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Telemobility through the pandemic: Longitudinal tracking, modeling and outlook

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Abstract

The COVID-19 pandemic disrupted the *status quo* of the telemobility landscape in the United States, forcing millions of Americans into lock down, significantly changing the way we work, travel, and spend our time and money for an extended period of time. After several months of adaptation, adoption, learning, and unlearning, while it would be immature to expect that all these pandemic-forced changes in the telemobility landscape will persist as cities open up and a large percentage of population is vaccinated, it is not inconceivable that there is a strong inertia for at least some proportion of these changes to stay with us in the post-pandemic era. This is because the COVID-19 pandemic induced disruption was forced and abrupt, leading to a system wide change for an extremely long duration, making it unprecedented and unlike anything we have seen in the recently history, and as a result, the pandemic potentially led to long-lasting change in human behavior, attitudes and cultural acceptability of this new way of life; along with economic and procedural streamlining of the relevant technology that can assist this change.

While an increase in telemobility adoption have significant quality of life benefits at the individual level, if the trends that we saw at the height of the pandemic are to continue at the same levels, this will likely have strong implications at the urban living and mobility front and this needs a deeper re-thinking of our urban systems that are typically located and optimized taking the historic demand patterns into consideration.

Two aspects of our lives that probably saw the most upheaval during the pandemic are how we work and how our daily needs for food and other essential items are fulfilled. In this regard, there are two big unanswered questions here. First, as the cities were lock downed and then later the restrictions were relaxed, how did remote work and e-commerce evolve over time and to what extent the pandemic accelerated trends in remote work and e-commerce will sustain in the post-

pandemic world? Second, if the pandemic accelerated trends in remote work and e-commerce are to sustain (even if to some extent, compared to pre-pandemic levels), what does these trends mean for the future of large metropolitan cities in the US, which are highly optimized based on the idea of weekday commute hours or presence of large number of individuals at the same place and time.

Dissertation Contributions

This dissertation is an effort to answer the above questions using data from multiple waves of online consumer, employee and employer surveys conducted in the United States amid the COVID-19 pandemic. To bring out important insights, using the data collected, I undertake a collection of four studies. I dedicate a majority of this dissertation to remote work and its evolution, because, in my opinion, this telemobility dimension is where I see big changes happening with potential for major societal implications. I study telework from three angles:

1. understanding the factors impacting *satisfaction with telework* during the pandemic using a *multiple indicator multiple cause (MIMIC)* model

2. analyzing *individual level trajectories* of remote work adoption through and beyond the pandemic using *hierarchical clustering and other predictive models*

3. understanding the *employer side perspective* on the evolution of remote work through and beyond the pandemic using data from *C-suite level employers* from 129 North American organizations

On the end of e-commerce, I present:

4. a *latent transition analysis with random intercepts (RI-LTA)* using consumer spending data on various *product categories (grocery, cooked food and non-food items)* and *acquisition*

channels (in-person, pick-up and delivery) across 4 different time points pre- and during the pandemic; which captures the nature and dynamics of household spending behavior in an omni-channel retail environment.

I rely on two longitudinally collected data sets for the four studies above, collected using multi-month and multi-wave online surveys conducted in the United States:

1. an online survey with *7 waves* of data collection conducted between *December 2020 and March 2022* with 1877 unique respondents from United States, and focused on collecting data on *evolving consumer spending, telework, and activity participation* behavior associated with the COVID-19 pandemic.

2. an online survey with *5 waves* of data collection between *October 2021 and August 2022* amongst *top executives of 129 unique North American companies*, focused on collecting data on employer side approach to remote work since the beginning of the pandemic and in the future.

Key Takeaways

From the first study on analyzing data on telework satisfaction, our results highlight diverse experiences of individuals with telework which will potentially shape the future of remote work landscape. An investigation of the data using an ordered model and a MIMIC model revealed several important insights. First, our results suggested that the satisfaction was higher for middle aged individuals compared to younger and older individuals, Hispanic or Latino respondents, and respondents with less than undergraduate degree, and those with higher levels of concerns about contracting the COVID-19 pandemic. On the other end, satisfaction was found to be lower for individuals with children attending school virtually from home.

Analysis using the MIMIC model confirmed several findings from the ordered model but also provided a more enriched structure to the model — through the inclusion of perceived / experienced benefits and barriers to telework latent variables. This enriched model suggests that the benefits and barrier to telework are disproportionately distributed across age groups, where higher barriers and lower benefits are experienced by those who are young or old compared to those in the middle aged group.

From a policy standpoint, some key factors captured in our model include commute, productivity gains, quality of life improvements aspects of remote work associated with higher perceived benefits and thus higher satisfaction, while factors like distraction from household members and lack of appropriate technology associated with higher barriers and lower satisfaction.

In the second study where I analyze the trajectories of telework at various time points before, during and beyond the pandemic, the results indicate presence of four clusters of telework trajectories with varying levels of remote work adoption over time — ranging from a group that maintained high in-person work even at the height of the pandemic; to a group that continued working from home for an extended period of time. An important insight through this data is that for three out of four clusters (72%) respondents, some form of remote work is expected going forward, suggesting a high level of hybrid work arrangement in the future.

Using these clusters as a dependent variable, a multinomial logit based membership model suggested that the telework trajectories through the pandemic were highly associated with nature of job in which one was employed, where higher in-person work was seen for transportation / manufacturing, logistics, healthcare sectors but higher remote work was seen for professional services, finance and insurance and information sectors. Other important insights included a higher level of remote presence by those with age 65 years or more, those without a vehicle and those with a young child at home. On the other end, results suggest lower remote presence for those who are students; while a hybrid presence was maintained by female respondents, those with at least an undergraduate degree, those with non-white ethnicity, those with a large household and those with income less than $100,000.

On the end of expected work location trends in April 2024, about 4 years since the beginning of the pandemic, our results indicate work location to be uncertain for about 15% of the respondents, who were more likely to be a female, a student or information sector employee but less likely to have a graduate degree. Amongst those that are certain regarding their work location in April 2024, higher in-person work is expected from those who are in education, healthcare and transportation / manufacturing sectors, those who are students or those with at least an undergraduate degree. On the opposite end, higher remote work is expected amongst those in the information sector, those without a vehicle or those with age more than 65 years. Results also suggest a high interaction between past telework behavior through the pandemic and the expected future behavior, along with a strong interaction between a respondent's outlook towards the impact of remote work on various work aspects like productivity and supervision, and their future work location decisions.

From a policy standpoint, these results highlight several implications. First, the results indicate a significant retention of pandemic accelerated trends in remote work with some form of hybrid work being the norm. However, there is still some uncertainty around future work location, potentially from the end of the employers — hence the decisions made at the end of employers will determine the true nature of the remote work landscape. Our results also suggest that those without a vehicle (who also tend to be transit users) are more likely to continue to work remotely — potentially indicating a slower rebound of transit ridership. A strong interaction between the occupational sector and remote work adoption level highlights that the impact of remote work on different cities across the United States may be different — dependent on the composition of the economy of a city. Further, a reduced level of commuting may hurt individuals employed in the third sector of the economy (especially in urban cores) — who largely rely on spending by commuters. Lastly, an increase flexibility may also motivate teleworkers to move away from urban cores in search of better value for their money — potentially changing the mobility landscape in urban cores, as well as at the location where teleworker may move.

In the third study, I analyze data from the employer end instead of employees, since they are the ultimate decision makers in the remote work equation — and any pandemic accelerated remote work adoption decisions will not exist if the employers decide to not provide remote work as an option.

Results from the employer end reinforce the results presented earlier from the employee end and are potentially indicative of permanency of trends on the emergence of hybrid form of work. Results from the employer end too suggest an increase in remote work as a results of the pandemic, with some form of hybrid work being the norm going forward. However, a higher rebound to in-person work in transportation / manufacturing / warehousing sectors, compared to other sectors exists and this trend also exists in the HR / Legal / Administration / Finance departments compared to IT / Sales. Some of the key concerns amongst employers include the ability to supervise and mentor, and the impact on creativity and innovation. On the opposite end, employers agree that remote work will have a positive impact on their ability to recruit and retain employees, their public image and their ability to compete. Results also suggest an association between the employers' outlook towards remote work and their sector of operations, where those with a negative outlook where found to be more likely from transportation / warehousing sector.

Lastly, the analysis on the end of e-commerce using the latent transition analysis revealed five different behavioral classes of consumer spending and the dynamics of movement between these classes as a result of the pandemic. The five classes revealed included: 1) a class with high probability of spending in-person across various product categories but at the same time a high probability of use of e-commerce for non-food items; 2) a class with low probability of spending on outside cooked food; 3) a class that rarely make use of the pick-up and delivery services , with the exception of some probability of use of delivery for non-food items; 4) a class with moderately high probability of the use of delivery services for all product categories; and 5) a class with high probability of use of pick-up services for all product categories. The results from the model also revealed that the pandemic's single biggest impact was in terms of suppression of demand for dine-in and take-out of food - potentially due to it being a high risk activity. However, over time a reversal of this behavior is seen, back to an increased dine-in and take-out activity. The second significant behavioral transition was of movement towards delivery and pick-up services where about 2-3 fold increase in their usage is visible — a large portion of which appears to be stable over time, more so in the case of delivery than pick-up. Important implications for these results are in the direction of potential increase of last mile delivery traffic in communities that cities need to plan for in the future.

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To my family, for their love and support.

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CHAPTER 1
INTRODUCTION

1.1 Motivation

The issue of interaction between information and communications technologies (ICTs) and travel has fascinated transportation researchers and practitioners for over four decades now. Early work in the late 1970s and 1980s [1–6] started with the idea of ICTs being a substitute for travel and that this could lead to significant energy savings and other societal benefits like congestion relief if a significant number of individuals decide to adopt the use of telecommunications technologies [7]. Most early work in this regard revolved around telecommuting, which led to some early experiments with incentivizing telecommuting [8] and later opened a pandora's box worth of questions regarding how to define telecommuting, who has the option to telecommute, who telecommutes given the option, and what kind of impact does it have on congestion [9–11]. The advent and increase in the penetration of internet made transportation researchers hopeful regarding the potential of ICTs to have a significant impact on urban congestion but ultimately transportation researchers identified and characterized a myriad of relationships between ICTs and travel like substitution versus complementarity, making it difficult to conclude whether ICTs have the potential to relieve congestion or reduce vehicle miles traveled (VMT) or emissions [3, 12].

The work that started with telecommuting expanded over the years with several new telemobility [1] dimensions added to it including e-shopping [12–16], tele-health [17–19], e-learning, and

[1]Oldest usage of the term 'telemobility' that I found was in 1966 edition of Kaiser Aluminum News Magazine titled *Telemobility: When far is near.* I found about magazine through an ebay listing with a picture of the following excerpt from the magazine: *"In 'Telemobility' we examine what we conceive to be a transition phase in which we begin to move away from a largely mechanical environment further and further into an electronic environment - in which*

e-recreation. Despite this rapidly expanded spectrum of dimensions and early speculations regarding the ICTs leading to the so-called *Death of Distance* [20], the wide spread adoption of several of these dimensions have remained limited (like for e-learning and tele-health), or in cases where the adoption is high (telework and e-shopping), the ability of ICTs in reducing VMT has been questioned by many [21–25]. Regarding telecommuting, the adoption largely remained limited to information workers but was still impacted by several issues like mentorship and supervision at the managerial end, personal need for socialization, visibility at workplace for career advancement and having appropriate environment to work from home at the individual end [26–30]. Even when there was an adoption of telecommuting, research suggested work trips were mostly replaced by an increase in non-work recreational or leisure trips, wiping out most of system level benefits in VMT and emissions [24, 31–35]. In the case of e-shopping, while the advent of internet and mobile devices, improvements in available online product information and sometime the ability to experience products using virtual or augmented reality increased adoption, evidence suggesting a multi-channel shopping behavior instead of movement from complete physical to virtual shopping reversed most transportation related benefits [15, 36–38]. On top of this, e-shopping also led to increased freight activity related to delivery of goods, leading to increased infrastructure stress and additional congestion [39–41]. Overall, the field of telemobility and its ability to reduce congestion, VMT and emissions went from a period of hopes to a period of lull, switching gears from "*this could solve our problems*" to "*its complicated*".

In March 2020, the COVID-19 pandemic significantly disrupted the *status quo*, forcing millions of Americans into lock down, significantly changing the way we work, travel, and spend our time and money for an extended period of time. The US national annual VMT estimates reached

human experience is increasingly based on the manipulation of wavelengths in the electromagnetic spectrum. This transition will profoundly affect the shape and characteristics of our urban life, our transportation systems, and the way in which business is conducted." I personally like to think of telemobility as technology mediated modification of physical mobility - for good or for worse.

2.84 trillion miles in 2021, dropping 13% compared to the previous year and lowest since 2001 [42]. On the demand/consumer end, the pandemic resulted in a tremendous growth in the adoption of tele-activities like telework, e-shopping, telehealth, e-learning and e-recreation. On the supply side, businesses and organizations positioned themselves to offer services online, employers became (or were forced to become) more accepting of remote work, and last mile delivery companies like Instacart and DoorDash expanded operations. Furthermore, global supply chains were significantly disrupted, a greater than usual number of individuals moved from cities to suburbs or across states, transit agencies across the nation reduced services, an unusually higher number of individuals resigned or moved jobs, and a visible uptick in use of active transportation modes such as biking and walking was evident. In the months to follow, COVID-19 vaccines were introduced, the economy recovered and VMT were back up significantly, almost at the pre-pandemic levels.

After several months of adaptation, adoption, learning, and unlearning (regarding how to survive during these tough times, or how we really like our lives to be, or whether the choices we made during the pandemic are sustainable going forward), while it would be immature to expect that all these pandemic-forced changes in the telemobility landscape will persist as cities open up and a large percentage of population is vaccinated, it is not inconceivable that there is a strong inertia for at least some proportion of these changes to stay with us in the post-pandemic era. This is because the COVID-19 pandemic induced disruption was forced and abrupt, leading to a system wide change for an extremely long duration, making it unprecedented and unlike anything we have seen since the second world war. While there have been several other disruptions since the 1950s including the economic recession of 2008, 9/11 attack on the world trade center, and the 2009 N1H1 pandemic, nothing comes close to being as system-wide and global as the COVID-19 pandemic in its impact. As a result, the COVID-19 pandemic potentially led to a long-lasting change in human behavior, attitudes and cultural acceptability of this new way to life; along with economic and procedural streamlining of the relevant technology that can assist this change. For example, a greater proportion of population is now exposed to these tele-activity options (like e-shopping and telework) and understands the value these services bring to their lives. Further, the supply side of tele-activity services are also better prepared than they were in the pre-pandemic era (like a majority of businesses are now choosing to take an omni-channel retailing approach and our supply chain networks are also better prepared to tackle delivery of goods including last-mile deliveries).

While an increase in telemobility adoption has significant quality of life benefits at the individual level, if the trends that we saw at the height of the pandemic are to continue at the same levels, this will likely have several strong implications at the urban living as well as mobility front and this needs a deeper re-thinking of our urban systems that are typically located and optimized taking the historic demand patterns into consideration [43–45].

On the end of telework, services like transit systems in many situations are only feasible due to demand concentration, and if a significant proportion of it is eliminated, it will likely lead to significantly reduced revenue for the transit agencies, potentially leading to budget deficits and deterioration of transit services in future. This may make life difficult for transit dependent individuals and may also force some transit users to switch to automobile or ride hailing services, further reducing transit ridership and revenue, as well as reducing the expected societal benefits of telework. Individuals commuting to downtown for work also support a large number of individuals in the third sector of the economy including transportation sector workers, restaurant workers, and retailers. The spending by commuters in urban core is also a source of a significant share of tax revenue (e.g. commercial real estate taxes from the third places or sales tax) for the cities, which eventually gets reinvested in the urban communities in some form. Decrease in frequency of commuting may in the short term impact this support economy and in the long run may shift the geography of spending as the third sector of the economy changes geography with the change in the geography of demand - leading to some form of urban exodus in the short run and significant land use changes in the long run - away from down towns. Telework also significantly changes the time available to an individual due to savings in time from the commute, hence potentially changing the time use patterns, along with a potential for a change in activity geography since without the need for commute and with the additional generated time, a large portion of activities may now be taken closer to the place of residence.

On the end of e-commerce, a changed landscape in terms of how we fulfill our everyday needs will have implications for freight, last mile delivery activity, urban land use by retailers and congestion. A large extent of this impact is already evident on aspects like significant decline in transit ridership across the nation, increased commercial real estate vacancy rates, and reduction in activity in urban cores, along with an impact on the third sector of the economy, increase in activity in non urban cores etc. [45–49]. Depending upon the extent to which these trends recover over time, at some point, cities will have to reconfigure the urban systems in light of the changing demand patterns and generated revenue. However, it is important for cities to do this in a way that it best caters to the changing societal needs while also minimizing the adverse impact on the vulnerable sections of the society.

While the literature in regards to the pandemic's impact on the growth of telemobility is growing, a thorough characterization of this evolution through the pandemic, the factors that impacted this evolution and will shape its future is still missing. If the cites have to plan for this changing geography of work and activities, it is important for them to gain a thorough understanding of how these telemobility options evolved through the pandemic, how they may look like in the future, how they are distributed spatially and across socio-demographic groups and what factors will likely shape the future landscape of telemobility in the United States.

In this context, two aspects of our lives that probably saw the most upheaval during the pandemic are how we work and how our daily needs for food and other essential items are fulfilled. Specifically, as lock downs hit cities around the world as a protective measure to slower the spread of the virus, both consumers/businesses and employers/employees found themselves in an environment full of constraints, where only option available was to transition toward previously unfavorable alternatives in order to improve the odds of survival. As a result, on the remote work end at least some employees are now hooked to the idea of remote work and the employers too are more accepting of it. In the context of shopping and consumption, we saw a significant jump in the number of households willing to move toward making purchases online for products like groceries, prepared food, and non-food items. On the supply side, the pandemic accelerated the already ongoing transition towards an omni-channel retailing approach, where retailers offer a seamless online/in-person purchase experience to consumers. There are two big unanswered questions here. First, as the cities were lock downed and then later the restrictions were relaxed, how did remote work and e-commerce evolve over time and to what extent the pandemic accelerated trends in remote work and e-commerce will sustain in the post-pandemic world? Second, if the pandemic accelerated trends in remote work and e-commerce are to sustain (even if to some extent, compared to pre-pandemic levels), what does these trends mean for the future of large metropolitan cities in the US, which are highly optimized based on the idea of weekday commute hours or presence of large number of individuals at the same place and time.

