios are tested against a baseline scenario. The first demonstrates how

remote work locations affect ride-pooling outcomes compared to a baseline where all locations are fixed. In the typical remote work scenario, 20% of passengers are assumed to have flexible destinations. Values from 5% to 30% are tested for Scenario 1. Passengers with flexible destinations are chosen at random, as no employment or demographic information is provided about the passengers in the NYCTLC dataset. These passengers choose between trips to each of the 10 selected WeWork locations. Because the destinations were changed to WeWork locations for Scenario 1, the locations are also changed in the baseline scenario to ensure that only the effect of passengers with multiple flexible destinations influences the results. To that end, all passengers with a flexible destination in Scenario 1 are assigned to the WeWork location with the least travel cost in the baseline scenario. The sensitivity of the results to the quantity and layout of these locations are also tested in Scenario 1 by re-running the experiment with 5 and 15 WeWork locations.

Scenario 2 adds different location capacity constraints from Eq. (6.3) to explore the impact of co-working space size on ride-pooling outcomes. Finally, the third scenario incorporates the associate constraints and dependencies described in Section 6.3 to contrast the results of the associate dependency benefits from Eqs. (6.6) - (6.8) with the results from the two previous scenarios. Each scenario is evaluated based on operator profit, pooled ride mode share, total vehicle-miles traveled (VMT), total agent utility, and solution time. The reported results are the average of 10 model runs as the demand model includes a stochastic discrete choice component, although the results do not vary significantly across simulation runs (the coefficients of variation are less than 3%).

6.5.2 Results

Table 6.6 compares the ride-pooling outcomes for different levels of passenger flexibility against equivalent baseline scenarios with no flexible destinations. Percentage changes in performance relative to the corresponding baseline scenario are reported. The results demonstrate that flexible destinations allow the ride-pooling platform to match travelers more efficiently, leading to a greater share of pooled rides, lower VMT, and more operator profit. Moreover, performance increases with respect to VMT, profit, and the number of pooled trips grow rapidly with the share of flexible passengers. The average utility for passengers is unchanged across scenarios, indicating that the discount for the additional pooled trips is sufficient to offset the disutility of sharing. The maximum ILP solution time for all experiments was 11.3 seconds using Gurobi v9.1 on a dual-core Intel i7-6600U CPU with 16 GB of RAM.

The reduction in VMT observed in the flexible destination scenario is entirely due to matching efficiency. Flexible destinations led to slightly longer trips being selected on average: the total *passenger* miles traveled (PMT) increases in the flexible scenario relative to the baseline scenario, indicating that the reduction in VMT is purely a consequence of the greater number of pooled trips. In brief, flexible destinations result in each vehicle mile serving more passenger miles.

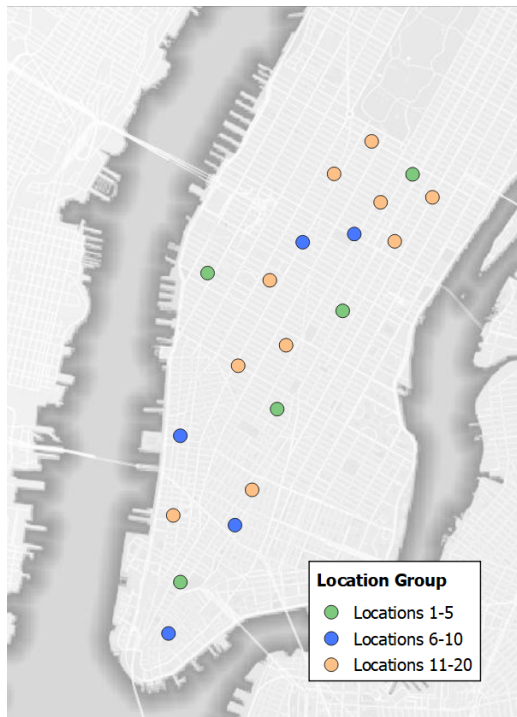
Evaluation Parameter	Share of passengers with flexible destinations				
	5%	10%	15%	20%	25%
Number of Pooled Trips	+1.3%	+1.8%	+2.7%	+4.1%	+6.3%
Operator Profit	+0.6%	+1.6%	+3.2%	+5.3%	+8.4%
Passenger Utility	+0.1%	+0.1%	+0.0%	+0.0%	+0.2%
Total VMT	-0.4%	-0.8%	-1.8%	-3.2%	-4.9%
PMT / VMT	+0.8%	+0.8%	+1.9%	+5.3%	+5.4%

Table 6.6: Ride-pooling platform performance with flexible destinations relative to the non-flexible scenario by share of flexible passengers

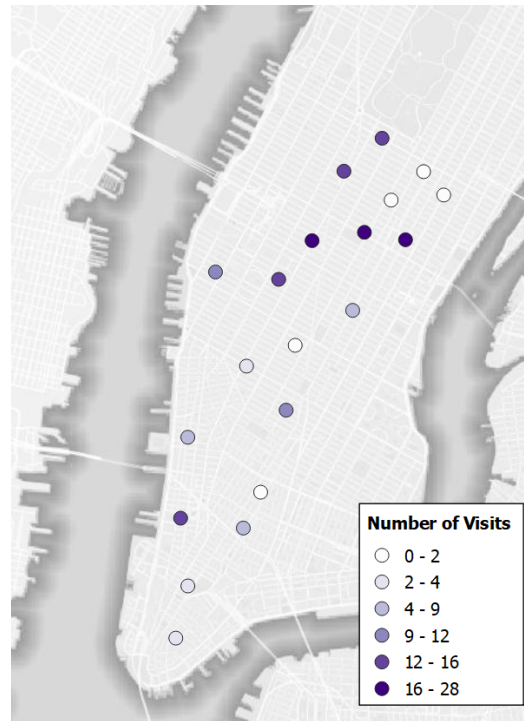
These results are encouraging; even with a low share of flexible travelers, outcomes are improved for all stakeholders. Unsurprisingly, the benefit of passengers having flexible destinations yields the greatest benefits for the operator (profit) and the system (VMT and pooled trips), rather than the passengers themselves, given that the objective of the ILP is to maximize operator profit. The increases in passenger utility appear to be largely incidental and are not affected by the share of passengers with flexible destinations. The efficient matching afforded by destination flexibility has positive externalities, namely reduced travel due to a higher pooling rate. It is perfectly reasonable to assume that the objective of the platform is to maximize profit, but other objective functions, perhaps achieved through regulation or a different incentive structure, could distribute the benefits differently.

The sensitivity of the results with respect to the number and spatial distribution of possible destinations provides insights into the impact of land use and available flexible workplaces on travel demand. The baseline scenario used to generate the results presented in Table 6.6 assumes there are 10 flexible workplaces available, with the locations corresponding to actual WeWork spaces in Manhattan. The simulation was also run for scenarios with 5 and 20 destinations, also selected from WeWork offices. The spatial distribution of the locations is presented in Figure 6-3a below. The number of visits by location for the 20-destination scenario is presented in Figure 6-3b.

Table 6.7 shows how the performance of the ride-pooling platform changes with respect to the number of destinations available to flexible travelers. Once again, the percentage improvement relative to the non-flexible baseline for each scenario is reported. Clearly, a greater number of flexible destinations available to flexible passengers creates more opportunities for efficient matching by expanding the shareability graph, leading to better performance and reduced externalities. Interestingly,



(a) Selected WeWork Locations



(b) Number of visits (20 flexible destinations)

Figure 6-3: Spatial distribution of flexible work locations and visits

PMT declines when 20 destinations are available relative to the 10-destination scenario because passengers are more likely to find an available destination nearby. As a result, the reduction in VMT is not a result of increased efficiency, but simply a result of shorter overall trip distances.

Scenario 2 adds location capacity constraints to the problem to model the ride-pooling problem for a co-working location or an employer with several small offices in an urban area. In the unconstrained problem, the most popular destination was visited by 50 agents. Figure 6-4 presents the trends for traveler utility and VMT as several increasingly restrictive occupant capacities are applied. The effects are limited for maximum capacity constraints above 35 people per location as only a few trips to

Evaluation Parameter	Number of available destinations		
	5	10	20
Number of Pooled Trips	+0.5%	+4.1%	+6.7%
Operator Profit	+3.1%	+5.3%	+6.2%
Passenger Utility	+0.0%	+0.0%	+0.0%
Total VMT	-2.3%	-3.2%	-4.0%
PMT / VMT	+0.5%	+2.0%	+1.2%

Table 6.7: Ride-pooling platform performance with flexible destinations relative to the non-flexible scenario by number of available destinations for flexible passengers

the most popular locations are affected. As the maximum capacities grow smaller, however, traveler welfare (as measured by utility) and system outcomes (VMT) begin to decline quickly. The most restrictive location capacity constraints decrease total traveler utility by 9.0% while increasing VMT by 6.6%, as the constraints force many remote workers to travel to less preferred and more distant locations. These impacts fall entirely on the remote workers, as they are the only travelers who can change their destinations in response to capacity constraints. The average travel distance for remote workers is 1.96 miles in the unconstrained scenario and 2.30 miles in the most constrained scenario.

These results imply that, in a remote work environment, workplaces that are easily accessible by remote workers will experience greater demand on a day-to-day basis. If demand begins to exceed the number of available workplaces at these centrally located remote work hubs, overall congestion will increase as remote workers must travel further to find an available space. Policymakers interested in travel demand management may consider tracking occupancy rates of remote workspaces in their regions and removing regulatory barriers to expansion where demand exceeds supply.

Finally, Scenario 3 adds associate dependencies to the objective function as given

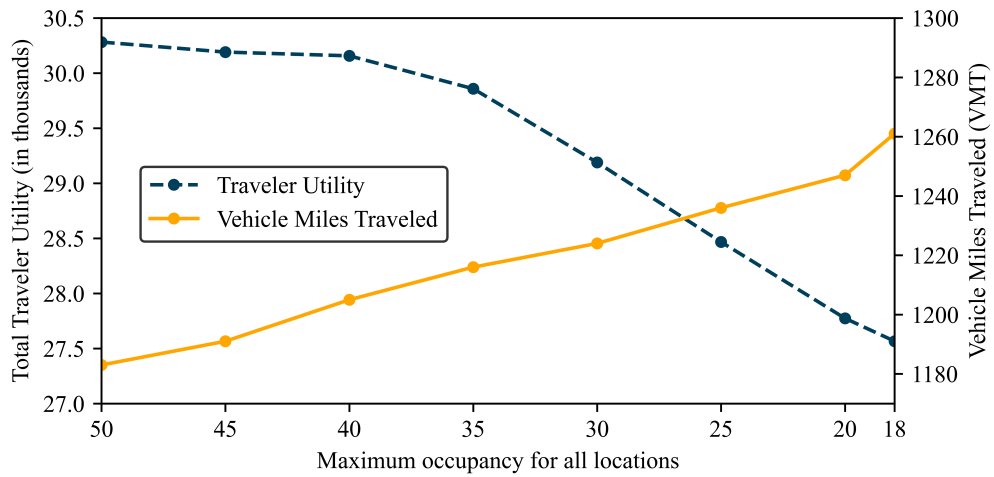


Figure 6-4: Sensitivity of total traveler utility and VMT to changes in location capacity

by Eqs. (6.6) - (6.8) while removing the location capacity constraint. The first is a hard constraint, requiring each flexible traveler to be co-located with a certain number of their colleagues. Figure 6-5 shows how co-locating two employees hardly affects the travel outcomes, but co-locating three or more colleagues results in a major degradation in performance. In fact, the co-location of three or more employees completely offsets the VMT reduction benefits of flexible destinations, leading to more total VMT than the baseline scenario with no flexible destinations. The co-location constraint forces flexible workers to destinations that are significantly suboptimal from a transportation efficiency perspective, limiting the amount of matching that occurs and driving up VMT. Traveler utility decreases as longer and more expensive trips are required to less desirable destinations in order to satisfy the co-location constraint.

The second associate dependency is a soft dependency, where team members are incentivized (but not required) to co-locate with one another. Travelers with flexible

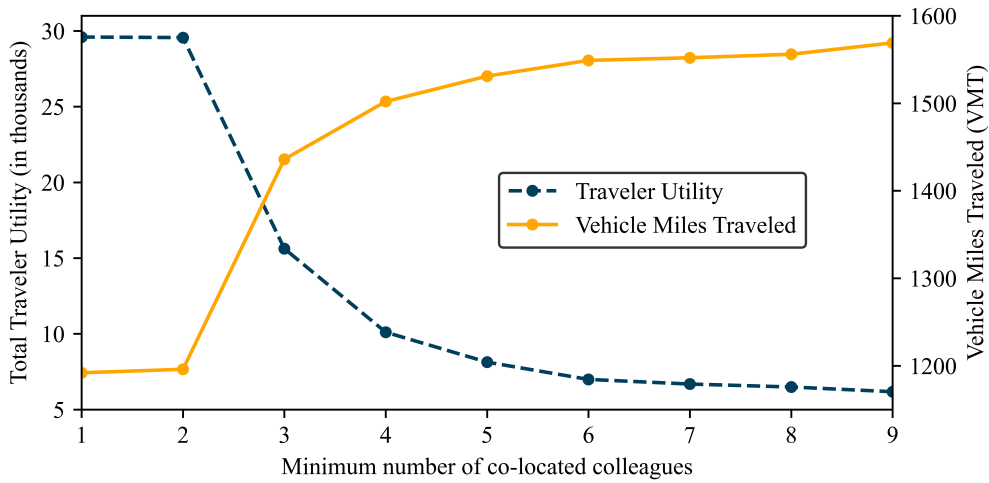


Figure 6-5: Sensitivity of total traveler utility and VMT to changes in the number of colleagues that must be co-located

destinations were divided at random into teams of constant size. Co-locating two team members results in a bonus payment of u^{\max} to the operator. The maximum solution time for these experiments was 10.3 seconds. Figure 6-6 shows how the number of co-located team members increases with u^{\max} for various team sizes. Even small values of u^{\max} can increase the number of team members working at the same location. For 15-person teams, the number of employees working with another team member increases from an initial 44 to 53 when $u^{\max} = 2.5\$$.

Figure 6-7 presents profit and VMT for increasing values of u^{\max} when the team size is fixed to 15 people. Like in Figure 6-6, the effect of the co-location bonus plateaus after \$2.50 for teams of 15 people; VMT and profit (without co-location bonus) are largely unchanged as the bonus grows from \$2.50 to \$5.00. There is an empirical upper bound for the number of co-located employees, as travel costs make it very unlikely for certain team members to travel to the same destination. While the total profits increase due to the addition of u^{\max} , the profits earned directly

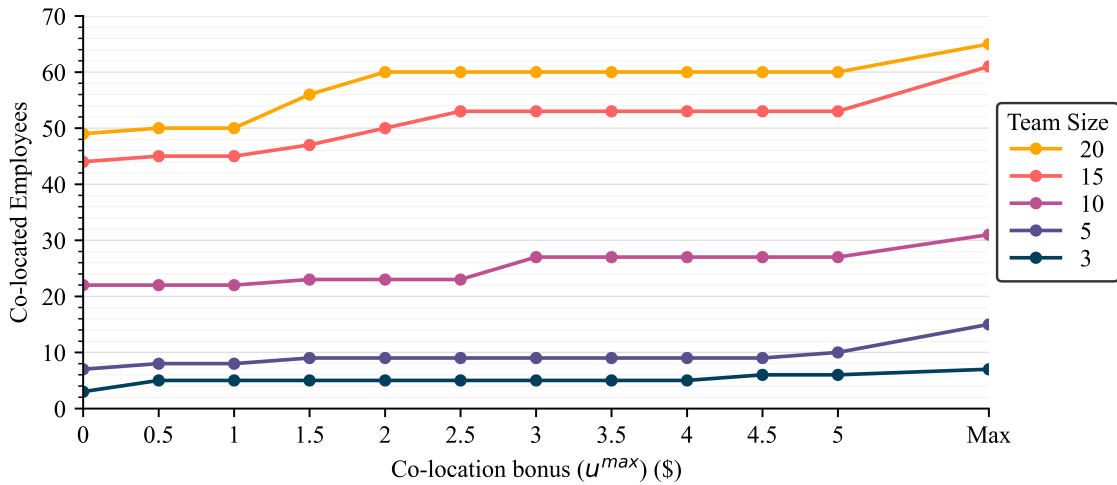


Figure 6-6: Sensitivity of the number of co-located employees to changes in the associate benefit u^{\max} for a range of team sizes

from passengers (profit without bonus) decrease when the incentive for co-location outweighs the incentive to operate the most profitable trips. Similar to the trends observed in Figure 6-4 where the location capacity constraint is applied, there is also a rise in VMT when co-location is heavily incentivized due to the additional travel required.

6.6 Policy implications

The experimental results show that, given the conditions described in Section 6.5.1, remote work policies can improve ride-pooling adoption rates and profits while reducing VMT. While the performance increases from destination flexibility may seem somewhat low, note that the experiment covers only people who live and work in a very small geographic area (Manhattan). Flexible ride-pooling platforms serving an entire urban region with medium and long-distance commutes could have an even

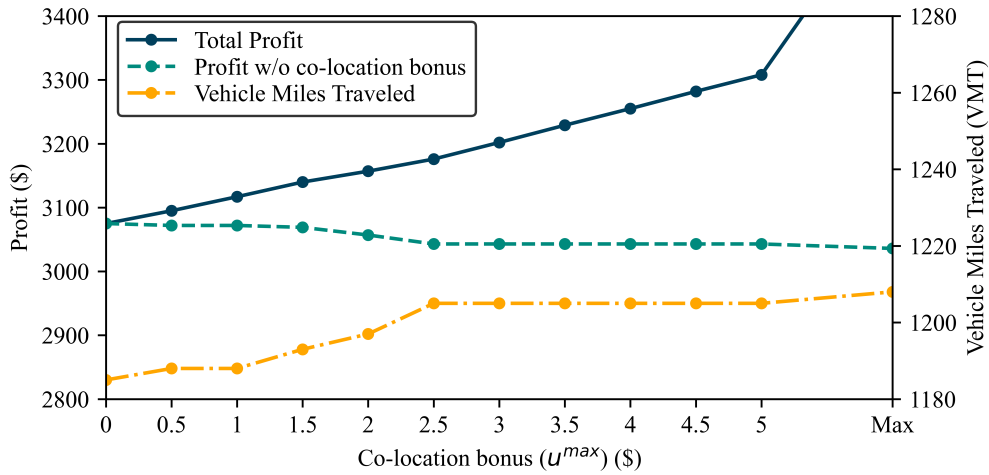


Figure 6-7: Sensitivity of total profit, profit without benefit and VMT to changes in the associate benefit u^{\max}

larger impact. Location capacity constraints, co-location constraints, and co-location incentives are found to temper the travel benefits of flexible destinations by requiring or encouraging travel to suboptimal locations. This research has implications for three different remote work stakeholders: employers, policymakers, and mobility services.

Employers considering remote work policies can use the tools presented in this study to evaluate different remote work policies and real estate portfolios. There is an ongoing tension between employers who prefer for their staff to have face-to-face interactions and remote workers who would prefer to avoid the costs of traveling to the workplace. This study shows that allowing more employees to work from multiple locations (e.g. co-working spaces) reduces VMT and improves traveler utility, even if co-location of team members is desired. Having a large portfolio of possible work locations spread across an urban region is also helpful in limiting travel costs for employees and avoiding transportation-related externalities. Ensuring that the

most easily accessed locations have sufficient capacity will allow employees to take advantage of nearby flexible work locations.

Given that flexible work locations have the potential to reduce VMT through increased ride-pooling, policymakers should consider how to encourage mobility operators to offer these features. Furthermore, flexible work location policies could be considered as part of a larger travel demand management program. Land use policies that allow for new collaborative workplaces in residential areas may also reduce the distance that remote workers need to travel when they choose to do remote work outside the home.

These results demonstrate that ride-pooling platforms could leverage the tools described herein to provide more efficient matching and greater adoption of pooled rides by allowing customers to enter multiple possible destinations for the same trip. Furthermore, future ride-pooling platforms could allow two friends or colleagues leaving from different origins to choose a central location for a meeting or social event based on some mutual combination of travel costs and destination preferences. Such features would extend existing ride-pooling platforms to more of a comprehensive trip-planning platform. Some have predicted that shared autonomous vehicles may eventually gain a substantial market share [262]; in such an environment, the efficiency gains from flexible destination ride-pooling could have a significant impact on overall travel demand. Platform operators could also create new business models by partnering with employers and co-working spaces to provide integrated mobility and workplace solutions for the future of work.

6.7 Conclusions

This chapter establishes a vocabulary and framework for modeling travel demand and supply optimization in the context of remote work. The framework is used to study the impacts of flexible remote work locations on ride-pooling outcomes. A new ride-pooling matching model is proposed with linear formulations that capture the dynamics of work location choice for the first time, including location capacities and the benefits of co-locating with colleagues. These formulations are tested using real demand, demonstrating the impacts of remote work dependencies and the tractability of the model formulations. While the model is applied to shared ride-pooling in this chapter, the methods can be easily modified for passenger-vehicle matching with other shared mobility modes such as demand-responsive transit by changing the vehicle passenger capacity and removing any exclusive rides from the set of possible trips.

This work extrapolates from current trends to provide high-level insights for a possible future. Real data was used wherever possible, but several assumptions were necessary to model travel behaviors and employment scenarios in the context of remote work. Surveys are needed to quantify travel preferences and employer plans regarding flexible work locations to improve the destination utility assumptions. Another limitation of the case study is that it compares a ride-pooling service with some flexible destinations against a ride-pooling service with no flexible destinations for a single period of operations that assumes a fixed number of customers and drivers. Given that flexible destinations are shown to improve operational efficiency, operational profitability, and utility for customers, more drivers and passengers may be attracted to the platform over time [263]. Future research in this area could extend the modeling framework to a day-to-day simulation of ride-pooling operations with

flexible destinations.

Other potential extensions of this research include developing multi-objective models to design remote work policies that balance travel utility and productivity. This could include a more sophisticated, graph theory-based approach to productivity modeling, where productivity is related to the presence of co-workers and random interactions between different organizations. Such interactions do not need to be random or exclusive to the workplace; future research could also include the design of a ride-pooling algorithm that matches agents strategically to promote idea flow.

Chapter 7

Tractable optimization models for evaluating transit capacity flexibility at the network scale

7.1 Introduction

The concept of “capacity flexibility” was proposed by Morlok and Chang [264] as a framework for evaluating the ability of a transportation system to handle changes in the distribution of demand. In their seminal paper, the authors develop a model for measuring the capacity of freight networks. Chen and Kasikitwivat [265] subsequently proposed a different model for the capacity flexibility of a road network for passenger transportation. They define three different metrics for capacity flexibility:

1. **Reserve capacity:** the largest multiplier that can be applied to the existing origin-destination demand matrix without violating any link capacities or exceeding a specified level of service.

2. **Network capacity with limited flexibility:** the summation of the current origin-destination demand and *additional* demand that the network can accommodate. The current demand pattern is preserved, but the additional demand has the flexibility to choose any destination.
3. **Network capacity with total flexibility:** the maximum number of passengers that the system can accommodate when all travelers in the network can choose their destination.

Freight networks and road networks both present a relatively simple application of capacity flexibility. A freight network operator has total control of the path of each unit of demand. Road networks, on the other hand, have nominal link capacities that cannot be adjusted on a day-to-day basis by adding or removing lanes. Models of road network capacity flexibility must account for driver autonomy in route choice, but there is no need to consider the adjustment of supply to match demand patterns (at least in the short term). The inflexible nature of road networks also limits the practical benefits of determining capacity flexibility; identifying potential capacity constraints in a network provides limited value if ameliorating those constraints is extremely costly and time-consuming.

Public transit networks present a challenging case from a methodological perspective because they feature the complexities of both freight networks and road networks. Passengers are free to choose any route to their destination, making the demand more flexible than a freight network. Furthermore, the transit operator can adjust the frequencies of each transit line to accommodate more demand. In brief, demand and supply respond to one another, creating a dynamic transportation system that can be rather difficult to model. However, these same features that create complexity also make public transit networks a much more compelling application

for capacity flexibility. Identifying whether resource constraints, minimum service requirements, or infrastructure limitations are preventing greater capacity can help a transit agency in short-term scheduling and long-term strategic planning.

Capacity flexibility for public transit networks is also especially relevant at the current moment. Public transit systems have seen a significant decline in ridership throughout the COVID-19 pandemic and recovery period. Transit agencies are concerned that ridership may not return to pre-pandemic levels in the short or medium term, primarily as a result of the dramatic increase in remote work. Commuters had historically made up a significant portion of the ridership base for transit agencies in urban areas. People are still choosing to travel, however, but at different times and to different locations than before. How transit networks might accommodate more travel within residential neighborhoods, or during off-peak periods, remains an open question for many transit agencies. These shifts represent changes in the spatial and temporal distribution of demand, and evaluating the capacity of the network to handle such changes is exactly the purpose of capacity flexibility models.

There have been two previous attempts to develop models for the capacity flexibility of public transit networks. The first, by Hang et al. [266], proposes a model for the reserve capacity of transit networks. Their model is highly non-linear, and the authors present a genetic algorithm-based heuristic solution method. The second, a recent paper by Zheng et al. [267], includes transit as one of three transportation modes in a multi-modal network capacity flexibility model. The authors propose a bi-level optimization problem and sensitivity-based solution algorithm that converges to a locally optimal solution.

These two papers have several limitations in common. First, the passenger assignment components are relatively simple and do not consider the disutility of crowding or the non-linear wait time functions that occur when passengers are denied boarding

on an overcrowded bus or train. The second and perhaps most important limitation is that these models are only shown to be tractable for toy-sized problems with less than 10 nodes each. This prevents them from being used in practice to evaluate the capacity flexibility of actual transit networks and develop policy recommendations.

In this chapter, a new mixed-integer non-linear programming formulation for each of the three transit capacity flexibility metrics is proposed. The model formulations provide a more accurate representation of transit dynamics than the previous literature by including the disutility of crowded trains and the non-linear effects of crowding on wait time. Then, a new iterative solution method is presented based on a first-order approximation of the passenger choice function and a fixed demand multiplier that solves a mixed-integer *linear* program at every iteration. An experiment using the full Massachusetts Bay Transportation Authority (MBTA) rapid transit network demonstrates how the novel model design and solution algorithm can be used to measure the capacity flexibility of a full-sized transit network for the first time in the literature. This problem-specific iterative solution method is shown to outperform the solution methods from previous transit capacity flexibility literature, as well as a state-of-the-art commercial solver.

7.2 Network capacity theory and literature

Network capacity is an important concept in transportation planning, yet the term “capacity” can refer to a wide variety of different metrics depending on the context. The canonical maximum network flow problem with fixed link capacities is a simple example; there exists some deterministic optimal solution that provides an upper limit on throughput. As noted by Kasikitwiwat and Chen [268], the maximum flow of passenger transportation networks must consider many other factors, including

passenger choice. Unlike in freight networks, passengers are empowered to choose a route and even a destination for some trips, making it unlikely that the theoretical maximum capacity of the network could ever be achieved. Traffic network capacity is therefore often described with two parameters: the system optimal traffic flow, a theoretical passenger throughput that could be achieved under centralized routing, and the user equilibrium traffic flow that occurs when passengers choose routes according to their own self-interest [269]. The practical capacity of a network is thus dependent on the interaction between the demand pattern and the network, not simply the structure of the network itself [270].

As an example, consider a public transit network in an urban area. Adding a new transit line to a sparsely populated region provides little practical capacity, as there would be little demand for the new line, even if it provides a relatively large increase in the theoretical capacity of the network. On the other hand, if land-use policies are such that the new line includes the development of relatively dense, transit-oriented neighborhoods at each station, both the practical and theoretical capacity of the network would be improved. While in both scenarios, the network changes are the same, it is the demand profile that ultimately determines the impact on practical capacity. Similarly, offering differential fare pricing for peak and off-peak periods could increase the total daily capacity of a transit network without making any changes to the network structure [271].

Other important considerations in passenger network capacity measurement include congestion-related delays, rather than fixed travel times, and lower bounds on the level of service. Congestion-related delay creates a network in which travel times can grow to the point where most users would consider the network to be over-saturated, even if it has yet to reach the maximum theoretical capacity [272]. Second-best constraints [273] can therefore be added to enforce bounds on the level of

service and other sociopolitical factors that limit the practical capacity of a network, even if it is not physically limited. In addition to the considerations mentioned by Kasikitwiwat and Chen [268], some transportation networks, such as public transit networks, can reallocate capacity between links in a relatively short timeframe, thus creating a dynamic problem that might have many optimal solutions.

Capacity flexibility can be designed to capture the complexity described above and provide both practical and theoretical perspectives on network capacity. It offers an evaluation of the practical maximum capacity of a network given a user equilibrium demand pattern, but also the theoretical capacity of the network under an entirely flexible demand profile. In this chapter, the practical component of transit capacity flexibility is highlighted through three metrics. The first transit capacity flexibility metric, “Reserve Capacity” (RC) assumes that the current origin-destination patterns are preserved, and only the magnitude of the demand can be adjusted. “Total Destination Flexibility” (PF) assumes that the trip origin patterns remain the same, but destinations for all passengers are flexible. Total Destination Flexibility is a slight departure from the Total Flexibility metric in Chen and Kasikitwiwat [265], where both origins and destinations are allowed to be flexible. Allowing origins to be flexible produces interesting theoretical results, but few practical implications, since it results in many trips along low-demand parts of the network which are unlikely to provide value to passengers. “Partial Destination Flexibility” (PF) is between Total Destination Flexibility and Reserve Capacity, wherein the existing demand patterns remain constant but all new demand has the flexibility to choose a destination. A baseline metric is also calculated for comparison. It is known as “Existing Capacity” (EC), which is similar to the Reserve Capacity metric except that the line frequencies are held constant, and cannot be changed by the network operator to match observed demand patterns.

There has been considerable research interest in capacity flexibility since the concept was introduced for freight networks by Morlok and Chang [264] and traffic networks by Chen and Kasikitwiwat [265]. Network capacity flexibility has frequently been used in the evaluation of freight networks to illustrate the importance of flexibility in supply chains and propose improvements [274, 275, 276]. Designing supply chains for capacity flexibility is considered to be a proactive measure to mitigate the effects of demand uncertainty [277]. Capacity flexibility is also used for assessing the theoretical capacity and resiliency of networks that are subject to disruptions [278, 279].

Research on passenger transport has largely focused on enhancing models of traffic networks. Wang et al. [280] develops a model for determining the reserve capacity model of a road network under *stochastic* user equilibrium conditions, rather than deterministic user equilibrium. Using a robust optimization approach, [281] develop a model of capacity flexibility for road networks that is robust to errors or inaccuracies in the demand measurements. Zheng et al. [267], describing network capacity flexibility as an urgent priority for transportation planners, designs a multi-modal subsidy scheme in which the goal is to maximize capacity flexibility, using the same measures as Chen and Kasikitwiwat [265]. In an interesting application, [282] extends the concept of capacity flexibility to the capacity of a single transit station to handle changes in demand patterns using a queuing model.

7.3 Model design

The primary inspiration for the model in this chapter is the transit frequency setting model developed by Bertsimas et al. [283]. Their model solves the frequency-setting and pricing problem for transit networks, and was shown to be tractable for

a medium-sized network. An entirely new model is required for the transit capacity flexibility problem. The two key differences between the three transit capacity flexibility problems and the frequency-setting problem are the objective function and the passenger choice function. First, the objective of the reserve capacity problem is to maximize total passenger throughput; therefore, the total passenger demand must be treated as a modeling decision variable rather than an exogenous constant. This introduces a new source of non-linearity into the model due to the multiplication of two decision variables: the demand multiplication factor (which is being maximized) and the demand at each origin-destination pair. Second, the limited and total flexibility problems allow for variable passenger destinations. The passenger choice function therefore has a new dimension, destination choice, and must consider all possible destination-route pairs, rather than route choices alone. As a result, the number of alternatives in the passenger choice function expands dramatically. Moreover, the destination choice model must be calibrated to replicate existing demand patterns. Both of these differences make the transit capacity flexibility problem much more complex to solve than the transit frequency setting problem.