1.2 Research Goals

The goal of this dissertation is to understand how the long-term and the COVID-19 pandemic accelerated transitions have altered the remote work and e-commerce environment in the United States and what does this evolution mean for the future of large metropolitan cities. These goals are achieved by addressing the following three questions related to remote work, e-commerce and the interaction between tele-activities and functioning of cities:

1. How did telework evolve as a result of the COVID-19 pandemic and how it may look like in the future? Do we expect to see more remote or hybrid work going forward and how does its adoption may vary spatially or socio-economically? What are the employers saying about the future of remote work who are the ultimate decision makers in the future adoption decisions, without whom any pandemic accelerated trends will not continue in the future?

2. How did e-commerce evolve as a result of the COVID-19 pandemic and whether the pandemic accelerated adoption of online and pick-up services is expected to stick beyond the pandemic? Will e-commerce emerge as an alternative to in-person shopping, or will it complement in-person shopping instead? Are the trends of adoption and attrition similar across product categories, geographic regions, and socioeconomic groups?

3. What does the changing trends in telework and e-commerce adoption (if any) mean for the future of cities?

1.3 Dissertation Contributions

This dissertation is an effort to answer the above questions using data from multiple waves of online consumer, employee and employer surveys conducted in the United States amid the COVID-19 pandemic. To bring out important insights, using the data collected, I undertake a collection of four studies. I dedicate a majority of this dissertation to remote work and it evolution, because, in my opinion, this telemobility dimension is where I see big changes happening with potential for major societal implications. I study telework from three angles:

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2. an online survey with *5 waves* of data collection between *October 2021 and August 2022* amongst *top executives of 129 unique North American companies*, focused on collecting

data on employer side approach to remote work since the beginning of the pandemic and in the future.

The methodological approaches used in this dissertation follow a *generalized latent variable modeling framework* which consists of both *observed and latent variables* that may be *continuous or discrete*. In the first study, I present an *ordered probit model* where an observed discrete/ordered outcome variable (telework satisfaction) is connected to socio-demographic covariates and later continuous latent variables or factor variables are introduced to enrich the model with additional information and to improve behavioral insights. In the second study, I utilize *hierarchical agglomerative clustering* of telework trajectories over time, followed by estimation of a *multinomial logit* based membership model to understand the impact of socio-demographic and occupational factors on the identified clusters. While the hierarchical clustering with deterministically defined clusters is not a typically utilized method within the latent variable modeling paradigm (where methods with stochasticity in latent variables are more preferred), this method comes with the benefit of taking sequential nature of the data into consideration while determining the clusters. However, in its crude form, the model is quite similar to a latent class model with covariates. The second study also includes a *latent class analysis*, where observed discrete data is used to define latent discrete classes as well as a *binary logit* and an *ordered logit* model is estimated that connects binary and ordered discrete outcome variables to covariates, respectively. While the majority of analysis in the third study is descriptive given the size of the sample available to us from the survey of only 129 employers, I utilized both latent class model and an ordered probit model for parts of the analysis. Lastly, in the final study, I utilize a longitudinal extension of the latent class analysis namely *latent transition analysis with random intercepts* to capture the latent behavioral classes in consumer spending (across food and non-food items and across various acquisition channels) and their between-class dynamics over time since the beginning of the pandemic.

Below, I provide a brief description of the two data sets and the four studies in this dissertation including the questions addressed, data and modeling methodologies utilized, key results and the policy implications of these results. In the last section of this chapter, I present an outline of the rest of this dissertation, which includes a detailed review of the existing and emerging literature, a detailed description of the data available for this dissertation, the methodological approaches utilized in various parts of this dissertation, the content of various chapters corresponding to the four studies on remote work and e-commerce, followed by a concluding chapter summarizing key contributions and identification of directions for future research.

1.3.1 Longitudinal tracking survey to understand changing consumer spending, telework and mobility patterns through the pandemic

Recognizing that the COVID-19 pandemic provided a unique natural experiment in the use of Information and Communication Technologies, a 7-wave longitudinal tracking survey was conducted to monitor the evolving consumer spending, telework, and activity participation behavior associated with the COVID-19 pandemic. The goal was to derive insights on expected post-pandemic telemobility patterns and its interaction with physical mobility. The 7-wave longitudinal tracking survey was conducted between December 2020 and March 2022 through an online platform named Prolific and resulted in data from 1877 unique respondents in the United States.

Questions on the following 13 categories were included in the survey: 1) weekly consumer spending on groceries, cooked food and non-food items; 2) monthly consumer spending on electronics, furniture, clothing and digital media; 3) home delivery frequency for groceries, cooked meals and other non-food items; 4) telework related travel frequency through the pandemic; 5) travel, trip-making and time use behavior; 6) attitudes, perceptions and experiences of the individuals with telework and e-commerce through the pandemic; 7) use of subscription services like amazon prime, streaming services as well as local transit pass; 8) additional related question on pre-pandemic and post-pandemic expected behavior; 9) individual intention to use contact-free deliveries like delivery robots in the post-pandemic era; 10) a detailed 24-hr activity diary data; 11) direct impact of the pandemic like job loss, and COVID-19 infections; 12) individual experiences with depression, anxiety or positivity in life as a result of the pandemic; and 13) socio-demographics.

Wave 1 of the survey started with 457 adults who were recruited to build a representative sample of the U.S. population by age, gender, and ethnicity. The 457 respondents were then later re-invited for waves 2 to 6, irrespective of whether they completed the previous wave of the survey. To make up for respondent attrition from the main sample, starting wave 2, a convenience sample with approximately 100 respondents was recruited in each wave till wave 6, who were then re-invited to participate in the subsequent waves, if they have completed the previous wave. In wave 7, everyone who joined waves 1 to 6 at least once was re-invited, along with a new U.S. population representative top-up of 905 individuals. This resulted in an overall sample of 1877 unique respondents, data from whom was ultimately utilized for all studies in this dissertation, except the study that focuses on the employers.

1.3.2 Longitudinal tracking survey to understand employer side remote work policies through and beyond the pandemic

To understand the employer side perspective, a 5-wave survey between October 2021 and August 2022 amongst top executives of 129 unique North American companies through the Northwestern University Transportation Center's Business Advisory Council (BAC) was conducted, where questions in the following five categories were asked: 1) demographic information of the employers like their industry of operations, organization size and region of operations; 2) their approach to employee remote work for whom it is possible at various time points before and during the pandemic and the expected work location in the future; 3) their opinion towards the potential impact of a 2-day-a-week remote work policy in their organization on various business aspects like their ability to recruit / retain employees, profitability, and their ability to compete; 4) extent of resumption of business travel of over 50 miles and in-person client interaction at the time of various waves of the survey; and 5) whether their organization has (or plan to) added, relocated office spaces in same or different area or building since the beginning of the pandemic.

The available sample of 129 employers consists of about 61% of employers from the transportation, logistics, warehousing and manufacturing sectors and the rest 39% from other sectors. More than 90% of the respondents in our data are vice president (VP) or chief operating officer (CEO) level senior executives, with the rest being director-level managers. A large share of companies in our sample have more than 10,000 employees, have more than $5 billion in annual revenue ($25 billion in many cases), and a majority have a presence across the United States (with several having an international presence). Overall, this highlights that the respondents in our data speak for a large number of employees and their decisions regarding remote work potentially have an impact on the work location decisions of a large number of individuals.

1.3.3 For whom did telework not work during the pandemic? Understanding the factors impacting telework satisfaction using a MIMIC model

While employer strategies will play a major role in defining the future forms and adoption of telework, employee preferences and constraints, such as access to appropriate technology to work from home or the home environment, are also going to be important factors that will shape the future of remote work. In this study, I focus on understanding the systematic heterogeneity in factors associated with telework satisfaction during the pandemic, with the general idea that those who were more satisfied with their experiences during the pandemic are going to be more likely to continue telework post-pandemic, given telework as an available option. Specifically, I utilize data from a representative sample of 318 working adults collected during wave 5 (late Feb 2021) of the 7-wave longitudinal survey to estimate two different models: 1) a reference ordered probit model controlling for socio-demographic variable effects on telework satisfaction levels, which is useful to understand the heterogeneity in telework satisfaction across various socio-demographic groups; 2) a multiple indicator multiple cause (MIMIC) model with an ordered probit component that links telework satisfaction with experienced and perceived benefits and barriers related to telework, and hence provides a causal structure to our understanding of telework satisfaction.

Our results highlight diverse experiences of individuals with telework which will potentially shape the future of remote work landscape. A deeper investigation of this data using an ordered model and a MIMIC model revealed several important insights. First, our results suggested that the satisfaction was higher for middle aged individuals compared to younger and older individuals, Hispanic or Latino respondents, and respondents with less than undergraduate degree, and those with higher levels of concerns about contracting the COVID-19 pandemic. On the other end, satisfaction was found to be lower for individuals with children attending school virtually from home.

Analysis using the MIMIC model confirmed several findings from the ordered model but also provided a more enriched structure to the model — through the inclusion of perceived / experienced benefits and barriers to telework latent variables. This enriched model suggests that the benefits and barrier to telework are disproportionately distributed across age groups, where higher barriers and lower benefits are experienced by those who are young or old compared to those in the middle aged group.

From a policy standpoint, some key factors captures in our model include commute, productivity gains, quality of life improvements aspects of remote work associated with higher perceived benefits and thus higher satisfaction, while factors like distraction from household members and lack of appropriate technology associated with higher barriers and lower satisfaction.

1.3.4 Trajectories of telework through and beyond the pandemic

Using retrospectively collected data from a nationally weighted sample of 905 working adults in the United States regarding their degree of adoption of remote work at 7 different time points (between 2019 and March 2022), in this study I undertake an in-depth analysis of individual level telework trajectories over time using a hierarchical agglomerative trajectory clustering approach, focused at identifying clusters of telework trajectories through the pandemic. I identify four clusters of trajectories with differing level of telework adoption, ranging from a group that maintained a significantly high in-person work participation even at the height of the pandemic, to a group that worked exclusively at home for an extended period into the pandemic and shows little sign of rebounding back to their pre-pandemic behavior.

With the identified clusters, I estimate a *multinomial logit (MNL)* based cluster membership model, where I identify how individuals in different occupational sectors, and in different age, gender, ethnic, educational, or other socio-economic groups followed distinct trajectories. I also present a set of comprehensive predictive models to understand how telework landscape looks like in April 2024, about four years since the beginning of the pandemic, when any COVID-19 related concerns are expected to be resolved. Specifically, I present models for two different outcome variables: 1) a binary logit (BL) for predicting who is still unsure about their April 2024 work location; 2) a set of ordered logit (OL) models to understand who is more likely to work in-person in April 2024, amongst those who have no uncertainty. I present three versions of the ordered logit model: a) a model with only socio-demographic information focused at understanding the distribution of telework across the population going forward; b) a model with socio-demographic information as well as trajectory clusters identified earlier as indicator variables (with the motivation that these clusters capture a mixture of information on changing employee preferences (due to their own experiences of working from home) as well as employer side decisions requiring workers to return back to the offices; and c) a model that builds upon the previous two models by adding an indicator variable on the individual outlook towards remote work identified through a latent class analysis (LCA) that focus on understanding the perceived impact of remote work on various work aspects like productivity, effectiveness, socialization with co-workers etc.

Some key results from this research includes existence of higher in-person work in transportation, manufacturing, healthcare and education sectors while higher remote work in professional, scientific and technical services, and information sectors during the pandemic. We also found household characteristics like vehicle ownership, presence of young children and household location, and size played critical role in determining the extent to remote work adoption through the pandemic. Regarding the future adoption levels, our results suggest higher uncertainty in work location in April 2024 for information sector workers, students and women, some of which may partially be explained by uncertainty from the end of the employers regarding non-existence of a firm remote work policy. Other than this, we also found a large portion of these trends seen during the pandemic are expected to continue in the future too, where higher in-person work in transportation, manufacturing sectors is seen compared to information sector; higher remote work is seen amongst those without a vehicle and amongst those with age 65 years or older.

From a policy standpoint, these results highlight several implications. First, the results indicate a significant retention of pandemic accelerated trends in remote work with some form of hybrid work being the norm. However, there is still some uncertainty around future work location, potentially from the end of the employers — hence the decisions made at the end of employers will determine the true nature of the remote work landscape. Our results also suggest that those without are vehicle (who also tend to be transit users) are more likely to continue to work remotely — potentially indicating a slower rebound of transit ridership. A strong interaction between the occupational sector and remote work adoption level highlights that the impact of remote work on different cities across the United States may be different — dependent on the composition of the economy of a city. Further, a reduced level of commuting may hurt individuals employed in the third sector of the economy (especially in urban cores) — who largely rely on spending by commuters. Lastly, an increase flexibility may also motivate teleworkers to move away from urban cores in search of better value for their money — potentially changing the mobility landscape in urban cores, as well as where the location where teleworker may move.

1.3.5 Employers' perspective on the future of work post-pandemic

Recognizing that any future trends in remote work are unavoidably going to be a function of both employee preferences and employer side decision to allow remote work, in this study, I switch sides and try to understand the employer perspective on the evolution of remote work policies and the planned future response using data from top executives of 129 North American companies, collected using a 5-wave survey between October 2021 and August 2022. Even though employers are the ultimate decision-makers in this evolving remote work landscape, only a handful of studies have looked at the employer's perspective to understand the future of work. However, these studies either focus on just the knowledge / information workers and do not present differences across various sectors or have surveyed human resources or mid-level managers only. Since the COVID-19 pandemic potentially proliferated telework beyond knowledge/information sectors and since ultimate company-wide telework policies are going to be driven by top-level executive decisions, we argue that a survey of a diverse set of top-level executives is necessary to gain a thorough understanding of the employers' perspective on telework in the post-pandemic world.

Using the available data, I analyze how the employer's approach to remote work (for those employees for whom remtoe work is possible) varied over time since the beginning of the pandemic and what approach they expect to take in the future. Specifically, I analyze how the average work location across organizations varied (or is expected to vary) over time at an aggregate level and also identify differences across various sectors of operations, departments within the same organization, and how it varied for organizations with different remote work approach pre-COVID and in early phase of the pandemic. I also dive deeper into understanding the remote work landscape in April 2024 by estimating an ordered probit (OP) model that associates an organization's sector of operations, pre-COVID and early pandemic approach to remote work and their outlook towards remote work on various business aspects with the expected April 2024 remote work approach. The employer outlook towards remote work on various business aspects like ability to retain or recruit talent, employee supervision and creativity was determined using a latent class analysis based on a question that asked employers to rate their view of how remote work will impact their organization's business if they adopt it for a 2-days-a-week. Lastly, I also present results on the extent of resumption of business travel and in-person client interactions since the beginning of the pandemic as well as whether employers have reconfigured their office spaces like moving to a smaller or new office location in light of the increased remote work.

Key results from this study suggest that at least some of the pandemic accelerated changes to the work location landscape will likely stick; with some form of hybrid work being the norm. However, the patterns will vary by department (HR/legal/sales/IT, etc.) and by sector of operations. Top three concerns amongst employers regarding remote work according to our analysis include: supervision and mentoring, reduction in innovation and creativity; and the top three benefits include their ability to retain / recruit talent, positive impact on public image and their ability to compete. The ordered probit model for April 2024 work location strategy revealed that those in transportation, warehousing, manufacturing sectors, those with a fully in-person approach to work pre-COVID, and those with negative outlook towards the impact of remote work likely to be more in-person-centered, while those with fully in-person approach in April 2020 are likely to be less in-person-centered.

1.3.6 Consumer spending Behavior and Adaptation Across Online and In-Person Channels Through the Pandemic

Apart from how we work, another dimension of telemobility that was significantly disrupted by the pandemic was how our daily need for food and non-food items is fulfilled. While the option to shop online did exist pre-pandemic, the pandemic potentially accelerated the growth of these option – reaching new set of users and new set of product categories. While there is a clear evidence that the pandemic resulted in the growth of e-commerce at several poduct categories, the question regarding sustenance of this growth over time and differences in usage patterns across various product categories and across acquisition channels is still unclear. Uncovering the complexity behind the consumer spending behavior across various channels and product categories requires an integrated framework.

Using nationally weighted data from 785 individuals from the United States at 4 different time points and across 10 different product categories and acquisition channels, I present a latent transition analysis with random intercepts that helps in understanding within-subject changes in latent discrete states (representing spending behavior in our case), while separating the temporally stable between-subject variation (representing individual latent trait).

We identify five distinct classes of spending behavior with varying degree of likelihood of spending in in-person, delivery and pick-up channels of acquisition for grocery, cooked-food and non-food items. Our results indicate a significant shift away from dine-in at restaurants at the height of the pandemic, which eased a little over time. Our results also suggest an increase in grocery and cooked food delivery, which is relatively stable over time; and an increase in grocery pick-up behavior, which is slowly declining. I also include covariates in time invariant latent trait, latent classes at initial time point and in transitions over time to capture the impact of these covariates on spending behavior and transitions.

Overall, the results suggest a significant decrease in spending on dine-in at restaurants, which we expect to ease as inflation eases, however, 2-3 times increase in grocery spending behavior is seen, which may have transportation implications from the perspective of last-mile deliveries. Important implications for these results are in the direction of potential increase of last mile delivery traffic in communities that cities need to plan for in the future.

1.4 Organization

Table 1.1 presents an outline of various chapters in this dissertation including the title, objectives, data, methodological approach and key results from various studies. In Chapter 2, I present a detailed review of the existing literature on impact of various telemobility mobility dimensions over the past 40 years, along with the new emerging literature on changes in telemobility landscape in the United States since the beginning of the pandemic and the associated changes in physical mobility landscape. In Chapter 3, I present a detailed description of the two data sets used in this dissertation and a detailed description of various methodological approaches is presented in Chapter 4. Chapters 5 to 7 focus on the three studies related to telework, while Chapter 8 focuses on consumer spending behavior study using the latent transition analysis framework. For these chapter, the mathematical details of various models and the data used has not been presented in detail for brevity since they are already presented in previous chapters. Rather focus is on the motivation behind the study, the adopted analysis framework, important results and the implications of these results. Finally, in chapter 9, I summarize the key contributions, identify implications for policy and directions for future research.

Table 1.1: Dissertation Structure

Chapter	Title	Objective	Data	Approach	Key Results
2	Literature Review	To present literature on last 40 research of telemobility and transportation interaction research and the emerging literature since the pandemic	--	--	--
3	Data	To present a detailed description of the data used	Consumer and Employee Survey Employer Survey	--	--
4	Methodological Foundations	Mathematical details of the various models used in this dissertation	--	Multinomial Logit Ordered Logit / Probit MIMIC Model Latent Class Analysis Latent Transition Analysis with Random Intercept Hierarchical Agglomerative Clustering	--
5	For whom did telework not work during the pandemic?	To understand the factors impacting telework satisfaction during the pandemic using a MIMIC Model	U.S. representative sample of 318 working adults	Ordered Probit Model MIMIC Model	• Young and Older individuals perceived lower benefits and higher barriers. • Disproportionate impact on Hispanic, Black individuals and those with young children
6	Trajectories of telework through and beyond the pandemic	To understand evolution of telework through and beyond pandemic using a trajectory analysis framework	Weighted telework trajectory data from 905 working adults	Hierarchical Agglomerative Clustering Latent Class Analysis Ordered Logit Binary Logit Multinomial Logit	• 4 trajectory clusters with varying degree of telework adoption are identified • Higher in-person work in transportation, manufacturing, healthcare and information sectors while lower in professional services, information sectors • Household vehicle ownership, presence of young children played critical role in determining the extent of telework through the pandemic • higher uncertainty in work location in April 2024 for information sector workers, students and women
7	Employers' perspective of the future of work post-pandemic	To understand employer side perspective to telework	5 wave longitudinal survey amongst 129 U.S. based employers	Latent Class Analysis Ordered Logit	• at least some of the pandemic accelerated changes to the work location landscape will likely stick; with some form of hybrid work being the norm • patterns will vary by department and sector of operations • Top three concerns: supervision and mentoring, reduction in innovation and creativity • Top benefits: ability to recruit / retain, positive impact on public image and ability to compete
8	Consumer spending behavior and adaptation across online and in-person channels through pandemic	To understand the evolution of consumer spending through the pandemic	U.S representative sample with 785 individuals across 4 time points	Latent Class Analysis with Random Intercept	• Five spending behavior classes are identified with varying degree of likelihood of spending in different channels and categories • significant shift away from dine-in at restaurants at the height of the pandemic, which eased a little over time. • increase in grocery and cooked food delivery, which is relatively stable over time
9	Conclusions and Future Research	--	--	--	--

CHAPTER 2
LITERATURE REVIEW

I divide this literature review in three key parts:

1. pre-pandemic conceptual and empirical literature published in the last four decades since the initial conception of the impact of ICTs on travel. Here, I focus on both the conceptual literature that characterizes the potential impact of tele-activities on physical mobility like substitution versus complementarity as well as empirical literature that focuses on quantifying such impact. On the empirical end, I focus on literature related to ICTs impact on energy savings and emissions, reduction in vehicle miles traveled, non-work travel, and residential relocation. In this regard, while I present the pre-pandemic empirical research on several aspects, in my opinion, a lot of it needs to be revisited due to the scale at which the pandemic may have impacted the telemobility and physical mobility landscape. Nevertheless, some important lessons can still be learned from the past literature.

2. emerging literature on the telemobility trends since the beginning of the pandemic — specifically in relation to telework and e-commerce. On the end of telework, I review literature on emerging trends in telework as captured by various data sources; the employee side perspective with regards to what worked for them, what did not, and what employees are expecting in the future; and the employer side perspective regarding why or why not they might continue to allow telework going forward. On the end of e-commerce, I review literature on the emerging trends in e-commerce from both the consumer end as well as literature on the factors impacting the use of e-commerce during the pandemic.

3. the emerging trends in relation to physical mobility landscape — specifically related to transit and commuter rail ridership, vehicle miles traveled, changes to the extent and geography of activity participation, the trends in commercial real estate and the pandemic's impact on third sector of the economy.

2.1 Four decades of telemobility research

On the end of the ICTs usage and travel interaction (as a whole), some important studies that characterize how these technologies can interact with travel include Polishuk [4], Salomon [50], Salomon [51], Mokhtarian [3], Salomon [52], Mokhtarian [53], Mokhtarian and Salomon [54], Salomon and Mokhtarian [55], Andreev et al. [56], Mouratidis et al. [57], Aguiléra et al. [58], Cohen-Blankshtain and Rotem-Mindali [59], Gössling [60].

Polishuk [4] was one of the earliest study to note the potential of telecommunications technologies to substitute for travel, which pointed out that this could lead to significant energy saving, especially from the perspective of commute travel, decentralization of central business district and suppression of business travel. However, Salomon [50] later present a set of arguments to make a case that the impact of telecommunications will be modification of travel instead of substitution, given the proposition that human beings are mobile animals. Building upon the Moslow's theory of motivation, he provided arguments to support the modification (instead of substitution) of both individual (work, recreation and shopping travel) and business travel. Salomon [51] provided a review of studies that support the modification of travel due telecommunications instead of substitution and identified four types of relationships between ICTs and travel: 1) substitution; 2) enhancement; 3) operational efficiency (first order complementarity); and 4) indirect impact (second order complementarity). Mokhtarian [3] expanded these relationships to include converse relationship as well (i.e. impact of transportation on telecommunications instead of telecommunications' impact on transportation). To dig deeper into the relationship between telecommunication and travel, Mokhtarian [53] and Mokhtarian and Salomon [54] present review at both conceptual and empirical level to suggest that most comprehensive studies point towards complementarity being the pre-dominant effect of telecommunications on travel and that the evidence of net substitution is nonexistent.

On the telework end, some seminal conceptual and review studies include Salomon and Salomon [5], Nilles [6], Mokhtarian [61], Hook et al. [62], O'Brien and Aliabadi [63]. Salomon and Salomon [5] present an employee perspective to telework and argue that the non-monetary cost of telework adoption for individuals is larger than the benefits, and that this will be a major deterrent to large scale telework adoption. The identified factors impacting adoption included social interaction at workplace and work-nonwork relationship. They also identified the importance of journey to work, building a case for neighborhood work centers instead of purely working from home. Nilles [6] highlight that telecommuting is a subset of teleworking and also present two forms of telecommuting: home based and regional center based. They also discuss various motivations for telecommuting: telecommuting for public good like to reduce congestion, organizational objectives like increase in productivity of the workers and personal factors like cost savings from not traveling or purchase of business clothing.

Mokhtarian [61] present one of the most comprehensive review of interaction between telecommuting and travel. She argues that evidence suggests that telework might impact activity patterns in various ways. Major research hypotheses presented by her are summarized in Table 2.1. The paper also identifies several directions for future research including understanding energy and air quality impact of telecommuting, safety impact becasue of higher speeds due to decongestion of roads, negative impact on ridesharing like carpool and vanpooling, interaction of telecommuting with other demand management strategies like childcare at workplace, impact of telecommuting on traditional forecasting of travel demand, role of telecommuting centers in promoting telework and the cost-benefit analysis related to telecommuting from employee and employer perspective. Hook et al. [62] and O'Brien and Aliabadi [63] present review of literature on energy savings aspect of teleworking and both found limited support in favor of the argument that telework saves energy, primarily due to increase in non-work related travel and increase in energy consumption at home.

Table 2.1: Research hypotheses regarding impact of telecommuting on travel [61]

Travel Activity dimension	**Potential Impact of Telecommuting**
Frequency	Work trips decrease and non-commute increase
Time-of-day / day-of-week	More trips shift to off-peak non congestion hours / days
Destination/length	Work trips to local center (decrease length); non-work trips closer to home
Mode	Less carpooling, loss of transit revenue, trips close to home may be on non-motorized modes; better efficiency for cars due to de-congestion
Trip chaining patterns	Breaking of efficient trip chains into one-stop trips
Person(s) making trips	Within household trip assignment may change to non-telecommuting person or the telecommuting person
Vehicle ownership	Need for a second car may be eliminated
Residential/job location	Telecommuters may move farther from home for better housing prices, corporate offices may move too

Lastly, on the e-commerce end, important papers include Mokhtarian [64], Visser and Lanzendorf [65], Cao and Mokhtarian [66], Cao [67], Mangiaracina et al. [68], Rotem-Mindali and Weltevreden [69], Le et al. [13]. Mokhtarian [64] present a conceptual paper on several issues related to transportation and spatial impact of e-shopping and conclude that neither in-store nor e-shopping fully dominate another forms of shopping. The authors argue that a continued growth in both in-store and online shopping is expected and the net outcome of future shopping related changes in transportation will be a net outcome of four processes: 1) changes in shopping mode share; 2) changes in volume of good purchased; 3) changes in per capita consumption spending; and 4) demographic changes. The relative advantage of online shopping identified by the authors include: unlimited selection, lower price / search cost, personalization, speed and convenience. On the other hand, relative advantages of in-store shopping include: sensory information, tangibility, and immediate possession with the added benefits related to social interaction, entertainment and movement.

2.2 Existing empirical evidence on interaction between telecommunications and travel

Given the research hypotheses identified above, here I discuss empirical evidence regarding the impact of ICT usage on various travel related aspects like vehicle miles traveled, non-work travel, energy and emissions, sustainable modes usage, and residential relocation.

Energy and emissions reduction

O'Brien and Aliabadi [63] and Hook et al. [62] provide a holistic review of energy impact of telework, both from the perspective of transportation-related and non-transportation related energy consumption and conclude that quantification of such impact is complex, however, while most studies tend to suggest some energy related benefits, some also suggest an increased energy usage.

On the transportation end, Henderson and Mokhtarian [70] found 49% and 53% decrease in oxides of nitrogen and particulate matter, respectively, on telecommuting days, compared to non-telecommuting days of individuals being studied, however, no difference in emissions related cold start process was found since the number of trips between telecommuters and non-telecommuters were not significantly different. However, they found that the regional level emissions impact of telecommuting at the time was much smaller since the proportion of telecommuting workforce was small. In another smaller study with data from state of California Telecommuting Pilot Project, Koenig et al. [71] found significant reduction in the number of cold starts, and emissions reduction (~60-70%). Shabanpour et al. [25] used POLARIS activity based model to estimate that an increase from current 12% to 50% telecommuting adoption in the city of Chicago will results in 0.71% reduction in greenhouse gas emissions and 1.14% reduction in particulate matter emissions. Mokhtarian and Varma [72] found a significant but lower than usual reduction in emissions in the case of center-based telecommuting due to an increase in total trip making by telecommuters who often travel home for lunch.

On non-transportation front (office spaces and home location), O'Brien and Aliabadi [63] review several studies to understand the potential energy benefits related to telework due to office space reduction, to what level office space is occupied on a given day, and whether or not computers/laptops used by teleworkers are same in the office and at home or if remote workstations are being used. They also identify literature on impact of teleworking on home energy cost and found significant differences in results across studies. Overall, the evidence suggests that while telework decreases energy use to some extend (with a lot more potential which is often not realized), there are significant rebound effects related to telework, often offsetting any energy savings.

Vehicle miles traveled

Choo et al. [22] present a robust analysis to make a case for reduction of passenger VMT by telecommuting. Using multivariate time series data from 1966-1999 for various external variables and 1988-1998 data on telecommuting, the authors assessed the change in annual VMT per telecommuter as well as VMT per telecommuting occasion for 1998 and found robust evidence that telecommuting leads to VMT reduction. Their estimate suggests that the reduction is of the order of 0.8% and is of similar magnitude as VMT reductions due to transit and far more cost effective.

Non-work travel

There is strong evidence regarding telecommuting inducing a significant amount of non-work travel, offsetting the commuting associated VMT reduction. Saxena and Mokhtarian [73] present a spatial analysis using geo-coded travel diary data from state of California telecommuting pilot project where they found that on telecommuting days 86 % telecommuters performed activities closer to home (an in all directions), compared to only 56% on non-telecommuting days (majority of which was oriented towards the workplace).

Kim et al. [32] shows that telecommuters' non-commute and non-work trips as well as his/her household members' non-work trips are greater than those of non-telecommuters and their household members', whereas telecommuting partially reduces commuting trips. However, an analysis stratified by household type reveals that the difference for household members is significant only in households with less than one vehicle per employed member: in such households (with insufficient vehicles available), the vehicle otherwise used for mandatory travel, such as for the household head's commute, can be used for non-commute purposes or by other household members if the household head does not use it for commuting.

Sustainable mode usage

Some studies point to a potential relationship between telework and non-motorized travel usage with the general idea that telecommuters / teleworkers are more likely to make a shorter non-work trip, which tend to attract more non-motorized modes of transportation like biking and walking. For example, using data from 2005 Canadian General Social Survey, Lachapelle et al. [35] found a 77% increase in the odds of non-motorized travel by teleworkers. Similarly, using 2009 National Household Travel Survey (NHTS) data, Chakrabarti [74] found a significantly higher odds of walking/biking greater than 1 mile, and physical activity. Specifically, he found that on a typical workday, telecommuters had 41% higher odds of walking/biking greater than 1 mile, 71% higher odds of 30+ minutes of physical activity.

Residential relocation

Several studies look at the residential relocation aspect of telework with the idea that the option to telework could fuel relocation to suburban areas or urban periphery in pursuit of lower housing cost or better lifestyle. Even if teleworkers need to travel a few times a day to the workplace, they might be willing to travel longer a few times a week instead of a shorter distance every day.

The literature on the causal impact of telework on residential relocation seems to be inconclusive but there seems to be higher evidence in favor of telework not being a primary reason for relocation in the cases where it was observed. Using data from Seoul, Korea, Kim et al. [75] argue that while telecommuters tend to live in the urban periphery, it is likely since the firms allowing telecommute are also situated in urban periphery, instead of telecommuting being a causal factor resulting in residential relocation. Another Dutch study by Muhammad et al. [76] too found limited support for the impact of telecommute on residential relocation and argues that traditional factors like life cycle stages remain the dominant explanatory factors to explain residential relocation. Lastly, Ory and Mokhtarian [77] and Mokhtarian et al. [78] too found limited impact of telecommuting on residential relocation farther away from workplace, reinforcing the positive view of telecommuting.

On the other end, Lund and Mokhtarian [79] found that while telecommuting reduces the number of work trips, in long-term it likely results in changes to residential relocation farther from workplace, wiping out the VMT related benefit of telecommuting, and this effect is more pronounced for metropolitan areas with flatter spatial variation in land prices. However, this study is mainly focused on monocentric cities and for workers employed in the metropolitan center.

2.3 Emerging trends in telework and e-commerce

There is a growing literature since the beginning of the pandemic regarding the changing telemobility landscape in the U.S. and how a large extent of pandemic accelerated adoption trends are likely to persist post-pandemic. Here, I review the literature with regards to telework, e-commerce and physical mobility.

Emerging telework trends

Several available data sets and studies point to the changing telework landscape in the United States as a result of the COVID-19 pandemic. I briefly discuss these emerging trends from a few of these U.S. based data sets / studies regarding the extent to which teleworking rates have evolved through the pandemic, and then discuss how these trends differ across sectors, cities, and internationally.

At an aggregate level, several studies point to a significant shift toward remote work since the beginning of the pandemic. The Survey of Working Arrangements and Attitude (SWAA) by Barrero et al. [80] has been tracking the remote work frequency in the United States using a repeated cross-sectional dataset since May 2020 with over a hundred thousand respondents across all waves. Their data from Fall 2022 shows that about 30% of paid full days are worked from home each week and this number was about 60% in May 2020 and about 5% pre-COVID (based on American Time Use Survey). Their results also align with two other data sets, one collected by the U.S. Census Bureau named the Household Pulse Survey [81] which started including a question on telework in June 2022, and another one is Google's Mobility Reports dataset [82]. Two surveys done by Pew Research in October 2020 [83] and January 2022 [84], respectively, reported that about 20% of employed adults with remote work friendly jobs worked from home all or most of the time pre-COVID but this number was found to be 71% during October 2020 and 59% during January 2022.

Another survey done in March/April 2022 by McKinsey and Company [85] reported that 58% of job holders in the United States can work remotely at least part-time.

At least two studies also provide an international perspective on telework trends [86, 87]. Global Survey of Working Arrangements (G-SWA) by Aksoy et al. [86] consists of data from 27 countries collected in mid-2021 and early 2022. Their study reports the number of full-time paid days (conditional mean values after controlling for other factors, though their sample over-represents highly educated respondents in most countries) spent working from home, in the week when the data was collected, to vary significantly across countries with the highest number of 2.6 days in India, followed by 2.4 in Singapore, 2.2 in Canada, 2.1 in Malaysia, 2.0 in the United Kingdom and Australia. Countries with the lowest rates of remote work include South Korea (0.5 days), Egypt (0.7 days), and Taiwan (0.8 days). Lund et al. [87] estimate the potential share of time spent working remotely for various countries and found it to be higher for advanced economies like UK, Germany, US, Japan, France, and Spain, compared to emerging economies like Mexico, China, and India since a large proportion of the workforce in emerging economies is skewed towards agricultural and manufacturing like sectors with require physical presence.

On the end of telework across various sectors, several studies [80, 87, 88] point to it being higher in sectors like Finance and Insurance; Management, Professional, Scientific, and Technical Services; and IT and Telecommunications; and lower in sectors like Agriculture; Accommodation and Food Services; Construction; and Transportation and Warehousing. Using data collected in January 2023, Barrero et al. [80] reported that the number of days working from home in the last week was 2.29 for the Information sector, 2.15 from the Finance and Insurance sector, 1.96 for the Professional and Business Services, 0.69 for Retail Trade, 0.63 for Transportation and Warehousing, and 0.58 in Hospitality and Food Services.

Lastly, Barrero et al. [80] and Chapple et al. [49] provide insights into the variation in telework trends across cities. Barrero et al. [80] report the percentage of paid full-time days worked from home to be higher in the top 10 cities by population compared to other cities and show these trends to be consistent throughout the pandemic. Chapple et al. [49] look at the downtown recovery data from various cities across the United States/Canada and found it to be lowest in cities like San Francisco, Portland, Indianapolis, and Seattle and this was correlated with the percent of jobs in sectors like Professional, Scientific and Technical Services in those cities, which other studies have shown to be high adopters of remote work.

Employee perspective on telework experiences during the pandemic

Recent literature and data sources point to several factors that are continuing to shape employee preferences regarding expected remote work adoption in the future including productivity while working from home, commute travel time savings due to remote work, ability to care for other household members, and children, etc. Here, we briefly discuss emerging evidence regarding the employee perspective on remote work in terms of their experiences through the pandemic and their expectation post-pandemic regarding telework. These factors will potentially shape how employers form their perspectives and decide on future telework policies.