To overcome the complexity challenge and solve the model to near optimality in a reasonable computation time, three significant contributions are introduced. First, a new mixed-integer non-linear programming model for evaluating the three transit capacity flexibility measures is developed. Then, a new problem-specific iterative solution algorithm that outperforms both previous transit capacity flexibility solution methods and commercial solvers is proposed. Finally, a technique for calibrating the destination choice model to reproduce observed origin-destination demand so that this model can be used by practitioners to evaluate real transit networks is presented.

The basic modeling environment is as follows. There are a set of N stations served by transit lines indexed by $l \in 1, \dots, L$. The set of stops served by the line

l is denoted by $\text{stops}(l)$. There are also a fixed number of time periods indexed by $t \in 1, \dots, T$. The variable representing the arrival frequency for trains that arrive in period t on line l is denoted by $x_t^l \in \mathbb{R}^+$. There is a minimum frequency for each line to ensure some lower bound on service quality, $x_{l,\min}$, and a maximum frequency for each line based on the physical constraints of the system, $x_{l,\max}$. The passenger capacity of each train is represented by K^l , and the total resource budget is B . The resources used in dispatching each train on line l are represented by c^l .

The set of routes from origin station u to destination station v is denoted by $\text{routes}(u, v)$ and indexed by r . The integer variable $z_t^{u,v,r,i}$ then represents the number of passengers that travel from origin u to destination v on route r aboard a train that departs during the time period t .

Each route can have several legs (representing transfers between lines), denoted by $\text{legs}(u, v, r)$. There is also the set of continuous variables $\theta_t^{u,v,r}(\mathbf{x}) \in [0, 1]$, that represent the share of passengers traveling from origin u to destination v that choose route r . Route choice is a function of \mathbf{x} because passengers' choices will depend on the frequencies of each route, which affects their expected wait time. By definition, $\sum_r \theta_t^{u,v,r}(\mathbf{x}) = 1$ for all u, v, t . Similarly, $\tilde{\theta}_t^{u,v,r}(\mathbf{x})$ is used to represent the share of passengers traveling from origin u at time t that choose both destination v and route r , which is used for the passengers with flexible destinations. In this case, $\sum_r \sum_v \tilde{\theta}_t^{u,v,r}(\mathbf{x}) = 1$ for all u, t . Finally, the demand multiplier that is maximized is denoted by $\Gamma \in \mathbb{R}^+$.

Then, the basic model for reserve capacity can be written as:

$$Z_{\text{reserve}} = \max_{x,z,\Gamma} \Gamma \tag{7.1}$$

$$\text{s.t.} \quad \sum_{t=1}^T \sum_{l=1}^L c^l x_t^l \leq B \quad (7.2)$$

$$x_{l,\min} \leq x_t^l \leq x_{l,\max} \quad \forall l = 1, \dots, L; \quad (7.3)$$

$$\forall t = 1, \dots, T$$

$$\sum_{t'=1}^t z_{t'}^{u,v,r,1} \geq \Gamma \sum_{t'=1}^t d_{t'}^{u,v} \theta_{t'}^{u,v,r}(\mathbf{x}) \quad \forall u = 1, \dots, N; \quad (7.4)$$

$$\forall v \in \text{dests}(u);$$

$$\forall r \in \text{routes}(u, v);$$

$$\forall t = 1, \dots, T$$

$$\sum_{t'=1}^t z_{t'}^{u,v,r,i} \leq \sum_{t'=1}^t z_{t'}^{u,v,r,i-1} \quad \forall r \in \text{routes}(u, v); \quad (7.5)$$

$$\forall i = 2, \dots, |\text{legs}(u, v, r)|;$$

$$\forall t = 1, \dots, T$$

$$\sum_{(w,v,r,i) \in \text{passthru}(l,u)} z_t^{w,v,r,i} \leq K^l x_t^l \quad \forall l = 1, \dots, L; \quad (7.6)$$

$$\forall u = \text{stops}(l);$$

$$\forall t = 1, \dots, T$$

$$\mathbf{z} \in \mathbb{Z}^+; \quad \mathbf{x}, \Gamma \in \mathbb{R}^+ \quad (7.7)$$

The objective, per the definition of reserve capacity, is to maximize the demand multiplier Γ . Constraint (2) enforces the resource budget. This budget constraint can represent financial resources, or simply the number of trains available. Note that this aggregate constraint assumes that trains are fungible across lines, which is not true for all transit systems. To split the budget constraint by groups of lines that share train cars, Constraint (2) can be replaced with an individual budget constraint

for each group, with a trivial effect on overall computational complexity.

Constraint (3) enforces the minimum and maximum frequencies for each line. The maximum capacity is a physical restriction; above a certain threshold, the trains simply cannot operate any closer together. Minimum capacity is a social concept, similar to the second-best constraints described by Liu et al. [273]. It is certainly possible to operate a transit line at very low frequencies, but for social and political reasons, it is often desirable to enforce a minimum frequency to ensure that the users of that line are not burdened with excessive waiting times. Constraint (4) ensures that the demand assigned to each route is equal to the share predicted by the route choice model, multiplied by the original passenger demand and the demand multiplier Γ . It is modeled as an inequality, but is effectively an equality constraint at optimality given that, for the optimal solution, Γ will be as large as possible. Constraint (5) is a temporal flow continuity constraint, ensuring that passengers must board the second leg of a route after boarding the first leg, and so on. Finally, Constraint (6) ensures that the number of passengers boarding each line during a time period does not exceed the total capacity of the trains that arrive during that time period. If the demand exceeds the capacity during the time period, some passengers will be forced to board in subsequent periods, thus capturing the effects of denied boardings that can occur in congested transit networks. Constraint (7) enforces integrality for the line frequency variables.

All constraints except Constraint (4) are used in all three models of transit capacity flexibility. Let Z_{partial} represent the model of network capacity with partial destination flexibility and Z_{total} represent the model of network capacity with total destination flexibility. For Z_{partial} , Constraint (4) is replaced with Constraint (8), and for Z_{total} , Constraint (4) is replaced with Constraint (9).

$$\sum_{t'=1}^t z_{t'}^{u,v,r,1} \geq \sum_{t'=1}^t d_{t'}^{u,v} \theta_{t'}^{u,v,r}(\mathbf{x}) + (\Gamma - 1) \sum_{t'=1}^t \left(\sum_{v' \in \text{dests}(u)} d_{t'}^{u,v'} \right) \tilde{\theta}_{t'}^{u,v,r}(\mathbf{x}) \quad (7.8)$$

$$\forall u = 1, \dots, N; \quad \forall v \in \text{dests}(u); \quad \forall r \in \text{routes}(u, v); \quad \forall t = 1, \dots, T$$

$$\sum_{t'=1}^t z_{t'}^{u,v,r,1} \geq \Gamma \sum_{t'=1}^t \left(\sum_{v \in \text{dests}(u)} d_{t'}^{u,v} \right) \tilde{\theta}_{t'}^{u,v,r}(\mathbf{x}) \quad (7.9)$$

$$\forall u = 1, \dots, N; \quad \forall v \in \text{dests}(u); \quad \forall r \in \text{routes}(u, v); \quad \forall t = 1, \dots, T$$

Constraint (8) is for network capacity under partial destination flexibility. The first term on the right-hand side requires the original origin-destination demand to be distributed among the possible routes according to the route choice function $\theta(\mathbf{x})$. The second term requires that any new demand at origin u is distributed according to the route-destination choice function represented by $\tilde{\theta}(\mathbf{x})$. The $(\Gamma - 1)$ term is a convention that simplifies the comparison of the optimal Γ values across each of the three transit capacity flexibility measures. When $\Gamma = 1$, only the original demand is included, similar to the result when $\Gamma = 1$ in the reserve capacity model. The partial destination flexibility is only valid when $\Gamma > 1$, otherwise the problem reduces to the reserve capacity model. Constraint (9) is for the total destination flexibility model and enforces that the sum of the demand at every origin station is distributed according to the destination and route choices predicted by the route-destination choice function represented by $\tilde{\theta}(\mathbf{x})$.

7.3.1 Passenger choice functions

The route choice and route-destination choice functions used in this chapter are modeled as multinomial logit functions, a common approach in the field of travel demand modeling [284]. The model design is sufficiently flexible to permit a wide range of choice function formulations, however. Other closed-form, differentiable choice functions such as the nested logit function could be used in place of the multinomial logit function without significant impact on tractability. Using common choice functions that do not have a closed form but whose choice probabilities can be simulated (e.g. mixed logit) is likely to increase computation time substantially.

The model design is also flexible with respect to the independent variables included in the choice model. Exogenous independent variables and individual-specific variables can be added to the choice functions with a negligible impact on tractability. Independent variables that are functions of the decision variables (i.e. endogenous independent variables) can also be included in the choice models, but may require additional considerations. For example, crowding is included as an independent variable in the route choice model, which is a dense function of the decision variables \mathbf{z} . To retain tractability, a near approximation of the actual crowding during each iteration is used. The details of this approach are described in the Solution Algorithm section.

Route choice function

The choice probability of route r is given by:

$$\theta_t^{u,v,r}(\mathbf{x}) = \frac{\exp(V_t^{u,v,r}(\mathbf{x}))}{\sum_{r' \in \text{routes}(u,v)} \exp(V_t^{u,v,r'}(\mathbf{x}))} \quad (7.10)$$

where $V_t^{u,v,r}(\mathbf{x})$ is the utility of the route r . The utility of a route is a function of the total journey time, which is given by the weighted sum of the waiting time and the constant in-vehicle time, denoted by $\Delta(u, v, r)$, and the disutility of crowding:

$$\begin{aligned} V_t^{u,v,r}(\mathbf{x}) &= \sum_{l \in \text{legs}(u,v,r)} \frac{1}{2x_t^l} + \Delta(u, v, r) \\ &+ \beta_1 \left(\sum_{l \in \text{legs}(u,v,r)} \psi \left(\frac{\sum_{(w,v,r,i) \in \text{passthru}(l,u)} z_t^{w,v,r,i-1}}{\bar{K}^l x_t^l} \right) \right) \end{aligned} \quad (7.11)$$

In this formulation, the average waiting time is assumed to be half of the time between successive train arrivals, which holds under the condition that passengers arrive independently according to a Poisson process. The disutility of crowding is a function of the occupancy of each leg of the journey, divided by a “comfortable” capacity, $\bar{K}^l \leq K^l$. The function $\psi(\kappa)$ is a convex and differentiable function such that the disutility increases linearly up to the comfortable capacity threshold, and then exponentially thereafter:

$$\psi(\kappa) = \begin{cases} \kappa, & \text{if } \kappa \leq 1 \\ e^{\kappa-1}, & \text{otherwise} \end{cases} \quad (7.12)$$

In practice, the set of “reasonable” routes for any given (u, v) pair is much smaller than the theoretical set of all possible routes, which could involve cycles or unnecessary transfers between transit lines. Given that the probability of selecting a given route is a function of wait times and travel times, any routes with significant detours or unnecessary transfers are very unlikely to be chosen. Heuristics to restrict the choice sets $\text{routes}(u, v)$ to “reasonable” routes are therefore recommended, as they can provide significant performance improvements without compromising modeling accuracy. For example, the numerical experiment described in the following sec-

tion omits any routes that exceed an upper limit on the travel time and number of transfers relative to the shortest path.

Route-destination choice function

The route-destination choice function used to determine network capacity with partial and total destination flexibility is similar to the route choice function from the previous section. The choice probability is taken over the sum of all possible routes and all possible destinations from any given origin station:

$$\tilde{\theta}_t^{u,v,r}(\mathbf{x}) = \frac{\exp(\tilde{V}_t^{u,v,r}(\mathbf{x}))}{\sum_{v' \in \text{dests}(u)} \sum_{r' \in \text{routes}(u,v')} \exp(\tilde{V}_t^{u,v',r'}(\mathbf{x}))} \quad (7.13)$$

where $\text{dests}(u)$ is the set of destinations reachable from origin station u . The new utility function $\tilde{V}_t^{u,v,r}(\mathbf{x})$ is no longer dependent on the route characteristics exclusively, but also the destination characteristics:

$$\begin{aligned} \tilde{V}_t^{u,v,r}(\mathbf{x}) &= \sum_{l \in \text{legs}(u,v,r)} \frac{1}{2x_t^l} + \Delta(u, v, r) \\ &+ \beta_1 \left(\sum_{l \in \text{legs}(u,v,r)} \psi \left(\frac{\sum_{(w,v,r,i) \in \text{passthru}(l,u)} z_t^{w,v,r,i}}{K^l x_t^l} \right) \right) + \beta_2 \omega_t^{u,v} \end{aligned} \quad (7.14)$$

The parameter $\omega_t^{u,v}$ represents the relative utility of destination v to travelers departing from origin u at time t , and β_1, β_2 are scaling parameters. The values of $\omega_t^{u,v}$ can be estimated using surveys or revealed preference data. For example, if someone would be willing to travel an additional 10 minutes to reach a destination v rather than travel to destination v' , simply set $\omega_t^{u,v} - \omega_t^{u,v'} = 10/\beta_2$. These values can also be calibrated to replicate observed demand patterns or assumed for some hypothetical future scenario. The impact of different settings for ω is explored through sensitivity

analysis in the numerical experiment.

Both of these choice models are written assuming a homogeneous population with identical preferences. It is possible to model heterogeneous preferences by dividing the population into multiple groups with identical preferences and solving the route and route-destination choice model for each group separately. This would, however, add another index to the z decision variable and increase the number of decision variables accordingly.

7.3.2 Solution algorithm

The multinomial logit functions described above are non-linear and non-convex in the decision variables \mathbf{x} . To resolve this issue, a first-order approximation approach is used that optimizes over a local linear approximation of the multinomial logit function. Taking an initial point $\bar{\mathbf{x}}$, the value of $\theta_t^{u,v,r}(\bar{\mathbf{x}}, \mathbf{x})$ is approximated with $\theta_t^{u,v,r}(\bar{\mathbf{x}}) + \nabla \theta_t^{u,v,r}(\bar{\mathbf{x}})'(\mathbf{x} - \bar{\mathbf{x}})$. An identical approach is used to approximate $\tilde{\theta}_t^{u,v,r}(\mathbf{x})$. This approximation is reasonably accurate when the new point \mathbf{x} is near the initial point $\bar{\mathbf{x}}$. Beginning with a feasible warm start, a new \mathbf{x}^j is found for each iteration $j = 1, \dots, J$ by solving the model with the additional constraint:

$$\mathbf{x}^{j-1} - \eta \leq \mathbf{x} \leq \mathbf{x}^{j-1} + \eta \quad (7.15)$$

where η is a constant representing the step size for the frequencies within which the local approximation is considered accurate. The value of η should be chosen such that the linear approximation remains accurate while being large enough to limit the number of iterations needed for convergence.

As mentioned earlier, the full occupancy expression in (14) is a dense function of the decision variables \mathbf{z} . To simplify the model, the occupancy at the previous

iteration is used rather than the full expression. Given that the step sizes η are relatively small, this provides a reasonable estimate of the occupancy at the current iteration.

Since the original problem is non-convex, the solutions may converge to a local optima rather than the global optima. To mitigate this concern, n randomized warm starts are generated and the solution with the maximal objective value is selected.

The first-order local approximation approach resolves the non-convex multinomial logit function for passenger destination and route choice. There is, however, an additional source of non-linearity in the transit capacity flexibility model. The reserve capacity model includes Constraint (4), while the partial destination flexibility and total destination flexibility models include Constraints (8) and (9), each of which contains a product of the decision variable Γ and the linearized choice function $\tilde{\theta}_t^{u,v,r}(\mathbf{x})$. As a result, the transit capacity flexibility models are mixed-integer *non-linear* programs (MINLPs). There are two primary means of solving these MINLPs. The first is to use traditional non-linear integer program solution procedures, such as a non-linear branch-and-cut algorithm. Many state-of-the-art commercial solvers, including Gurobi, have recently developed the capability to solve a range of MINLPs, although computation time can be a concern even for moderate problem sizes due to the complexity of non-linear problems. Moreover, the convergence of the iterative first-order approximation method towards even a local optimum is no longer guaranteed due to the non-linear $\Gamma * \tilde{\theta}_t^{u,v,r}(\mathbf{x})$ term in constraints (4), (8) and (9), although when η is small, the MINLP approach can return relatively good solutions.

To improve both the solution quality and computation time, an alternative heuristic approach is proposed for solving the transit capacity flexibility model. It involves iteratively solving the model for fixed values of Γ , which eliminates the non-linear constraints, and checking the resulting mixed-integer *linear* program (MIP) for fea-

sible solutions. The MIP version of each capacity flexibility model has the same constraints and variables as the MINLP version, but a fixed value of Γ :

$$\begin{aligned} Z_{\text{reserve}}^{\text{MIP}}(\Gamma) &= \max_{x,z} \Gamma & (7.16) \\ \text{s.t.} & \quad (2) - (7), (14) \end{aligned}$$

Starting at a low value (e.g. $\Gamma = 1$), Γ is incremented by a small constant ε until no feasible solution can be found. The largest value of Γ for which there exists a feasible solution is the optimal solution to the MINLP. The convergence speed is highly dependent on the choice of ε . An adaptive approach is proposed wherein ε is adjusted between iterations to grow quickly at the beginning and then more slowly when approaching the maximum value of Γ .

With this iterative solution method, finding a feasible warm start, which is required for initializing the first-order linear approximation algorithm, becomes more and more difficult as Γ approaches the optimal value. The infeasible warm start issue can be resolved by relaxing the budget constraint (2) and applying a heavy objective penalty to any solutions that violate the constraint. Since Γ is constant, the relaxed model can be written as:

$$\begin{aligned} Z_{\text{reserve}}^{\text{R}}(\Gamma) &= \min_{x,z} \left(\sum_{t=1}^T \sum_{l=1}^L c^l x_t^l - B \right) & (7.17) \\ \text{s.t.} & \quad (3) - (7), (14) \end{aligned}$$

The relaxed versions of the other two models, denoted by $Z_{\text{partial}}^{\text{R}}$ and $Z_{\text{total}}^{\text{R}}$, are

similarly derived. The relaxation allows feasible warm starts to be generated. Due to the relaxation, the termination condition for the relaxed problem must include any cases where the objective value $Z^R > 0$, as this represents an infeasible solution to the initial problem. The choice of a warm start becomes an important design choice for this solution method. If the values of \mathbf{x}^0 are small, the warm start risks being infeasible when Γ approaches the optimal value. If \mathbf{x}^0 values are too large, the solution method will involve many iterations of the first-order approximation, given that the initial values will be highly suboptimal and the step sizes at each iteration are limited by (14).

The advantage of the iterative approach is that it only involves solving a MIP at each iteration, which is much faster than solving an MINLP, especially for larger problem sizes. This approach also allows the first-order approximation algorithm to be terminated as soon as a feasible solution to the original problem is found, since in this case only a feasible solution is needed for a given value of Γ , rather than an optimal solution. In addition, it allows the modeler to reduce computation time if they have a priori knowledge of a tight lower bound on Γ . Tight lower bounds can be easy to determine when the model is run repeatedly with minor adjustments to the network or input parameters. The downside is that without an initial lower bound, this solution method can involve solving the overall problem many times to reach optimality, in addition to the iterative procedure for the first-order approximation that may be required to find a feasible solution for each value of Γ . The overall solution algorithm is summarized below, using the reserve capacity model as an example.

Algorithm 1 Transit Capacity Flexibility Solution Algorithm

```
 $\Gamma_0 = 1$   
 $i = 0$   
while  $Z^{\text{MIP}}(\Gamma_i)$  feasible do (loop 1)  
   $i = i + 1$   
  for  $k = 1, \dots, n$  do (loop 2)  
    Generate a random warm start  
    Solve  $Z^R(\Gamma_i)$   
    if  $Z^R(\Gamma_i) < 0$  then  
       $\Gamma_i = \Gamma_{i-1} + \varepsilon$   
      exit loop 2  
    else if  $k = n$  then  
      exit loop 1 (no feasible solution)  
    end if  
  end for  
end while  
 $\Gamma_{\text{opt}} = \Gamma_{i-1}$ 
```

7.4 Numerical experiment

7.4.1 Experiment design

To demonstrate the ability of these new models to generate insights for a large transit network, an experiment was designed using the full 2019 MBTA rail network with eight route patterns and 121 stations. The experimental network includes the entirety of the existing rail lines (Red, Blue, Orange, and Green) in both directions. Because the Red Line has two branches and the Green Line has four branches, the test network features nine bidirectional lines ($L = 18$). Transfers between lines can be made at 22 of the 114 stations. The Ashmont-Mattapan Trolley line, a short streetcar extension of the Red Line, was excluded due to a lack of demand data, and the Silver Line bus routes were also excluded. The test network topology is shown in Figure 7-1 below.



Figure 7-1: Map of the 2019 MBTA rapid transit network used as the basis for the numerical experiment

Source: Massachusetts Bay Transportation Authority [285]

Given the size of the network, many origin-destination pairs have dozens or hundreds of possible alternative routes. To limit the size of the problem, routes were

only considered valid if they involved no more than one additional leg (i.e. transfer) compared to the shortest path. The choice probabilities for other, more circuitous routes with multiple transfers are likely to be very small due to the much higher waiting time and travel time relative to the shortest path.

The resulting baseline model has $L = 18$ integer x_t^l variables and 8,394 continuous $z_t^{u,v,r,i}$ variables per time period. The problem was solved using real origin-destination demand data, train maximum and comfortable capacities, existing frequencies, and the number of available trains. All of the input data was collected from the MBTA for the pre-pandemic period (January 2019), which was shared with the author through a formal research partnership. Each of the transit capacity flexibility models was solved for four 15-minute periods ($T = 4$) in the AM peak period (8:00 AM - 9:00 AM) using the iterative MIP solution algorithm described in the previous section. Twenty warm starts for the first-order approximation algorithm were used in each iteration.

The partial and total destination flexibility models both contain a destination choice function. To illustrate how these models can be used in long-term transit planning, the maximum demand multiplier was determined for two destination utility scenarios representing alternative commuting paradigms. These scenarios were coded into the model by adjusting the values of $\omega_t^{u,v}$ in (14).

The “Centralized” (C) scenario represents a return to the pre-pandemic travel patterns, where many of the most visited destinations are located in the central business district in downtown Boston. As previous transit capacity flexibility models have not been applied to actual transit networks, there has been no previous discussion about choosing accurate destination utilities for the partial and total destination flexibility models. The destination utilities were calibrated using the 2019 origin-destination demand matrix as ground truth data to ensure that the experiment would replicate

observed demand patterns. The destination utilities $\omega_t^{u,v}$ were adjusted using an iterative approach until the root-mean-square error between the observed visits to each destination and the estimated visits to each destination was minimized. As a result, the optimal solutions for reserve capacity and total destination flexibility in the Centralized scenario are expected to be quite similar. Any variation in the optimal solutions would be a result of the increased destination flexibility of the modeled riders, allowing them to deviate from their observed destination choice only when travel becomes highly inconvenient. This is more realistic for discretionary trips than the reserve capacity model, which retains the original destinations regardless of the performance of the transit network.

The “Decentralized” (DC) scenario represents a possible future where employers shift towards satellite offices and co-working spaces spread across a region to reduce the commuting burden for employees. This possible future is hypothesized as a potential outcome of the widespread adoption of remote work catalyzed by the COVID-19 pandemic and is referred to as “working close to home” in the literature [223]. For the Decentralized scenario, $\omega_t^{u,v}$ was decreased by 15% for all stations in or adjacent to Boston’s central business district and increased by 15% for selected peripheral stations (e.g. Coolidge Corner, Jackson Square, Quincy Center). In this way, the Decentralized scenario represents a shift in destination preferences away from downtown cores and towards regional sub-centers and smaller retail-oriented areas.

Note that the numerical experiment assumes that available train sets can be deployed on any of the MBTA rail lines, which is not possible in practice due to varying operational characteristics. For this test case, however, using an aggregate budget provides more flexibility to the operator and thus better illustrates the differences between the capacity flexibility measures. Moreover, many U.S. and international

rapid transit systems are designed to allow the same trains to be used on most or all of the lines (e.g. Washington DC, Copenhagen, Sydney). Train sets can easily be restricted to specific lines in the model by changing constraint (2) from an aggregate budget to a line-specific budget.

7.4.2 Results

All results are presented in Table 7.1 below, including the computation times for the iterative MIP solution method and the direct MINLP solution method. Given that the warm starts are stochastic and have a strong impact on the quality of the direct MINLP solutions, the mean solution and computation time across 5 model runs is reported. The model was implemented in Julia and solved using Gurobi version 10.0.0 on a dual-core Intel i7-6600U CPU with 16 GB of RAM.

Baseline and reserve capacity

First, a baseline version of the model with line frequencies fixed to the existing MBTA arrival frequencies was solved. The result provides a benchmark evaluation of the reserve capacity of the network as it exists today, without any adjustments to the schedule, and is referred to as the “existing capacity” (EC). For the baseline model, $\Gamma = 1.29$, suggesting that even without adjusting frequencies, the current origin-destination demand matrix could be increased by 29% without exceeding the capacity of the network. This limited slack in the network is consistent with a transit system that nears capacity during the AM peak period. The model is already linear due to the fixed frequencies, so the iterative method is not needed.

Then the Reserve Capacity (RC) model was solved. The results improve substantially compared to the fixed-frequency model; the network can accommodate a

demand multiplier of $\Gamma = 4.11$ by adjusting line frequencies to match the distribution of demand during the given time period. Solving the relaxed MIP took an average of 15 seconds per iteration, with a minimum computation time of 4.04 seconds and a maximum of 31.14 seconds. Starting with $\Gamma = 1$ and incrementing by 1 until an infeasible solution was found, then incrementing by 0.1 and finally 0.01 to improve the precision of the result, the optimal solution was found in 1,051 seconds or about 17.5 minutes. This is a naive iteration strategy that could be improved with a priori knowledge of the problem. More than half of the total solution time was spent confirming infeasibility for each of the twenty warm starts for each of the incrementation steps (1, 0.1, and 0.01); a more efficient iteration strategy might begin with smaller increments as it is generally much faster to confirm the existence of a feasible solution than to verify infeasibility across all warm stars. Despite having to solve the model 70 times, the iterative method significantly outperforms the direct MINLP solution method due to shorter computation times in each step, thus reducing computation time by 92.4%.

Metric	Scenario	Iterative		Direct		Opt. Gap (Direct)	Time Savings (Iterative)
		Γ	Time (s)	Γ	Time (s)		
EC	-	1.29	68.7	-	-	-	-
RC	-	4.11	1051	4.06	13794	-1.2%	-92.4%
PF	C	3.57	7864	3.49	38442	-2.2%	-79.5%
	DC	3.12	6097	3.09	35787	-1.0%	-83.0%
TF	C	4.41	4703	4.32	14959	-2.0%	-68.6%
	DC	3.42	5421	3.28	15903	-4.1%	-65.9%

Table 7.1: Optimal capacity flexibility results and computation times for the MBTA network-based numerical experiment

Plotting the results of the two solution methods over time, shown in Figure 7-2

highlights the strength of the iterative MIP solution approach. The iterative approach quickly confirms feasibility for $\Gamma = 1, 2, 3, 4$ in succession, then takes a moderate amount of time to improve the precision of the incumbent solution to $\Gamma = 4.1$ and finally $\Gamma = 4.11$. The direction solution approach is much slower, taking an average of 689 seconds to find a locally optimal solution for each warm start. While some warm starts result in near-optimal solutions, the best result across all warm starts still has an optimality gap of 1.2% relative to the iterative solution, which was found in less than one-tenth of the computation time. Increasing the number of warm starts could be expected to improve the average solution quality of the direct MINLP method, but it would also increase the already long average computation time.

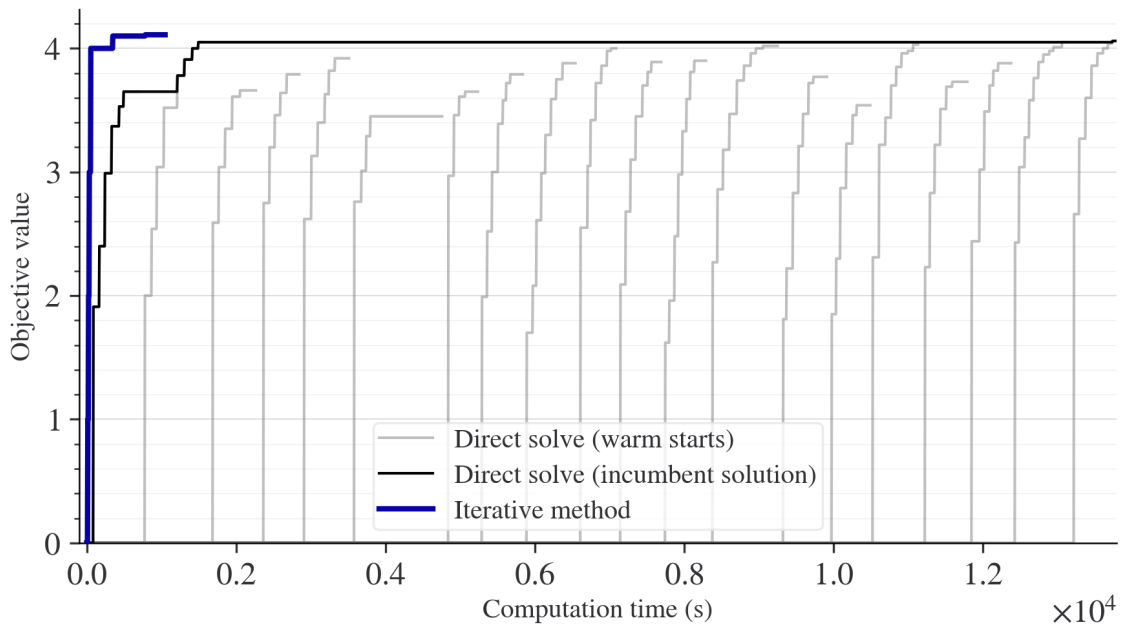


Figure 7-2: Comparison of the incumbent objective value over time for the iterative and direct solution methods

Network capacity with flexibility

Next, the model was solved to optimality for Partial Destination Flexibility (PF) under the Centralized (C) scenario. The maximum demand multiplier is $\Gamma = 3.51$, which took 7864 seconds to compute with the iterative solution method. Introducing the destination choice model for all new riders combined with some fixed origin-destination demand substantially increases the number of variables and constraints in the model, making it more difficult to solve for both methods. For the Decentralized (DC) scenario, an optimal solution of $\Gamma = 3.12$ was found in somewhat less computation time.

For both scenarios, the iterative method took about one-fifth of the time to solve compared to the direct MINLP solver average and produced better solutions. Solving the relaxed MIP during each iteration takes about the same amount of time for the partial destination flexibility model and the reserve capacity model. The overall computation time took substantially longer, however, because the model was solved 126 times rather than just 70 times for the reserve capacity model. The total number of iterations needed to find an optimal solution can be controlled by modifying the Γ incrementation algorithm to match the problem, rather than using the naive approach taken for benchmarking purposes.

The significant difference in capacity flexibility between the Centralized and Decentralized scenarios implies that the network is better suited to handle increased demand towards the central business district. For partial destination flexibility, the decentralized destination preferences result in a reduction of capacity by 39% of the original demand, or about 15,600 passengers per hour. This is largely by design; the MBTA rail network has a “hub-and-spoke” topology, where all of the rail lines feed into the downtown core with no opportunities to transfer between lines outside of the

hub. Such networks are effective at delivering commuters in and out of downtown, but limited capacity to handle increases in demand for the peripheral stations that are only served by a single line. All passengers seeking to travel from a residential area on one line (e.g., Brookline Hills) to a regional sub-center on another line (e.g., Harvard Square) must pass through the downtown core, creating additional congestion in the busiest part of the network.

Finally, the network capacity with the total destination flexibility (TF) model was solved for both scenarios. The optimal values of Γ were found to be 4.41 and 3.42 for the Centralized and Decentralized scenarios, respectively. The large gap between the two scenarios is similar to the results for the partial destination flexibility model, providing further evidence that the MBTA rail network can adapt better to increases in demand oriented towards the central business district rather than demand oriented towards the periphery of the service area. Once again, the iterative solution method offers strong performance improvements, with solution times that are approximately one-third of the direct MINLP solution computation times.