Most sources suggest that the remote work experiences during the pandemic were positive for most individuals due to several contributing factors. For example, as Barrero et al. [80] note, the work productivity experiences during the pandemic were largely positive for the employees. From the data collected from about 30,000 respondents in the United States, they report that only 13.9% of individuals reported worse than expected productivity levels, 26.7% reported about the same level of productivity than before and the rest 59.5% reported better, substantially better or hugely better level of productivity than before. Another report by Owl Labs and Global Workplace Analytics [89] with data from over 2300 full-time U.S. workers reported that 62% of the workers feel more productive when working remotely, with 66% of the millennials feeling more productive while working from home while this number is only 46% for boomers. A 2021 version of this survey with data from 2050 full-time U.S. workers reported that about 90% of individuals felt equally or more productive working from home. However, Owl Labs [89] pointed out that measuring productivity may be difficult due to definitional differences and may also be impacted by most of these numbers being self-reported. They also pointed to a large difference between productivity gains reported by employees and the employee productivity gains reported by their employers.

Several other factors played a role in either overall satisfaction with telework or in terms of their impact on the productivity of working from home. Barrero et al. [80] and Aksoy et al. [90] talk about commute time savings as a factor that makes telework valuable to employees. Barrero et al. [80] found out that the commute length was longer for higher-earning employees so they might value telework more than others. Aksoy et al. [90] quantified the commute time savings associated with working from home based on data from 27 countries to be 72 minutes in their sample, with values in the range of 100 minutes for individuals in China, India, and Japan; around 70-80 minutes for Australia, Austria, Brazil, Russia, United Kingdom and South Korea; and 55 minutes for United States. They also found out that about 40 percent of the time saved gets allocated to work and about 11 percent is allocated to caregiving activities. Along the lines of career advancement and visibility to managers, Owl Labs [89] reports that about 49% of respondents feel that their managers view office-going employees to be more hardworking and trustworthy than others. They also report that hybrid workers save about $19.11 each day due to remote work, a majority of which comes from commute expenses and expenses on lunch. They also mention feeling disconnected from others during hybrid/remote meetings and internet problems to be some of the contributing factors impacting the telework experiences of employees. Similar factors were also identified by Parker et al. [83, 84] and Teevan et al. [91].

Literature also suggests changed expectations by the employees regarding remote work which will play an important role as employers decide on their remote work policies in the future. Owl Lab's 2021 state of remote work report [89] reported that 65% of employees in their data expect some form of remote work going forward, with 1 in 3 ready to quit their jobs if they could not work remotely after the pandemic. Their report's 2022 version stated that 66% of workers would start looking for another job that would offer flexibility if the ability to work remotely is taken away. They also reported that 52% of the employees would take a pay cut of 5% or more and 23% would take a pay cut of 10% or more to have more flexibility. Dua et al. [85] reported flexible working arrangement is one of the top motivators for finding a new job for employees. Parker et al. [83] report that only 11% of employees with telework-friendly jobs want to work rarely or never from home. Parker et al. [84] in a follow-up study reported that while the COVID-19 contagion risk was a motivator for individuals to work from home early in the pandemic, most employees now cite personal preferences for doing so like childcare responsibilities. Barrero et al. [92] found out that 40% of the employees with the ability to work from home at least once a week are ready to seek a new job if they are recalled back to the office full-time.

Employer perspective on telework experiences during the pandemic

A limited number of studies exist that present the employer's perspective of remote work. We present a brief review of the emerging insights from these studies regarding employers' experiences with remote work during the pandemic and their plans for the future.

A report from McKinsey and Company [93] surveyed 100 C-suite, vice president and director-level executives from around the world and found that 9 out of 10 organizations are planning to take a hybrid approach to work going forward however most do not have a detailed plan on the implementation aspect. Most respondents also reported an improvement in productivity, customer satisfaction, employee engagement, diversity, and inclusion, however, the productivity improvements were higher for those who kept their employees connected. They also found out that organizations, where productivity improved, were those who trained their managers to deal with situations like providing feedback to employees in an online setting and those who are continuously experimenting with different strategies regarding remote work. The organization leading in productivity improvements also reimagined their hiring processes with more and more recruiting events being held remotely.

Another study by Good Hire, a background check service for businesses [94] surveyed 3500 managers in the United States to understand their remote versus in-person preferences for their employees and found out that 75% of the managers preferred at least some form of in-person work, and 60% of the managers agreed or strongly indicated a full-time in-person work in the near future. They also found that 73% of managers agree that productivity and engagement has improved or remained the same during the pandemic and that 68% of managers agree that fully remote operation would add or not impact their profits.

Gartner Inc. [95], a technology research and consulting firm, consisting of 127 company leaders found that 82% of them plan to allow some form of remote work amongst their employees, with 47% allowing full time remote work.

A study done in the early phase of the pandemic is by Ozimek [96] who collected data from 1500 hiring managers including executives, VPs, and managers. They found out that a majority of managers agree that remote work functioned somewhat to much better than expected during the pandemic with no commute, reduced non-essential meetings, fewer distractions, and increased productivity being some of the main benefits. About one-third of managers also reported reduced team cohesion, difficulty in communications, and disorganized teams as some of the aspects that worked poorly during the pandemic. 61.9% of the managers reported more remote work than before going forward with 21.8% reporting an entirely remote workforce.

A more comprehensive dataset on employers side policies on remote work is presented by Flex Index [97] which reports that about 49% employers plan to take a fully on-site approach, 20% plan to take a structured hybrid approach (where an employer specifies the number of days or what days an employee should come to the office), and about 31% employers plan to take a fully remote or fully flexible approach to remote work. Amongst those who plan to follow a structured hybrid approach, their data reports the average number of days required on-site to be 2.49 days, with Tuesday, Wednesday and Thursday being more popular for on-site work compared to Monday and Friday. Their data also report technology, professional services, media/entertainment, financial services and insurance to be most flexible industries compared to others.

Emerging trends in e-commerce

Emerging literature captures a mixed trends in the adoption and future of e-commerce — varying significantly by product categories like grocery, restaurants and general merchandise.

On the end of overall spending across various product categories and acquisition channels, Said et al. [98] used the data from 720 US households and found that about 28% decline in the prepared food spending as a results of the pandemic but found that the overall spending was similar to pre-pandemic levels. They also found that more educated and higher income households shifted away from in-person spending, whereas politically conservative respondents were more likely to shop in-person and via pick up. Meyersohn [99] highlight that spending behavior potentially was impacted by inflation and forced individuals to shop in-person. Another aspect of in-person shopping is that of socialization, that too played a role in bringing individuals back to in-person. Townsend [100] point out that in come categories, such as clothing, percent of sales made online is back to pre-pandemic levels, since consumers are allocating more money to travel and entertainment.

With regards to grocery delivery, Thakker [101] highlight that, in march 2020, 1/3 U.S. households used online grocery, more than double of August 2019 — out of which 26% were first time buyers and 39% of those who were 60 years or older were first time buyers — suggesting that a significant number of new users were attracted towards online grocery. Data by Adobe [102] points that 41.8% of e-commerce (in 2021) was driven by only three categories: groceries, electronics, and apparel; with groceries contributing 8.9% to the overall share, which was about 6.3% in 2019.

With regards to food delivery, Ahuja et al. [103] found out that spending on online food delivery has doubled due to the pandemic and is about 4-7 times compared to 2018 levels - primarily driven by the convinence sought after Gen Z and Millenaials. However, they highlight that the consumers are paying a significant premium for delivery, which may impact the growth of food delivery. However, their data also suggest a growth of food delivery in suburban areas not just in urban areas.

2.4 Emerging trends in changed mobility landscape

Transit ridership and vehicle miles traveled

The impact of increased remote work since the pandemic is evident from several data sets related to transit ridership, and vehicle miles traveled [42, 46]. For example, as of mid-March 2023, U.S. national weekly transit ridership is about 68% of the pre-pandemic levels, with more severe impact in certain cities [46]. This number is 70% for New York city Metropolitan Transportation Authority (MTA), 67% for Chicago Transit Authority (CTA), 55% for Washington Metro Area Transit Authority (WMATA), 48% for Metra Commuter Rail in the Greater Chicago area, 49% for Metro Atlanta Rapid Transit Authority, 42% for San Francisco Bay Area Rapid Transit District (BART). Data also suggests a better recovery for transit buses compared to trains and regional rail, potentially related to remote workers making more local trips using buses instead of commuting longer distances using trains or commuter rail. U.S. national vehicle miles traveled estimates published by Federal Highway Administration (FHWA) show about 3% decrease between 2019 and 2022, potentially attributable to both remote work and inflation, but still far less given the multi-fold increase in remote work frequency in the last few years [42].

Activity participation

On the end of activity participation, studies suggests a significantly decreased activity in urban cores of large metropolitan cites and an increased activity in the peripheral areas of these cities due to movement of households outside of urban cores [45, 49, 104]. Chapple et al. [49] present activity recovery patterns for downtowns in various cities in the United States over time since the beginning of the pandemic. As of November 2022, the activity recovery is only about 31% for San Francisco, 38% for Portland, 47% for Detroit, 50% for Chicago, 53% for Boston, 55% for Minneapolis, 58% for Austin, 60% for Atlanta, and 74% for New York. They also present information on the relative recovery of downtown of a city compared to the overall city, which is far less than 100% for most major cities, suggesting that that recovery in downtown areas is less than in other parts of the cities, potentially related to teleworkers now making more trips around their place of residence instead of their work locations. As of April 2022, on the higher end, this value was 94% for Atlanta, 89% for Washington D.C., 87% for Tampa. On the lower end, this value was 43% Minneapolis, 48% for San Francisco, and 49% for Portland. Along the same lines, Ramani and Bloom [104] use data from U.S. postal service and Zillow to understand the migration patterns of households since the beginning of the pandemic and found a significant out flow of households from urban cores to peripheral areas of the cities. They term this as the 'donut effect' to highlight the hollowing of the urban cores and found this effect to be more prominent in big cities, less so in medium sized cities and a lot less in small sized cities. Emerging evidence on the activity participation of teleworkers also suggest teleworkers are taking significantly shorter out-of-home non-work trips (in terms of trip distance) and of shorter duration compared to those who do not telework. Furthermore, those who telework are less likely to perform out-of-home non-work activities and those who do so are performing these during 9 AM to 3 PM or 6-9 PM, compared to other times of the day. [88, 105]

Commercial real estate and impact on third sector of the economy

On the end of impact on commercial real estate and the third sector workers, emerging data sets point to an increased commercial real estate vacancy rates across the nation and a significant impact on the third sector workers who typically depend on spending by the commuters in the urban core for their income [45, 47, 48]. The quarterly vacancy rates were steady at about 11-12% pre-pandemic but have increased to about 15% since the beginning of the pandemic, with higher rates in some cities [47]. The vacancy rates are highest at 22.5% in Houston, 20.5% in Atlanta, 20.4% in Austin, 19.2% in San Francisco and Chicago; with lowest at 9.8% in Boston, 12.7% in Charlotte and 12.8% in Miami [48]. Althoff et al. [45] look at the impact of remote work on the consumer spending and its economic impact on non-skilled scalable services and found a significant decrease in consumer spending in big cities and they conclude that the workers in non-skilled scalable services sector were dis-proportionally impacted economically by the pandemic.

CHAPTER 3
DATA

Here, I discuss the two data sets used in this dissertation. I mainly focus on the overall structure of the survey design for various waves, timelines for data collection, sampling strategy, incentives provides to the respondents, response rates and descriptives of the respondent's socio-demographics. To maintain brevity, I omit the exact language of the questions in this chapter but rather talk about it in the respective chapters where data from those questions have been utilized. For the consumer / employee survey, detailed information on all the questions asked in the survey (including those that were not utilized in this dissertation) is available in Tahlyan et al. [106].

3.1 Longitudinal tracking survey to understand changing consumer spending, telework and mobility patterns through the pandemic

A 7-wave longitudinal tracking survey was conducted to monitor the evolving consumer spending, telework, and activity participation behavior associated with the COVID-19 pandemic, with the goal of deriving insights on expected post-pandemic telemobility patterns and its interaction with physical mobility. The survey was conducted between December 2020 and March 2022 through an online platform named Prolific [107] and resulted in data from 1877 unique respondents from the United States.

The data collected through the longitudinal online panel survey totaled *seven waves* at the emphfollowing time points, where the first six waves were disseminated about every two weeks between December 21, 2020, and March 8, 2021 and were followed by a seventh wave disseminated on March 28, 2022 *(about one year after wave 6)*:

- Wave 1: December 21, 2020
- Wave 2: January 11, 2021
- Wave 3: January 25, 2021
- Wave 4: February 08, 2021
- Wave 5: February 22, 2021
- Wave 6: March 08, 2021
- Wave 7: March 28, 2022

Questions on the following 13 categories of questions were included in the survey across 7 waves: 1) weekly consumer spending on groceries, cooked food and non-food items; 2) monthly consumer spending on electronics, furniture, clothing and digital media; 3) home delivery frequency for groceries, cooked meals and other non-food items; 4) telework related travel frequency through the pandemic; 5) travel, trip-making and time use behavior; 6) attitudes, perceptions and experiences of the individuals with telework and e-commerce through the pandemic; 7) use of subscription services like amazon prime, streaming services as well as local transit pass; 8) additional related question on pre-pandemic and post-pandemic expected behavior; 9) individual intention to use contact-free deliveries like delivery robots in the post-pandemic era; 10) a detailed 24-hr activity diary data; 11) direct impact of the pandemic like job loss, and COVID-19 infections; 12) individual experiences with depression, anxiety or positivity in life as a result of the pandemic; and 13) socio-demographics. This is followed by information on the survey dissemination strategy and incentives provided to the respondents and the response rate across various waves of the survey.

Figure 3.1 presents a summary of various blocks of questions asked in the 7-wave longitudinal survey, along with information on the waves in which they were asked. The 7-wave panel study consisted of several independent blocks of questions that allow for modularity across waves. Each survey is kept to a length of about *10 minutes (15-20 minutes for Wave 7)*. Several questions on household spending are included in every survey wave, representing a *core block* of the survey. Other questions were only included in a subset of the seven survey waves. A pre-COVID baseline questions were also included in waves 3 and 4 for some questions, where respondents were asked, retrospectively, for their typical frequency or amoount of a certain quantity like spending by various channels or frequency of telework.

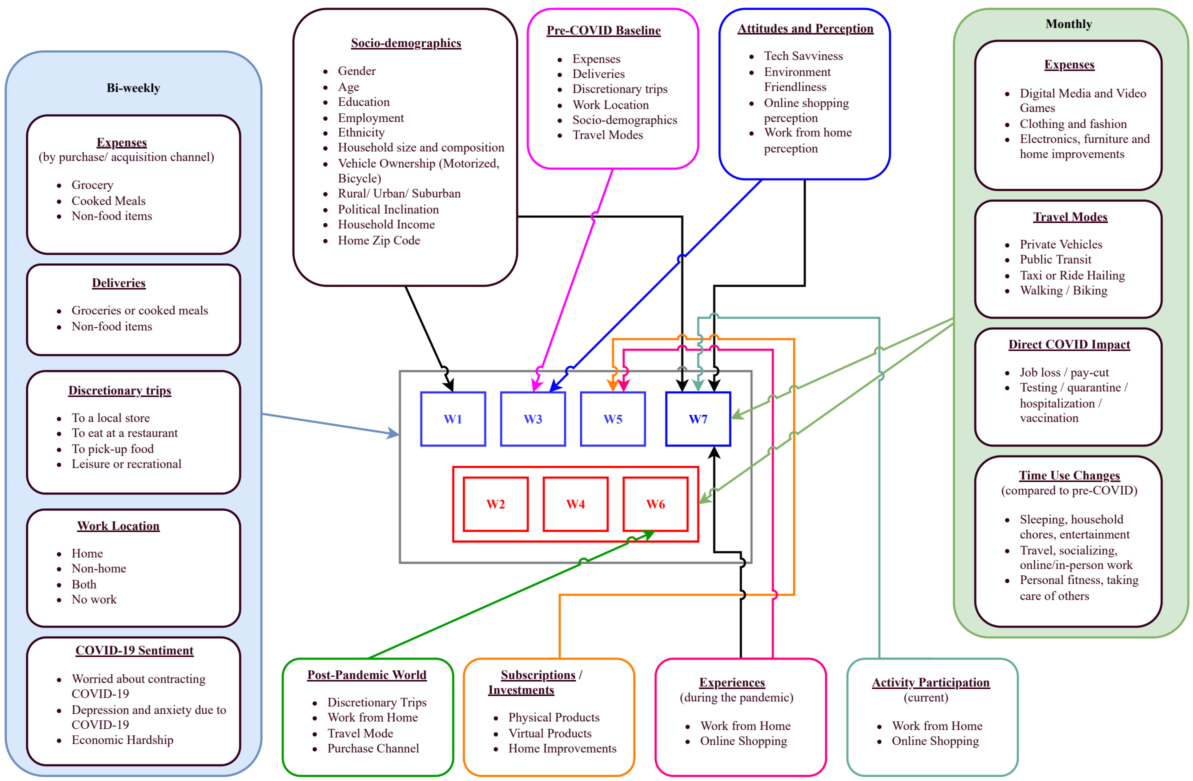


Figure 3.1: An overview of the 7-wave longitudinal survey

3.1.1 Survey Dissemination Strategy, Incentive Structure and Response Rate

Survey Dissemination

Table 3.1 presents the number of new, returning, total and cumulative unique respondent in each wave of the survey. Wave 1 of the survey started with 457 adults who were recruited to build a U.S. population representative sample by age, gender, and ethnicity. The respondent group was informed about 5 more subsequent waves of the survey and how much they would be paid each wave before they agreed to complete the survey. The 457 respondents were then later reinvited for waves 2 to 6, irrespective of whether they completed the previous wave of the survey. I call this the main sample of respondents.