Comparing the three measures, it is evident that the reserve capacity and total flexibility results for the Centralized scenario are quite similar. The flexibility to choose a different nearby destination when travel is inconvenient creates origin-destination demand patterns that are slightly easier for the network to accommodate. Interestingly, the partial destination flexibility measure is lower than both the reserve and the total destination flexibility measures. Recall that the difference between the models is that the partial destination flexibility measure retains the original origin-destination demand, then adds new demand with flexible destinations. A mix of fixed and flexible destinations is more difficult for the network to accommodate than demand with entirely fixed or entirely flexible destinations.

The hypothesis that mixed demand is more difficult to service is supported by

the optimal line frequencies (\mathbf{x}) for each model, which are a function of the demand patterns. The distribution of optimal line frequencies for each metric is shown in Figure 7-3. For the reserve and total destination flexibility capacity models, the optimal \mathbf{x} values feature several lines with high frequencies (16 - 23 trains per hour) and others at or near the minimum frequency (4 trains per hour). The median value of \mathbf{x} is 7.9 trains per hour for the reserve capacity metric and 7.6 for the total destination flexibility metric. Conversely, the median of \mathbf{x} for the partial destination flexibility metric is 6.6 trains per hour, and the optimal frequencies are more even across the lines. The mix of ridership fixed and flexible destinations, rather than a demand profile with homogeneous behavior, forces the solution to provide moderate service on all lines rather than concentrating resources on the most popular lines.

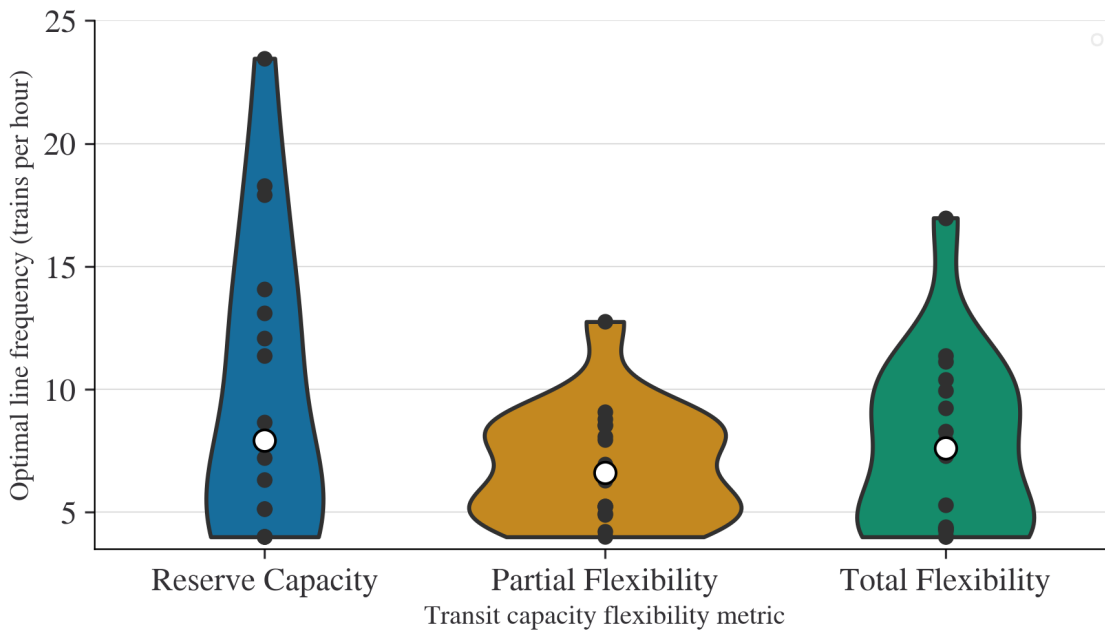


Figure 7-3: Distributions of optimal line frequency (x_l) by transit capacity flexibility metric

7.5 Discussion

This chapter creates new integer programming models and solution algorithms for evaluating the capacity flexibility of a transit network. It demonstrates how relaxation and a novel iteration-based solution method can be used to solve larger problems than the previous state of the art. The proposed solution method outperforms commercial solvers, and is shown to be tractable for a full-sized rapid transit network with 18 lines and 114 stations, suggesting that this modeling framework and solution method could be used to determine transit capacity flexibility for a range of large networks in a reasonable timeframe.

The value of solving network-sized problems is illustrated using a numerical experiment that models a highly topical problem for transit agencies: whether a network can accommodate the changes in demand that might occur due to the rapid growth in remote work. As only toy-sized models could be solved previously, transit capacity flexibility has not been used as a measure for policy analysis. Transit agencies, such as the MBTA, could use these models to evaluate the capacity of their networks to handle changing demand during this uncertain time. The remote work example is just one of many possible scenarios that could be evaluated using the modeling framework developed in this chapter. The framework could also be used to evaluate alternative network expansion scenarios, or how the network would respond to increased demand arising from future transit-oriented development. Determining which modeling constraints are binding could help to identify bottlenecks in the network, and shadow prices from the budget constraint could be used to quantify the potential capacity and flexibility gains from additional resources. The optimal \mathbf{x} values could also help to develop operating strategies and timetables that adapt to new origin-destination patterns.

There are many possible directions for this area of research in the future. First, there are relatively straightforward technical improvements that could be made to the solution algorithm. The total solution time is highly dependent on the number of iterations, so a more sophisticated adaptive strategy for incrementing Γ , perhaps based on machine learning techniques, is likely to provide significant performance improvements. Problem-specific MIP or MINLP heuristics could also be investigated to speed up the solution time within each iteration.

Next, some limitations of the experiment could be addressed. The experiment could be expanded to include the full MBTA rail network or even the entire multi-modal transit network with buses and commuter rail for a more comprehensive accounting of the network capacity flexibility. As demonstrated in the experiment, this modeling framework scales well with increasing complexity and could be expected to remain tractable for much larger problem sizes, unlike previous transit capacity flexibility models. In addition, the modeling of destination utility would benefit from enhancements that reflect the complex decisions underlying destination choice, although that area of research was not the focus of this chapter. Rather than static values, destination utilities could be represented as stochastic variables, or heterogeneous across the population, or be modeled as a function of other endogenous or exogenous modeling variables.

Finally, future work could include extensions and applications of this modeling framework to other problems. A comparative analysis of transit networks with different topologies could offer insights into the capacity flexibility implications of common network design philosophies. Practical tools, such as an open-source software package for converting machine-readable transit network representations (e.g. the Generalized Transit Feed Specification) into the inputs for this model, could be developed to allow any transit agency to evaluate the capacity flexibility of their

networks with little effort. Tractable model formulations for multi-modal network capacity flexibility, perhaps based on robust optimization concepts, could also be developed and compared.

Chapter 8

Optimal location of shared workplaces with social objectives

8.1 Introduction

The common term “working from home” belies the fact that remote workers in the United States are choosing to work at shared workplaces for one-third of their remote work hours on average [3]. These shared workplaces, which include cafés, libraries, and co-working spaces, afford many of the social and productivity benefits of in-person interactions while avoiding the congestion and environmental externalities associated with the traditional commute. Yet transportation and land use policies are still primarily designed around the outdated norm of repeated trips during peak hours to a centralized workplace. The limited capacity of existing urban mobility and land use systems to satisfy the observed demand for remote work at shared workplaces has resulted in socially suboptimal outcomes. New data-driven policies are needed to adapt urban mobility systems to the emerging travel demand patterns

of the future of work.

Working at home has many benefits: reduced carbon emissions from commuting, less time spent sitting in traffic, greater individual productivity, and improved worker well-being. There are also downsides for workers, however: feelings of loneliness, more distractions, and the cost of additional space and equipment, among others. To many remote workers, “working close to home” at shared workplaces offers a welcome balance between the isolation of home and the inconvenience of the primary workplace.

Recently, governments have begun to recognize that shared workplaces can also be used to mitigate the negative societal externalities of working from home. Working from home has been shown to increase segregation between income groups in an urban area, and reduce the number of spontaneous interactions that contribute to idea flow and economic growth. It has also devastated the retail businesses that catered to downtown workers. To address these issues, the Irish and Welsh governments have each created a country-wide network of remote working hubs (see Figure 8-1). In the United States, the state of Maine has established a grant program to encourage private operators to build new co-working spaces. The Canadian government has recently begun operating several shared workplaces for federal employees who work remotely.

These early examples of public shared workplace development involve a pragmatic, ad hoc approach to location selection, guided by general principles, availability of locations, and a set of societal goals. A formal optimization scheme for selecting locations based on the specific objectives of the program is needed to ensure that scarce resources (e.g. funding) are allocated in such a way that the benefits to the public are maximized. Estimating the decisions of remote workers about where to work, and incorporating societal goals into a facility location model, are both

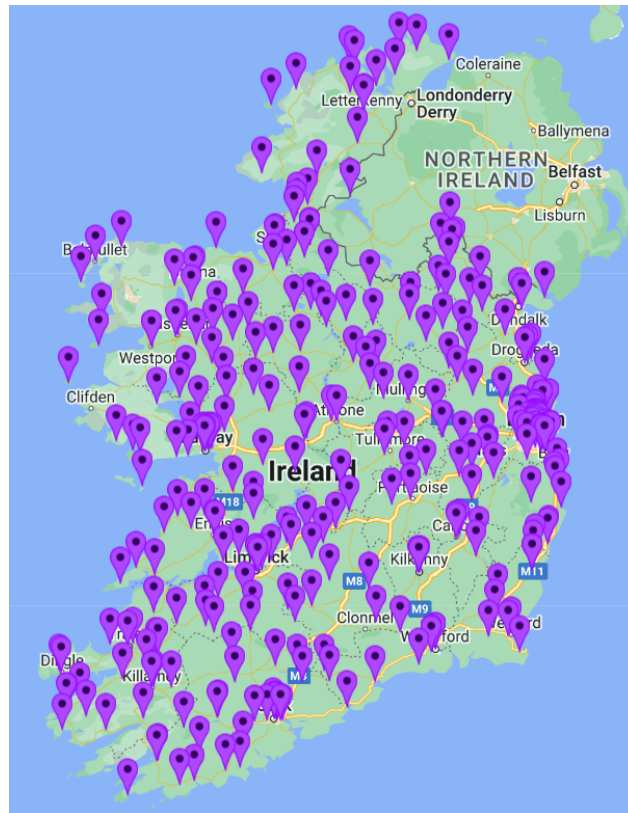


Figure 8-1: Locations of remote working hubs in the Irish government’s National Hub network

Source: ConnectedHubs.ie [286]

significant methodological challenges, however.

This paper introduces a new modeling framework to optimize socially-optimal collaborative workplace capacities and locations for the remote work era. The new models address two areas of complexity specific to shared workplaces for remote work: 1) heterogeneous preferences for shared workplaces across industries, occupations, and demographic groups, and 2) the potential for productivity and other social goals in addition to system efficiency objectives. Integrating these areas of complexity requires introducing concepts from organizational behavior into travel behavior

modeling, a long overdue connection between two often disparate disciplines. Moreover, the need for continued cross-disciplinary collaboration is demonstrated through the use of examples to show how relying on organizational behavior models and travel behavior models in isolation can produce socially suboptimal outcomes in the context of shared workplaces.

The proposed modeling framework has two primary areas of novelty. The first contribution is to extend existing facility location and capacity model constraints to capture the unique dynamics of workplace choice. A general random utility-based destination choice model is incorporated in the optimization model to capture the agency of remote workers to choose a work location (including working at home) that maximizes their utility. An exterior approach allows non-linear choice models to be modeled with linear constraints, preserving tractability. The second major contribution is the design and evaluation of social objective functions for the shared workplace location problem. System efficiency objectives (minimizing generalized travel costs, maximizing demand) are compared against social objectives to maximize productivity, maximize the number of potential social interactions, and limit social segregation, using concepts from the organizational behavior literature. Two of the social objectives are quadratic functions of the decision variables; a compact linearization formulation and cutting planes are derived to avoid loss of tractability. The sensitivity of the results to different combinations of objectives is tested using a realistic numerical experiment for the first time in the literature. Opportunities to use this research to inform land use and transportation policy for remote work are discussed.

8.2 Literature review

Several recent papers have documented the use of third places by remote workers, both before [71] and after the tremendous increase in remote work spurred by the global COVID-19 pandemic [3]. These studies find that co-working spaces and other shared workplaces are among the most popular third places for remote work. Early research into location choice for so-called “telecommuting centers” found that careful site selection is critical to success [89]. Additional empirical research has uncovered the spatial, social, and political factors that influence the location of shared workplaces across the globe, including Finland [287], Italy [102], and the United States [288]. Yu et al. [98] provides an overview of the literature on shared workplaces, finding that they can produce a range of benefits, including reduced congestion and pollution from travel, improved economic productivity, greater employee well-being, lower fixed costs for employers and more opportunities for social interaction. Avdikos and Papageorgiou [289] gives an excellent overview of government programs that seek to capture some of these benefits by subsidizing or operating shared workplaces in their jurisdictions.

The model proposed in this paper is an extension of the facility location problem, a canonical integer programming problem with many variants. Facility location problems have been developed for locating freight distribution centers [290], emergency response facilities [291], and retail outlets [292], among many other applications. Farahani and Hekmatfar [293] provides an excellent description of the history and taxonomy of facility location problems. The shared workplace location problem falls within the class of “competitive facility location” problems [294], as remote workers have the discretion to choose from any facility or reject all facilities (i.e. work at home).

Rather than a gravity-based or deterministic utility approach, which is often used in literature, the shared workplace model incorporates a random utility function for workplace choice. Specifically, a discrete choice model is proposed, of which multinomial logit (MNL) is perhaps the most commonly used form [125]. The MNL function yields a non-linear formulation, making it challenging to incorporate into optimization problems while maintaining tractability. Benati and Hansen [295] was one of the first papers to present linearization techniques for incorporating random utility functions such as MNL into competitive facility location problems. Haase and Müller [296] compares the performance of the Benati and Hansen [295] formulation with two other proposed MNL linearization approaches. Shortly afterward, Mai and Lodi [297] introduced the exterior simulation approach for linearization of a mixed MNL model within a “maximum capture” facility location problem whose objective is to maximize market share. Their approach leverages the convexity of the objective function to design an efficient solution algorithm. Subsequent research on the maximum capture problem has shown that different families of inequality cuts can improve performance [298, 299].

The exterior simulation approach to linearizing discrete functions is based on the technique proposed in Paneque et al. [300]. The authors use the pricing and capacity allocation for parking services as a case study, demonstrating how the exterior approach allows differentiation of utility functions between customer segments. Recent preprints have used the same approach to show how any discrete choice function can be incorporated into the competitive facility location problem [301] and the “cooperative maximum capture” facility location problem [302]. Subsequent applications of the method include optimizing the locations of electric vehicle charging stations [303], air taxi skyports [304], and logistics hubs [305].

Only two previous projects are known to have investigated the problem of opti-

mal site selection for shared workplaces. Mastio et al. [306] develops a site selection model for co-working spaces to minimize total carbon emissions from commuting. In an earlier paper, Logins et al. [307] designs a large-scale site selection and capacity model for generic public facilities to minimize total travel time. Co-working spaces are used as a hypothetical application in testing the computational performance of the algorithm. Both papers use innovative methodologies to solve a challenging problem: reducing the externalities of travel to shared workplaces. However, shared workplaces have specific features that are not shared by generic public facilities. As *workplaces* (rather than facilities for socializing, recreation, or leisure), their utilization impacts individual and collective economic productivity. They also produce social externalities beyond the travel costs used in the objective functions of previous models. Using an agent-based modeling approach, Ge et al. [86] show that the congestion and pollution reductions associated with the use of shared workplaces can be offset or even reversed by corporate remote work policies and organizational structures, implying that organizational behavior is an essential component of shared workplace site selection. Moreover, shared workplaces are *shared* and therefore represent an opportunity to increase social interactions and reduce social segregation within an urban area. Extending site selection models to include complex social objectives and realistic organizational behavior constraints remains a critical gap in the literature.

8.3 Methods

The mixed-integer linear programming (MILP) model for the shared workplace location problem is built in stages, starting with the canonical facility location model as a foundation, then introducing new constraints and objectives specific to shared

workspaces. Finally, a tight reformulation for solving the model with quadratic objective functions is proposed.

8.3.1 Facility location problem

The canonical capacitated facility location integer program (ILP) involves a set representing the demand for facilities. The set \mathcal{I} will represent demand from a given origin location, indexed by i . The demand at each location can be divided into disjoint sets of customers. Examples of customer segments could be income quantiles or occupations. Customer segments should be used either to differentiate customers whose preferences for shared workplaces will be estimated with different random utility functions, or to differentiate customers who have disparate effects on the objective function. For example, customer segments corresponding to income quartiles would be used if the social objective is to encourage interactions across income groups to avoid social segregation. The extreme case would be to assign each person to a separate group in order to model each decision-maker with a different utility function. There is a tradeoff between the number of customer segments and the problem size, however. The global set of passenger segments is denoted by \mathcal{J} , indexed by j . Let D_{ij} represent the total population of segment j at origin location i .

The problem will also involve a set of potential shared workplace sites, \mathcal{K} , which is indexed by k . For the shared workplace problem, the set \mathcal{K} includes the “null” option of working at home, which will be chosen if no shared workplaces offer sufficient benefits to overcome the cost of travel. In describing the model, the work-from-home location option will be denoted by $k = \text{WFH}$. Finally, in order to capture the stochasticity of the random utility-based discrete choice function, a set of scenarios, denoted by \mathcal{R} , is introduced here and explained in the next subsection. The number

of scenarios will be denoted by $|R|$

There are two groups of binary decision variables: w_{ijk_r} , which represents the decision to assign the demand segment j from origin i to the facility k in scenario r , and y_k , which represents the decision to construct the facility k . The objective function is often a minimization of the total travel time for all agents, but we will use a generic function $f(\mathbf{w}, \mathbf{y})$ as a placeholder until specific objectives are introduced in a later section. The capacitated facility location model can then be written as an ILP:

$$Z = \min_{x,y} f(\mathbf{w}, \mathbf{y}) \quad (8.1)$$

$$\sum_{k \in \mathcal{K} \setminus \text{WFH}} y_k = B \quad (8.2)$$

$$\sum_{k \in \mathcal{K}} w_{ijk_r} \leq 1 \quad \forall i \in \mathcal{I}, j \in \mathcal{J}, r \in \mathcal{R} \quad (8.3)$$

$$w_{ijk_r} \leq y_k \quad \forall i \in \mathcal{I}, j \in \mathcal{J}, l \in \mathcal{K}, r \in \mathcal{R} \quad (8.4)$$

$$\frac{1}{|R|} \sum_{i \in \mathcal{I}} \sum_{j \in \mathcal{J}} \sum_{r \in \mathcal{R}} D_{ij} w_{ijk_r} \leq C_k \quad \forall k \in \mathcal{K} \setminus \text{WFH} \quad (8.5)$$

$$w_{ijk_r}, y_k \in \{0, 1\} \quad \forall i \in \mathcal{I}, j \in \mathcal{J}, k \in \mathcal{K}, r \in \mathcal{R} \quad (8.6)$$

Constraint (8.2) enforces that the number of facilities built is less than some budgeted number of facilities B . This can easily be converted to an aggregate budget with facility-specific opening costs if desired. The constraints also enforce that demand is assigned to no more than one location (8.3) per scenario, that agents can only be assigned to locations that have been selected for opening, (8.4), and that the capacity C_k of each location k is not exceeded (8.5). Note that constraint (8.5) assumes that the true demand for each facility is the average of the demand across

all $|R|$ simulation scenarios. Constraint (8.6) limits the decision variables to integer values. Collectively, these variables and constraints create the foundation for the shared workplace location model.

8.3.2 Modeling workplace choice

The choice of workplace for remote workers is estimated using exterior simulation of an MNL discrete model. This approach, first proposed by Paneque et al. [300], permits any discrete choice model form, including mixed logit. Given that remote work was a very uncommon working arrangement until the COVID-19 pandemic, few discrete choice models have been estimated for workplace choice, but there are several examples of MNL being used for the decision between working at home and working at a remote work hub [48, 37, 114, 41].

The utility of each location k to the segment of workers j at origin i is determined using a generic utility function with exogenous and endogenous variables. Exogenous variables are any segment-specific or alternative-specific variables unaffected by the problem's decision variables (e.g., price sensitivity of the customer segment, or travel time to reach the location). Endogenous variables are affected by the decision variables; variants of the shared workplace location problem could include admission fees or facility amenities as decision variables. Given that these workplace features affect workplace choice, they would be incorporated into the workplace choice utility function as alternative-specific endogenous variables for all non-home locations. Let x^{exo} represent the exogenous variables and x^{endo} represent the endogenous variables. Moreover, let V_{ijk} represent the deterministic utility of alternative k for segment j

at location i . Then the V_{ijk} is computed as follows:

$$V_{ijk}(x_{ijk}^{\text{endo}}, x_{ijk}^{\text{exo}}) = \sum_n \beta_{ijn} x_{ijn}^{\text{endo}} + h_{ijk}(x_{ijk}^{\text{exo}}) \quad (8.7)$$

where x_{ijn}^{endo} is the n^{th} endogenous variable associated with origin i , segment j and location k . The exogenous variable utility function $h_{ijk}(x_{ijk}^{\text{exo}})$ is entirely separate from the optimization model and can therefore be precomputed.

A random deviate, ε_{ijk} , is then added to the deterministic utility term. For MNL, ε_{ijk} is assumed to be independent and identically distributed across i , j , and k , with an extreme value distribution. The probability of choosing location k is then given by:

$$P_{ij}(k|x_{ijk}^{\text{endo}}, x_{ijk}^{\text{exo}}) = \frac{y_k e^{V_{ijk}(x_{ijk}^{\text{endo}}, x_{ijk}^{\text{exo}})}}{\sum_k y_k e^{V_{ijk}(x_{ijk}^{\text{endo}}, x_{ijk}^{\text{exo}})}} \quad (8.8)$$

This is a non-linear and non-convex function in the decision variables $y_k, x_{ijn}^{\text{endo}}$. Finding exact solutions to optimization models with random utility functions is therefore a significant challenge. The framework of [300] is used to specify the discrete choice model in terms of utility, which is linear in the decision variables, rather than the choice probability. This framework also permits more complex random utility functions including mixed logit models.

The linearization framework captures the stochasticity of random utility models by drawing from the distributions of ε_{ijk} across several scenarios. The continuous variable $U_{ijkr} = \sum_n \beta_{ijn} x_{ijn}^{\text{endo}} + f_{ijk}(x_{ijk}^{\text{exo}}) + \varepsilon_{ijkr}$ is used to represent the utility of location k to segment j at origin i in simulation r . If there are no endogenous variables in the utility function, U_{ijkr} can be precomputed for all scenarios, otherwise it is a linear function of the decision variables. It is assumed that the values of x_{ijn}^{endo} are bounded, so upper and lower bounds for the utility across all locations in scenario

r can be derived. Let l_{ijr} and m_{ijr} represent the lower and upper bounds on utility across all locations.

Another term, called “discounted utility”, is introduced to ensure that only locations included in the optimal solution can be chosen by remote workers. Let the discounted utility of location k for segment j at origin i in scenario r be represented by $z_{ijk} \in \mathbb{R}$. Then the discounted utility z_{ijk} should be equal to U_{ijk} if $y_k = 1$, and some very low value (e.g. l_{ijr}) otherwise. Then the following linear constraints enforce the relationship between z_{ijk} and U_{ijk} :

$$z_{ijk} \leq U_{ijk} \quad \forall i \in \mathcal{I}, j \in \mathcal{J}, k \in \mathcal{K}, r \in \mathcal{R} \quad (8.9)$$

$$z_{ijk} \leq l_{ijr} + y_k(U_{ijk} - l_{ijr}) \quad \forall i \in \mathcal{I}, j \in \mathcal{J}, k \in \mathcal{K}, r \in \mathcal{R} \quad (8.10)$$

$$l_{ijr} \leq z_{ijk} \quad \forall i \in \mathcal{I}, j \in \mathcal{J}, k \in \mathcal{K}, r \in \mathcal{R} \quad (8.11)$$

$$U_{ijk} - (1 - y_k)(U_{ijk} - l_{ijr}) \leq z_{ijk} \quad \forall i \in \mathcal{I}, j \in \mathcal{J}, k \in \mathcal{K}, r \in \mathcal{R} \quad (8.12)$$

$$z_{ijk} \in \mathbb{R} \quad \forall i \in \mathcal{I}, j \in \mathcal{J}, k \in \mathcal{K}, r \in \mathcal{R} \quad (8.13)$$

The constraints (8.9) and (8.10) ensure that $z_{ijk} = U_{ijk}$ when $y_k = 1$, while the constraints (8.12) and (8.11) ensure that $z_{ijk} = l_{ijr}$ otherwise.

Lastly, the choice of location is modeled as the binary decision variable w_{ijk} , which was introduced in the previous section. There can only be one location chosen by each segment j at each origin i in scenario r , which is already enforced by (8.3). Furthermore, (8.4) ensures that only an available facility is chosen. That choice should also correspond to the available location that provides the greatest discounted utility. Let the continuous decision variable u_{ijr} represent the maximum utility for the segment j at origin i in scenario r across all locations. The following constraints

ensure that the location with the greatest discounted utility is chosen:

$$z_{ijk_r} \leq u_{ijr} \quad \forall i \in \mathcal{I}, j \in \mathcal{J}, k \in \mathcal{K}, r \in \mathcal{R} \quad (8.14)$$

$$u_{ijr} \leq z_{ijk_r} + (1 - w_{ijk_r})(m_{ikr} - l_{ijr}) \quad \forall i \in \mathcal{I}, j \in \mathcal{J}, k \in \mathcal{K}, r \in \mathcal{R} \quad (8.15)$$

$$u_{ijr} \in \mathbb{R} \quad \forall i \in \mathcal{I}, j \in \mathcal{J}, r \in \mathcal{R} \quad (8.16)$$

This framework captures the choice of workplace location by a remote worker with purely linear constraints. The option to work at home is also included in the choice set. The generic shared workplace location problem with a linearized random utility destination choice function is then to optimize over the set of decision variables $\mathbf{u}, \mathbf{w}, \mathbf{y}, \mathbf{z}$, subject to constraints (8.2) - (8.6) and (8.9) - (8.16). Assuming a linear objective function, it is a MILP with continuous and binary decision variables.

8.3.3 Modeling social objectives

The shared workplace location problem framework permits a variety of objective functions to optimize for the many different social goals that a public shared workplace incentive program might have. There are three key stakeholders in the establishment of shared workplaces: remote workers, workplace operators, and governments who are interested in benefits to society as a whole. When the workplace is established by the public sector (e.g. a library renovated to accommodate remote work), the government also acts as the workplace operator. In this section, five different classes of objective functions are presented, each aligned with a specific social goal and each having implications for one or more stakeholder groups. A summary of the objectives is provided in Table 8.1 below.

The first class of objective function is typical for the canonical facility location

Social goal	Stakeholders	Function	Complexity
Minimize travel costs	Workers, Society	(8.17)	Linear
Maximize travel benefits	Workers, Operators	(8.18)	Linear
Maximize interaction benefits	Workers, Society	(8.20)	Non-Linear, Non-Convex
Maximize social mixing interactions	Workers, Society	(8.21)	Non-Linear, Non-Convex
Maximize diversity of visitors	Workers, Society	(8.22)	Non-Linear

Table 8.1: Summary of potential objective functions for the shared workplace location problem

problem: minimizing the total individual or social travel cost. The classical cost measure is travel distance, but different coefficients for each segment-origin-location combination can be used to represent other costs such as generalized travel cost (which may include travel time and travel expenses), or carbon emissions from travel. Any travel cost coefficients associated with working at home should be set to zero. Depending on the cost measure, this objective affects remote workers (who prefer minimal travel costs) or governments (who prefer less congestion), or both. If the generic cost coefficient for the assignment of customer segment j from origin i to represented by c_{ijkr} , then the first class of objective functions can be represented by Z_1 :

$$Z_1 = \min_{u,w,y,z} \sum_{i \in \mathcal{I}} \sum_{j \in \mathcal{J}} \sum_{k \in \mathcal{K}} \sum_{r \in \mathcal{R}} c_{ijkr} w_{ijkr} \quad (8.17)$$

The second class of objective function is simply the opposite of the first: maximizing the total individual or operator benefits that arise from traveling to a shared

workplace. This might include maximizing demand for workplaces, which benefits the workplace operator. Similarly, if the operator has different revenue or profit margins for each customer segment, those benefits can be maximized by setting the benefits coefficients of the objective function, c_{ijkr} accordingly. One major benefit of embedding the linearized discrete choice model in the shared workplace problem is that customer utility associated with any feasible solution is known. This objective could therefore maximize customer utility by setting c_{ijkr} equal to U_{ijkr} . If U_{ijkr} is a function of endogenous variables, the objective function would be a non-linear product of decision variables, but the product of a bounded continuous variable and a binary variable can easily be linearized through substitution [308]. The functional form of the second class of objectives is as follows:

$$Z_2 = \max_{u,w,y,z} \sum_{i \in \mathcal{I}} \sum_{j \in \mathcal{J}} \sum_{k \in \mathcal{K}} \sum_{r \in \mathcal{R}} c_{ijkr} w_{ijkr} \quad (8.18)$$

The third class of objective functions is a non-traditional objective for the facility location: maximizing interaction opportunities between remote workers. Widespread remote work reduces the spontaneous face-to-face interactions between associates or even strangers that lead to the building of social networks and the spreading of ideas across regional populations [10, 309, 310]. These interactions are widely accepted to be one of the main drivers of the economic advantage of modern cities [311], and their reduction is a major concern for urban leaders [312]. Shared workplaces are one opportunity to encourage these productive interactions; working at co-working spaces has recently been shown to increase self-reported feelings of innovation relative to working at home [313]. The economic benefits of social interactions are primarily realized by governments and the remote workers themselves.

An interaction opportunity exists if two segments choose to work from the same

non-home location. As a result, the objective function for maximizing interaction opportunities is non-linear and non-convex, as it involves the product of the binary choice variables. The objective can involve maximizing total interaction opportunities, with no preference for interactions within a segment or between particular segments, or it can be weighted to favor interactions that are expected to have a greater impact on social goals. For example, if segments are defined according to work industry or occupation, then within-segment interaction opportunities might have a better chance of producing knowledge transfer than across-segment interaction opportunities. Moreover, the objective coefficients can be weighted to favor interaction opportunities at specific locations; some shared workplace locations might be more conducive to socializing than others. The interaction weight coefficient s_{jlk} can be used to weight interaction opportunities between segments j and l at location k accordingly. Maximizing interaction opportunities is likely to produce similar solutions to maximizing demand, but favor solutions where most remote workers are concentrated at a few locations. For brevity, the total population of remote workers of segment j who choose location k is denoted by:

$$p_{jk} = \sum_{i \in \mathcal{I}} \sum_{r \in \mathcal{R}} \frac{D_{ij} w_{ijk} r}{|R|} \quad (8.19)$$

The objective function for maximizing interaction opportunities is then given by:

$$Z_3 = \max_{u, w, y, z} \sum_{k \in \mathcal{K} \setminus \text{WFH}} \left[\sum_{j \in \mathcal{J}} \sum_{l \in \mathcal{J} \setminus j} s_{jlk} p_{jk} p_{lk} + \sum_{j \in \mathcal{J}} s_{jjk} p_{jk} (p_{jk} - 1) \right] \quad (8.20)$$

The fourth class of objective functions is a special case of the third class: maximizing social mixing opportunities. Remote work has been shown to reduce the income diversity of interactions at urban destinations [11], which impairs the devel-

opment of social capital and economic growth. Governments may therefore include interactions across social groups as a goal for shared workplace development. The solution for maximum social mixing is likely to be similar to the solution for Z_3 , although with more emphasis on shared workplace locations that attract a diverse group of remote workers. For this objective, it is assumed that the customer segments are defined such that they represent the social classes targeted for mixing. As before, interaction opportunities between segments can be weighted differently, as it might be more beneficial to have interactions between the first and second income quartiles than interactions between the first and fourth quartiles. Then, as within-group interactions no longer have benefits, the objective function reduces to the following non-linear, non-convex formulation:

$$Z_4 = \max_{u,w,y,z} \sum_{k \in \mathcal{K} \setminus \text{WFH}} \sum_{j \in \mathcal{J}} \sum_{l \in \mathcal{J} \setminus j} s_{jlk} p_{jk} p_{lk} \quad (8.21)$$

The fifth and final class of objectives is also intended to mitigate the decreasing diversity of urban interactions. Rather than maximizing *total* interactions across social groups, however, it seeks to ensure that each shared workplace is chosen by a diverse group of remote workers. This approach treats the experience of remote workers at each workplace equally, and does not result in the concentration of remote workers at a few highly popular locations in order to maximize interaction opportunities. The objective is constructed to minimize the deviation between the diversity of the visitors to each location and the diversity of the population as a whole. Let Q_j represent the share of segment j in the population. Then the final objective can

be written as follows:

$$Z_5 = \min_{u,x,y,z} \sum_{k \in \mathcal{K} \setminus \text{WFH}} \sum_{j \in \mathcal{J}} \left| \frac{p_{jk}}{\sum_{j \in \mathcal{J}} p_{jk}} - Q_j \right| \quad (8.22)$$

Together, these five classes of objective functions enable the shared workplace problem to address many of the costs and benefits of remote work. The objectives can also be combined in a multi-objective optimization or Pareto optimization framework to quantify the trade-offs and complementarity of the social goals for shared workplaces. The implications of each objective function and combinations of multiple objectives in practice are explored further in Section 8.4.