Table 3.1: Overview of Longitudinal Survey Design and Respondent Recruitment

Wave	Date*	New Respondents	Returning Respondents	Total Responses	Cumulative Unique Respondents
1	Dec 21	457	-	457	457
2	Jan 11	107	372	479	564
3	Jan 25	103	421	524	667
4	Feb 08	101	466	567	768
5	Feb 22	103	485	588	871
6	Mar 08	101	516	617	972
7	Mar 28	905	386	1291	1877

* Wave 1 was disseminated in the year 2020; waves 2-6 were disseminated in 2021; wave 7 was disseminated in 2022

To make up for respondent attrition from the main sample, starting wave 2, a convenience sample with approximately 100 respondents was recruited in all waves till wave 6, who were then re-invited to participate in the subsequent waves, *if they have completed the previous wave*. We call this convenience sample as the top-up sample of respondents. Note that while the respondents in the main sample were reinvited for the subsequent waves regardless of whether they completed the previous wave, the respondents in the top-up sample were only invited if they had completed the previous wave of the survey.

In wave 7, everyone who joined waves 1 to 6 at least once was re-invited, along with a new U.S.

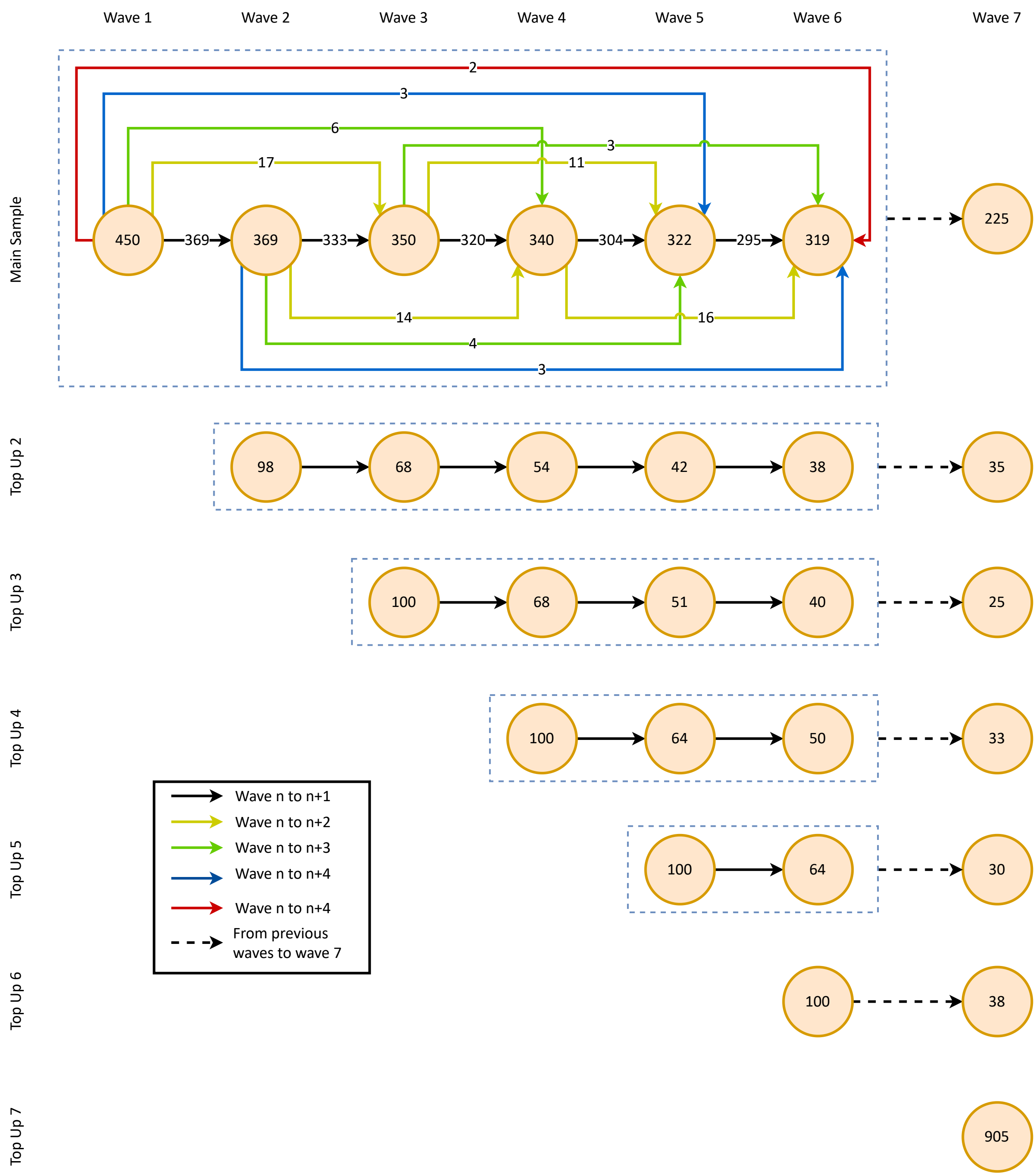


Figure 3.2: Respondents' retention / return dynamics across the 7 waves of the survey

population representative top-up of 905 individuals. Overall, the seven waves of surveys resulted in data from 1877 individuals, with a smallest size of 457 respondents in wave 1 and the largest sample size of 1291 in wave 7. Figure 3.2 presents detailed dynamics of the respondents' return in various waves of the survey, (which excludes individuals who either returned for a wave of the survey but didn't complete that wave or individuals whose responses didn't pass the quality checks like straight lining, failing the attention check question etc.).

Table 3.2: Incentive structure for various waves of the survey

Wave	Main Sample - Static	Main Sample - Growing	Top up
1	$1.00	$1.00	NA
2	$1.80	$1.25	$1.00
3	$1.80	$1.50	$1.00
4	$1.80	$1.75	$1.00
5	$1.80	$2.00	New Respondents = $1.00 Returning Respondents = $1.50
6	$1.80	$2.50	New Respondents = $1.00 Returning Respondents = $1.50
7	Ethnic minorities^ = $7.50 Others = $5.00 New Respondents = $3.50		

NA = not applicable since no top-up data were collected
^ethnic minorities include those who reported their ethnicities to non-white or non-asian

Incentive Structure

Table 3.2 presents the information on monetary incentives provides to the respondents in each wave of the survey. The sample initially started with $1 incentive in wave 1 but was randomly split into two group; 1) a group with a growing incentive payment amount for each subsequent wave starting from $1.25 in wave 2 to $2.50 in wave 6; 2) a group with a static incentive structure of $1.80 in each wave. This was done to test whether changing the incentive structure could potentially lead to better return rate than usual. In the top-up sample, a $1 incentive was offered for waves 2 to 4 for both the new respondents as well as the returning respondents. However, in wave 5 and 6, the returning respondents were offered $1.50 to help improve retention. For wave 7, since the survey was sightly longer than the previous surveys due to inclusion of an activity diary, everyone who was re-invented from the previous 6 waves (both main sample and top-up sample) was offered an incentive of $5 if the respondent was of White or Asian ethnicity but was offered an incentive of $7.5 otherwise. This was done to improve the return rate from ethnic minorities since our data from the previous waves showed lower return rate from ethnic minorities. Lastly, new respondents in wave 7 were offered an incentive of $3.50.

Response Rate

As summarized in Table 3.1 and Figure 3.2, a total of 1877 unique respondents participated in the survey over the seven waves. Across these seven waves, 180 individuals participated in all 7 waves, 97 participated in 6 waves, 80 participated in 5 waves, 72 participated in 4 waves, 102 participated in 3 waves, 135 participated in 2 waves and 1211 participated in 1 wave (including wave 7 top-up). Out of the 972 respondents who participated in waves 1 to 6, who were then invited for wave 7, 386 returned to complete the survey. This corresponds to a return rate of 39.7%.

3.1.2 Sample Description and Statistics

Table 3.3 (also included in Tahlyan et al. [106]) presents the sample statistics of respondents from each of the 7 waves and its comparison with the U.S. population statistics. Further, Figure 3.3 presents the location of centroids of the zip codes of the respondents' residential locations at the time when they first joined the panel. The size of the markers is proportional to the number of respondents who joined from a zip code. Collectively, several important observations can be made from Table 3.3 and Figure 3.3 which highlights the quality of the data collected across the 7 waves of the data collected. Spatially, the respondents are well distributed across the United States and data have been collected from 49 out of 50 states (excluding Vermont) and Washington D.C. A comparison of sample share and population share for a few selected states is presented in Table 3.3 where the sample shares for data in each wave is within a few percentage points of the population share.

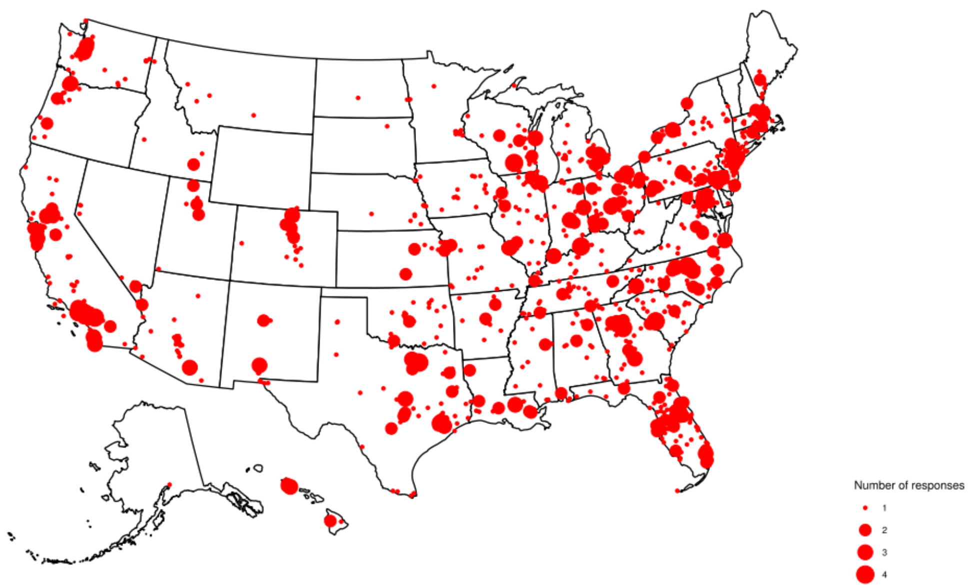


Figure 3.3: Zip Code centroid of respondent's location at the time of recruitment

Our data is slight younger than the population. Specifically, our sample has higher proportion of respondents in the 55-64 years age group compared to 65 years or older, which is generally expected from online panels since the older individuals tend to find technology driven online survey difficult. Even though our samples were designed to be age representative (at least in parts) this mismatch is also a likely manifestation of the fact that oldest age group coded in prolific panel is 58 years or older instead of 65 years or older.

Our sample matches well with the population shares in terms of ethnicity expect a marginally

Table 3.3: Sample statistics per wave compared with U.S. population

Statistics†	Wave 1	Wave 2	Wave 3	Wave 4	Wave 5	Wave 6	Wave 7	U.S. population / other sources* (%)
State								
California	10.5%	10.5%	11.4%	10.5%	12.5%	11.6%	11.2%	12.0%
Florida	8.7%	7.8%	8.3%	9.1%	7.6%	7.6%	8.1%	6.7%
New York	8.0%	8.5%	8.3%	8.2%	8.0%	7.6%	6.0%	6.2%
Texas	6.7%	7.6%	6.7%	6.9%	7.6%	8.5%	7.9%	8.3%
Gender								
Male	48.7%	48.7%	48.0%	48.0%	48.4%	48.8%	47.5%	49.2%
Female	50.0%	50.2%	50.4%	50.2%	50.0%	50.6%	50.8%	50.8%
Non-Binary	1.3%	1.1%	1.6%	1.8%	1.6%	0.7%	1.54%	-
Age								
18-24 years	10.9%	12.9%	12.0%	11.1%	11.1%	11.1%	11.7%	11.9%
25-34 years	19.3%	20.4%	21.3%	20.0%	20.2%	19.6%	20.0%	17.9%
35-44 years	19.1%	18.2%	18.4%	18.9%	19.6%	19.3%	18.0%	16.4%
45-54 years	16.7%	15.3%	14.4%	15.8%	15.6%	16.7%	16.7%	16.0%
55-64 years	19.6%	19.6%	19.8%	20.0%	19.6%	19.6%	19.0%	16.6%
65 years or older	14.4%	13.6%	14.0%	14.2%	14.0%	13.8%	14.6%	21.2%
Race & Ethnicity								
White	70.2%	69.6%	70.2%	69.8%	70.2%	70.9%	73.2%	74.1%
Black	14.4%	12.9%	12.7%	13.3%	12.7%	12.2%	11.7%	12.3%
Asian	8.0%	9.8%	8.7%	8.9%	8.7%	8.7%	6.7%	5.7%
Hispanic or Latino‡	4.4%	4.9%	5.6%	5.3%	5.1%	4.7%	5.3%	-
Other	2.9%	2.9%	2.9%	2.7%	3.3%	3.6%	3.1%	7.8%
Political Leaning								
Liberal	53.6%	56.3%	56.0%	57.9%	60.4%	58.8%	57.9%	26.0%
Moderate	19.2%	18.2%	18.7%	16.7%	16.6%	16.6%	19.9%	36.5%
Conservative	27.1%	25.5%	25.3%	25.5%	23.1%	24.6%	22.3%	37.5%
Income								
< $25,000	14.4%	15.5%	16.1%	16.5%	16.2%	16.4%	17.6%	14.9%
$25,000 - $49,999	25.6%	26.9%	26.6%	25.2%	26.3%	24.9%	24.5%	19.1%
$50,000 - $99,999	30.8%	32.8%	31.6%	34.0%	32.6%	33.1%	37.6%	32.0%
$100,000 - $149,999	16.0%	14.1%	14.9%	14.2%	14.2%	13.7%	12.7%	17.3%
≥ $150,000	13.2%	10.7%	10.8%	10.1%	10.7%	11.9%	7.6%	16.7%

‡*Survey inquired about race and ethnicity as a single category, whereas the census inquires about Latin/Hispanic origins separately (18.4% of the population)*

**Sources: U.S. Census (U.S. Census Bureau, 2019): state, gender, age, race, ethnicity, and income*
Gallup 2020 Sample (Saad, 2021): political leaning

over-representation of respondents with Asian ethnicity. Politically, the sample is *liberal leaning*. Finally, the sample has some under-presentation of high-income individuals, especially in the $100,000 or above income group. I correct for some of the representative-ness related deficiencies of the data using sample weights derived using the American Community Survey (ACS) data set as needed and the details regarding this is presented in the respective chapters later.

3.2 Longitudinal tracking survey to understand employer side remote work policies through and beyond the pandemic

The data used in the employer study comes from a 5-wave longitudinal survey conducted between October 2021 and August 2022 amongst top executives of 129 unique North American companies. Initial invitations consisted of a total of 198 unique employers, primarily associated with Northwestern University Transportation Center (NUTC)'s business advisory council (BAC) [108]. Upon invitation, respondents had an option to either opt out of the current and future surveys, complete the current survey but opt out of future surveys or to complete the current survey and express interest in being invited for the future surveys. Based on the respondent's responses to this question, they were re-invited for future surveys.

The survey was designed via the Qualtrics platform and was sent to the respondents via email. The timelines for various waves of the survey are given below:

- Wave 1: October 2021
- Wave 2: December 2021
- Wave 3: January 2022
- Wave 4: March 2022
- Wave 5: August 2022

Five categories of questions were asked of the respondents regarding their organization:

1. *demographic information*, which included questions on:

   (a) the sector of operations of the organization defined as per the North American Industry Classification System (NAICS) [109] with an option to also describe their specific sector in their own words.

   (b) percentage of the workforce that is typically customer-facing and/or must perform their work on-site (to be expressed using a sliding scale varying from 0 to 100)

   (c) number of employees in their organization (options included: 1-9, 10-49, 50-99, 100-499, 500-999, 1000-4999, 5000-9999, 10000 or more)

   (d) annual revenue of their organization (options included: less than \$10 million, \$10 million - \$100 million, \$100 million to \$500 million, \$500 million - \$1 billion, more than \$1 billion, prefer not to disclose)

   (e) the region of operations (option included (select all that apply): Northwest, West, Midwest, Southwest, Southeast, Mid-Atlantic, Northeast, Nationally across the U.S., Internationally).

   These questions were asked in every wave of the survey.

2. *employers' approach to employee remote work for whom it is possible* at various time points before and during the pandemic and the expected work location in the future. The time points included:

   (a) *September 2019* (before the pandemic)

(b) *a few past time points during the pandemic relative to when the survey was done* (Wave 1: none, Wave 2: April 2020 [1] , Wave 3: April 2020 and October 2021 [2] , Wave 4: April 2020, October 2021, and January 2022, Wave 5: April 2020, October 2021, January 2022 and April 2022)

(c) *current time point* (Wave 1: October 2021, Wave 2: November 2021, Wave 3: January 2022, Wave 4: April 2022, and Wave 5: August 2022)

(d) *few future time points relative to when the survey was conducted* (January 2022 [3] , April 2022, October 2022 and April 2024)

The possible response options included: Fully in-person, Mostly in-person, About 50/50, Mostly remote, Fully remote and I don't know[4]. For the future time points in each wave, an additional option of 'wait and see' was also included to capture the responses where an employer has not yet decided on their future remote work policy. Given that the remote work approach potentially varies by department, we inquired separately for the following three departments within an organization (if applicable): sales / marketing, IT / development, administration / finance / legal / human resources.

3. their opinion towards the potential impact of a 2-day-a-week remote work policy in their organization on various business aspects. Specifically, we asked the employers to imagine

[1] This time point was included in wave 2 and beyond to capture the remote work policies during the early peak of the pandemic

[2] Note here that October 2021 was a past time point in wave 2 and beyond but was current time point in wave 1. Similarly, January 2022 was past time point in wave 4 and 5 but was current time point in wave 3; and April 2020 past time point in wave 5 but was current time point in wave 4.

[3] Note here that January 2022 and April 2022 were future time points during waves 1 and 2. However, during wave 3 while January 2022 was current time point, April 2022 was a future time point. Similarly, during wave 4, April 2022 was a current time point.

[4] While we provided the respondent to choose 'I don't know' as an option in accommodate cases where the respondent does not know the approach their organization took or will take (potentially due to the respondent not being in a decision-making position), no respondent chose this option in any of the waves.

that their company committed to a future work program allowing a hybrid workforce with an option of remote work for 2 days a week and what effects will such program have on the following 9 business aspects:

(a) ability to recruit / retain employees
(b) profitability
(c) long-term viability
(d) ability to compete
(e) ability to innovate
(f) public image
(g) employee productivity
(h) employee creativity
(i) employee supervision and mentoring

The possible response options included: very negative, somewhat negative, neither negative nor positive, somewhat positive, very positive, and no opinion. This question was asked in every wave of the survey.