8.3.4 Reformulation of quadratic objectives

The objectives Z_1 and Z_2 are linear in the decision variables and thus allow their respective models to be solved as MILPs. While the simplest version of the facility location problem is known to be NP-hard, modern solvers are able to solve even large problems in a reasonable timeframe. The absolute value penalty in objective Z_5 can also be linearized easily through substitution [314] with a negligible impact on the size of the problem. The objectives Z_3 through Z_4 are non-linear and non-convex in the decision variables, however, making them difficult to solve directly even with state-of-the-art solvers. Moreover, the standard Glover-Woolsey linearization technique for binary quadratic functions involves introducing new variables and constraints for each quadratic term in the objective function [315], resulting in a set of binary variables and related constraints that grow exponentially with the number of feasible customer choices $w(i, j, k, r)$.

A technique known as the reformulation-linearization technique (RLT) can be

used to improve the tightness of the formulation and reduce the number of additional constraints [316, 317]. For ease of notation, assume that the set of origin-segment-scenario triplets (i, j, r) is denoted by \mathcal{A} , and ordered in some fashion with index a . The choice variable w_{ijk_r} can then be replaced by w_{ak} . A new continuous variable γ_{akbm} is used to substitute for each binary quadratic term $w_{ak}w_{bm}$ in the objective function. Then the following constraints are added to ensure equivalency between the reformulation and the original binary quadratic program [317].

$$\sum_{k \in \mathcal{K}} \gamma_{akbm} = w_{bm} \quad \forall a < b, b \in \mathcal{A}, m \in \mathcal{K} \quad (8.23)$$

$$\sum_{k \in \mathcal{K}} \gamma_{bmak} = w_{bm} \quad \forall a > b, b \in \mathcal{A}, m \in \mathcal{K} \quad (8.24)$$

$$\gamma_{akbm} \geq 0 \quad \forall a, b \in \mathcal{A}, k, m \in \mathcal{K} \quad (8.25)$$

As shown in Zetina et al. [317], the formulation can be tightened further by adding more and more polynomial constraints, but the computational benefits of the tighter formulation are generally offset by the increase in the model size. As shown in the numerical experiment below, the RLT formulation above performs reasonably well for realistic problem sizes.

Additional practical considerations for reducing computation time is to reduce the size of the problem by eliminating infeasible (i, k) pairs. One promising heuristic to prune the number of feasible pairs is to apply a maximum travel distance beyond which any remote worker is likely to choose to work at home. Additionally, if there are no endogenous variables in the utility function, then any non-home location whose utility is computed to be lower than the utility of working at home across all scenarios can be eliminated as a feasible location choice for the corresponding origin-segment pair. There are also trade-offs between accuracy and computation time

when determining the appropriate number of scenarios to simulate and the number of customer segments to include.

8.4 Numerical experiment

A numerical experiment is constructed based on a plausible real-life scenario to demonstrate the practical applications of the shared workplace location model and to test the performance of the model as formulated. The experiment imagines that public funding has been obtained to renovate five existing libraries in order to accommodate collaborative remote work. The Boston Public Library (BPL) system, with 26 existing branches spread across the City of Boston, is used as the basis for the experiment. The 176 populated census tracts within the City of Boston constitute the set of origin locations. The four household income quartiles for the City of Boston are used as the customer segments, with the employed population of each income group by census tract taken from the 2021 American Community Survey 5-year estimates [1]. Travel times are calculated from the census tract centroid to each library branch using the road network and average driving speeds. The model is tested with 10 scenarios to simulate the stochasticity of the random utility function. The result is a problem with set sizes $|I| = 176$, $|J| = 4$, $|K| = 27$ (26 library locations and 1 work-at-home alternative), and $|R| = 10$, producing as many as 190,080 feasible, binary workplace choice variables. However, many (i, j, k) combinations can be eliminated by eliminating non-competitive locations from the choice set of certain remote workers.

To simulate realistic workplace choice behavior, an MNL utility function for workplace choice is estimated from a survey of remote workers: the SWAA [3]. As a reminder, the SWAA is a national survey of U.S. adults above the age of 19, conducted monthly since May 2020. The survey asks respondents about their chosen

distribution of workplace choices between working at home, at their employer’s workplace, or at a third place such as a co-working space or coffee shop. Respondents also provide their estimates of travel time to each location and annual income. The estimated MNL model includes travel distance as an alternative-specific endogenous variable and income as an individual-specific, categorical endogenous variable. The alternative-specific constant for the work-at-home alternative is set to 1 for scaling when estimating the model. The results of the model estimation are provided in Table 8.2 below. As expected, working at a third place is somewhat less popular than working from home in general, and decreases in popularity with increased travel time. However, working from third places is relatively more popular among the two upper income quartiles. The estimated coefficient for the second income quartile was not found to be statistically significant and was therefore excluded from the workplace choice model.

Parameter	Estimated Coefficient	Standard Error	$P > z$
Third place alternative-specific constant (β_0)	-0.3337	0.049	0.000
Third place travel time (min) (β_{tt})	-0.0037	0.001	0.000
Income Q2 (β_{Q2})	-0.0427	0.052	0.411
Income Q3 (β_{Q3})	0.2206	0.051	0.000
Income Q4 (β_{Q4})	0.4448	0.058	0.000

Table 8.2: MNL model estimation results for shared workplace choice

Note that for the three lowest income quartiles, both the third place alternative-specific constant and the distance coefficient are negative. These estimation results imply that working from home is the expected choice for those below the top income quartile, and third places are only chosen when the random utility deviate is positive

and sufficiently large. This aligns with existing data on workplace choice, which show that working from home is considerably more popular than working at a third place Barrero et al. [3]. It also seems reasonable that there would be many factors beyond income and travel distance that contribute to the choice between working at a third place and working at home. Indeed, Asmussen et al. [169], using a different model structure, finds that a wide range of geographic, job-related, and demographic factors contribute to the choice of workplace for remote workers in Texas. Rather than focusing on the comprehensiveness and goodness-of-fit of the MNL model, this experiment seeks to represent expected aggregate workplace choice behavior (i.e. working at third places represents a small but consequential share of remote work hours, and the probability of selection decreases with distance from home) in order to test the shared workplace choice model in a realistic setting. The sensitivity of the results to changes in the estimated MNL model parameters is provided in C, and other discrete choice model designs can easily be incorporated into the shared workplace location problem in the future.

To account for people unable to work remotely, the employed populations in each customer segment were reduced by a fixed percentage across all census tracts. Remote work days as a percent of all worked days by income quartile was computed from the most recent (May 2023) SWAA survey data. These are national results scaled to the demographics of the U.S. population to mitigate any sampling bias. The results for remote work as a percentage of all worked days by income quartile are presented in Table 8.3.

The shared workplaces are assumed to be free to the public and operationally identical, so the location choice model does not include any endogenous variables such as the price of admission or quality of amenities. As a result, the utility of each location to each customer segment can be pre-computed. Choice variables associated

Income Quartile	Remote Work Percentage
Q1	29.8%
Q2	35.4%
Q3	55.2%
Q4	65.6%

Table 8.3: Remote work percentage of total worked days by income quartile

with locations that are not chosen in any of the simulation scenarios were pruned from the model to reduce the model size. For simplicity, it is assumed that the renovated libraries are the only shared workplaces available, so the total number of visitors to any given location is higher than would be expected if there were competition from other private and public shared workplaces. Existing shared workplaces could be incorporated into the model as alternative locations with the restriction that $y_i = 1$ for all existing workplaces.

Five versions of the shared workplace location model were solved, each with a different class of objective function:

1. Minimize total travel distance
2. Maximize total shared workplace demand
3. Maximize total interaction opportunities
4. Maximize total interactions opportunities between shared workplace users the first and second income quartiles
5. Minimize total income segregation across all shared workplaces

In addition, a multi-objective version was solved with a weighted combination of the first four objective functions. The weights are set such that a 1% deviation from

the optimal value in any of the four individual objective terms is equivalent. Finally, the Pareto frontier between the first two objectives is mapped to illustrate the policy trade-offs between competing social goals.

For each model, the objective value is reported and a map with the locations selected in the optimal solution are presented. Furthermore, the performance of each model with respect to each of the five objectives is reported to illustrate how the choice of objective affects social outcomes. The computation time required to reach the optimal solution is also included; all experiments were implemented in Julia and solved with Gurobi version 10.0.0 on a dual-core Intel i7-6600U CPU with 16GB of RAM.

8.4.1 Objective #1: Minimize travel distance

On its own, minimizing travel would not be a reasonable goal for building new shared workplaces, but it can be useful as a complement to other goals. The key to minimizing travel distance is to choose the set of locations that maximizes working at home, given that working at any shared workplace has a non-zero travel distance. It is unsurprising, then, that the optimal solution involves selecting locations nearest to the experiment boundary in neighborhoods with low population density relative to other parts of Boston, as shown in Figure 8-2. The total population near the chosen locations is minimized, and much of the population is too far from an available shared workplace for the shared workplaces to represent a desirable alternative to working at home.

The results in Table 8.4 show that the solution is effective in minimizing travel by limiting demand for shared workplaces. The total travel distance is very small relative to the other models because the demand is less than a quarter of the maximum

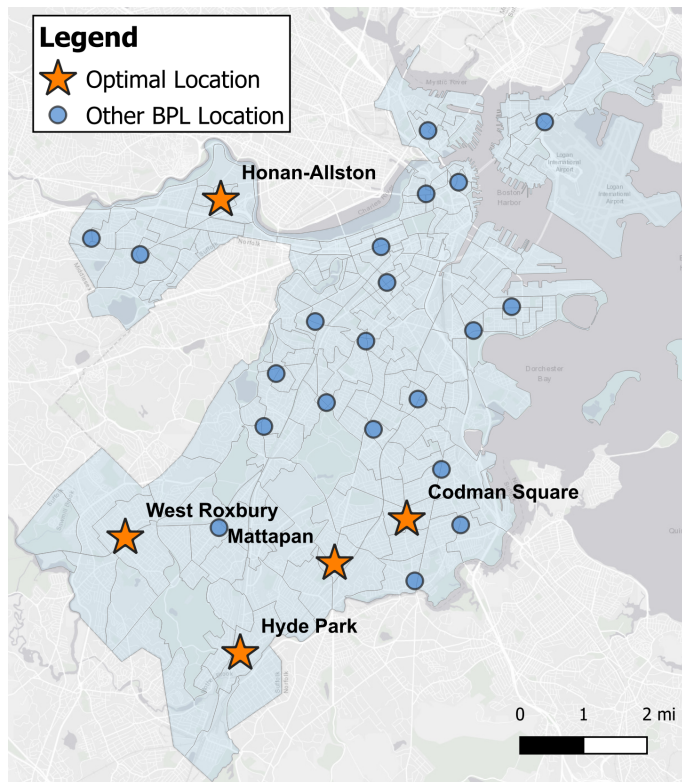


Figure 8-2: Optimal locations for Objective #1: Minimize travel distance

possible demand. Only about 3.3% of the remote worker population chooses a shared workplace. The interaction opportunities and interaction opportunities between the lowest income quartiles, which are related to the demand, are similarly low compared to other models. The linear objective function results in a very short computation time.

8.4.2 Objective #2: Maximize shared workplace demand

As shown in Figure 8-3, the locations chosen in the optimal solution to the second model have no overlap whatsoever with the locations chosen for the first model. The disutility of travel distance to remote workers forces the maximum demand objec-

Measure	Value	Optimal Value	% of Optimal
Travel distance (mi)	5,059	5,059	100%
Workplace users	8,996	40,899	22%
Interaction opportunities	10.72 M	173.23 M	6%
Q1-Q2 interaction opportunities	1.51 M	17.53 M	9%
Deviation from population diversity	0.0267	0.0205	131%
Computation time (s)	0.7		

Table 8.4: Results for Objective #1: Minimize travel distance

tive produces to locate shared workplaces in central neighborhoods with the highest population density, even when they appear close enough together to compete with one another. Moreover, high income workers are more likely to have the opportunity to work remotely, so the optimal solution chooses several locations near high income neighborhoods such as Back Bay (Central branch) and Beacon Hill (West End branch). This concentration of shared workplaces in central, high-income neighborhoods is certainly good for maximizing utilization of the facilities, but does not promote equal access across neighborhoods or income groups.

The demand for shared workplaces under the maximum demand objective is much higher than the previous objective, at 15.1% of the remote worker population. This comes at a cost of a 3.7x increase in travel distance. The optimal solution for this model also performs well with respect to interaction opportunities, although there remains a small gap compared to the result under Objective #3. The diversity of the population is poor relative to the previous model and relative to the result under Objective #4, which indicates that maximizing diversity is not complementary with maximizing demand. Like the previous model, this model has a linear objective and therefore can be solved very quickly.

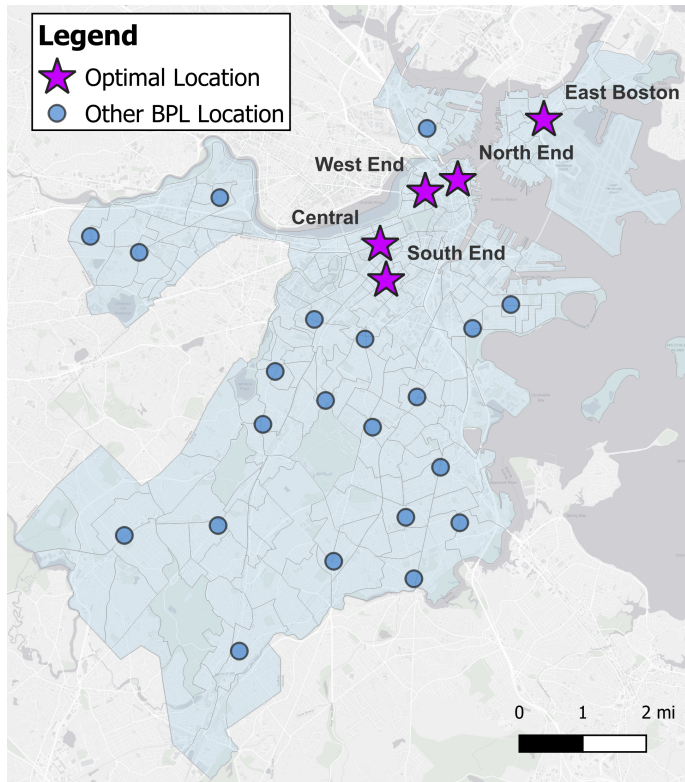


Figure 8-3: Optimal locations for Objective #2: Maximize demand

Measure	Value	Optimal Value	% of Optimal
Travel distance (mi)	18,569	5,059	367%
Workplace users	40,889	40,899	100%
Interaction opportunities	171.79 M	173.23 M	99.2%
Q1-Q2 interaction opportunities	15.81 M	17.53 M	90%
Deviation from population diversity	0.0430	0.0205	210%
Computation time (s)	0.7		

Table 8.5: Results for Objective #2: Maximize demand

8.4.3 Objective #3: Maximize interaction opportunities

The optimal solution to the third model is similar to the previous solution, with only one difference in location: the South Boston branch of the BPL is chosen instead

of the West End branch. Figure 8-4 shows the selected locations. This choice set eliminates some competition between the West End branch and nearby facilities, thus slightly increasing the total number of visitors (and number of potential interactions) at the three most central locations. It retains a high demand as South Boston is also a relatively dense area. The spatial distribution is somewhat more diffuse than the previous solution, although the chosen locations remain concentrated near the high-density downtown core.

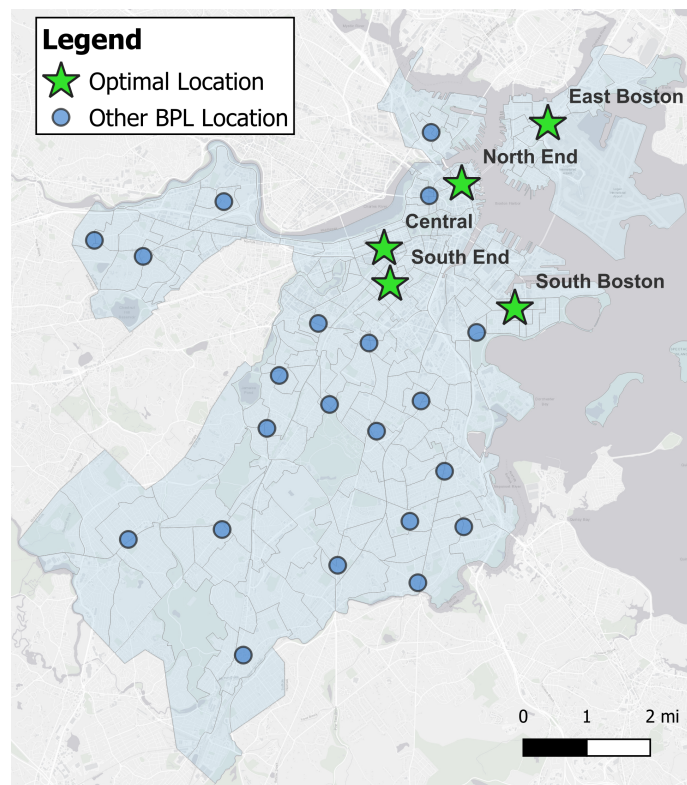


Figure 8-4: Optimal locations for Objective #2: Maximize demand

The optimal solution, by choosing a less central fifth location, slightly increases the demand at the four locations that it shared with the previous model. As a result, it creates more opportunities for interaction than the solution to the previous model,

even though the demand for the fifth location is relatively low. Travel distances have increased further despite the lower demand. As this model has a binary quadratic objective, linearized using the RLT methods described in Section 8.3, it has a longer but otherwise reasonable computation time.

Measure	Value	Optimal Value	% of Optimal
Travel distance (mi)	18,046	5,059	357%
Workplace users	40,793	40,899	99.7%
Interaction opportunities	173.23 M	173.23 M	100%
Q1-Q2 interaction opportunities	15.40 M	17.53 M	87.9%
Deviation from population diversity	0.0503	0.0205	246%
Computation time (s)	7.9		

Table 8.6: Results for Objective #3: Maximize interaction opportunities

8.4.4 Objective #4: Maximize interaction opportunities between lowest income quartiles

The optimal solution shares three locations with each of the two previous models, but chooses two new locations that are not part of any previous optimal solution. Figure 8-5 presents the optimal locations for the fourth model. It retains the South End, North End and East Boston branches, all of which have low income communities nearby. The two new locations are in areas with high residential density and a mix of low and middle income residents, including many students. By selecting these locations, the solution retains a high overall demand, while attracting more demand from the two lowest income quartiles.

This optimal solution performs relatively well with respect to demand and the total interaction opportunity measures, although it is somewhat worse than both

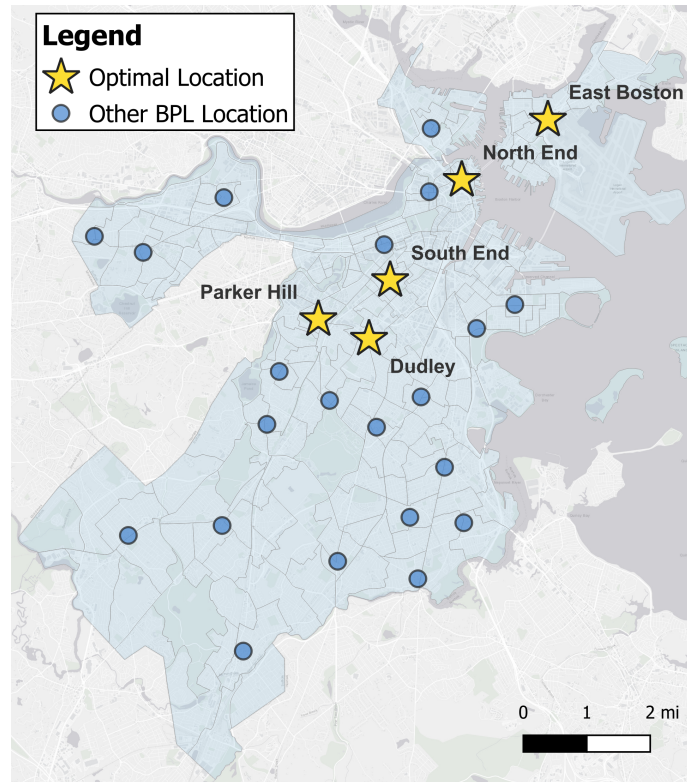


Figure 8-5: Optimal locations for Objective #4: Maximize interaction opportunities between lowest income quartiles

of the previous models. It also produces a high total travel distance. The income diversity of the locations is reasonable due to the deliberate focus on attracting visitors from the two lowest income quartiles, and it is better than the two previous models. The computation time is also quite low, as there are many fewer quadratic terms in the objective function relative to the previous model.

8.4.5 Objective #5: Minimize income segregation

Minimizing income segregation by attracting an equal share of each income quartile to each location produces another unique set of locations. Figure 8-6 presents the

Measure	Value	Optimal Value	% of Optimal
Travel distance (mi)	18,108	5,059	358%
Workplace users	36,400	40,899	89%
Interaction opportunities	148.90 M	173.23 M	86%
Q1-Q2 interaction opportunities	17.53 M	17.53 M	100%
Deviation from population diversity	0.0358	0.0205	175%
Computation time (s)	1.1		

Table 8.7: Results for Objective #4: Maximize interaction opportunities between lowest income quartiles

optimal locations along with the income quartile of the median household income in each census tract. Unsurprisingly, most of the selected locations are located at the intersection of different income groups. Notably, the selection avoids exclusively high income areas, since the highest income quartiles are already over-represented in the sample of remote workers.

This solution is actually relatively balanced compared to the previous models. It has a moderate demand profile, with moderate opportunities for interactions. The total travel distance remains much higher than the first model, but lower than models 2 - 4. As expected, it outperforms all other models with respect to diversity. The computation time is also minimal due to the efficient linearization technique for the absolute value functions in the objective function.

8.4.6 Multi-objective model

The last scenario is the multi-objective model, which combines the objectives of each of the first four models. It produces yet another unique solution, although each of the locations are included in the solution of at least one previous model. The

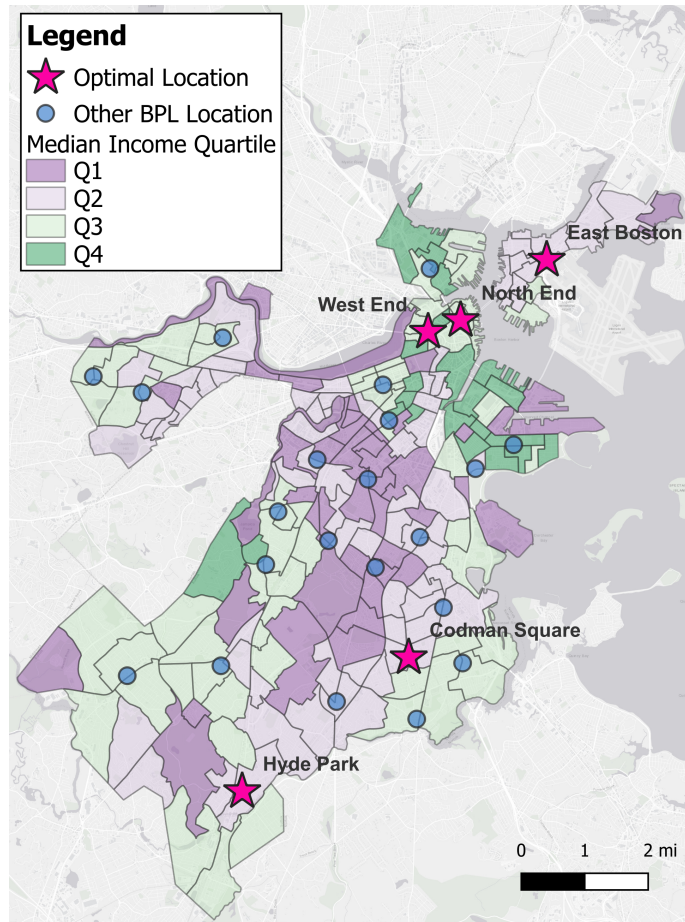


Figure 8-6: Optimal locations for Objective #5: Minimize income segregation

chosen locations have a much more even spatial distribution than any of the previous solutions. The South End and East Boston branches are chosen, which provide high demand and interaction opportunities, while the three remaining branches are distributed across the city to limit travel.

The multi-objective model finds a very balanced solution that performs reasonably well across all objectives. Given that models 2 through 4 all have related objectives, the multi-objective model results are closer to the optimal values for those measures, and further from the optimal solution for the travel distance model. Nev-

Measure	Value	Optimal Value	% of Optimal
Travel distance (mi)	11,678	5,059	231%
Workplace users	29,365	40,899	72%
Interaction opportunities	105.25 M	173.23 M	61%
Q1-Q2 interaction opportunities	8.11 M	17.53 M	46%
Deviation from population diversity	0.0205	0.0205	100%
Computation time (s)	0.7		

Table 8.8: Results for Objective #5: Minimize income segregation

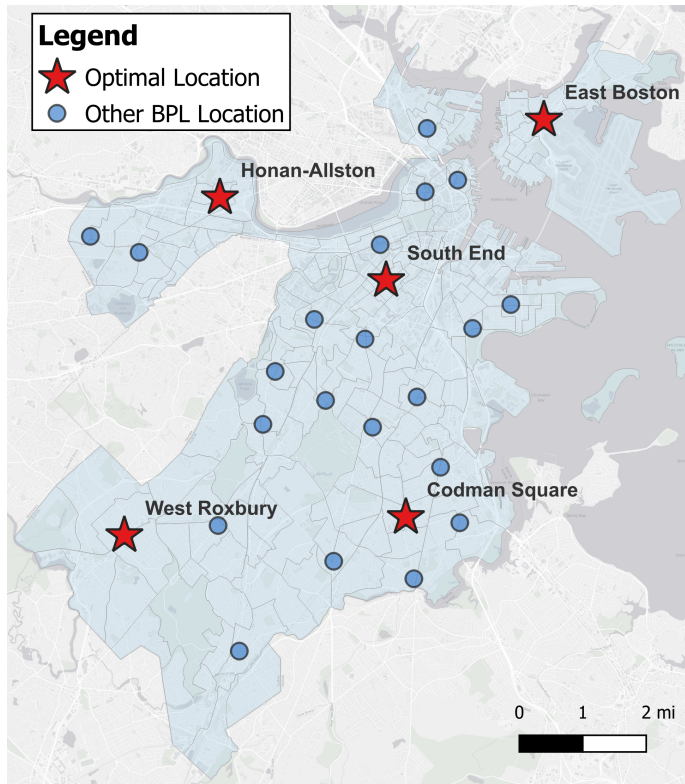


Figure 8-7: Optimal locations for weighted objective

ertheless, the total travel distance is reduced by 43% compared to model #2, while the demand is reduced by only 27%. The computation time for this model is similar

to the other quadratic objectives at 6.5 seconds.

Measure	Value	Optimal Value	% of Optimal
Travel distance (mi)	10,569	5,059	209%
Workplace users	25,678	40,899	63%
Interaction opportunities	110.68 M	173.23 M	64%
Q1-Q2 interaction opportunities	12.00 M	17.53 M	68%
Deviation from population diversity	0.0295	0.0205	144%
Computation time (s)	6.5		

Table 8.9: Results for the multi-objective model

8.4.7 Pareto frontier analysis

An interesting application of the shared workplace location model for policy development is mapping the Pareto frontier between two conflicting objectives to find the appropriate solution for a given policy trade-off. For this example, the Pareto frontier is mapped for the objectives to minimize total travel and maximize total demand. Figure 8-8 demonstrates there are many possible optimal solutions depending on how policymakers value each objective relative to one another. Even a minor shift towards higher demand can increase travel quite dramatically, and vice versa, making this trade-off a difficult political decision. The same map could be created for other combinations of two or more objectives to facilitate the policy development process and avoid choosing sub-optimal solutions.

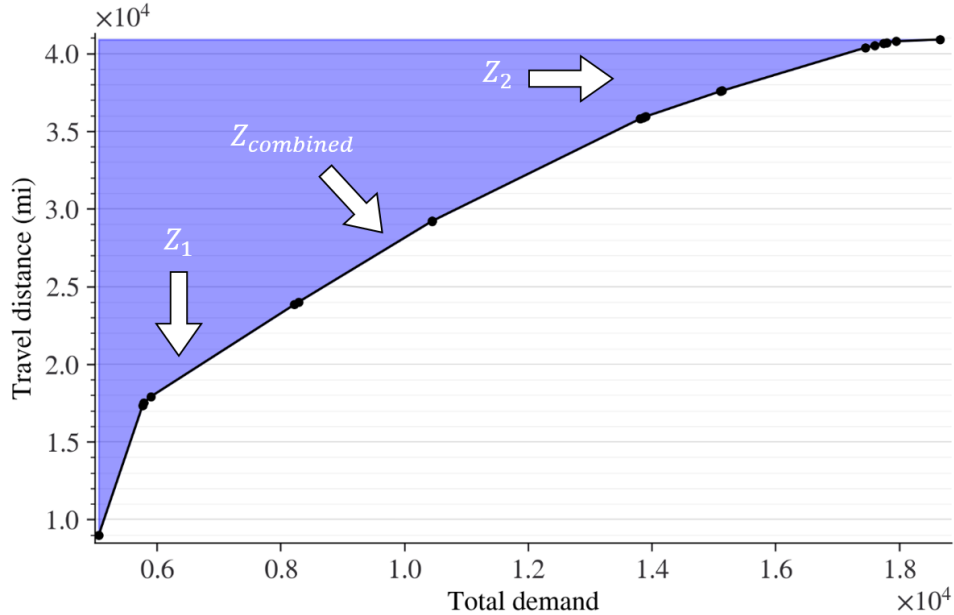


Figure 8-8: Pareto frontier for Objectives #1 (minimize travel distance) and #2 (maximize demand)

8.5 Policy implications

This area of research has numerous policy implications for many different classes of remote work stakeholders. While it is primarily designed as an analysis tool to inform remote work policymaking, it can also be adapted to support decision-making by real estate providers, private shared workplace operators and large employers.

The implications for policy making are evident. This optimization framework can be used to select locations for a network of remote working hubs that provide a convenient compromise between working at home and working at the office. It allows policymakers to estimate the performance of the selected locations along a variety of social goals, and make trade-offs between competing objectives depending on political priorities. The Pareto frontier for two or more objectives can be drawn to highlight

optimal solutions and avoid the selection of any dominated solutions. The numerical experiment shows that distributing shared workplaces across the urban area, with an emphasis on high-density neighborhoods, provides a solution that balances travel considerations with the desire for high utilization and many opportunities for social interactions.

There are applications even for policies that do not involve the direct financing or construction of new shared workplaces. For example, this framework could be used to select parcels of land to be zoned for shared workplaces, or identify locations where overly restrictive zoning has high social costs. By comparing the model solutions with different data inputs that represent alternative scenarios, it could also demonstrate how introducing new high-density housing or transportation infrastructure would affect the workplace choices of remote workers. Finally, policies such as subsidising the use of shared workplaces, or combining shared workplace passes with public transit tickets, could be tested by adjusting the MNL model and solving the optimization problem.

Real estate developers and shared workplace operators are the second category of stakeholders impacted by this research. It could certainly be a powerful tool for choosing future private shared workplace development locations from among a set of candidate sites, given that the framework allows profit maximization as an objective function. Existing shared workplace locations would need to be included in any model for determining the expected demand and profit of a new facility. The highly flexible MNL component could be adjusted to test different design decisions for new facilities, such as facility capacity or amenity bundles, or even pricing changes for existing facilities. Customers could also be segmented into different groups in the model to evaluate new products or promotions (e.g. monthly vs. weekly subscriptions).

In a sense, employers may be best suited to take advantage of this new optimiza-

tion framework. They have considerable information about their employees and can easily issue surveys to understand how employees would react to facility location choices. Many large employers are considering significant changes to their real estate portfolios, including a shift towards distributed satellite offices (also referred to as a “hub-and-spoke” model) [318, 319]. The optimization framework can help employers choose the right set of distributed locations to maximize the productivity and utility of their employee base, while avoiding investment in little-used facilities. Like the public sector, they can also evaluate the impact of different remote work policies and incentives on the workplace choices of their employees. The public sector is also a large employer, so if other governments follow the example of the Canadian federal government described earlier, they may use this framework for data-driven planning of shared workplaces for government employees.

8.6 Conclusions

Remote work is expected to remain a popular working arrangement well into the future, but there are individual and society downsides to working exclusively at home. Policymakers around the world are beginning to recognize that shared workplaces, a compromise between working at home and working in the office, can help to alleviate these issues. This paper establishes a new optimization framework for the shared workplace location problem with five different classes of objectives that correspond to the challenges of working at home. The specific dynamics of remote work location choice make the optimization framework difficult to solve, however. Non-linear workplace choice dynamics, including the option to work at home rather than a third place, are incorporated as linear constraints using an flexible exterior simulation approach. Complex social objectives are also linearized with a special family of

constraints to improve the tightness of the linear relaxation, allowing realistic problems to be solved in a reasonable timeframe. Data from the City of Boston is used to show the divergence in solutions across objectives and how certain social objectives for shared workplaces are in conflict. A multi-objective optimization approach provides further insights by mapping the Pareto frontier and solving the problem for weighted combinations of the objectives to find a balanced solution.

This optimization framework provides the foundation for many future research directions. First, the MNL model for workplace choice could be refined using purpose-specific survey data with additional variables. Alternative discrete choice model designs, such as nested logit or latent variable models could also be tested given the flexible nature of the exterior simulation approach. Accounting for the effect of one person's workplace choice on another person's workplace choice (e.g. a pair of co-workers or friends) is another example of a future model enhancement that could capture subtle behavioral dynamics. While the existing model framework can be solved relatively quickly for a city-scale problem, more efficient linear formulations or solution methods for the quadratic social objective functions could facilitate the solution of much larger regional or national scale problems, or problems with a much greater resolution. Second, new social objectives could be introduced. For example, it has been hypothesized that working at home could increase carbon emissions due to the relative energy inefficiency of many individuals working from residential buildings rather than a single floor of a modern commercial building. A social objective function to minimize *total* carbon emissions, including carbon and building emissions, would be useful in sustainable land use planning for remote work. Third, additional decision variables could be added to the model, such as the admission price, facility capacity, or quality of amenities. These decision variables would be especially relevant to private shared workplace developers (i.e. co-working platforms)

who build and operate heterogeneous facilities catering to different market segments. Even more complex problems, such as combining the location model with a transportation network design components could inform future integrated land-use and transportation model for sustainable remote work. Finally, new experiments could investigate the same question in other locales, or explore related remote work policy challenges. The shared workplace optimization framework could be applied to the problem of deciding which vacant commercial buildings should be converted into shared workplaces, or which transit stations would benefit most from transit-oriented development with remote work amenities.

Chapter 9

Conclusions and Recommendations

This chapter concludes the dissertation with a summary of the findings and recommendations, then describes some of the limitations of the research. Finally, it offers many opportunities for future research at the intersection of remote work and urban transportation.

9.1 Summary

The widespread rise of remote work in the wake of the COVID-19 pandemic represents one of the largest disruptions to urban life in a generation. Travel patterns have changed dramatically as a large segment of the population has the newfound flexibility to choose where (and occasionally when) to conduct their work. Urban transportation systems, largely designed to accommodate peak hour commuting from residential areas to downtown business districts, have been forced to re-evaluated their design, operations, and even their role in society. Employers, through their remote work policies, now play an important role in the travel choices of their workforce,

with major downstream effects on transportation systems and the urban economy. Policymakers, faced with limited or conflicting evidence, have taken a range of different approaches to urban remote work policy, leading to diverging outcomes for their residents. Each of these stakeholder groups (remote workers, service providers including transportation system operators, employers, and policymakers) has an important role to play in determining how remote work evolves going forward. This dissertation seeks to arm these stakeholders with a comprehensive framework for considering remote work problems, detailed data on remote work-related travel behavior, and new analytical methods for adapting urban mobility systems to the changes caused by remote work.

There has been considerable research into remote work trends and impacts since the onset of the COVID-19 pandemic. Yet two barriers prevent the translation of this work into evidence-based policy. First, studies often take a narrow, discipline-specific approach to remote work that ignores the much larger impacts of remote work on other relevant stakeholders. Second, the lack of a comprehensive framework to describe remote work settings can make it difficult to identify the factors contributing to diverging results between seemingly similar studies. This dissertation addresses both issues by mapping the stakeholder relationships related to remote work, providing a common taxonomy for many remote work terms, and proposing a conceptual framework for describing and classifying remote work studies.

Next, this dissertation presents a new, large-scale source of primary data on remote work arrangements and travel behavior. One of the most surprising findings is that many people are choosing to conduct work outside of their homes at nearby third places, such as coffee shops or co-working spaces. Commuting trips to these third places have different characteristics than traditional commutes; people leave later in the day, are more likely to use sustainable travel modes, and travel shorter

distances. The use of third places varies by many of the traditional categories used in travel behavior models, such as socioeconomic status and geography, but also by characteristics related to employment, employer policies, attitudes towards remote work, and household amenities. These factors provide a new link between employers and travel demand that does not exist for traditional employer workplace-based working arrangements.

The influence of employers is just one complication that makes third place commuting difficult to estimate with existing travel behavior models. The mixed continuous-discrete distribution of preferences for remote work is another challenge, as is estimating the choice of destination. This dissertation shows how ZOIB regression, the introduction of new travel behavior model variables, and mobile phone records can be used to produce accurate models of third place trip characteristics. These techniques allow travel demand modelers to account for third place commuting when planning transportation infrastructure investments and evaluating remote work policies.

Third place commuting has a significant impact on carbon emissions. This dissertation shows how the methods described above can be used to update pre-pandemic estimates of commuting travel across an urban area. It finds that remote work has reduced carbon emissions from commuting travel in the Chicago area by more than 30%. Ignoring third place commuting, however, leads to an underestimation of commuting emissions by 16.6%. These results highlight the importance of accounting for third place commuting in travel demand modeling. Using the same analysis method, the change in commuting visits to different neighborhoods is also estimated. Relative to 2019, visits to the downtown core have declined precipitously, but some high-amenity neighborhoods in the inner suburbs have seen an increase in visits due to third place commuting. If employers' plans for remote work are realized in the future, more visits to the downtown core and distant suburban commercial

neighborhoods could be expected.

Given all of this new information about the travel behavior of remote workers and the potential impact of remote work on travel demand, the obvious question is: what should be done? Three new analytical tools are provided for adapting urban systems to remote work with each targeting a different remote work stakeholder. The first study imagines a new type of shared mobility service that takes advantage of the spatial flexibility offered by remote work. It develops an optimization model for matching passengers and vehicles in a ride-pooling platform where passengers have flexible destinations (e.g. “take me to a co-working space” rather than “take me to one specific WeWork location”). The destination flexibility is shown to enable more efficient passenger-vehicle matching arrangements, reducing overall vehicle travel while simultaneously increasing profit for the platform relative to a fixed destination service.

Public transit agencies are another important stakeholder whose ridership patterns have shifted dramatically as a result of remote work. A novel, computationally tractable method for evaluating the potential of entire transit networks to handle changes in ridership is developed to inform future operational and strategic planning. The optimization model allows for destination flexibility on the part of transit riders, allowing it to capture the dynamics of remote work and other discretionary trips. A case study of the MBTA rapid transit system shows that the hub-and-spoke topology of the network is well-suited to handling traditional commuting demand from the periphery to downtown, but does not have the same capacity to serve a mix of traditional commuting and decentralized commuting to third places in neighborhood centers. The optimal service patterns for each scenario are also determined. Transit service that adapts to new demand patterns is more likely to attract ridership; agencies can use this new modeling framework to test alternative operating

strategies or network designs based on capacity to handle emerging remote work travel patterns.

The last adaptation study is aimed at land use, which is an integral part of travel demand. Motivated by the growing need for new remote work hubs to accommodate the rise in demand for third places, the study develops an optimal location choice model for shared workplaces. While private co-working developers are primarily concerned with maximizing demand and profit, public sector developers, who have recently begun to engage in shared workplace development, have a range of social goals. To that end, the integer programming model permits objectives related to travel, demand, and profit, but also interaction opportunities, social segregation, and diversity of visitors. A numerical experiment investigates the optimal selection of Boston Public Library branches to renovate to support collaborative remote work. The results demonstrate the variation in optimal solutions for individual objectives, and how objectives can be combined to produce a balanced and spatially distributed solution. This modeling framework can be used to support evidence-based shared workplace investment that maximizes positive social outcomes.

These are still the early days of the remote work era, and there is an opportunity to adapt mobility systems to this new reality in order to improve the quality of life for urban residents and visitors. Bold actions, informed by strong evidence, will be needed to adapt to the new reality of remote work-influenced travel patterns. By providing the conceptual framework, empirical data, and analytical tools for remote work stakeholders, this dissertation is a step toward evidence-based decision-making for a more sustainable and vibrant urban future.

9.2 Recommendations

The research in this dissertation was designed to provide practical policy and research recommendations by adopting the perspective of the urban stakeholders affected by remote work. Chapters 2 through 8 each present detailed policy recommendations derived from the results of the individual studies. Those recommendations are synthesized below for each of the important remote work stakeholder groups: academia, transportation services, policymakers, employers, real estate services, and remote workers.

Academia. Recommendations for academia are primarily addressed in Chapter 2. As discussed, many existing remote work research articles, while excellent, are challenging to translate into policy. Future research projects should take advantage of the proposed taxonomy and stakeholder to ensure that their findings consider the broader context of remote work. To the same end, scholars should invite collaborators from outside of their disciplines wherever possible for a wider perspective on remote work issues. Researchers should also take advantage of the proposed conceptual framework to classify their studies and facilitate comparison with other similar studies to isolate key similarities and differences.

Transportation services. This dissertation is predominantly focused on providing information and adaptation tools for urban transportation service providers. The evidence demonstrates that remote work has a deep impact on travel demand; about 30% of all worked days in the United States are now taking place remotely. Two-thirds of these days are worked at home, thus eliminating the need to commute. The remaining third is happening at nearby out-of-home remote work locations such as libraries and co-working spaces. The flexibility regarding when and where to commute has resulted in an uneven distribution of work trips across days of the

week, and a shift towards later departure times on the days that they do occur.

Transportation services must adapt their schedules and operating patterns to account for these new temporal and spatial patterns to ensure that they continue to provide convenient service to commuters. Shared mobility services should adopt flexible destinations as a means to improve the efficiency of their services, as shown in Chapter 6. Transit agencies should use the transit capacity flexibility models developed in Chapter 7 to evaluate the ability of their networks to accommodate these new commuting patterns and make changes if necessary. Shifting resources towards off-peak hours and focusing on connecting neighborhoods (rather than suburb-to-downtown corridors) will certainly benefit remote workers, but also anyone who works an irregular schedule or uses transit for non-downtown trips. A rise in commuting to third places may benefit transit agencies, as people are more likely to use public transit for third place commutes than traditional commutes. By building shared workplaces near transit hubs, public transit agencies can make transit an even more convenient third place commuting mode.

Policymakers At a high level, this research underscores the tremendous impact of remote work on the functioning of urban systems. Policymakers should review the evidence presented in Chapters 1-4 to understand how remote work affects their aspirations for urban mobility and urban society more broadly. As shown in Chapter 5, policymakers must not overlook the dynamics of remote work, such as commuting to third places, when estimating the impacts of future policies.

Another conclusion of this research is that employers have much more freedom to influence the travel behavior of their employees than ever before. By setting the frequency of remote work, types of hybrid work schedules, and the distribution of office locations, a few large employers could make a measurable difference in travel demand in an urban area. For policymakers, this opens up space for new travel

demand management policies. One example could be incentivizing employers with fixed hybrid schedules to offset their required in-person days as a means to spread travel demand throughout the week. The methods described in Chapter 4 can be used to enhance the travel demand models used to evaluate such policies.

Lastly, policymakers should consider promoting shared workplaces as a compromise between the benefits of working at home (reduced commuting, more flexibility) and the benefits of working in the office (opportunities to interact with others, less social segregation, no need to invest in a home work environment). Governments worldwide are considering how to build networks of shared workplaces that promote social goals; the models presented in Chapter 8 provide one method for prioritizing investment across potential locations. Other policy approaches, such as multi-use zoning in residential areas and transit-oriented development with remote work hubs, could also be effective in promoting remote work at shared workplaces.

Employers. Employers stand to benefit from this research in multiple ways. First, this research illuminates the preferences of workers in the United States. Employers should review these preferences and adjust their remote work policies where appropriate. For example, understanding that remote workers with young children, poor home internet, and those living with roommates all have stronger preferences for conducting remote work outside of the home might influence employers to offer subsidies for the costs of working at third places. Employers can also use the findings related to their influence on the travel behavior of employees to align their remote work policies with their corporate sustainability goals.

It is also recommended that employers review the speculative components of this research as inspiration to advocate for new services and policies that improve the productivity and quality of life of their employees. Employers could adopt the methods presented in Chapter 8 to build their own network of shared workplaces for

employees, or to push civic leaders to establish a similar public network. Based on the results of Chapter 5, employers might also approach shared mobility platforms and co-working providers about creating new services that streamline travel and workplace recommendation for their remote staff.

Real estate services. The changing nature of workplace choice identified in this dissertation should act as a catalyst for new real estate development patterns. There is an opportunity to capture latent demand for remote work at third places by expanding the network of shared workplaces. Real estate services can use the data on third place adoption for investment planning at an aggregate level, and the optimization model in Chapter 8 for targeting specific facility locations. In addition, it is recommended that short-term workplace providers such as co-working spaces explore future partnerships with mobility platforms to create an all-in-one mobility and workplace recommendation service for remote workers.

Remote workers. One benefit of this research for remote workers (and other workers for that matter) is to see how their own attitudes towards remote work and travel compare to their peers and the plans of employers. It is recommended that remote workers leverage the information provided herein to understand their role in shaping the future of remote work. Remote workers can lobby their employers for smart remote work policies by citing the benefits of working at third places and the evidence that remote work reduces emissions from commuting. They can also keep policymakers informed of opportunities to shift public transit and shared mobility services to better accommodate the travel needs of remote workers.

9.3 Limitations

The overall body of research in this dissertation has certain high-level limitations related to the scope of the research, the data collected and the methods developed. Many of the limitations described could be addressed through the future work proposed in Section 9.4. The specific limitations of the methods and the data used for the studies in each chapter are described therein.

To begin at a high level, the scope of the dissertation, while ambitious, is intentionally broad. Each of the topics explored in the individual chapters is sufficiently complex and important to support multiple dissertations. One reason for this is the timing of publication; this dissertation was written during the three years following the initial rise in remote work during early 2020. While remote work certainly existed in years prior, it was not practiced on a widespread basis and therefore attracted relatively limited attention from the academic community. This dissertation, therefore, aims to fill critical gaps in evidence and methods to address the immediate challenges faced by a range of remote work stakeholders. Given the severe disruption presented by the rise in remote work, this broader approach was anticipated to have the greatest potential for meaningful impact in the short term. An alternative approach would have been to investigate all of the implications of remote work for a single stakeholder (e.g. public transit agencies) and develop comprehensive evidence to support proposed adaptation strategies. This dissertation, through its conceptual, empirical, and methodological contributions, is intended to provide a strong foundation for exactly those types of in-depth research projects in the future.

Another limitation of this research is the geographic scope of the data collection and the case studies. The SWAA, highlighted in Chapter 3, exclusively collects data from remote workers residing in the United States, and the case studies in

later chapters are largely based on large American cities (e.g. Chicago, Boston, New York City). The methods are designed to be applicable in any geographic context, however. Moreover, the SWAA survey methodology has been applied to a global survey: the Global Survey of Working Arrangements, or “G-SWA” [320]. It would be very interesting for future researchers to conduct the same analysis in this dissertation for other countries and compare them to the results herein, as many countries have not seen the same level of remote work uptake as the United States. Ultimately, defining the scope of a dissertation involves many trade-offs, and it was determined that the work required to collect and analyze data for other geographies would undermine the ability to deliver on the research objectives.

By definition, this research focuses entirely on the behavior of remote workers and the implications of their behavior for urban systems. As a result, it entirely ignores people who do not have the luxury of being able to work remotely. It is low-income workers, including many in critical occupations such as transportation and health care, who are most likely to work jobs that cannot be done remotely, as discussed in Chapter 3. This dissertation therefore intentionally avoids making recommendations that would exclusively benefit remote workers. The experiments herein find that adapting transportation and land use systems to widespread remote work have benefits for society writ large by reducing many of the negative externalities of commuting. Furthermore, adapting transportation systems for remote workers can improve service for a broad group of people who do not work traditional schedules, such as shift workers, gig workers, retirees, and caregivers. Readers are referred to [321] for a discussion of the equity impacts of remote work and to [322] for recommendations to expand access to remote work across socioeconomic groups.

One shortcoming of this research is that it does not address one of the significant challenges of remote work for urban mobility: funding. The reduction in commuting

has produced a sharp drop in fare collections for urban transit agencies and even some toll roads. These issues are discussed in Chapter 2, but the focus of the dissertation is to develop tools and evidence for operational and strategic planning, rather than opportunities for new funding sources. Many of the recommendations provided herein would be likely to increase revenue for transit agencies (e.g. building shared workplaces near transit hubs and offering discounted passes for occasional but regular riders), while others may require additional capital or operating funds to implement (e.g. expanding off-peak service). In the short to medium term, however, fare revenue for public transit agencies is unlikely to recover to pre-pandemic levels even if these recommendations are adopted, and therefore addressing the funding gap remains largely in the realm of policymaking. [323] and [324] are among the many excellent articles about the need for alternative funding sources for public transit in the United States, and policy-oriented research on this topic is left for future research.

Lastly, this dissertation is aimed at addressing issues facing *urban* areas. Chapter 3 shows that remote work is most prevalent in urban areas, and the operational challenges faced by large urban mobility systems are generally much larger than those in suburban and rural areas. Nevertheless, remote work has increased substantially in suburban and rural areas as well. In many cases, remote work is seen as an opportunity for economic growth in exurban and rural areas [325, 227], as fully remote workers may be enticed to move out of cities if they no longer have to commute to an urban office. When taken to the extreme, the residential relocation trend has created new issues for certain small towns that experienced a remote work-related population boom [326]. These issues are quite different from the challenges faced in urban settings, where overall travel has generally declined due to remote work, or shifted to new patterns. New research is needed to understand and address the

remote work issues that are specific to rural and suburban areas.

9.4 Future Work

This dissertation is simply one step toward a comprehensive body of research around remote work and urban mobility. There remain many unexplored research areas connecting the two topics. As discussed in Chapter 2, an interdisciplinary approach to this research is essential for evidence-based policy. The four categories of stakeholders identified in Chapter 2 all stand to benefit from further research. Employers, workplace providers, and governments are currently operating with considerable uncertainty about the future of work and would benefit from an optimization framework that can be used for data-driven decision-making. For example, employers could incorporate employee preferences, home locations, and productivity functions when designing remote work policies and incentives. Workplace operators can leverage trip record data for locating and sizing new facilities, and for setting subscription prices. Governments would benefit from a strategic approach to planning remote work land uses to spur economic growth in struggling neighborhoods or to mitigate congestion within the transportation network. Each of these applications requires a robust source of data as well as new methodologies that can incorporate remote work dynamics. For that reason, the remote work research needs described in this section are categorized into two important subsets: empirical research and methodological research. The section concludes with detailed examples of two future research projects.

9.4.1 Empirical research

While the long-term trend towards remote work has yet to be observed due to ongoing concern about the COVID-19 pandemic and related economic restrictions, it is not too early to begin to collect empirical evidence. Empirical research needs can be further categorized into three major themes: 1) Changes in individual behavior, 2) Employer policies, and 3) Remote work infrastructure. The empirical research goals are summarized by theme at the end of this subsection.

Surveys of individual behavior have been conducted since the onset of the COVID-19 pandemic, as outlined in Chapter 2, including many that ask about future intentions. Unfortunately, the methodologies of these surveys are inconsistent, making it difficult to compare them against one another. The first empirical research goal should be to develop a standardized set of survey questions that would allow comparison over time, between different geographic areas and between socioeconomic groups.

Second, in order to predict long-term trends, surveys of both employers and workers should be continued on a regular basis. Typical sources of socioeconomic and travel behavior data, such as the American Community Survey and the National Household Travel Survey, are conducted infrequently and thus not suitable for understanding the rapidly changing dynamics of remote work. Attitudes towards the pandemic are in flux due to the emergence of virus variants on one hand and continued vaccination progress on the other, therefore attitudes towards remote work might also evolve. Panel studies or updated versions of previous studies would allow researchers to study how these attitudes have changed over time and to associate these changes with the dynamics of the pandemic. The results could also provide insight into the temporal evolution of general behavioral trends during public health

crises.

Next, empirical studies should expand their scope beyond the immediate questions around remote work to include detailed questions about preferred working arrangements, housing choices, commuting, and non-work travel. Except for working arrangements, these themes have been included in a handful of COVID-19 era surveys, but rarely in sufficient detail to support modeling efforts or policy development. Eliciting the factors that influence the decision of remote workers to move home locations, to start cycling to work, or to switch to a different grocery store, will have important implications for transportation services, real estate markets, and public policy. The extent to which employer-provided perks such as free on-site parking or transit passes have changed after the pandemic, and how those perks affect remote work decisions, is another potential research topic.

Detailed surveys of preferences for different work arrangements remain limited. Determining whether the large cohort of remote workers prefers remote work to take place at home alone, at a café with friends, or at a co-working space with colleagues is one of the most critical research needs in this area. Well-designed stated choice surveys of remote workers would allow researchers to infer the willingness-to-pay and willingness-to-travel measures for different workplaces and associates. Comprehensive studies of these preferences, contributing factors, and population heterogeneity could be used to inform transportation planning, employer policies, and investment decisions, among many other decisions.

Stated choice surveys are helpful, especially when forecasting future trends, but there are also opportunities to collect and analyze revealed-preference data related to remote work. Established methods for tracing mobility patterns, such as mobile phone traces and transit smartcards, can and have been used to study changes in demand for travel during the COVID-19 pandemic [327]. Datasets that allow

for longitudinal comparison of individuals before and after COVID-19 restrictions are especially valuable, as they permit quantification of the spatial and temporal changes in work activities. New methods could be applied to revealed-choice data, such as credit card transactions and mobility patterns, to estimate demand functions for different workplace types. Machine learning and statistical inference techniques might leverage these datasets to identify new patterns of behavior related to remote work. This information would help transit agencies and other transportation providers adapt to changing demand patterns.

One application of this preference data is in cost-benefit analysis for transportation projects. A greater prevalence of remote workers might change the determination for new transit services, bike-sharing programs, or road projects. Previous calculations would have considered a low or moderate amount of induced demand for new transit projects as a result of travelers switching from other modes or changes in destination for some discretionary trips. The destinations of commuting trips, however, are largely considered to be fixed [328]. Collecting empirical data about workplace preferences allows planners to model the changes in work locations that result from improvements to the transportation network, and would ultimately affect which projects are proposed and implemented.

Turning to the employer policy theme, the degree to which employers share the preferences of their employees, or have countervailing preferences is perhaps more important, as employers ultimately determine remote work policies. Much like mobility patterns, recent research around employee and firm productivity has focused on the period at the beginning of the COVID-19 pandemic, when most remote work was conducted at home due to mandatory restrictions [112, 113]. Given that a much larger share of the population is expected to engage in remote work in the future, it is important to understand how different work arrangements affect individ-

ual and organizational outcomes. Rigorous case studies of employers who adopted widespread remote work or distributed satellite offices before the pandemic, their organizational structures, remote work policies, and communication practices could be informative. Furthermore, the actions and stated intentions of major employers during the COVID-19 period related to work site relocation, remote work policies and organizational restructuring should be cataloged.

Finally, there is the issue of creating and curating new sets of data that can facilitate remote work travel demand models. One important research need is the location, capacity, and occupancy of potential workplaces for remote work within different urban areas. This would include each of the facility types described in Chapter 2, such as cafés, libraries, and co-working spaces. Previous studies of remote work destinations, such as Ge et al. [86], have made strong assumptions about available workplaces due to a lack of ground truth data. Going forward, an accurate representation of availability will be necessary to generate actionable insights.

Table 9.1 summarizes the empirical research needs described above:

9.4.2 Methodological research

The collection of new empirical data will have a limited impact if the dynamics of remote work cannot be captured by analytical models. These models should address the need for long-term strategic planning by mobility providers, employers, and workplace providers, but also operational decisions such as employee coordination and transit schedules. This may involve adding new complexities to existing methods to reflect the dynamics introduced by remote work, or integration of multiple existing methods or models from different disciplines. Finally, two of the research needs call for entirely new methods to quantify important remote work dynamics that are

Theme	Research topic
Individual behavior	<p>Establish a set of standard questions for future remote work surveys and continue collecting data from existing surveys</p> <p>Expand surveys to include comprehensive questions about changes in lifestyle brought about by an increase in remote work</p> <p>Collect or synthesize <i>revealed-preference</i> data to study actual changes in mobility patterns</p> <p>Focus surveys on preferences for different remote work arrangements</p>
Employer policies	<p>Survey employers across industries and compare the difference in remote work preferences between employers and staff</p> <p>Track aggregate trends in workplace relocation, remote work policies, and organizational restructuring</p> <p>Review the practices and outcomes of organizations who adopted extensive remote work before March 2020</p>
Infrastructure	<p>Create new datasets identifying the location and capacity of available remote workplaces</p>

Table 9.1: Summary of empirical research needs

known to exist but difficult to analyze effectively. Similar to the empirical research, these needs have been organized into three categories: 1) Travel demand modeling, 2) Supply adaptation, and 3) Land use and public policy. The travel demand modeling tasks will benefit from the individual and employer-focused empirical research described in the previous section. The supply adaptation research needs are then built on top of the demand modeling improvements, offering a response that caters to the needs of remote workers. Lastly, the land use and public policy research needs incorporate all three themes of empirical research, including remote work infrastructure.

First, associate dependencies imply a joint decision between multiple individuals, a scenario that has been historically difficult to encode into the discrete choice modeling framework. The remote work location choice of one colleague could affect the decision of another, and so on; these effects should be captured within the choice model. There have been notable efforts to include a single decision made by a multi-person household [329], or decisions where social effects are incorporated [330], but models of day-to-day decision-making with correlated outcomes are limited (for an example, see Zemo and Termansen [331]). These efforts could involve improving the traditional econometric models or perhaps creating new choice models altogether. For example, when a group of colleagues with remote work is given the freedom to choose a time and place for a collaborative meeting, the negotiation between alternative destinations could be modeled as a set of strategic choices between decision-makers, thus introducing game theory concepts into destination choice models. Machine learning for travel behavior modeling has been growing in popularity; such techniques may prove more suitable for the collective choice between remote work arrangements. Moreover, work arrangements are likely to be influenced by previous choices. Choice models should incorporate memory of previous decisions, and the competing desires between exploration of new possibilities and exploiting known work arrangements.

Modeling the choice of working arrangements necessarily includes a utility function for different destinations; empirical research described in the previous section can help to calibrate the function parameters. This is one example of adding new complexity to an existing method.

Many classical travel demand models [332, 333] do not include occupancy in the destination utility function, or require that destination utility is a monotonic function of occupancy to guarantee that a solution exists and that it is unique. Des-

tion choices, including workplace choices, are often non-monotonic, however. For example, the utility gained from working at a co-working space might increase with occupancy, but only up to a certain threshold, after which utility begins to decrease rapidly due to crowding and noise. Other, more complex functions are certainly possible. Generalized travel demand models that accommodate such functions are therefore necessary for accurate estimates of transportation outcomes in the future of work. Collaboration between econometricians, behavioral psychologists, and activity modelers is needed to develop workplace choice functions that can be used to estimate the effects of new remote work policies.

Advances in the modeling of remote work arrangements and destination utility could be leveraged for a new application: recommendation engines for remote workers. Some of the stakeholder partnerships identified in Chapter 2 involve collaboration between mobility platforms and workplace providers to sell integrated services to workers or their employers. Imagine, for example, a platform that combines ride-hailing services and co-working spaces to offer combined transportation and workplace solutions for remote workers who prefer to work outside of the home. Methods for identifying remote workers who would benefit from new services, and for learning how preferences change over time, would help these partnerships recommend service bundles to prospective users.

The research needs described above are largely related to demand modeling, but supply models must also be adapted for remote work. One of the biggest concerns around remote work is the overall uncertainty. As described in Chapter 2, there is much speculation around remote work trends, and the majority of studies simply estimate remote work in the near future, rather than five or ten years hence. Across all transportation modes, one critical research need is supply optimization models that allow for uncertainty and future changes in the quantity, location, and timing

of travel demand. There are several methodological approaches that incorporate uncertain parameters, including stochastic optimization and robust optimization, which could be applied to transportation planning problems. For example, transit network design models should be capable of including the possibility that remote work grows to 40% of worked hours in the long run, as well as the possibility that it continues to account for less than 10% of worked hours. These new techniques should then find solutions that work well in each of the possible scenarios, or solutions that are inherently flexible, resilient, and adaptable to changing trends.

Much like ride-sharing, transit assignment modeling has typically assumed fixed destinations for most transit trips (e.g., Olikar and Bekhor [334]). Remote workers, on the other hand, may adjust their destinations each day based on the availability and quality of transit service, or even due to new information received en route, such as the presence of downstream incidents. New transit assignment models are needed that can capture these dynamics, including the effect of real-time information, with tractable formulations to support transit planning applications.

Moreover, transit networks and schedules are generally designed around the stable spatiotemporal demand produced by fixed commuting patterns. New trends may emerge as people become more comfortable with remote work; one might imagine that more remote work will occur on Mondays and Fridays than mid-week, but that people are more likely to work from non-home locations on Fridays than Mondays to pursue social activities after work. These trends have not been a major issue for transit agencies due to limited remote work before March 2020 but could create significant disparities in aggregate travel demand between weekdays. Adjusting to these patterns could require the creation of different transit schedules or even route patterns for each weekday, which is not common practice today. Creating these individual timetables will require new methods for rapid data collection and sched-

ule optimization, as well as research into the dissemination and communication of complex timetables to the public and transit operators. Schedule optimization models could also be updated to endogenize the remote work policies of major regional employers, which have a substantial effect on the demand for public transit.

Finally, there are remote work research needs in fields related to transportation planning, such as organizational behavior and land use planning. Practitioners in both fields, like those in transportation, are responding to rapidly changing conditions with a general lack of evidence and information. Employers are currently tasked with setting remote work policies for the post-pandemic period, despite considerable uncertainty around how different policies will affect performance, morale, and retention. Methodological innovations that can provide an accurate link between these policies and their organizational outcomes are sorely needed; some may even include transportation components.