4. additional questions on:

   (a) the extent of resumption of business travel of over 50 miles and in-person client interactions at the time of various waves of the survey; Specifically, we asked the employers to report the extent to which (in terms of percentage) business travel of over 50 miles and in-person client interactions in their organization has resumed compared to the pre-pandemic levels, with zero percent being that none has resumed and a hundred percent being that all have returned. This question was included in all waves of the survey.

(b) whether their organization has (or plan to) added, reduced, relocated office space in the same or different area or building since the beginning of the pandemic. This question was only included in wave 5.

Our survey also included questions on policies regarding masking, vaccinations, testing for COVID-19 infection at the work location and the work location policies their peer companies have adopted, return of business travel of over 50 miles, local in-person client interactions, and firm's office space reorganizations decisions. However, for brevity, we have not included results from the data corresponding to these sets of questions. Most of these questions were asked in every wave of the survey but a few were included in one or two specific waves taking into consideration the evolving telework trends at the time of the survey.

3.2.1 Sample Descriptives

Table 3.4 presents the descriptive statistics for the data corresponding to each wave of the survey as well as for the combined data. Figure 3.4 present the distribution of region of operations of various organizations in the data.

In terms of the sample size, our data correspondent to 129 unique employers across the 5 waves who completed the survey in at least one of the waves, where 62 employers completed the survey in wave 1, 43 completed it in wave 2, and 34 completed it in wave 3. In wave 4 and 5, we augmented our invitation list with new employers to boost the sample size and this led to 45 respondents completing the survey in wave 4 and 56 respondents completing the survey in wave 5. Overall, we send invitations to 198 unique employers. Across the 5 waves, 71 employers responded to only one wave, 29 responded to two waves and another 29 respondents to three or more waves of the survey.

Our sample consists of about 61% of employers from the transportation, logistics, warehousing

Table 3.4: Sample statistics for data in various waves and the combined data

Variable		All waves	Wave 1	Wave 2	Wave 3	Wave 4	Wave 5
Number of Respondents		129	62	43	34	45	56
Number of Employees	1 to 99	14.00%	10.30%	9.10%	8.80%	11.60%	13.70%
	100 to 999	28.70%	29.40%	27.30%	38.20%	34.90%	31.00%
	1000 to 9999	22.50%	29.40%	29.50%	23.50%	20.90%	15.50%
	10000 or more	34.90%	30.90%	34.10%	29.40%	32.60%	39.70%
Sector	Transportation	53.50%	51.50%	54.50%	64.70%	44.20%	58.60%
	Manufacturing	7.80%	10.30%	11.40%	8.80%	9.30%	8.60%
	Others	38.80%	38.20%	34.10%	26.50%	46.50%	32.80%
Annual Revenue	Less than $100 mil	24.80%	17.70%	11.40%	20.60%	18.60%	31.00%
	$100 mil to $1 bil	16.30%	22.10%	22.70%	29.40%	25.60%	13.80%
	$1 bil to $5 bil	27.10%	32.40%	31.80%	23.50%	25.60%	20.70%
	More than $5 bil	27.90%	26.50%	29.50%	26.50%	25.60%	31.10%
	Prefer not to disclose	3.90%	1.50%	4.50%	0.00%	4.70%	3.40%
Percentage of workforce required to in-person	Percentage	55.48%	54.03%	59.45%	55.94%	49.93%	56.59%

and manufacturing sectors and the rest 39% from other sectors (which is because members of the NUTC's BAC are primarily transportation, logistics, and warehousing companies). Figure 3.5 presents a word cloud of the sector of operations of various respondents in the survey in their own words, which highlights that the transportation sector is prominent in the data. Other sectors included employers from freight, railroad, third-party logistics, software, consulting, management, and data services.

On an average, 55.48% of the workforce of the organizations in our data is customer-facing or must perform work in person with the standard deviation being 29.53%. A large share of companies in our sample have more than 10,000 employees, have more than $5 billion in annual revenue ($25 billion in many cases), and a majority have a presence across the United States (with several having an international presence). More than 90% of respondents in our data are vice president (VP) or chief executive officer (CEO) level senior executives, with the rest being director-level

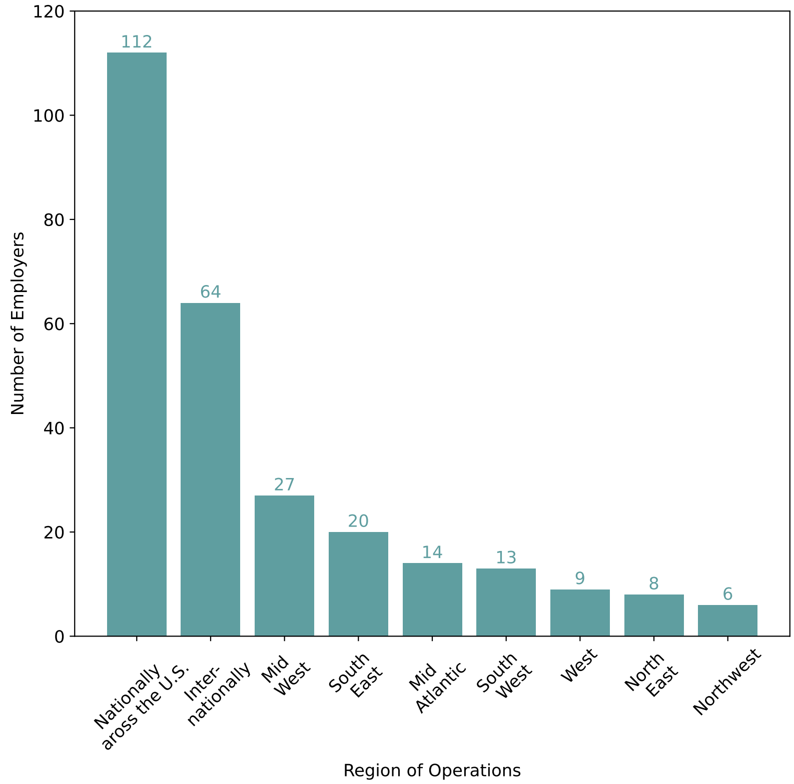


Figure 3.4: Employers' organizations' region of operations

Figure 3.5: Employers' organizations' region of operations

managers.

Overall, this highlights that the respondents in our data speak for a large number of employees and their decisions regarding remote work will potentially have an impact on the work location decisions of a large number of individuals.

CHAPTER 4
METHODOLOGICAL FOUNDATIONS

4.1 Generalized Latent Variable Modeling Framework

The methodological approach followed in this dissertation can be broadly put in a generalized latent variable modeling framework (see Figure 4.1, adapted from Muthén and Muthén [110]), which consists of two types of latent (unobservable) variables: continuous (also known as factors, f) and categorical (also known as classes, c). Here, x corresponds to observed covariates (continuous or categorical, typically socio-demographic variables), y corresponds to continuous observed outcome variables and u corresponds to ordered, count or binary variables — both of which can either be used to measure the latent variables (known as indicators) or are being predicted as a function of latent variables or directly as a function of covariates (known as distal outcome). Ellipse A corresponds to a model with only continuous latent variables and ellipse B corresponds to a model with only categorical latent variables. While not shown here, the model could have multiple factors regressed on each others, multiple classes interacting with one another, or covariates directly regressed on outcome variables.

Several popular models in the field of transportation can be thought to follow some form of this generalized framework. For example, a multinomial/ordered logit/probit model consists of categorical or ordered outcome variables specified as a function of observed covariates. Similarly, an integrated choice and latent variable model (ICLV) consists of a discrete choice distal outcome, a set of continuous latent variables and a set of covariates regressed on both latent variables as well as discrete choice variable.

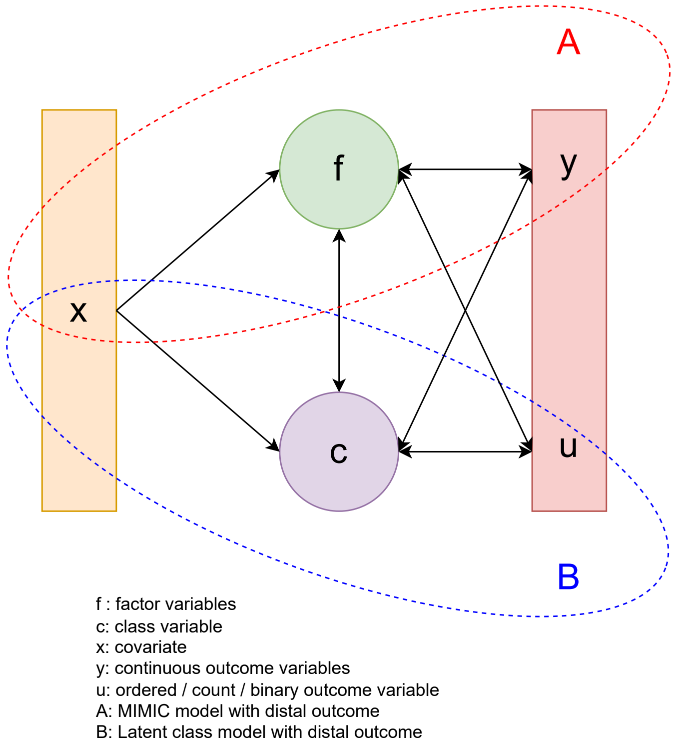


Figure 4.1: A generalized latent variable framework ([110])

In this dissertation, I utilize several model types: a) those that use no latent variables — multinomial / binary logit and ordered logit / probit; b) those that use one or more factor variables — a multiple indicator multiple cause model (MIMIC); c) those that use latent class variable — latent class analysis without and with covariates; d) those with interacting latent classes over time as well as factor variables — latent transition analysis with random intercepts. In a part of this dissertation, I also utilize hierarchical agglomerative clustering, followed by estimation of a multinomial logit based membership model. While the hierarchical clustering with deterministically defined clusters is not a typically utilized method within the latent variable modeling paradigm (where methods with stochasticity in latent variables are more preferred), this method comes with the benefit of taking sequential nature of the data into consideration while determining the clusters. However, in its crude form, the model is quite similar to a latent class model with covariates.

I briefly discuss these models in this chapter. In the respective chapters where I utilize these model, only relevant mathematical details will be discussed for brevity.

4.2 Ordered Logit / Probit

The ordered probit / logit model [111] is utilized to estimate a predictive model that connects an ordered outcome with a set of covariates. An ordered model consists of a latent propensity u^* such that:

$$u^* = x^{'}\gamma + \epsilon \tag{4.1}$$

where x is a vector of exogenous variables, γ is a vector of estimable parameters and ϵ is standard normally distributed error term in case of a probit framework and logistically distributed in case of logit framework. The latent propensity function u^* is related to the reported $J - point$ response item u in the following manner:

$$u = \begin{cases} 1 & \text{if} \quad u^* \leq \psi_1 \\ j & \text{if} \quad \tau_{j-1} < u^* \leq \tau_j \; \forall \; j \; \epsilon \; (2, \ldots, \; J-1) \\ J & \text{if} \quad \tau_{J-1} \leq u^* \end{cases} \tag{4.2}$$

where $\tau_j \; (j = 1, \; 2, \; \ldots, \; J-1)$ are estimable thresholds dividing the propensity function. Note here that to ensure model identification, either τ_1 or a constant in u^* can be estimated and the other parameter should be fixed to zero. Given the above equations, probability $P(u)$ of observing the ordered variable u is written as:

$$P(u) = \begin{cases} \Phi(\tau_1 - x^{'}\gamma) \\ \Phi\left(\tau_j - x^{'}\gamma\right) - \Phi\left(\tau_{j-1} - x^{'}\gamma\right) \ \ \forall\, j\, \epsilon\, (2, \ldots,\ J-1) \\ 1 - \Phi\left(\tau_{J-1} - x^{'}\gamma\right) \end{cases} \tag{4.3}$$

where $\Phi(\cdot)$ is standard normal cumulative distribution for a probit framework and logistic distribution cumulative function for a logit framework.

I utilize this model in three different studies. In chapter 5, I utilize an ordered probit model to study the factors impacting telework satisfaction during the pandemic. Next, in chapter 6 I utilize an ordered logit model to understand the factors impacting April 2024 expected work location of employees. Lastly, in chapter 7, I again utilize an ordered probit model to understand factors impacting expected April 2024 work location decision of employers.

4.3 Multinomial Logit

A multinomial logit model is a discrete outcome model that is often used to associate a multinomial variable with a set of covariates (x). The model, often associated with a utility maximization decision rule, consists of a discrete outcome variable u, for an individual n, using a linear-in-parameter function T_{un} such that:

$$T_{un} = \beta_u^{'} x_{un} + \epsilon_{un} \tag{4.4}$$

$$P_n(u) = P\left(T_{un} \geq T_{Un}\right) \quad \forall\, U \neq u \tag{4.5}$$

$$P_n(u) = P\left(\beta_u^{'} x_{un} + \epsilon_{un} \geq\ \beta_U^{'} x_{Un} + \epsilon_{Un}\right)\ \ \forall\ U \neq u \tag{4.6}$$

$$P_n(u) = P\left(\beta'_u x_n - \ \beta'_U x_{Un} \geq \epsilon_{Un} - \epsilon_{un}\right) \ \forall \ U \neq u \tag{4.7}$$

where β_u is a vector of estimable parameter for category u, x_{un} is a vector of covariates and ϵ_{un} is a gumbel distributed error term. The probability of being in category u for observation n, $P_n(u)$, can be written as the following closed form expression:

$$P_n(u) = \frac{e^{\beta_u x_{un}}}{\sum_{\forall u} e^{\beta_u x_{un}}} \tag{4.8}$$

I utilize a multinomial logit model in two different occasions in this dissertation: 1) in chapter 6 where I estimate a cluster membership model that associates a set of individual characteristics like age or sector of their job with the discrete trajectory cluster variable that was determined using a hierarchical clustering technique; 2) later, in the same chapter, where I estimate a binary logit model (i.e. with only two possible options in the discrete outcome variable) to associate an individual's socio-demographic information with an outcome variable that captures whether or not there is certainty in their future work location in April 2024.

4.4 Multiple Indicator Multiple Cause (MIMIC) Model

In chapter 5, I estimate a multiple indicator multiple cause model [112] that allows for an inclusion of continuous latent factors (measured using a set of discrete binary indicators in this dissertation) in an ordered probit model in order to control for latent factors like perceived benefits or barriers while understanding the effect of other socio-demographics.

Figure 4.2 presents a graphical representation of a MIMIC model. The MIMIC model, in my case, consists of an ordered probit distal component where latent factors capturing information regarding perceived / experienced benefits or barriers are to be included. This is done using two sets

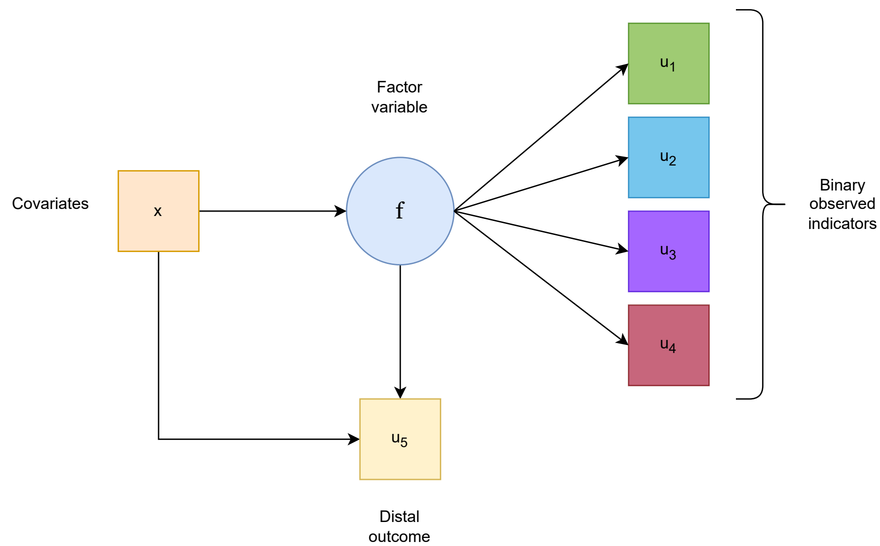


Figure 4.2: A graphical representation of a MIMIC Model

of equations: 1) *a structural model*, capturing the inter-relationship between different latent factors and the relationship between socio-demographic information and latent factors; 2) *a measurement model*, capturing the relationship between continuous latent variables and their observed indicators (all of which are binary in my case) [113]

Structural Model

The structural model defines the inter-relationships between continuous latent variables and the relationship between the latent variables and observed socio-demographic information. In its general form, the structural model can be written as:

$$f = \alpha + Bf + \Gamma x + \epsilon \tag{4.9}$$

where f is a vector of latent variables, α is a vector of intercepts, B is matrix of parameters governing the relationship between latent variables, Γ is a matrix of regression parameters representing the relationship between observed socio-demographic information and latent variables and ϵ is a vector of error terms.

Measurement Model

The measurement model specifies the relationship between the latent variables and its indicators using the following equation:

$$u^* = \nu + \Lambda f + Kx + \mu \tag{4.10}$$

where u^* is a vector of continuous latent variables (assuming that the indicators are categorical), ν is a vector of intercepts, Λ is a factor loading matrix and μ is a vector of measurement errors, and K is the regression parameter matrix defining the relationship between u^* and x. The relationship between u^* and the observed response u to the indicator can be defined using an ordered logit type framework as mentioned earlier.

4.5 Latent Class Analysis

Figure 4.3 presents graphical representation of latent class analysis that I use at several occasions: 1) in chapter 6 where I study employee attitudes / outlook towards the impact of remote work on various work aspects; 2) in chapter 7 where I use the employer side on a similar question as earlier - but now from the employer perspective instead of employees.