Productivity modeling presents an opportunity for the development of entirely new methods to capture remote work dynamics. First, detailed methods for identifying and predicting the effects of different remote work arrangements on attitudes such as trust between colleagues and self-identification with a career or employer, and relate these attitudes to organizational outcomes (e.g. productivity, retention). Second, “knowledge spillover” is an economic benefit that arises from interactions and discussions between people, even if those people are in different industries or professions [335, 336]. These benefits have been observed at a macro scale, but it is difficult to measure the conditions or policies that affect knowledge spillover when the interactions are often spontaneous and their effects can take some time to materialize. As employers evaluate different remote work policies, such as leasing space in a co-working environment or incentivizing employees to choose collaborative remote work arrangements, it is critical to model the productivity benefits of these policies

that result from interacting with others. Adapting methods from network science to this problem is one promising direction of research.

Land use planners are in a similar position to large employers. Knowledge spillover can benefit the local economy, so designing policy and land use to encourage interactions between individuals should be prioritized, but new methods will be necessary to do so. There is little consensus on how remote work will change the demand for different land uses, including infrastructure, in the long term. Improved urban economic models that allow for new remote work-oriented land uses, travel patterns, and the impact on agglomeration effects should be developed to guide future decision-making.

Table 9.2 summarizes the methodological research recommendations:

9.4.3 Highlighted future research topics

This section describes two important areas of research at the intersection of remote work and urban mobility in greater detail than the projects listed above, with the hope of inspiring investigation by researchers in the future. The first is understanding the broader CO₂ impacts of remote work, specifically within the transportation and buildings sectors.

Impacts of remote work on overall urban CO₂ emissions

As discussed in Chapter 2, there has been substantial debate around the overall impact of remote work on carbon emissions relative to the more traditional employer premises-based work [150]. On one hand, remote work eliminates the need to travel, thus reducing the transportation-related emissions from commuting (see Chapter 4). Yet people who work at home still engage in leisure and household maintenance

Theme	Research topic
Travel demand	<p>Incorporate correlation and negotiation between the destination choices of individuals within discrete choice-based travel demand models</p> <p>Expand the exploration-exploitation trade-off for destination choice models to include the choice of workplace</p> <p>Develop tractable travel demand models that permit non-monotonic destination utility functions</p> <p>Explore new methods for synthesizing mobility and location choices in order to support a recommendation service for remote workers</p>
Supply adaptation	<p>Build supply optimization models that can handle uncertainty in remote work trends</p> <p>Create optimal passenger-vehicle matching algorithms that can capture associate, geographic, and facility dependencies</p> <p>Propose new transit and multi-modal network design and scheduling problems that involve irregular and flexible commuting patterns</p>
Land use & policy	<p>Build dependencies into regional planning models to predict how new zoning regulations or developments will affect location choices and commuting patterns</p> <p>Develop new methods for modeling the impact of remote work arrangements on knowledge spillover</p> <p>Create models for individual and firm productivity in a remote work environment with dependencies, enabling evidence-based employer policies</p>

Table 9.2: Summary of methodological research needs

activities, and the evidence of overall reductions in personal travel due to remote work is mixed and highly variable (e.g. 70, 76). Moreover, commercial buildings are

generally more energy efficient than residential buildings, so a group of colleagues all working at their own homes is likely to increase building-related carbon emissions relative to the same colleagues working in a modern office building. Like travel, this is also highly context-dependent, as energy use depends on several factors, such as building age, material, outdoor temperature, other building occupants, and so on. [337] provides an in-depth exploration of the different mechanisms by which remote work affects carbon emissions. As a result of these complications and mixed findings, the overall CO₂ impact of remote work remains relatively uncertain despite the obvious and important policy implications.

Recently, a combination of rich new data sources has emerged that may shed light on this issue at an aggregate level. Following a remarkable data collection effort, Huo et al. [133] has published near real-time carbon emissions data, broken out by sector, for 1500 cities across the world. The sectors include ground transportation and residential buildings, allowing for a detailed investigation of the types of emissions that might be expected to change as a result of increased remote work. The incredible temporal resolution of the data permits tracking of trends over time and comparing them to the aggregate measures of remote work published by mobile technology companies (see Finazzi [338]). Both the emissions data and the remote work data span from before the onset of the COVID-19 pandemic well into 2022, a period during which commuting and general mobility varied significantly.

The massive spatial extent of the data makes it possible to disentangle the many possible confounding and contributing factors. For example, one might expect that remote work has a weaker effect on residential building emissions in cities with moderate temperatures, as people working at home would need less heating and air conditioning. New residential buildings tend to be more energy efficient, so a similar trend might be seen in cities with newer housing. Conversely, cities in which

driving is the dominant mode share for commuting might see a stronger relationship between remote work and carbon emissions, as fewer commutes would have an outsized impact on emissions from ground transportation. Collecting data on buildings, weather, demographics, industry mix, and transportation across cities would provide powerful evidence that could be used to inform future urban policies.

This empirical research remains in the conceptual stage, however, there are many promising opportunities to quantify the effect of remote work on carbon emissions. An initial step could be straightforward statistical analyses, such as linear regression, of the longitudinal data on emissions and remote work by city. Additional city-level variables could then be introduced to isolate the specific effects of the built environment, atmospheric conditions, and population demographics. Machine learning techniques could be useful to identify non-linear or unexpected relationships. Luckily reverse causality is unlikely to be an issue in this analysis, as no one would be expected to change their remote work behavior in response to urban area-level changes in carbon emissions.

The expected outcome of this research project would be a prediction model that could determine the expected change in carbon emissions for a given shift in the level of remote work. The model would incorporate all of the relevant city-level variables, ensuring applicability to a wide range of cities across the globe. Such a model could help to inform data-driven policy making around remote work, such as incentives to encourage remote working during months with moderate temperatures, or targeted investment in sustainable transportation infrastructure for cities with inefficient residential buildings. It could also provide insights for an even more ambitious research project: modeling the emissions consequences of employer remote work policies.

Connecting employer remote work policies to societal outcomes

Another logical extension of the research agenda contained in this dissertation is to evaluate the impacts of employer remote work policies in a similar manner to the evaluation of shared workplaces in Chapter 8. While the future research project described is concerned with macro-level emissions effects, this project would investigate the environmental, economic, and social trade-offs between the various remote work policies that an employer might choose. These policies could include number of remote work days allowed, fixed vs. flexible hybrid schedules, hub-and-spoke office models, or various remote work-related incentive programs. Evaluation criteria could be a combination of carbon emissions, employee productivity, employee well-being, real estate costs, interactions within and across teams, and urban retail spending.

If fruitful, this area of research could be expected to garner significant interest from the public and private sector, and may have the potential for commercialization. There would certainly be strong interest in estimating the productivity impacts of any proposed changes to a remote work policy or real estate portfolio. Furthermore, reducing corporate carbon emissions is a boon for the environment, but also for corporate bottom lines. There remains a strong market for investment products with a commitment to Environment, Social, and Governance (ESG) factors, giving public companies an incentive to improve the sustainability of their operations. Depending on the jurisdiction, corporations may also be able to take credit for emissions reductions as part of a carbon tax or cap-and-trade system if the emissions reduction can be verified.

Building on the previous project, the initial steps of this research would be to build a model of individual carbon emissions, productivity, and well-being for each potential workplace (including shared workplaces). There will be a trade-off between

the accuracy of the model and the amount of data needed, but it could be possible to provide upper and lower bounds rather than exact figures. Then, a predictive model of workplace choice should be developed using the SWAA data or perhaps more detailed primary data sources. This predictive model should account for changes in behavior due to the type of hybrid schedule or the availability of remote work-related incentive programs. The outcome of the model would be an estimated distribution of workplace choices for each employee under each alternative remote work policy. Then the performance along each of the evaluation criteria can be computed and the scenarios can be compared against each other.

This research requires both empirical and methodological innovation and would benefit from collaboration between disciplines. New training and validation data will be needed to develop and evaluate the prediction models. Connecting individual and group workplace decisions to productivity outcomes has long been a significant challenge that would benefit from novel methodological approaches and measurement techniques. The SWAA survey provides estimates of self-reported productivity changes for different remote working arrangements, and there have been some estimates of productivity changes in a very narrow sense (e.g. lines of code written). Like the previous project, machine learning techniques may provide the breakthroughs needed to model these dynamics on a broader level, given their complexity. Network science methods might be useful in understanding group decision-making and the effect of group decisions on well-being and productivity in a work setting. Collaborations between organization behavior theorists and mathematicians or computer scientists could be effective in developing new model structures with greater accuracy.

The expected outcome of this research project would be a practical tool for large organizations to use for data-driven remote work policy. As mentioned, it may also allow them to collect financial rewards when their decisions have positive social

externalities, depending on the government programs in their jurisdiction. If the results are sufficiently accurate, this research project could be expected to steer corporate remote work policy in a more productive and sustainable direction with benefits for all of society.

Appendix A

Remote work trends, plans and preferences (Chapter 3)

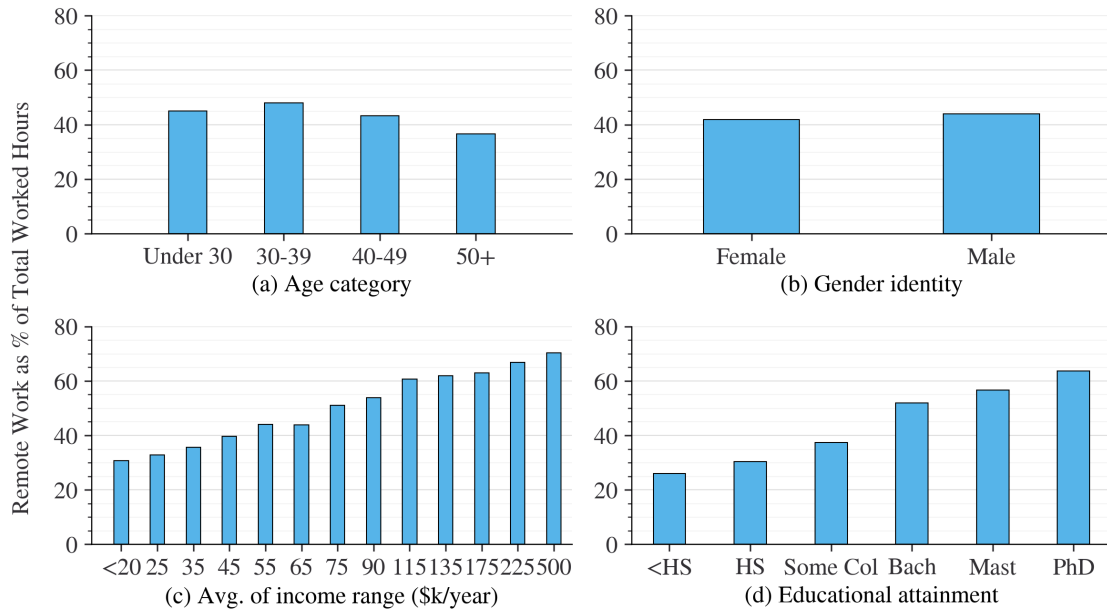
This section presents supplementary results from the SWAA related to current remote work trends, employee preferences for remote work in the future and employer plans for remote work in the future.

A.1 Current remote work shares

First, the observed trends in remote work. The results are based on a question asking respondents what percent of paid full days in the past week were conducted remotely. Responses for people who were not employed at the time of the survey are excluded.

Remote work shares by demographic group are shown in Figure A-1. Consistent with previous studies, the SWAA finds that younger people, men, and those with higher incomes and education generally engage in more remote work than the average.

Current remote work shares by household characteristic are shown in Figure A-2.



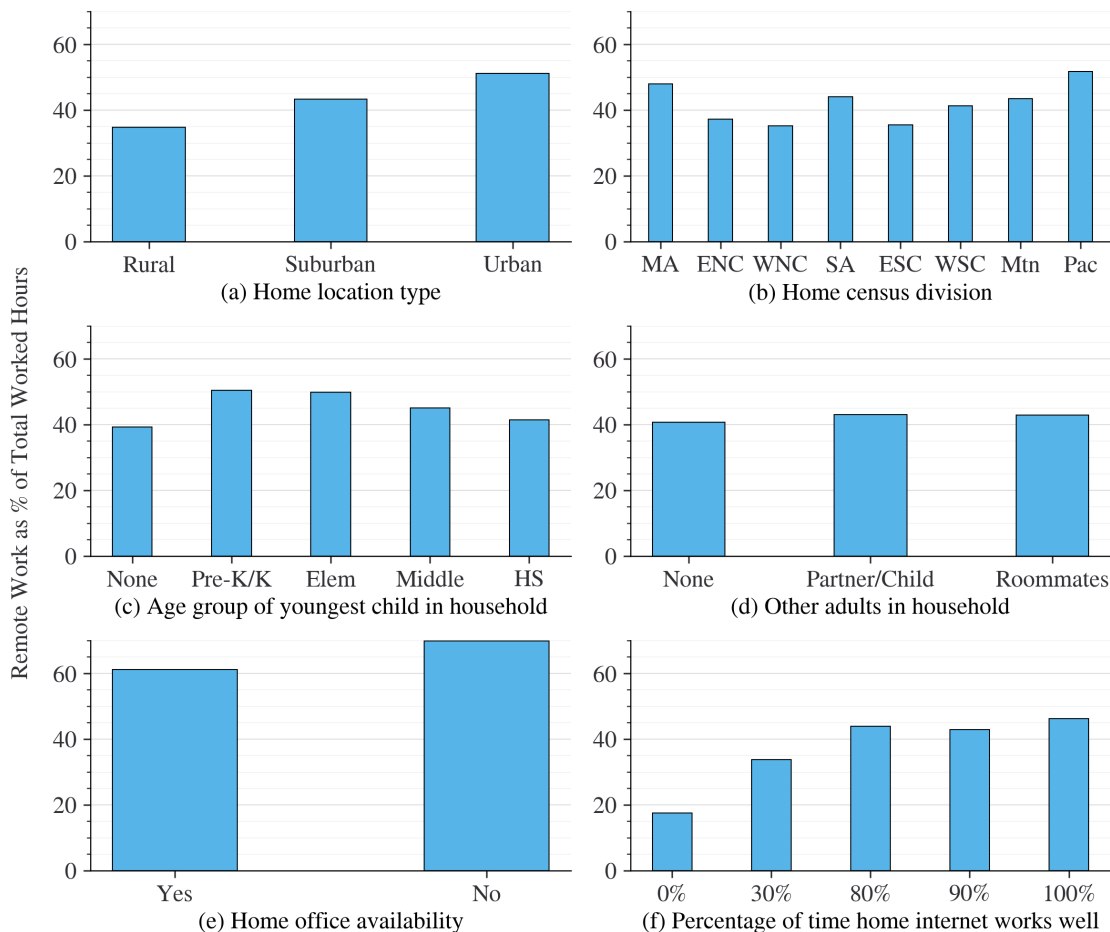
All: May 2020 - Jan 2023, N = 108,804.

Figure A-1: Current remote work share by demographic group

Urban dwellers are much more likely to be working remotely. There is significant variation by census division, with Mid-Atlantic, South Atlantic, Mountain and Pacific engaged in the highest amount of remote work. Remote work shares are also differentiated by children’s age and internet quality in an intuitive sense. Those without a home office are actually more likely to prefer remote work, but that trend is thought to be a result of home offices being correlated with other characteristics such as age and home location.

Current remote work shares by employment characteristics are shown in Figure A-3. Team size and number of hours worked both appear to have higher remote work shares among people with the lowest and highest response values. There is limited variation in current remote work by employer size.

Current remote work shares by job task characteristics are shown in Figure A-4.



(a): Aug 2020 - Jan 2023, N = 100,572; (b): May 2020 - Jan 2023, N = 108,801; (c): Jul 2020 - Oct 2022, N = 91,809; (d): Jul 2020 - Jan 2023, N = 101,045; (e): May 2020 - Dec 2021, N = 39,873; (f): May 2020 - Jan 2023, N = 65,705.

Figure A-2: Current remote work share by household characteristics

As expected, a general trend can be observed that people who use a computer less often and people who spend more time in meetings or engaged in collaborative tasks are less likely to conduct their work remotely.

Current remote work shares by remote work policy types are shown in Figure A-5. People who get to set their own remote work schedule are generally conducting more

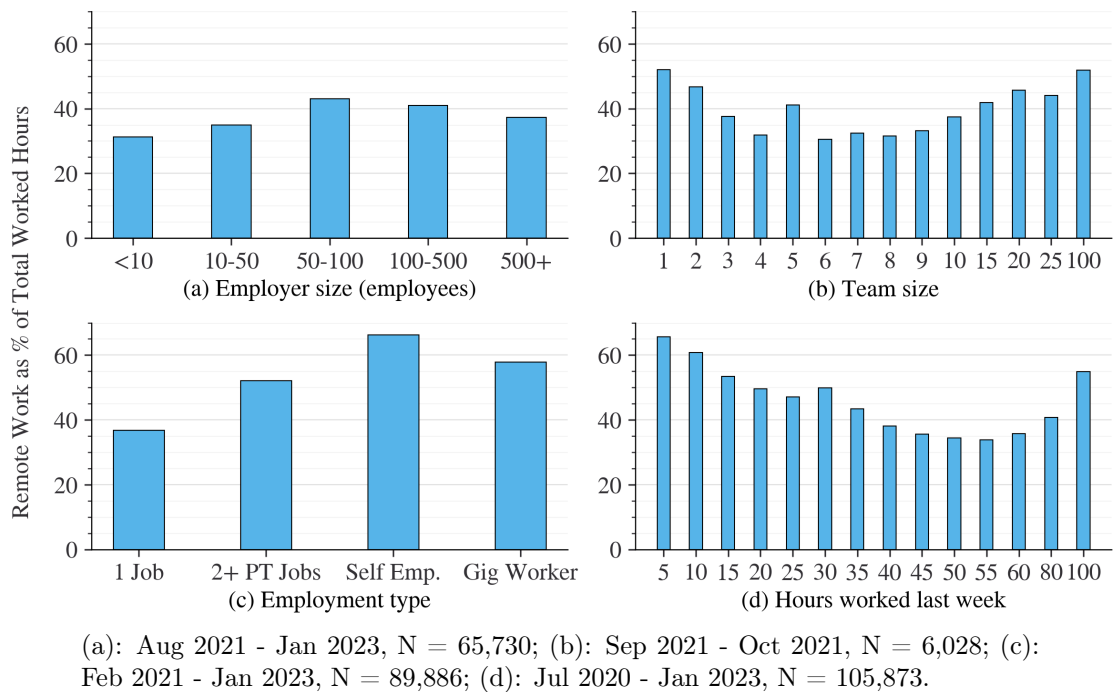


Figure A-3: Current remote work share by employment characteristics

remote work, as are those who choose not to follow their employer’s guidelines for number of remote work days. The difference in current remote work share between those whose employers set a common remote work schedule and those whose remote work schedule varies is relatively small.

Current remote work shares by attitudes towards remote work coordination with colleagues are shown in Figure A-6. Those who are less interested in coordination across all four questions generally conduct more remote work than those who value coordination.

Current remote work shares by attitudes towards remote work more generally are shown in Figure A-7. Those who find remote work to increase their effectiveness or less stressful are broadly more likely to be conducting higher levels of remote

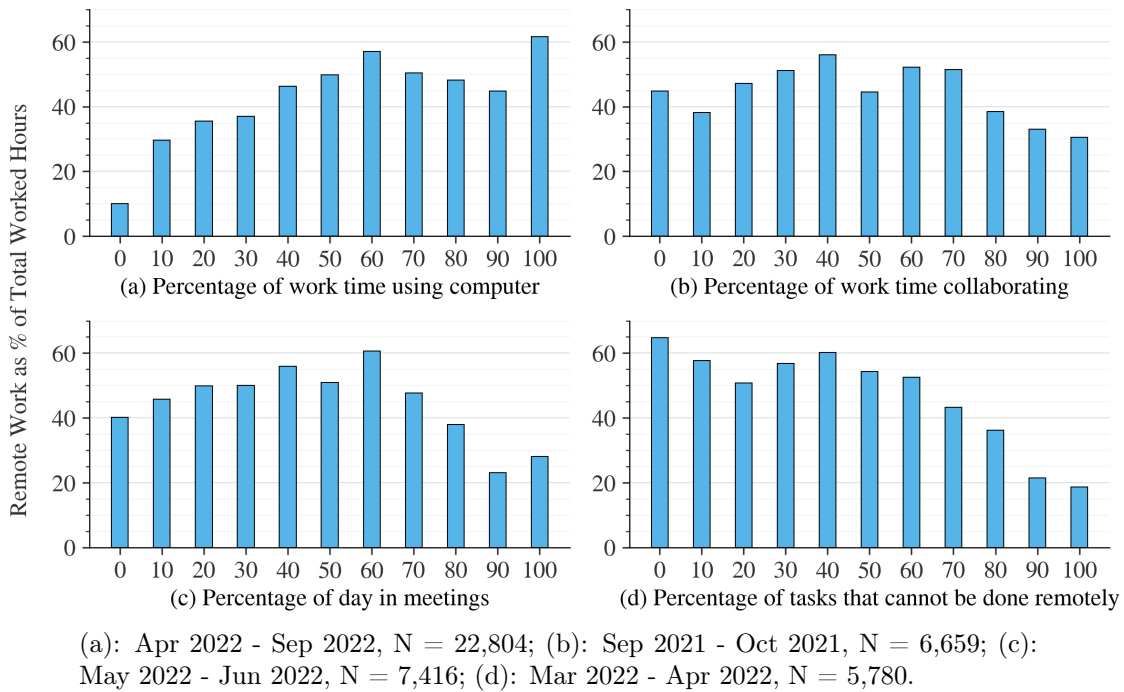


Figure A-4: Current remote work share by task characteristics

work. Similarly, people who think remote work increases their chances of promotion have higher levels of remote work. Results for the survey question about whether respondents are willing to work harder than expected to help their organization succeed are somewhat mixed. As with all questions, the effects are likely to be bi-directional, so those who are allowed to do more remote work may be perceive the additional remote work as a personal benefit and therefore have a stronger positive attitude towards their employer.

Current remote work shares by the perceived benefits of remote work are shown in Figure A-8. There is very little variation among response groups with respect to current shares of remote work. Greater variation is observed with respect to remote work preferences which are presented in the next section.

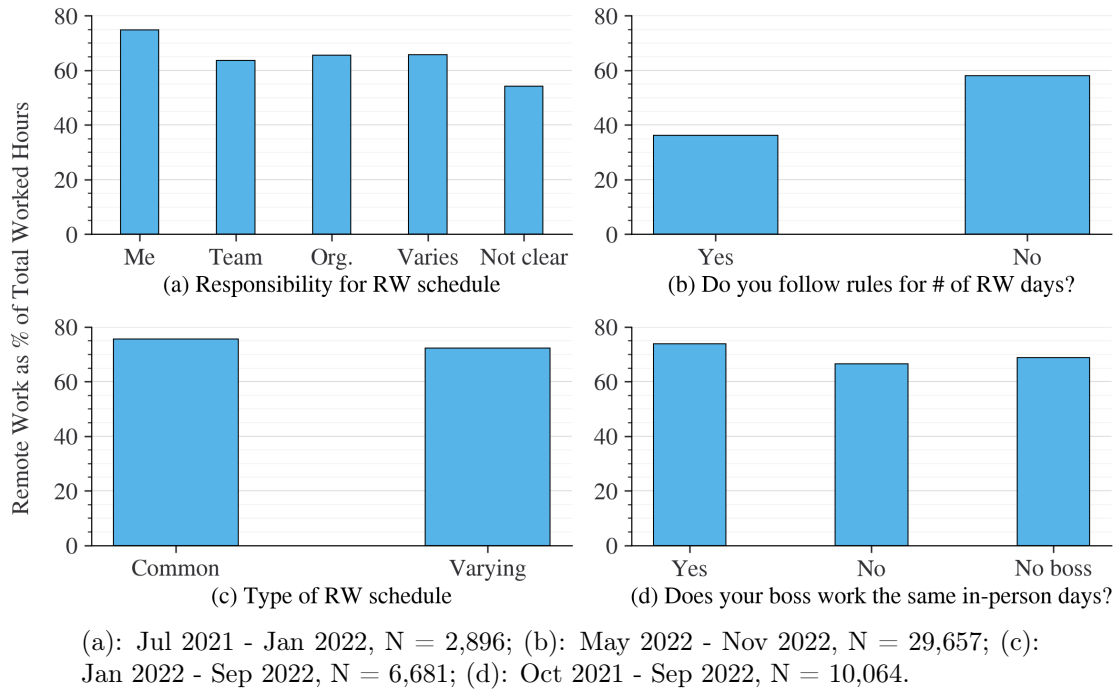


Figure A-5: Current remote work share by remote work policy

Finally, current remote work shares by life priorities are shown in Figure A-9. Interestingly, those who value leisure and friends highest and lowest are participating in the most amount of remote work. A high value of work and low value of family are both positively associated with additional remote work, which is somewhat counter-intuitive.

A.2 Preferred remote work shares

Second, the employee preferences for remote work are presented. The results are based on a question asking for respondents' preferences for remote work in future, assuming remote work did not affect their pay.

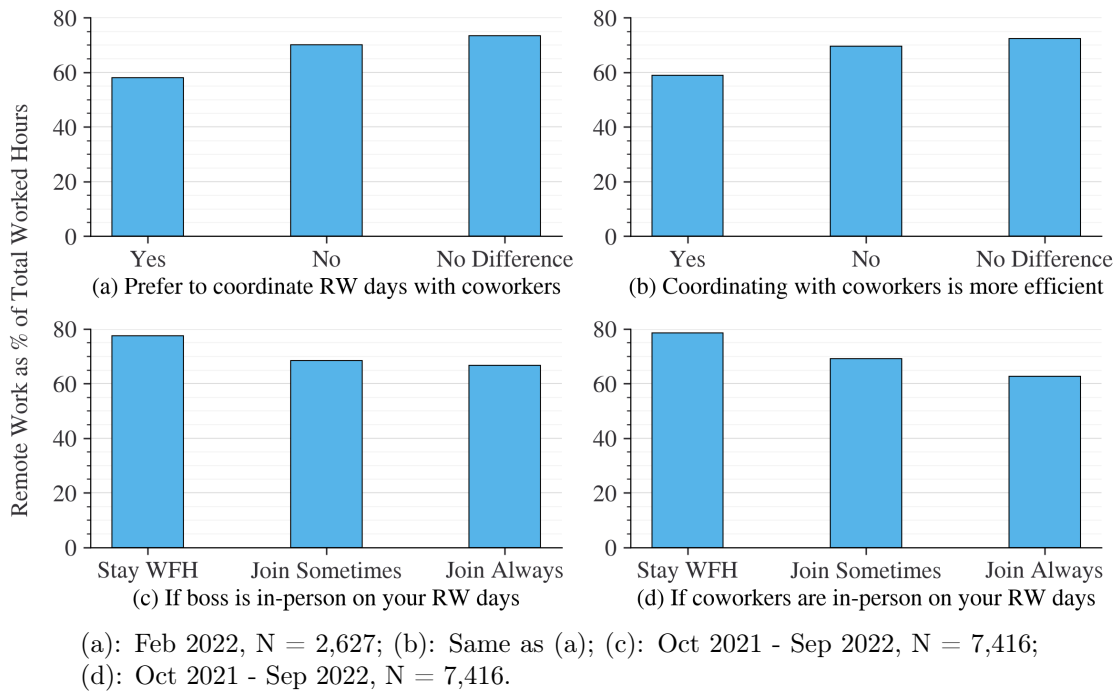


Figure A-6: Current remote work share by attitudes towards coordinating with colleagues

Remote work preferences by demographic group are shown in Figure A-10. Age, income and education largely track with observed remote work shares. Men prefer less remote work than women, despite conducting remote work more often in their current positions.

Remote work preferences by household characteristic are shown in Figure A-11. Preferences by home location type and census division are quite even. The presence of children or other adults in the home also does not seem to be associated with different preferences for remote work. Internet quality, however, is somewhat correlated with higher preferences.

Remote work preferences by employment characteristics are shown in Figure A-12. Team size and number of hours worked have less variation with respect to

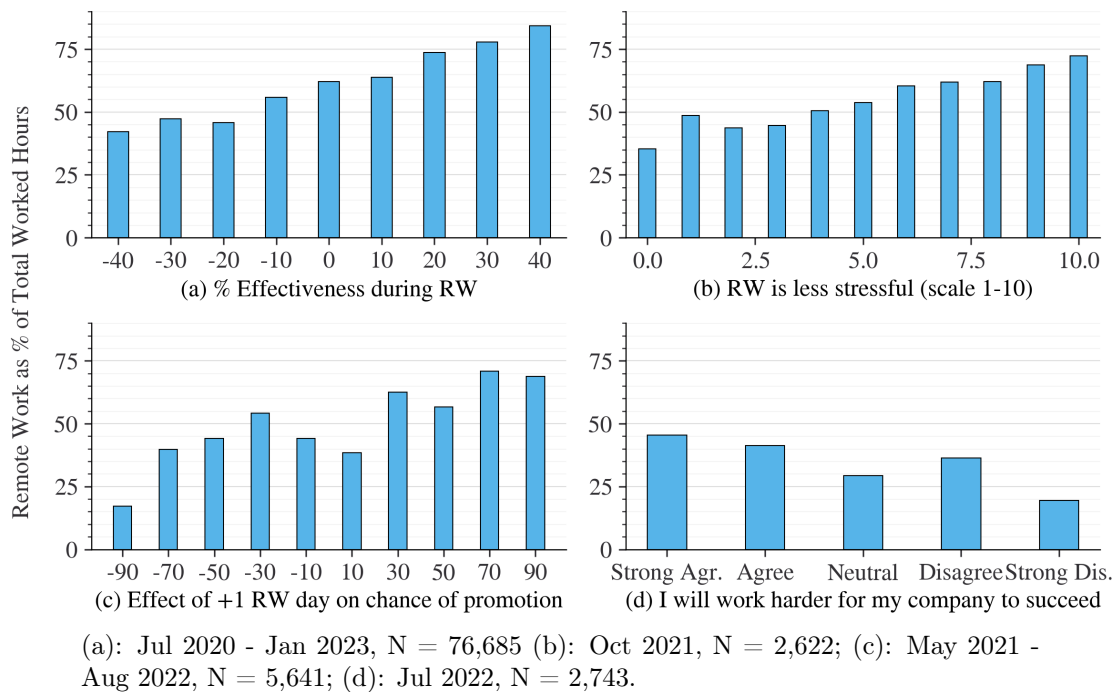
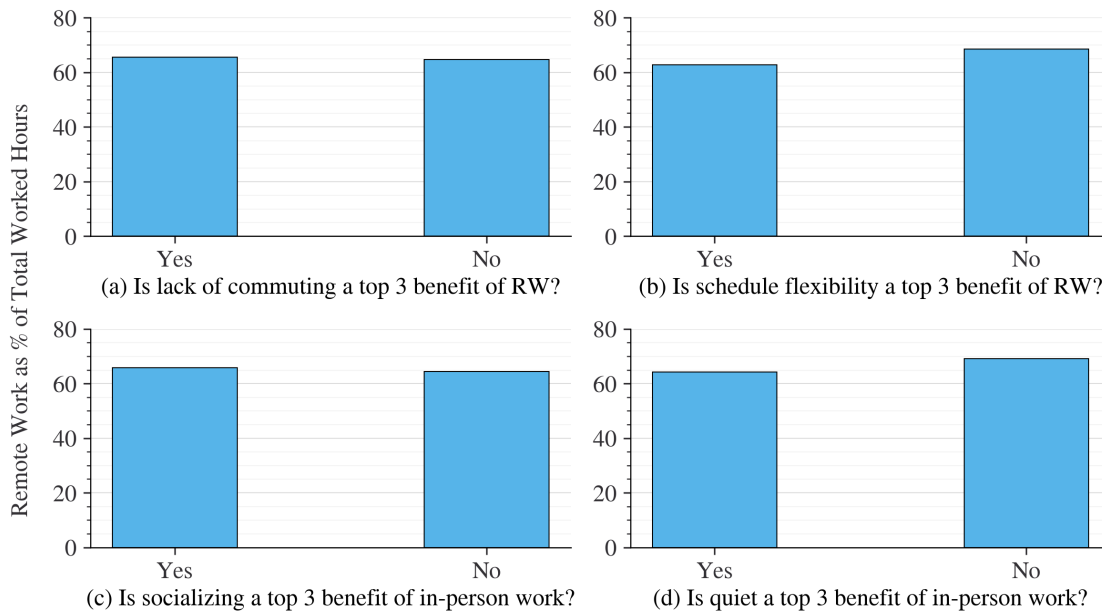


Figure A-7: Current remote work share by attitudes towards remote work

preferences than the observed remote work shares shown in Figure A-3. Employees of large companies and those who are self-employed or gig workers are more likely to prefer high levels of remote work.

Remote work preferences by job task characteristics are shown in Figure A-13. Percentage of time using the computer and percentage of tasks that can be done remotely appear to have a stronger correlation with remote work preferences than percentage of work time spent in meetings or on collaborative tasks. The average person who works 100% of the time on a computer and all of whose tasks can be done remotely prefers about 60% remote work, which is high relative to other groups but still includes a substantial amount of in-person work.

Remote work preferences by remote work policy types are shown in Figure A-14.

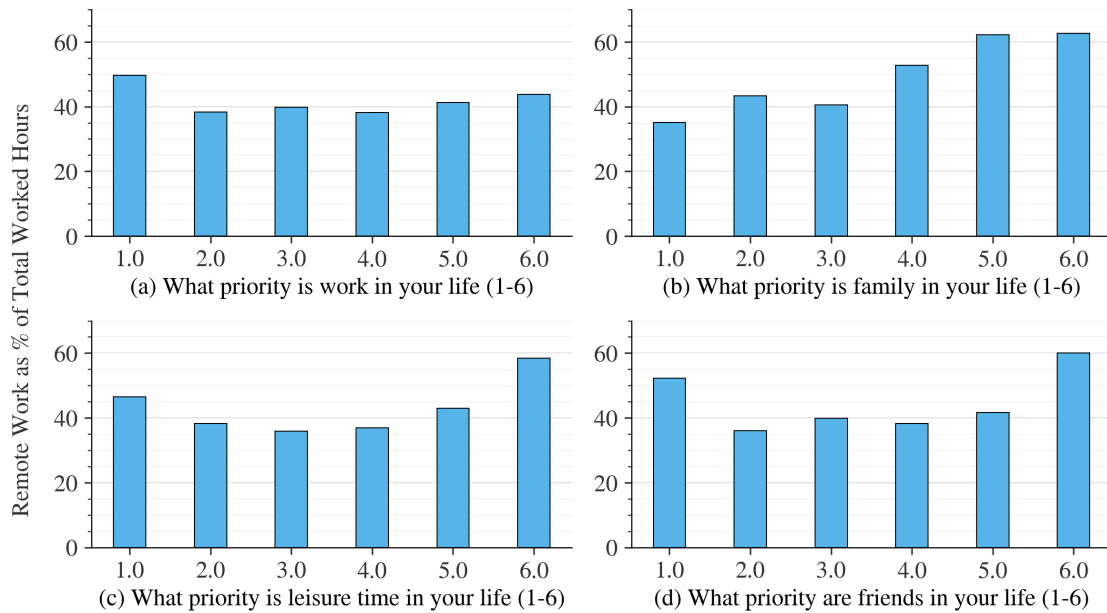


All: Feb 2022 - Sep 2022, N = 24,685.

Figure A-8: Current remote work share by perceived benefits of remote work

People who prefer higher levels of remote work are those who set their own remote work schedule and those who do not follow their employer’s guidelines for remote work. Working the same in-person days as one’s boss is associated with slightly greater preferences for remote work, suggesting that face-to-face encounters during in-person days allows people to feel more comfortable with additional remote work time.

Remote work preferences by attitudes towards remote work coordination with colleagues are shown in Figure A-15. There is a substantial difference in preferences between those who prefer to coordinate with their colleagues and those who do not (or those who do not perceive any difference). This result is intuitive and highlights how attitudes and employment factors are now important to consider when estimating travel preferences.

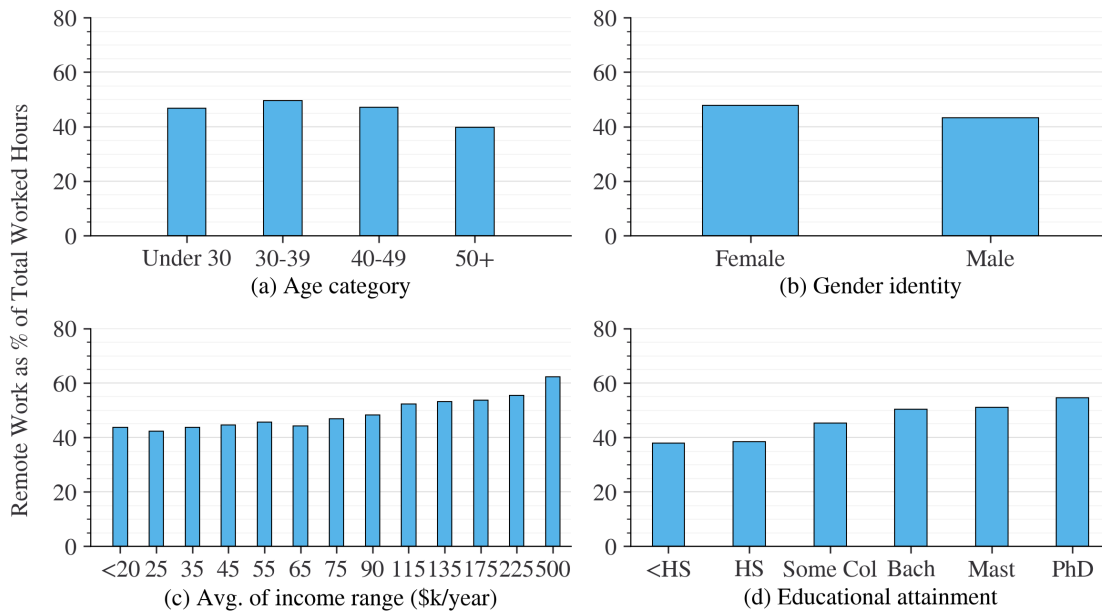


All: Jul 2022, N = 2,636.

Figure A-9: Current remote work share by life priorities

Remote work preferences by attitudes towards remote work more generally are shown in Figure A-16. Unsurprisingly, those who find remote work to increase their effectiveness or less stressful prefer more remote work. Remote work preferences in relation to the question about the degree to which remote work affects chances of a promotion have a bi-modal distribution. People who expect remote work to increase their chances of a promotion have an understandable preference for higher levels of remote work. The second peak is those who expect that remote work lowers their chance of a promotion by 30 to 50 percent, but prefer remote work regardless. That peak might also be reflective of the dynamics shown by the “disagree” respondents in Figure A-16(d), who prefer remote work at higher levels and are not particularly interested in working harder in order for their organization to succeed.

Remote work preferences by the perceived benefits of remote work are shown in



All: May 2020 - Jan 2023, N = 139,465.

Figure A-10: Current remote work share by demographic group

Figure A-17. People who enjoy remote work due to the commuting and schedule flexibility benefits are actually less likely to prefer remote work. Those who enjoy the social benefits of in-person work prefer slightly less remote work than those who do not.

Finally, preferred remote work shares by life priorities are shown in Figure A-18. Unlike the observed remote work share results shown in Figure A-9, preferences are relatively constant across each of the life priority questions. This is somewhat of a surprising result that suggest remote work is not widely perceived as a means towards fulfilling any of the life priorities presented in the survey.

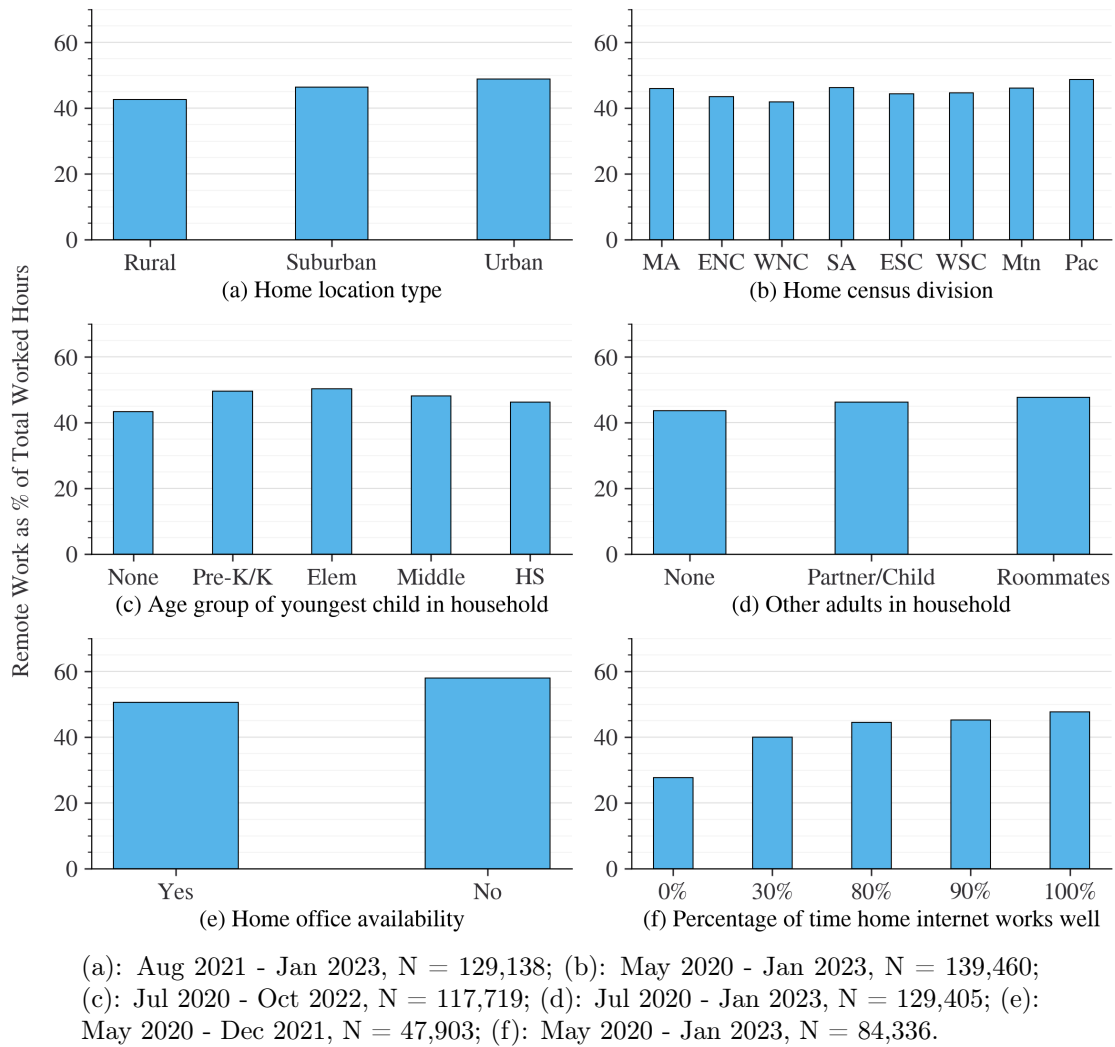


Figure A-11: Current remote work share by household characteristics

A.3 Employer planned remote work shares

Lastly, the survey data allows exploration of the employee’s perceptions of their employer’s plans for remote work in the future. The aggregate results are generally lower than the results for preferences, confirming that there is a gap between employer plans for remote work and employee preferences.

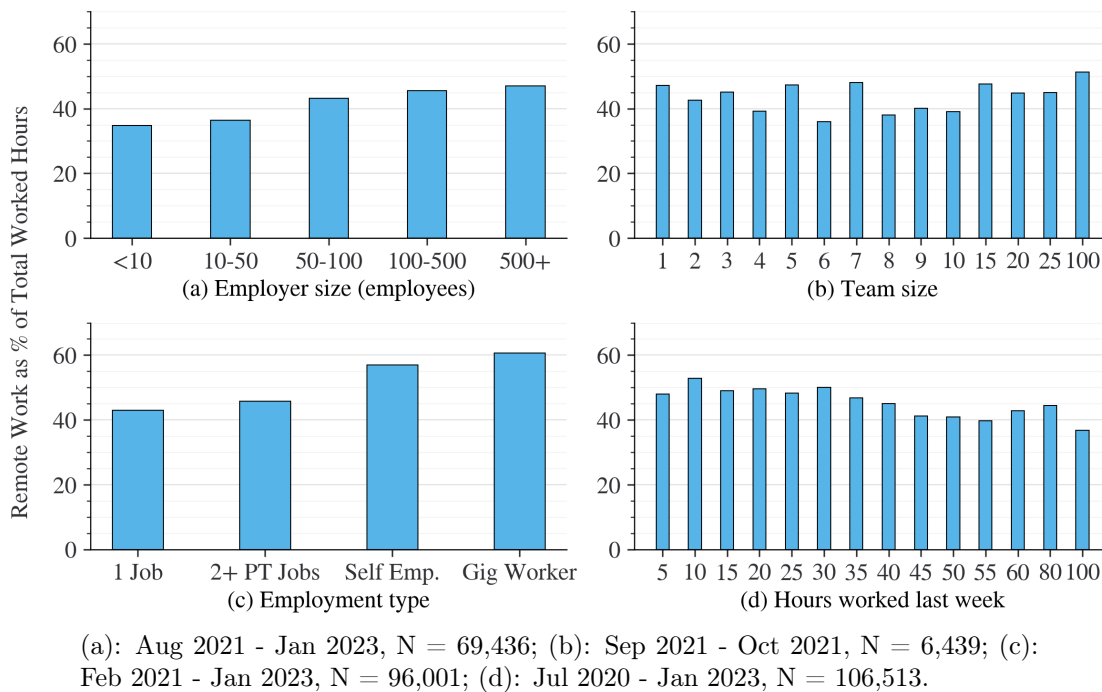


Figure A-12: Current remote work share by employment characteristics

Remote work plans by demographic group are shown in Figure A-19. The trends are similar to the current remote work share results in Figure A-1, albeit at a lower overall level of remote work than currently worked. People in the lowest income categories, those with a high school education or less, and people aged 50 and above expect their employers to allow them to work remotely for 20% of their hours on average, equivalent to one day per week for a typical full time job.

Employer planned remote work shares by household characteristic are shown in Figure A-20. Home location type and census division appear to have a stronger association with employer plans than with employee preferences. The availability of a home office and the presence of other adults in the household do not appear to be correlated with employer plans for remote work, but people with young children

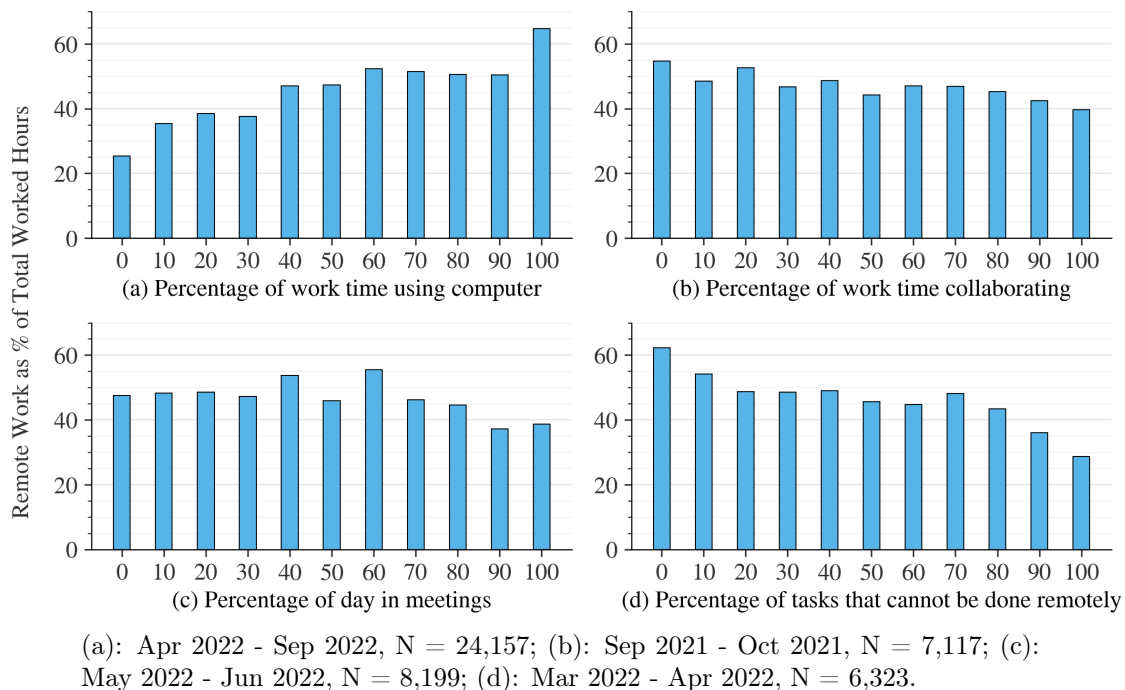


Figure A-13: Current remote work share by task characteristics

expect to be granted more remote work than those who have older children or no children at all.

Employer planned remote work shares by employment characteristics are shown in Figure A-21. People in very large teams appear to expect higher remote work plans than those with medium-sized teams. Interestingly, people who work relatively few hours or very many hours also expect to be granted more remote work by their employers than those who work 40 to 60 hours per week. There is limited variation in planned remote work by employer size, with medium-sized employers expected to offer more remote work than very large or small employers.

Employer planned remote work shares by job task characteristics are shown in Figure A-22. Interestingly, the people whose employers are planning the highest

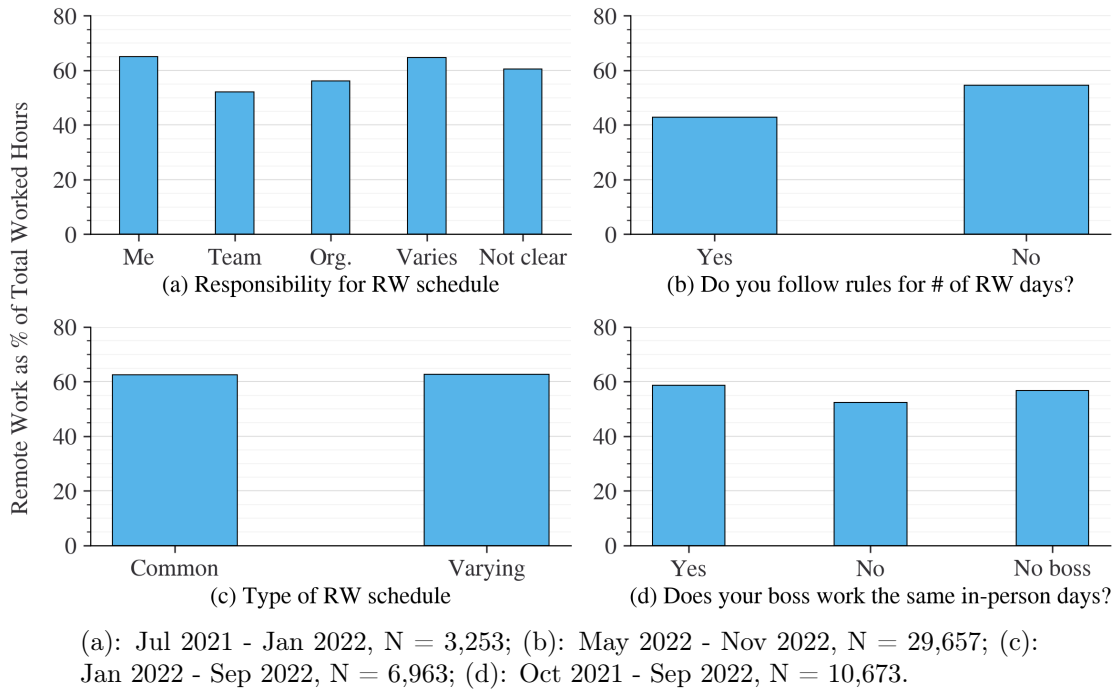


Figure A-14: Current remote work share by remote work policy

levels of remote work are those whose jobs involve meetings and collaborative tasks 60% of the time. Employer plans also appear to change little for people for whom 10% to 70% percent of tasks cannot be done remotely, but plans are quite low above the 70% threshold.

Employer planned remote work shares by remote work policy types are shown in Figure A-23. It seems reasonable that people who get to set their own remote work schedule are expecting to be afforded greater levels of remote work. Remote workers who work the same in-person days as their boss also expect to be allowed more remote work in the future.

Employer planned remote work shares by attitudes towards remote work coordination with colleagues are shown in Figure A-24. The difference in employer plans

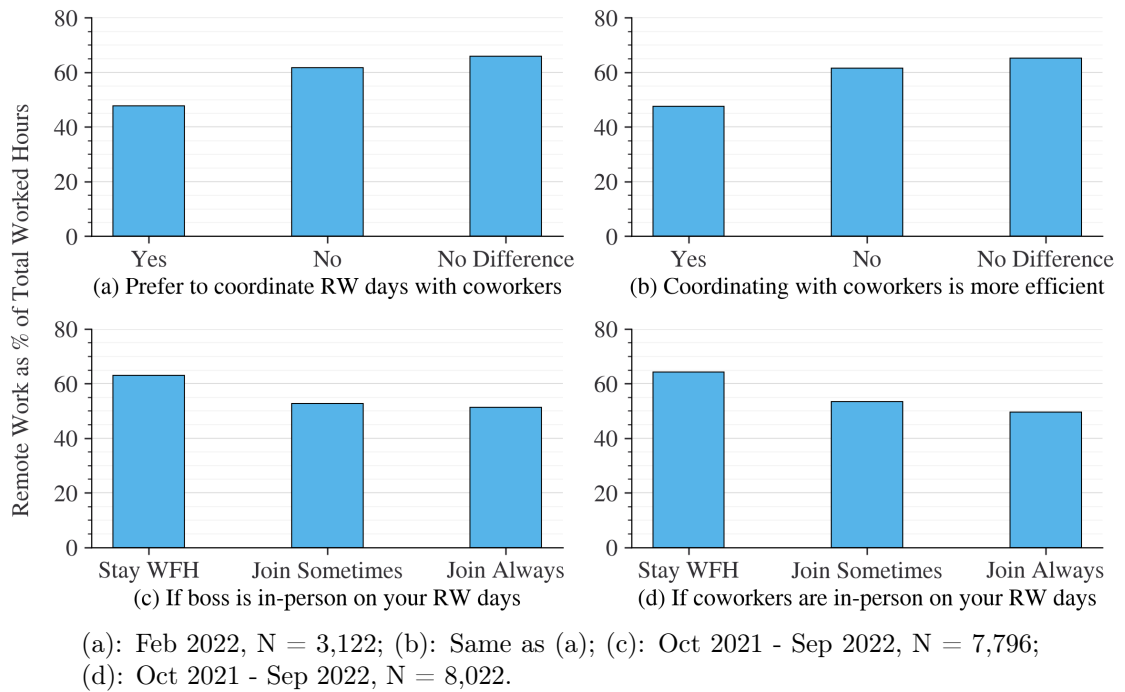


Figure A-15: Current remote work share by attitudes towards coordinating with colleagues

between those who prefer to coordinate with colleagues are less pronounced than differences in remote work preferences for the same groups. Interestingly, people who join their boss or colleagues working in-person expect to receive less remote work in the future, suggesting expectations of a wider return-to-office shift within their organization.

Employer planned remote work shares by attitudes towards remote work more generally are shown in Figure A-25. Those who find remote work to increase their effectiveness appear to expect their employers to respond to this increased effectiveness by offering greater levels of remote work, although the effect is almost certainly bi-directional. In contrast, people do not expect their employer to consider their stress levels when setting remote work plans, as there is no obvious trend across groups.

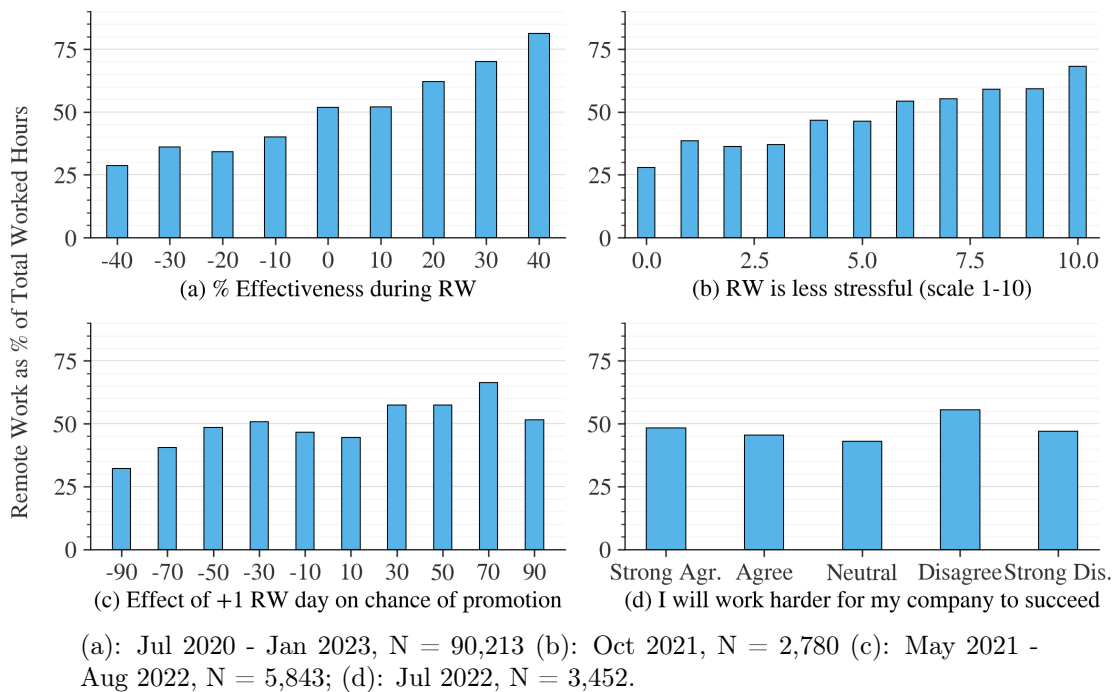
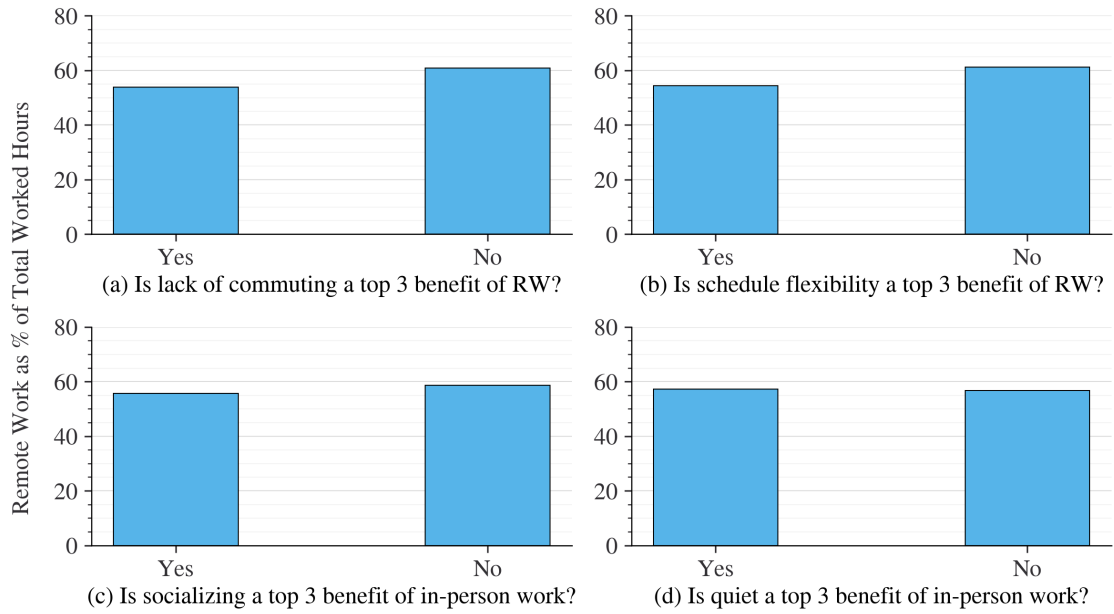


Figure A-16: Current remote work share by attitudes towards remote work

Those who are particularly eager to work harder to support their organization’s success do expect more remote work, and those with the opposite attitude expect their employer to allow them to work remotely for less than 10% of their hours.

Employer planned remote work shares by the perceived benefits of remote work are shown in Figure A-26. There is little variation among the response groups with respect to employer planned shares of remote work.

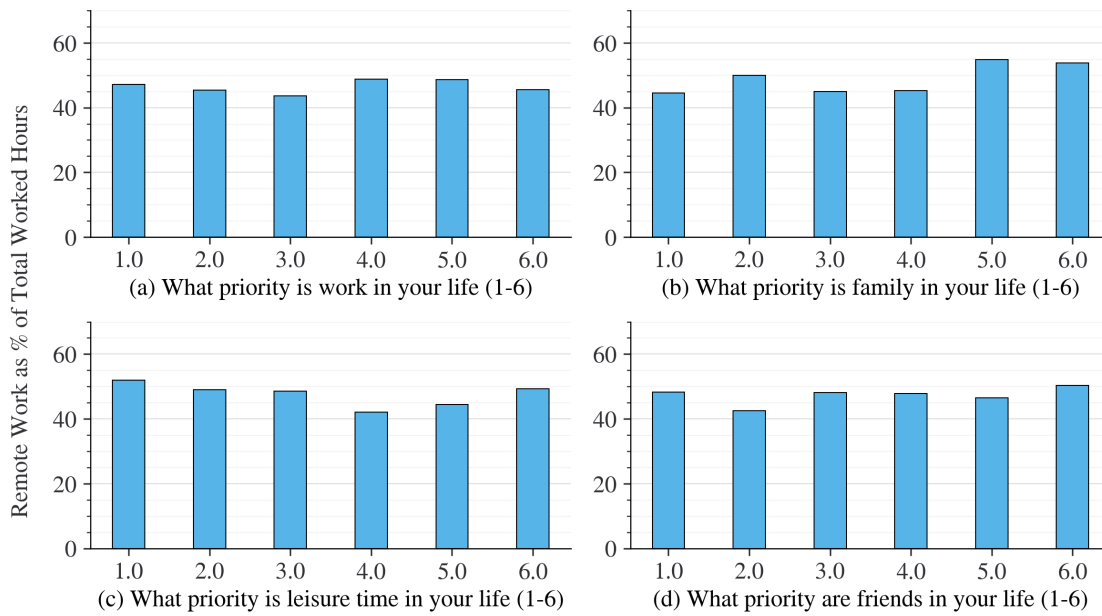
Finally, planned remote work shares by life priorities are shown in Figure A-27. As with the observed shares of remote work in Figure A-9, there are some notable differences between response groups. Placing a higher priority on work and a lower priority on family is associated with higher levels of remote work. Employer plans for high levels of remote work are also associated with the extremes for priority of



All: Feb 2022 - Sep 2022, N = 28,836.

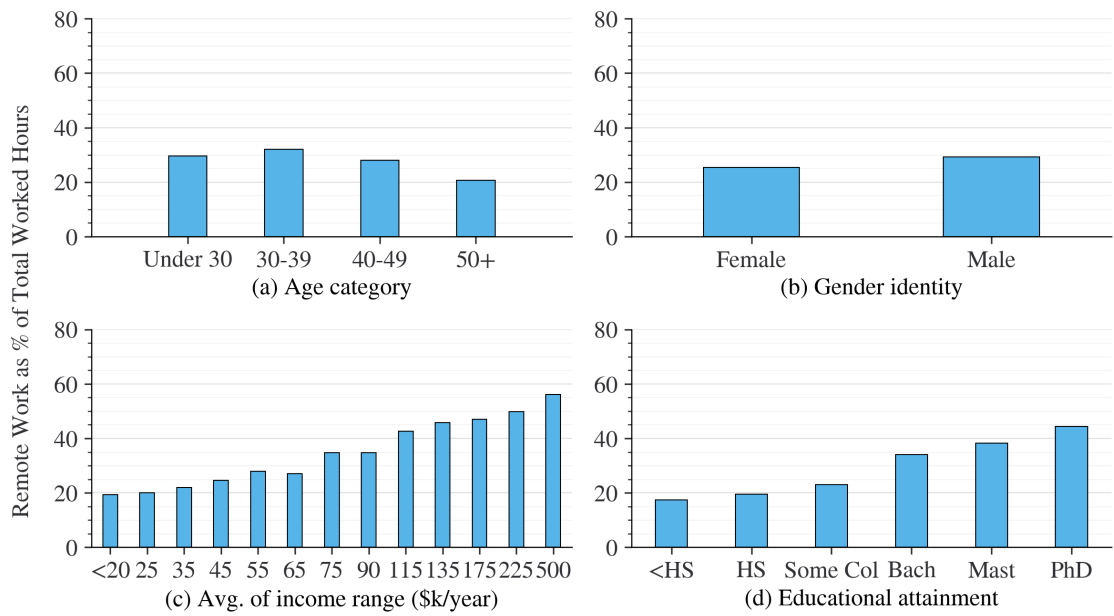
Figure A-17: Current remote work share by perceived benefits of remote work

leisure and friends.