A latent class model can be unconditional (i.e. without the covariates) or conditional (i.e. with covariates). For an unconditional latent class model, consider, $u_k \; \forall \; k = 1, 2, ..., K$ observed variables with $r_{u_k} = 1, 2, ..., R_{u_k}$ response categories in each observed variable, which forms a vector of observed response patterns for each respondent, $\mathbf{y} = (r_{u_1}, r_{u_2}, ..., r_{u_K})$. We are interested

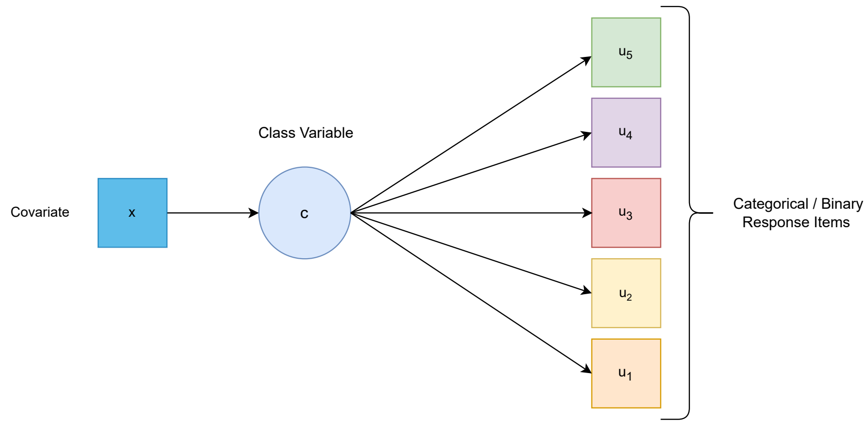


Figure 4.3: A graphical representation of a latent class model

in $P(Y = \mathbf{y})$, where Y is a vector of response pattern and $\sum P(Y = \mathbf{y}) = 1$. Two sets of parameters are estimated here: 1) γ_{c_j}, which represents the percentage of respondents in the data belonging to a latent class c_j, where $j = 1, 2, J$; 2) $\rho_{u_k, r_{u_k}|c_j}$, which represents the probability of responding r_{u_k} to the u_k^{th} observed variable conditional on membership in class c_j. The response vector probability conditional on latent class c_j in the model is written as:

$$P\left(Y = \mathbf{y}|c = c_j\right) = \prod_{k=1}^{K} \prod_{r_{u_k}=1}^{R_{u_k}} \rho_{u_k,\, r_{u_k}|c_j}^{I\left(y_{u_k}=r_{u_k}\right)} \tag{4.11}$$

where the fundamental expression to be estimated can be derived using the total probability theorem as:

$$P\left(Y = \mathbf{y}\right) = \sum_{j=1}^{J} \gamma_{c_j} \prod_{k=1}^{K} \prod_{r_{u_k}=1}^{R_{u_k}} \rho_{u_k,\, r_{u_k}|c_j}^{I\left(y_{u_k}=r_{u_k}\right)} \tag{4.12}$$

and the class membership probability for each respondent conditional on their response vector can be estimated using the Bayes' theorem as below:

$$P\left(c = c_j | Y = \mathbf{y}\right) = \frac{P\left(Y = y | c = c_j\right) P(c = c_j)}{P(Y = y)} \tag{4.13}$$

$$P\left(c = c_j | Y = \mathbf{y}\right) = \frac{\prod_{k=1}^{K} \prod_{r_{u_k}=1}^{R_{u_k}} \rho_{u_k,\, r_{u_k}|c_j}^{I\left(y_{u_k} = r_{u_k}\right)} \cdot \gamma_{c_j}}{\sum_{j=1}^{J} \gamma_{c_j} \prod_{k=1}^{K} \prod_{r_{u_k}=1}^{R_{u_k}} \rho_{u_k,\, r_{u_k}|c_j}^{I\left(y_{u_k} = r_{u_k}\right)}} \tag{4.14}$$

The estimation of a membership model to incorporate exogenous variables (x) in the model, γ_{c_j} can be expressed as a function of x and the fundamental expression conditional on x can be written as:

$$P\left(Y = \mathbf{y} | x\right) = \sum_{j=1}^{J} \gamma_{c_j}(x) \prod_{k=1}^{K} \prod_{r_{u_k}=1}^{R_{u_k}} \rho_{u_k,\, r_{u_k}|c_j}^{I\left(y_{u_k} = r_{u_k}\right)} \tag{4.15}$$

where instead of estimating γ_{c_j}, a logit formulation is used and its parameters are estimated.

4.6 Latent Transition Analysis (LTA)

Figure 4.4 presents a graphical representation of a latent transition analysis framework, which is a longitudinal extension to the latent class analysis and is useful when data are available for more than two time points. I utilize a more advanced version of LTA called LTA with random intercepts (RI-LTA) in Chapter 8, however, here I discuss LTA first to highlight the shortcomings of LTA which are corrected by a RI-LTA model. Details regarding the RI-LTA model are presented in the next section.

LTA is essentially a type of latent markov model and falls in the category of models where a latent variable in treated as categorical in nature, as opposed to factor analysis where a latent variable is treated as continuous. The categorical nature of the latent variable allows for the measurement of different classes in the data, defined based on different likelihood of response to various indicators.

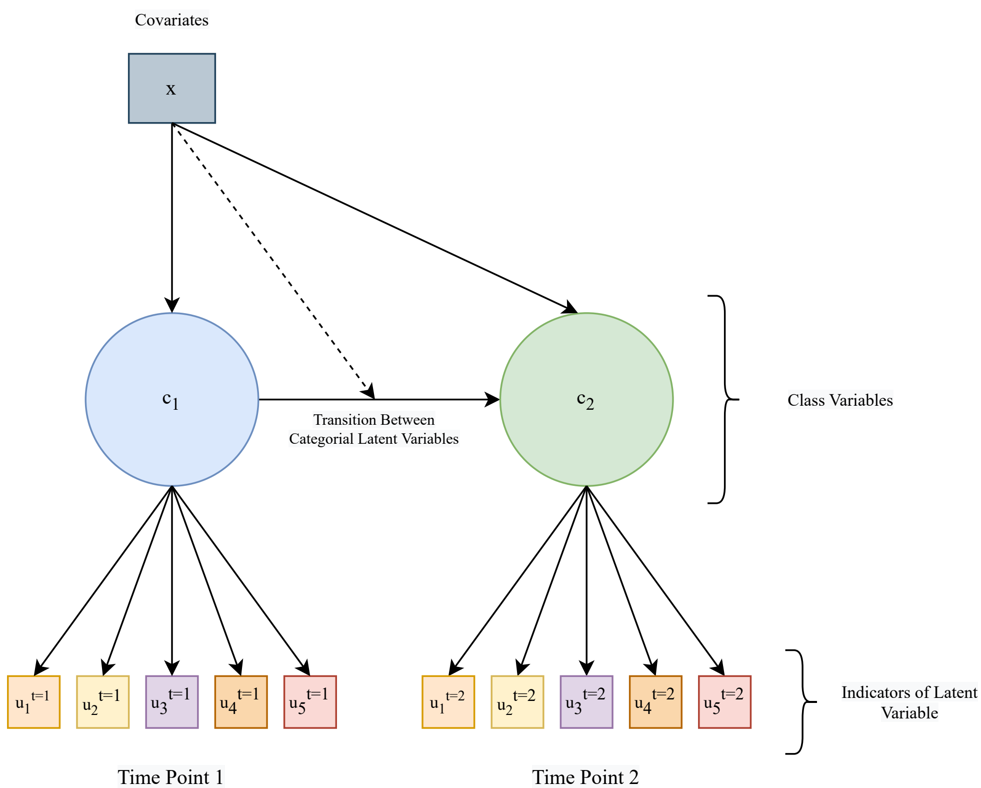


Figure 4.4: A graphical representation of a latent transition model

Similar to LCA, LTA can also be estimated without or with covariates. In Figure 4.4, $u_1^{t=1}$, ..., $u_J^{t=1}$ and $u_1^{t=2}, \ldots, u_J^{t=2}$ are the indicators used at the two time points to measure the latent variables. Further, arrows pointing from the latent variables to the indicators depict how the latent variable impacts the indicators and the arrow pointing from c_1 to c_2 depicts how the latent variable at time point 1 impacts the latent variable at time point 2. Note that the process is considered a markov process since LTA normally assumes no arrows pointing from t_{n-2} to t_n or further in the past and only the relationship of latent variables at t_{n-1} to t_n is allowed (i.e. only first order effects are allowed, not second order and beyond).

For a more mathematical representation of the latent transition analysis framework, in an unconditional LTA, consider, $u_k^t \; \forall \; k = 1, 2, ..., K$ and $\forall \; t = 1, 2, ..., T$ with $r_{u_k^t} = 1, 2, ..., R_{u_k^t}$ response categories in each observed variable at different time points, which forms the response vector for each respondent, $\mathbf{y} = (r_{u_1^1}, r_{u_2^1}, ..., r_{u_K^1}, ..., r_{u_1^T}, r_{u_2^T} ... r_{u_K^T})$. We are interested in $P(Y = \mathbf{y})$, where Y is a vector of response pattern and $\sum P(Y = \mathbf{y}) = 1$.

Consider c_t to be a categorical latent variable at time t where $c_t = c_{t,1}, ..., c_{t,J}$ are latent classes in c_t. For simplicity, assuming that the number of latent classes are same across time periods (i.e. J classes at each time period), there are three sets of parameters that are estimated in an unconditional LTA:

- $\delta_{c_{t,j}}$ (latent class prevalence at time t such that $\sum_{j=1}^{J} \delta_{c_{t,j}} = 1$). In simpler terms, this is interpreted as the proportion of individuals in the data corresponding to a latent class $c_{t,j}$ at time point t.

- $\rho_{u_k^t, r_{u_k^t} | c_{t,j}}$ (item response probabilities) which are usually constrained to be equal across time periods and correspond to a *measurement invariance* assumption in the model. The item response probability is interpreted as the probability of responding $r_{u_k^t}$ to item u_k^t conditional on class membership $c_{t,j}$ at time t.

- $\tau_{c_{t+1,j'} | c_{t,j}}$ (probability of transition between latent classes between consecutive time points. Transition probabilities are usually presented in a transition matrix as below.

$$\text{Transition Matrix} = \begin{bmatrix} \tau_{c_{t+1,1}|c_{t,1}} & \tau_{c_{t+1,2}|c_{t,1}} & \cdots & \tau_{c_{t+1,J}|c_{t,1}} \\ \tau_{c_{t+1,1}|c_{t,2}} & \tau_{c_{t+1,2}|c_{t,2}} & \cdots & \tau_{c_{t+1,J}|c_{t,2}} \\ \cdots & \cdots & \cdots & \cdots \\ \tau_{c_{t+1,1}|c_{t,J}} & \tau_{c_{t+1,2}|c_{t,J}} & \cdots & \tau_{c_{t+1,J}|c_{t,J}} \end{bmatrix} \tag{4.16}$$

Using the above notations, the fundamental expression, $P(Y = \mathbf{y})$, of interest in LTA is written as:

$$P(Y = \mathbf{y}) = \sum_{c_1=1}^{J} ... \sum_{c_T=1}^{J} \delta_{c_1} \tau_{c_2|c_1} ... \tau_{c_t|c_{t-1}} \prod_{t=1}^{T} \prod_{k=1}^{K} \prod_{r_{u_k^t}}^{R_{u_k^t}} \rho_{u_k^t, r_{u_k^t}|c_{t,j}}^{I(y_{u_k^t} = r_{u_k^t})} \tag{4.17}$$

Note here that the latent class prevalence parameters (δs) are estimated only for time period 1 and then determined using the transition parameters for the remaining time periods. A standard and more popular version of the LTA makes two important assumptions. The first is of *local independence* of the indicators which states that the observed variables are independent of each other conditional on the latent variables. In other words, the local independence assumption assumes that the latent class variables accounts for the association between the observed variables. Second, assumption is of *measurement invariance* across time periods which means that the number of latent classes and their definitions are assumed to be constant over time. This means that the ρs are fixed across time periods. While this assumption can be relaxed in the standard LTA model, it is often made to allow for easy interpretation (since class definitions are now fixed and only proportions and transitions are interpreted) and estimation of the model (since significantly less number of parameters are to be estimated now).

Multiple ways of introducing covariates in an LTA model exists, with second parameterization presented by Muthén and Asparouhov [114] being more popular and is utilized in this dissertation (see Table 2 of Muthén and Asparouhov [114]), where a a logit based membership model for initial time point latent classes is estimated, along with one logit for a class at time point $t-1$ to all classes in time point t. All of these are estimated jointly, along with the measurement model.

While LTA has been a popular model for more than a decade, it has a few limitations as highlighted in Muthén and Asparouhov [115] recently. Main criticism of regular LTA is that it does not separate time-invariant between-level variation across subjects from within-level variation over time — which is important and particularly of interest to understand behavioral transitioning. Muthén and Asparouhov [115] also show that estimating a estimating a regular LTA model where time-invariant between-subject variation is not captured leads to distortion of transition probabilities – specifically with respect to over-estimation of diagonal values of the transition matrix (i.e. the probabilities of staying in the same class).

4.7 Latent Transition Analysis with Random Intercept (RI-LTA)

To correct for the limitations of the regular LTA model, I use a random intercept LTA in Chapter 8 of this dissertation. Figure 4.5 presents a graphical representation of a random intercept latent transition analysis framework where an additional normally distributed factor f has been introduced — which too can be a function of covariates. Unlike regular LTA where $logit(P(u^t_{k,i} = 1|c_{t,j,i})) = \alpha_{u_k,j}$ (assuming measurement invariance and where i is the respondent identifier), a new time invariant factor is introduced such as $logit(P(u^t_{k,i} = 1|c_{t,j,i}, f_i)) = \alpha_{u_k,j} + \lambda_k f_i$ where $\alpha_{u_k,j}$ varies over latent class indicators and latent classes (if measurement variance is allowed) and f_i is a subject specific random factor that has a different factor loading (λ_k) in each type of indicator but is constant over time. Factor f_i is essentially a time stable latent trait of an individual but has a different impact on different types of indicator. While f_i is standard normally distributed, it can be made a function of covariates to capture systematic heterogeneity in latent trait.

4.8 Hierarchical Agglomerative Clustering

In chapter 6, I utilize Agglomerative Hierarchical Clustering [116–118] with Levenshtein or Edit distance [119] as a similarity metric (calculated using TraMineR [120]) and with agnes [121] package in R programming language. Agglomerative hierarchical clustering is a bottom-up clustering

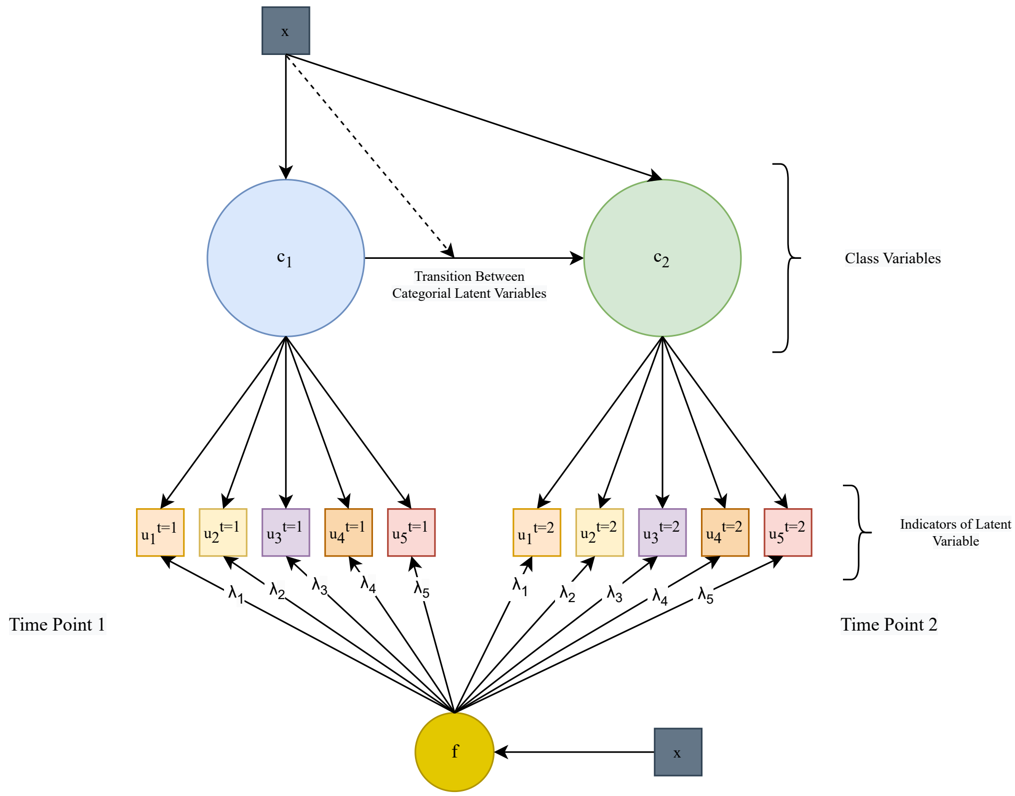


Figure 4.5: A graphical representation of a latent transition model with random intercept

approach with the benefit of not needing to pre-specify a set number of clusters (unlike k-means). It uses a pairwise similarity measure to combine observations into clusters in a hierarchical framework beginning with each data point as a unique cluster and then merging closer points into a single cluster until the entire dataset is one big cluster. Determination of number of clusters is done using dendrogram, which is a graphical representation of the hierarchical structure of clustering process. Given the sequential nature of the trajectories, Levenshtein distance metric is used as a similarity measure instead of other distance metrics that do not recognize sequential nature of the data. Levenshtein distance determines the similarity between trajectories based on the minimum number of insertions, deletions or substitutions required to make two trajectories similar and is a popular metrics with origins in protein/DNA sequence alignment and bioinformatics.

CHAPTER 5
FOR WHOM DID TELEWORK NOT WORK DURING THE PANDEMIC?

5.1 Introduction

One of the most impactful transformations triggered by the COVID-19 pandemic is the massive transition of employees and businesses to work from home. According to a U.S. survey conducted by Pew Research in October 2020 [83], while only 20% of working adults reported working from home before the pandemic, the number of working adults that reported working from home during the pandemic had grown significantly to 71%. A key finding from this study is that workers were highly divided: only 54% of working adults would like to work from home once the pandemic is over. This finding is significant; while several studies [122, 123] have shown positive impact of the option to telework and of actual telework, the experience from the pandemic has been mixed for many. Thus, the extent of continued future adoption of telework when it is an available option remains an open question for employers and policy makers in a post-pandemic world. On the positive side of the argument, we note that the resources that corporations have spent during the pandemic to make teleworking easier, increased schedule flexibility, and inclusion aspects of telework may permanently change the way Americans expect to work, and this may lead to maintaining high levels of telecommuting [124, 125]. On the other hand, the current level of adoption may not be sustained in the wake of growing evidence related to decline in innovation and productivity [126, 127], and lack of clearly defined boundaries between work and private life [128, 129]. This is further complicated by the fact that the pandemic forced organizations to suddenly adopt remote work, sometimes without providing employees with the necessary skills and support to thrive in the remote work environment [130].