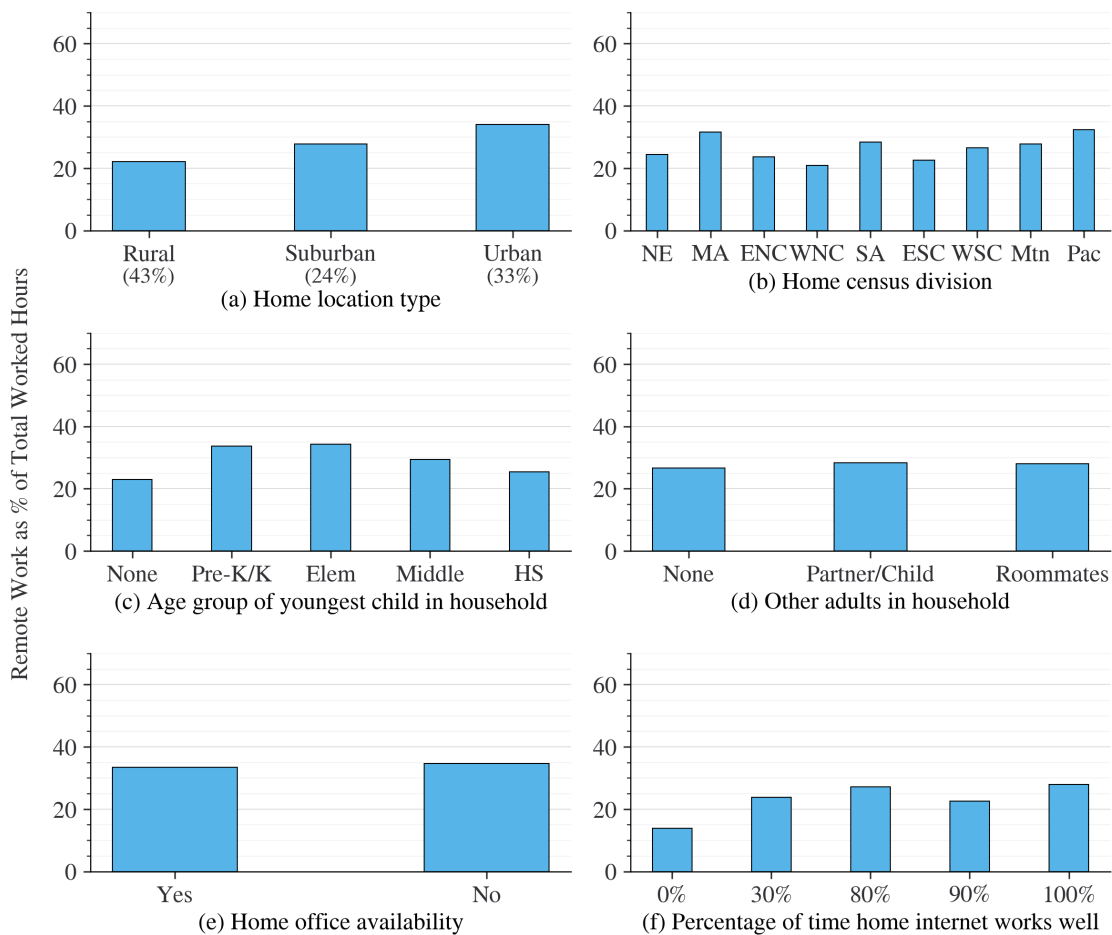
All: Jul 2022, N = 3,309.

Figure A-18: Current remote work share by life priorities



All: May 2020 - Jan 2023, N = 139,465.

Figure A-19: Current remote work share by demographic group



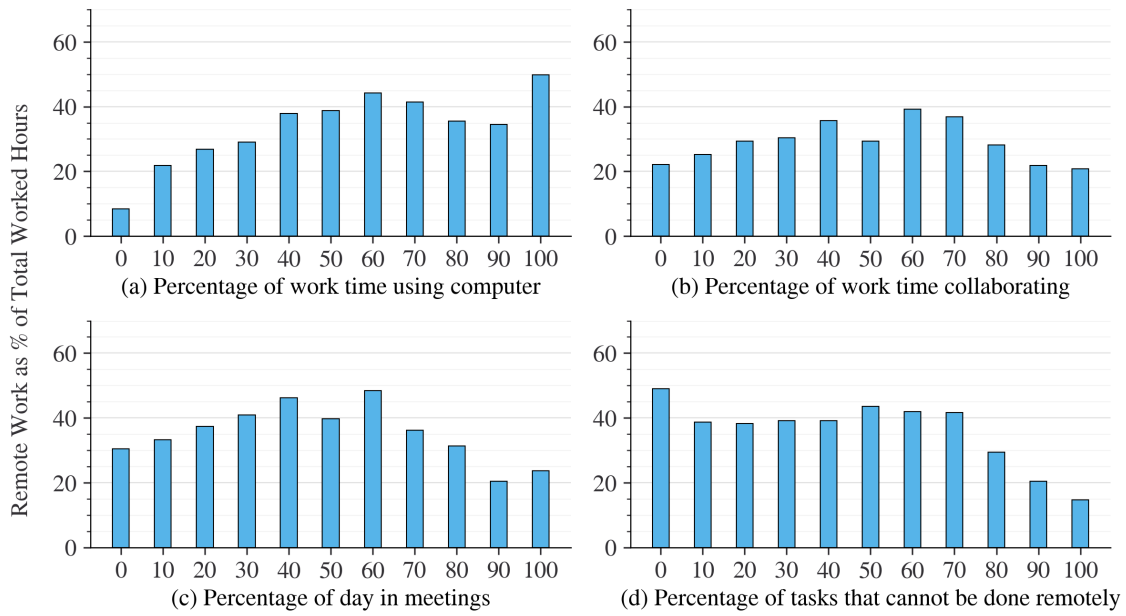
(a): Aug 2021 - Jan 2023, N = 129,138; (b): May 2020 - Jan 2023, N = 139,460;
(c): Jul 2020 - Oct 2022, N = 117,719; (d): Jul 2020 - Jan 2023, N = 129,405; (e):
May 2020 - Dec 2021, N = 47,903; (f): May 2020 - Jan 2023, N = 84,336.

Figure A-20: Current remote work share by household characteristics



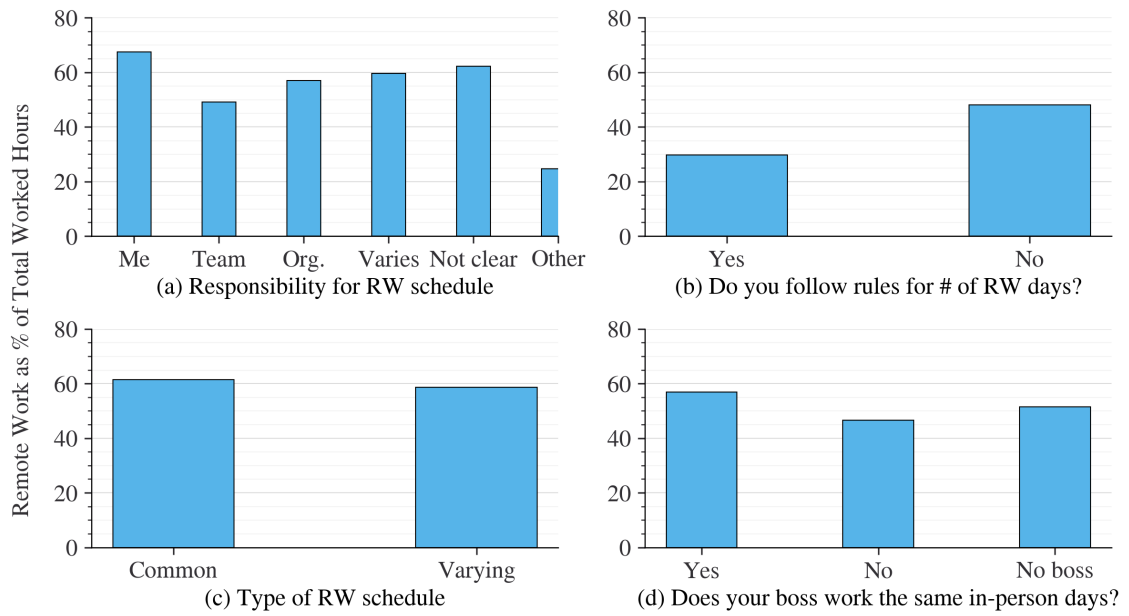
(a): Aug 2021 - Jan 2023, N = 69,436; (b): Sep 2021 - Oct 2021, N = 6,439; (c): Feb 2021 - Jan 2023, N = 96,001; (d): Jul 2020 - Jan 2023, N = 106,513.

Figure A-21: Current remote work share by employment characteristics



(a): Apr 2022 - Sep 2022, N = 24,157; (b): Sep 2021 - Oct 2021, N = 7,117; (c): May 2022 - Jun 2022, N = 8,199; (d): Mar 2022 - Apr 2022, N = 6,323.

Figure A-22: Current remote work share by task characteristics



(a): Jul 2021 - Jan 2022, N = 3,253; (b): May 2022 - Nov 2022, N = 29,657; (c): Jan 2022 - Sep 2022, N = 6,963; (d): Oct 2021 - Sep 2022, N = 10,673.

Figure A-23: Current remote work share by remote work policy

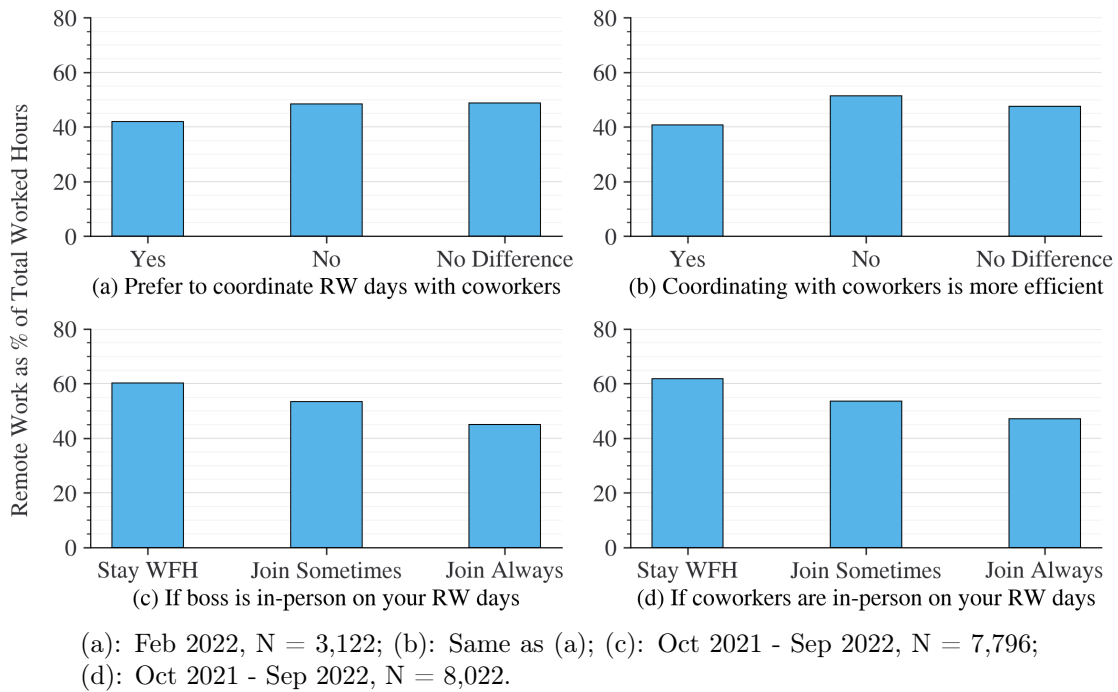


Figure A-24: Current remote work share by attitudes towards coordinating with colleagues

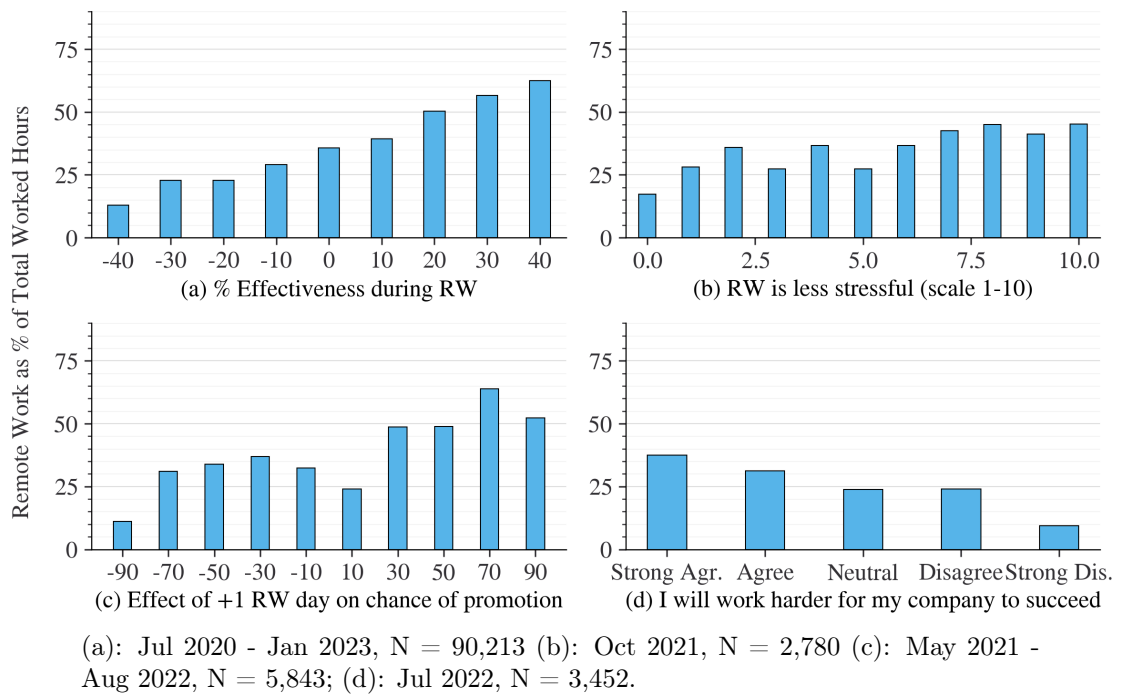
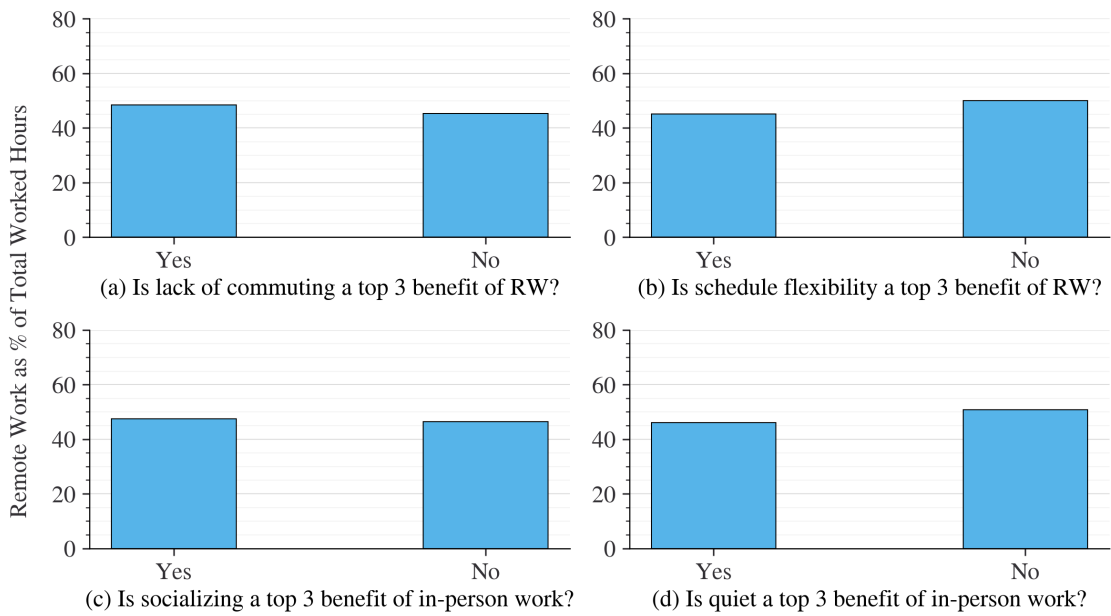
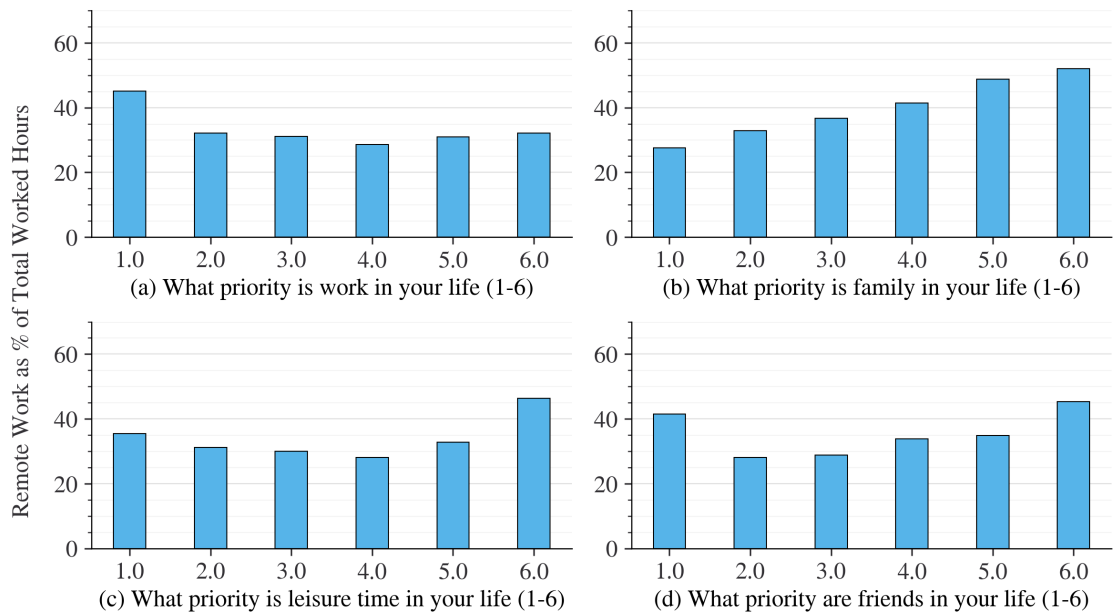


Figure A-25: Current remote work share by attitudes towards remote work



All: Feb 2022 - Sep 2022, N = 28,836.

Figure A-26: Current remote work share by perceived benefits of remote work



All: Jul 2022, N = 3,309.

Figure A-27: Current remote work share by life priorities

Appendix B

Details of travel behavior model inputs (Chapter 4)

Note that the dependent variables used in each of the travel behavior models (remote work arrangement, mode choice, departure time choice and trip frequency) in Chapter 4 were asked to different respondents to limit the cognitive burden of individual survey questionnaires. As a result, the sample compositions and sizes are somewhat different for each model. A model summary is provided in Table B.1, the endogenous variables for all models are summarized in Table B.2, and the descriptive statistics of the exogenous variables are presented for each model in Tables B.4 - B.6 that follow.

Table B.1: Summary of travel behavior models

Endogenous variable	Model structure	Survey waves	Sample
Remote work arrangement	ZOIB regression	May 2022	2128
Third place trip frequency	Ordinal logit	Nov. 2022 - Jan. 2023	1852
Third place departure time	Multinomial logit	Nov. 2022 - Jan. 2023	1536
Third place mode choice	Multinomial logit	Jan. 2022 - Apr. 2023	3662

Table B.2: Summary of endogenous variables for travel behavior models

Model	Question	Count
Arrangement	For each day <i>last week</i> , did you work a full day (6 or more hours) , and if so where? [remote % of days computed]	
Trip frequency	Last week, how many times did you travel from your home to work at each of the following locations? [choose from third place types]	
	<i>0</i>	658
	<i>1</i>	102
	<i>2</i>	109
	<i>3</i>	198
	<i>4</i>	133
	<i>5+</i>	652
Departure time	Approximately what time of day did you travel to the third place that you worked at most recently?	
	<i>Before 7:00am</i>	82
	<i>7:00am - 7:59am</i>	227
	<i>8:00am - 8:59am</i>	250
	<i>9:00am - 9:59am</i>	260
	<i>10:00am - 11:59am</i>	392
	<i>12:00pm - 1:59pm</i>	162
	<i>2:00pm - 3:59pm</i>	78
	<i>4:00pm or later</i>	85
Mode choice	What is your primary transportation mode for commuting to the third place where you usually work?	
	<i>Drive alone</i>	2470
	<i>Carpool</i>	162
	<i>Public transit (train, bus, ferry)</i>	380
	<i>Bicycle</i>	140
	<i>Walking</i>	225
	<i>Taxi / Ridehailing</i>	285

Table B.3: Exogenous variables included in ZOIB regression model

Variable	Type	Mean
Education (years)	Continuous	15.87
Home ZIP population density	Categorical	
<i>Urban (>3000 people/sq.mi)</i>		0.49
<i>Suburban (1000 - 3000 people/sq.mi)</i>		0.19
<i>Rural (<1000 people/sq.mi)</i>		0.32
Child under 5	Categorical	
<i>Yes</i>		0.23
<i>No</i>		0.77
Employer size (C1)	Continuous	458.97
Percent of work on computer	Continuous	59.51
Percent of work in meetings	Continuous	48.45
Percent of work in meetings with coworkers	Continuous	34.42
Change in perception of RW among people you know (E2)	Categorical	
<i>Better for almost all</i>		0.44
<i>Better for most</i>		0.25
<i>Better for some</i>		0.09
<i>No change</i>		0.17
<i>Worse for some</i>		0.02
<i>Worse for most</i>		0.02
<i>Worse for almost all</i>		0.01

Table B.4: Exogenous variables included in the third place trip frequency model

Variable	Type	Mean
Annual income (\$USD, thousands)	Continuous	111.54
Age (years)	Continuous	39.37
Education (years)	Continuous	15.77
One-way commuting time (minutes)	Continuous	27.82
Efficiency of remote work relative to in-person (%)	Continuous	10.45%
Home ZIP population density	Categorical	
<i>Urban (>3000 people/sq.mi)</i>		0.47
<i>Suburban (1000 - 3000 people/sq.mi)</i>		0.23
<i>Rural (<1000 people/sq.mi)</i>		0.30
Gender identity	Categorical	
<i>Male</i>		0.51
<i>Female</i>		0.49
Remote work arrangement (A1)	Categorical	
<i>Hybrid</i>		0.39
<i>Fully remote</i>		0.61
Employer size (C1)	Categorical	
<i>Large (≥ 500 staff)</i>		0.49
<i>Moderate (50 - 499 staff)</i>		0.15
<i>Small (<50 staff)</i>		0.36
Manage others (C3)	Categorical	
<i>Yes</i>		0.54
<i>No</i>		0.46
Living arrangements (D3, D4)	Categorical	
<i>Live with roommates</i>		0.03
<i>Live with partner and/or child</i>		0.76
<i>Live alone</i>		0.21

Table B.5: Exogenous variables included in the third place departure time model

Variable	Type	Mean
Annual income (\$USD, thousands)	Continuous	136.56
Age (years)	Continuous	37.42
Education (years)	Continuous	16.21
One-way commuting time (minutes)	Continuous	31.26
Efficiency of remote work relative to in-person (%)	Continuous	11.23%
Home ZIP population density	Categorical	
<i>Urban (>3000 people/sq.mi)</i>		0.57
<i>Suburban (1000 - 3000 people/sq.mi)</i>		0.19
<i>Rural (<1000 people/sq.mi)</i>		0.25
Gender identity	Categorical	
<i>Male</i>		0.61
<i>Female</i>		0.39
Remote work arrangement (A1)	Categorical	
<i>Hybrid</i>		0.42
<i>Fully remote</i>		0.58
Employer size (C1)	Categorical	
<i>Large (≥ 500 staff)</i>		0.45
<i>Moderate (50 - 499 staff)</i>		0.43
<i>Small (<50 staff)</i>		0.12
Manage others (C3)	Categorical	
<i>Yes</i>		0.67
<i>No</i>		0.33
Supervisor prefers no remote work in the future (B5)	Categorical	
<i>Yes</i>		0.10
<i>No</i>		0.90
Continue social distancing (E6)	Categorical	
<i>Yes</i>		0.48
<i>No</i>		0.52
Living arrangements (D3, D4)	Categorical	
<i>Live with roommates</i>		0.03
<i>Live with partner and/or child</i>		0.80
<i>Live alone</i>		0.17

Table B.6: Exogenous variables included in the third place mode choice model

Variable	Type	Mean
Annual income (\$USD, thousands)	Continuous	168.98
Age (years)	Continuous	37.28
Education (years)	Continuous	16.34
One-way commuting time (minutes)	Continuous	31.90
Home ZIP population density	Categorical	
<i>Urban (>3000 people/sq.mi)</i>		0.62
<i>Suburban (1000 - 3000 people/sq.mi)</i>		0.17
<i>Rural (<1000 people/sq.mi)</i>		0.19
Gender identity	Categorical	
<i>Male</i>		0.66
<i>Female</i>		0.34
Remote work arrangement (A1)	Categorical	
<i>Hybrid</i>		0.38
<i>Fully remote</i>		0.62

Appendix C

Sensitivity analysis for shared workplace locations (Chapter 8)

This appendix explores the sensitivity of the results in the numerical experiment to variations in the estimated MNL model coefficients. It is possible that preferences for shared workplaces may change over time, therefore it may be helpful for policy makers to understand how the results and performance of the shared workplaces would change in response. Four alternative scenarios are imagined:

1. Preferences for shared workplaces **increase** relative to working at home ($\beta_0 \times 0.75$)
2. Preferences for shared workplaces **decrease** relative to working at home ($\beta_0 \times 1.25$)
3. The perceived disutility of traveling to shared workplaces **increases** ($\beta_{tt} \times 1.25$)
4. The perceived disutility of traveling to shared workplaces **decreases** ($\beta_{tt} \times 0.75$)

In each scenario, the magnitudes of either β_0 or β_{tt} is artificially increased or decreased by 25% compared to the values shown in Table 8.2 as appropriate. Table C.1 indicates the number of optimal locations that differ from the initial solution, for each objective function 1 through 6, for each of the four sensitivity analysis scenarios described above. Rather than exploring the new optimal solutions in full, only changes in the selected locations are reported for brevity. Table C.2 shows the changes in each of the performance measure by objective and sensitivity analysis scenario.

C.1 Changes in optimal solution by objective

Due to the discrete nature of the shared workplace location problem, the optimal solutions are fairly robust to changes in the choice model parameters. There are 30 locations chosen across all six objectives in each of the four sensitivity analysis scenarios, for a total of 120 locations. Only 14 location choices were changed relative to the optimal solutions shown in Section 8.4. The number of changed locations in the optimal solution by sensitivity analysis scenario and objective is summarized in Table C.1.

Scenario	Number of changed locations, by objective					
	#1	#2	#3	#4	#5	#6
Scenario 1: $\beta_0 \times 0.75$	1	0	0	1	0	0
Scenario 2: $\beta_0 \times 1.25$	0	1	0	0	0	0
Scenario 3: $\beta_{tt} \times 1.25$	1	0	0	1	2	1
Scenario 4: $\beta_{tt} \times 0.75$	1	1	0	1	2	1

Table C.1: Sensitivity of optimal location choices to changes in the estimated workplace choice model coefficients

11 of the optimal location choice changes occurred in the scenarios where β_{tt} was modified, indicating that the choice of β_{tt} has a stronger effect on the outcomes

than the choice of β_0 . The optimal solution for Objective #3 (maximum interaction opportunities) was unchanged across all sensitivity analysis scenarios. The solution under Objective #5 (minimize income segregation) was the most susceptible to change under different choice model parameters.

C.2 Changes in performance measures by objective

The performance measures change slightly for each objective in each scenario. Generally, the performance changes in the same direction across all objectives. The first four performance measures are all related in some sense to the total demand for shared workplaces, so they tend to rise when the model parameters are adjusted to increase the utility of shared workplaces, and decline when the utility of shared workplaces is adjusted downwards. The diversity of the visitors to each location is entirely unrelated to demand and to the parameters adjusted in the sensitivity analysis, so the changes in that performance measure are more variable in magnitude and direction.

Adjusting the magnitude of the shared workplace alternative-specific constant (Scenarios 1 and 2) has less of an impact on the performance measures. Generally, if the new solution involves a different set of locations, the changes in performance are greater. In Scenarios 3 and 4, where the β_{tt} parameter is adjusted, the optimal solutions under Objectives #1, #4, #5, and #6 all involve a new set of locations and the performance metrics vary substantially relative to the initial solutions.

Measure	Percent change in value, by objective					
	#1	#2	#3	#4	#5	#6
Scenario 1: $\beta_0 \times 0.75$						
Travel distance (mi)	+3.5	+0.5	+0.0	+2.5	+1.2	+0.1
Workplace users	+0.2	+0.0	+0.0	+6.7	+0.4	+0.0
Interaction opportunities	-1.2	+0.0	+0.0	+7.4	+8.6	+0.0
Q1-Q2 interaction opportunities	+7.4	+0.1	+0.1	+0.0	+6.7	+0.2
Deviation from pop. diversity	+4.6	-0.1	-0.1	+3.9	+0.7	+0.3
Scenario 2: $\beta_0 \times 1.25$						
Travel distance (mi)	-0.6	-5.0	-2.3	-1.2	-0.4	-2.7
Workplace users	-1.5	-2.3	-2.0	-1.6	-3.7	-2.3
Interaction opportunities	-3.5	-4.0	-4.8	-3.4	-3.0	-5.4
Q1-Q2 interaction opportunities	-0.1	-7.7	-5.2	-5.3	-4.8	-5.2
Deviation from pop. diversity	7.2	19.2	1.7	-0.8	11.0	0.4
Scenario 3: $\beta_{tt} \times 1.25$						
Travel distance (mi)	-12.1	-7.2	-10.3	-12.0	-18.0	-12.8
Workplace users	-12.2	-4.6	-4.6	-5.7	-36.8	-9.0
Interaction opportunities	-18.6	-8.9	-9.2	-9.7	-50.9	-11.9
Q1-Q2 interaction opportunities	-21.6	-9.6	-10.8	-11.4	-59.6	-11.2
Deviation from pop. diversity	+2.5	+1.9	+6.7	-1.4	-0.9	-5.5
Scenario 4: $\beta_{tt} \times 0.75$						
Travel distance (mi)	+20.7	+12.8	+16.1	+17.3	+6.0	+43.3
Workplace users	+10.3	+6.2	+6.5	+13.6	-3.3	+33.5
Interaction opportunities	+18.0	+14.6	+13.6	+20.4	-2.4	+43.1
Q1-Q2 interaction opportunities	+27.8	+8.1	+11.0	+11.7	-3.8	+27.2
Deviation from pop. diversity	+7.4	+17.3	+0.1	+4.8	-1.3	+10.0

Table C.2: Sensitivity of performance measures to changes in the estimated workplace choice model coefficients

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