While we note that employer strategies will play a major role in defining the future forms and adoption of telework, employee preferences and constraints, such as access to appropriate technology or environment to work from home, are also going to be extremely important factors. Overall, there is consensus that different remote work models will persist and that hybrid forms of work will be sustained post COVID-19 pandemic [131]. Yet, there is a need for further research to understand employee perceptions, barriers and assets related to remote work, as well as the variation among different employee groups. The resulting behavioral insight will be an important input to establishing the forms and strategies to maintain productivity, worker well-being and company culture in a remote work world.

The broad and durable nature of telework adoption during the pandemic across sectors and user-groups presents a rare and unique opportunity to study telework. Most studies prior to the pandemic treated teleworking as a choice, part of an intentional telework program from the employer's end. Instead, analysis of remote work in the COVID-19 era needs to account for the fact that the pandemic broadly forced employers and workers to adopt telework for an extended period except for individuals for whom onsite presence was essential.

In past research, telework has been considered as a means to reduce congestion and the environmental impact of the transportation sector for several decades [9, 22, 132–136]. Employee telework adoption has been tied to schedule flexibility [25], worker age and educational attainment [28, 30], and interaction with the employer's expectations [137]. In terms of attitudes, telework adoption preferences are linked to both constraints (family effects, commuting, job suitability) as well as opportunities (interaction with co-workers) [11, 138, 139].

A comprehensive understanding of the long-term viability of remote work and related spatially and temporally flexible work arrangements is still taking shape [140, 141], and many of the earlier findings may need to be revisited in this new context. For example, earlier research suggests that attitudes may be more consistently important than sociodemographic status like presence of children [11]. Among the unique features shaping the COVID-19 telework situation is the frequent occurrence of multiple members of the same household teleworking simultaneously, including children attending school online. Overlapping telework arrangements potentially impose resource, time, and space restriction on individuals and increased work-life conflicts.

In light of the above discussion, this chapter is focused at understanding the systematic heterogeneity and factors associated with telework satisfaction during the COVID-19 pandemic amongst a representative sample of working adults in the United States. We use data regarding self-reported telework satisfaction ratings, responses to several other questions related to benefits of and barriers to teleworking, and socio-demographics and contextual variables from a survey with *318 working adults*. We employ a *multiple indicator multiple cause* (MIMIC) model capable of measuring both the direct and indirect impact (via the latent factors) of socio-demographic information on telework satisfaction, hence providing a causal structure to our understanding of the drivers of telework satisfaction. Our methodology relates telework satisfaction with the perceived/experienced benefits of and barriers to telework and thus helps in identifying factors that may impact telework frequencies in the future. It is known from prior work that satisfaction acts as an antecedent to future behavioral intentions [142–148]. A common structure in adoption studies is to frame use intentions from the perspective of perceived benefits and barriers, which, in turn, are driven by experiences [149–154].

Given the novelty of the setting in which telework is experienced by workers, our chosen approach is to frame the MIMIC modeling around the identification of two latent variables: benefits and barriers. This underpins the three main contributions of this work, namely: defining benefits/barriers of remote work in the unique circumstances of the pandemic, revealing casual structures stemming from the experience during the pandemic, and finally uncovering the systematic differences by respondent features and household status. These findings can help employers determine how to balance employee well-being and aspirations for work flexibility, while maintaining innovation and productivity. More broadly, insights about remote work intentions can aid urban and transport planners in making decisions related to mobility provision and urban design.

The rest of the chapter is structured as following. Section 2 presents the data available for this study, and descriptive statistics of socio-demographic and attitudinal variables. Section 3 presents the modeling approach using ordered probit and MIMIC models. Section 4 presents the estimation results and is followed by summary, key takeaways, policy implications and limitations of this study in section 5.

5.2 Data

5.2.1 Telework satisfaction rating data

On a 5-point Likert scale (*very dissatisfied* to *very satisfied*), individuals with full-time or part-time employment status and those who have not been working from an office in the past week (i.e. workers with at least some experience of working from home recently) were asked to rate their level of satisfaction with their telework experience using the following question: *"How satisfied are you with your experience of working from home?"* Individuals who are employed but have been working exclusively from an office (i.e., workers with no *recent* experience of working remotely) were instead asked to rate their expected level of satisfaction with teleworking in a hypothetical scenario[1] where telework is a viable option using the following question: *"Imagine you were*

[1]From the data available to us, it is difficult to say whether this was truly a hypothetical scenario or not since the question specifically asked about work location in the "recent" weeks and no particular time frame was provided. It is possible that the respondent did telework in the early period of the pandemic or may have telework experience prior to the pandemic. Further, the hypothetical scenario version of the question was presented to 78 out of 318 respondent and almost all of them were working exclusively on-site due to employer mandates (i.e., working from home was not an available option). Lastly, 59 of 78 individuals were essential workers.

asked to work from home. How satisfied do you think you would have been working from home?" Similar questions were asked to students with recent or no experience of working from home in the context of *"attending classes from home"*. In the telework satisfaction rating data, merely 2.52% (8 respondents) of the 318 individuals responded that they were or would have been *very dissatisfied* with teleworking. Hence, we converted the 5-point response scale to a 4-point scale by combining the "very dissatisfied" and "somewhat dissatisfied" response categories. Figure 5.1 shows the distribution of reported telework satisfaction with about 74.21% individuals reporting they were or would have been somewhat or very satisfied with telework. This 4-point satisfaction response item is eventually used in the presented models as a dependent variable.

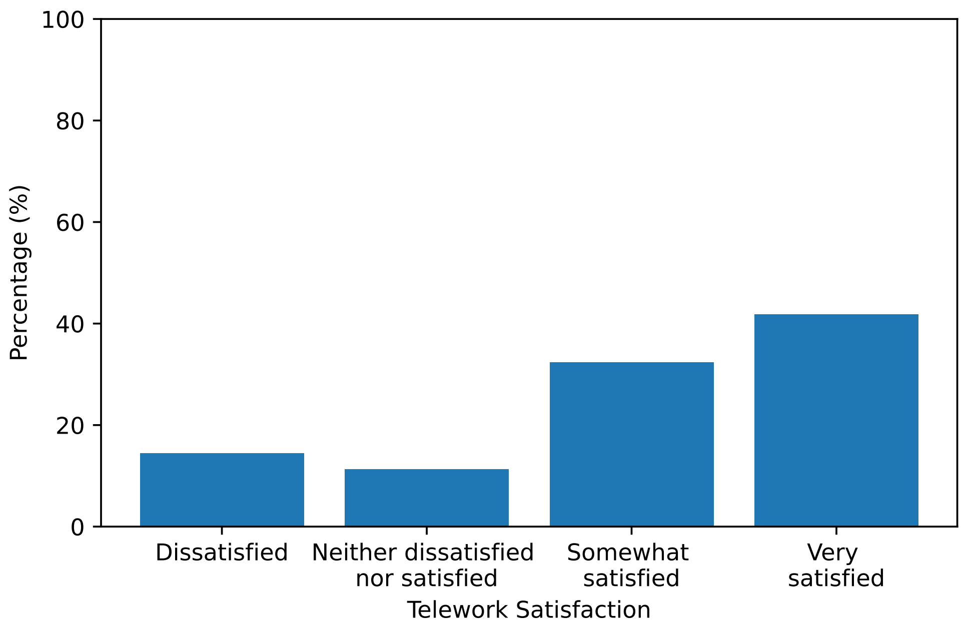


Figure 5.1: Distribution of reported telework satisfaction in the data.

5.2.2 Telework related experience, perception, and contextual data

The study included questions on telework perceptions, experiences and other contextual variables related to household factors and COVID-19 concerns. This data was also collected for cases where telework was not an available option, such as essential workers. Questions asked to the respondents and the response distribution is presented in Table 5.1. Although the variables shown in Table 5.1 were measured on a 4- or 5-point scale, they were recoded to binary variables to reduce the complexity of estimated models, given the relatively small sample size[2]. As observed, a significant proportion of individuals did not agree with potential benefits related to telework like productivity gains or quality of life improvements. These findings are in line with the findings by the survey conducted by PwC [155] in December 2020 in the U.S., however, it contrasts with the research by [156] in Belgium where respondents mainly attribute positive characteristics to telework. These differences likely reflect the dynamic nature of telework experiences during the pandemic where while early experiences with telework were largely positive but more recent studies suggest a mixed experience. Furthermore, only about 15% of individuals reported lack of technology being a hindrance to telework given that the required technologies like a laptop or a webcam or access to internet have a significantly high market penetration in the U.S.

The data from these questions were used to first conduct an exploratory factor analysis, used as foundation to identify factors related to perceived benefit and barriers to telework incorporated into the final MIMIC model. The identification of these latent variables is anchored upon several existing studies on telework before and during the COVID-19 pandemic [152, 157–160].

[2]The 5 statements on a 5-point Likert scale were recoded to 1 if the respondent somewhat or strongly agreed with the statements or 0 otherwise. The statement on work location flexibility was recoded as 1 if there was partial or complete flexibility to choose work location and 0 otherwise. The statement on the job's remote work suitability was recoded to 1 if the job was mostly or very suitable to remote work and 0 otherwise. Lastly, the COVID-19 related worry variable was recoded as 1 if the respondent reported being worried or very worried about potentially contracting the virus and 0 otherwise.

Table 5.1: Distribution of telework related experience, perception, and contextual data

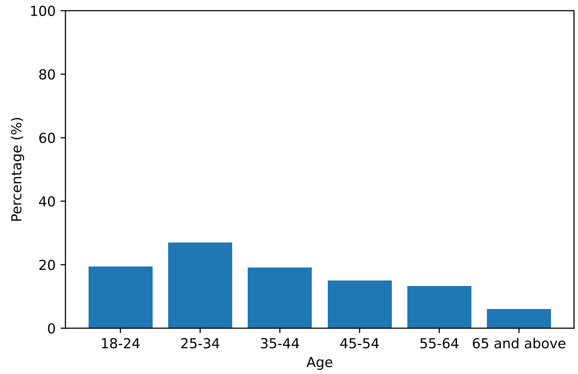
Indicator / Statement	Abbreviated Variable Name	Disagree (%)	Agree(%)
I have been/would be more productive working from home	Work productivity gains	55.0	45.0
Not needing to commute to work has improved/would improve my ability to work from home.	Time savings due to not needing to commute	28.6	71.4
The option to work from home has improved/would improve my quality of life.	Quality of life improvements	36.2	63.8
Lack of technology like a laptop or a webcam has/would hinder my ability to work from home.	Lack of appropriate technology	85.2	14.8
Distractions from other household members have/would hinder my ability to work from home.	Distraction from other household members	61.6	38.4
Indicate who determines their work location: the employer; there is partial flexibility in the determination of work location; or if there is complete flexibility	Work location flexibility	57.8	42.2
Indicate level of suitability of the respondent's job to remote work: not suitable at all; somewhat suitable; mostly suitable; very suitable.	Job's remote work suitability	45.0	55.0
Indicate level of worry (on a 4-point scale of not at all to very worried) about potentially contracting the COVID-19 virus.	Worried regarding contracting COVID-19	61.6	38.4

5.2.3 Socio-demographic data

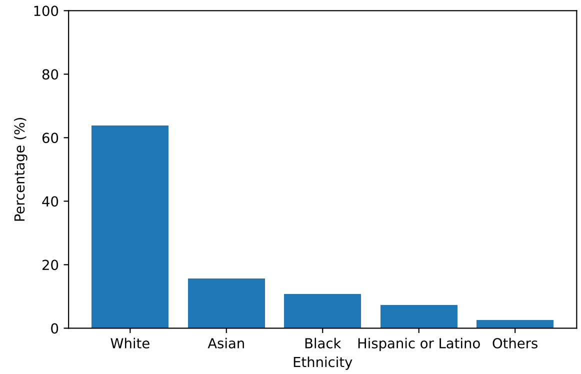
The survey also collected socio-demographic variables that are relevant to study variation in experiences and satisfaction with remote work. Figure 5.2 presents the descriptive statistics of the socio-demographics used in this study. The variables include age, ethnicity, household location type (urban, rural, suburban), highest level of education, household setup type (living alone or with others), vehicle ownership status etc. Another important variable that we include in our analysis is whether or not an individual works in one of the following four remote work suitable industries: communications and information technology, educational services, media and communications, and professional and business services.

5.3 Methodology

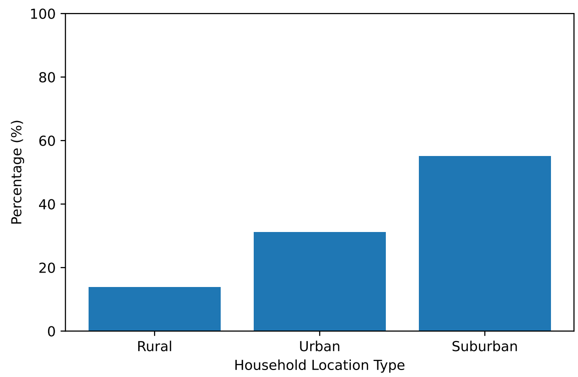
To understand the drivers of satisfaction and heterogeneity in the self-reported telework satisfaction, we present two models based on the available data. The reference model is an *ordered probit* model controlling for socio-demographic variable effects on telework satisfaction levels. This model is useful to understand the heterogeneity in telework satisfaction across various socio-



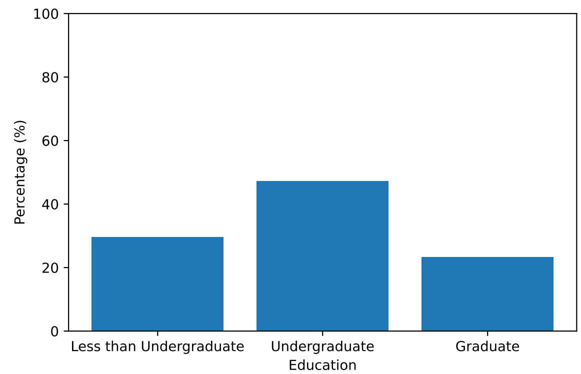
(a) Age



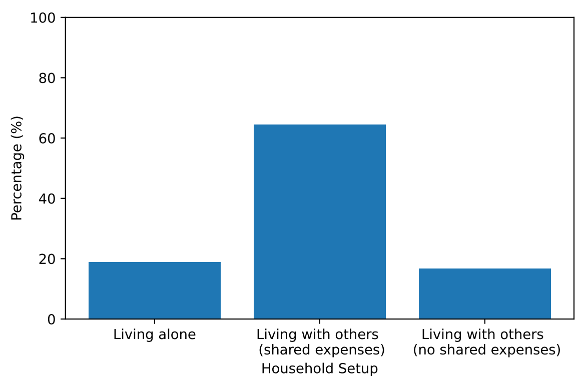
(b) Ethnicity



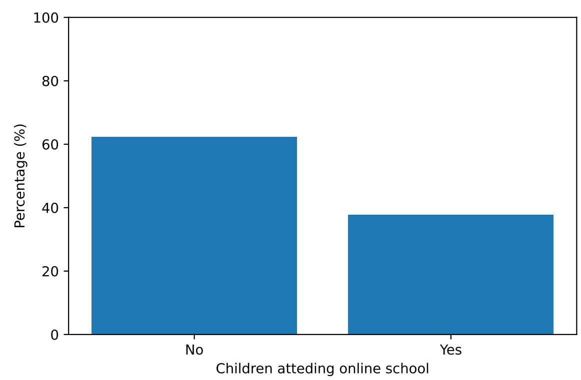
(c) Household Location Type



(d) Level of Education

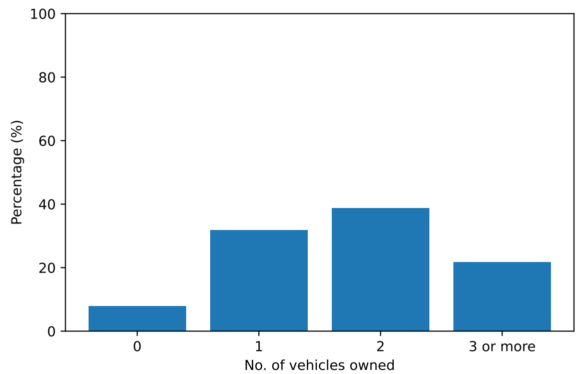


(e) Household Setup

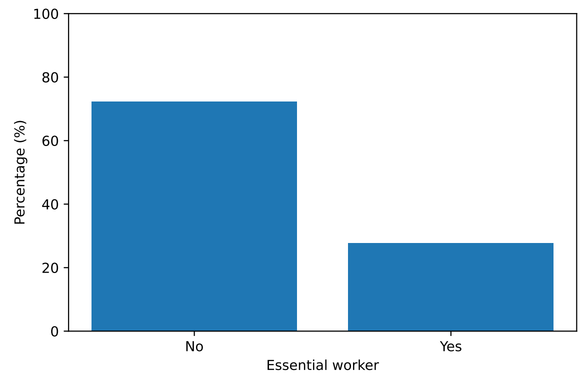


(f) Presence of children attending online school

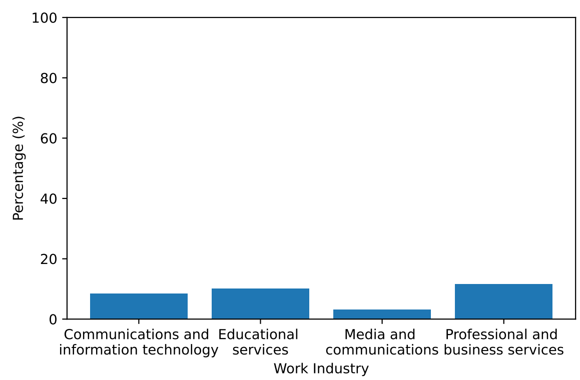
Figure 5.2: Descriptive statistics of socio-demographic variables available in the data



(g) No. of vehicles in the household



(h) Essential workers or on-site work required



(i) Work Industry

Figure 5.2: Descriptive statistics of socio-demographic variables available in the data (cont.)

demographic groups. The second model is a MIMIC model with an ordered probit component relating socio-demographic information as well as latent variables with self-reported telework satisfaction. The model provides a causal structure to our analysis for understanding telework satisfaction. Mathematical details related to both models are presented in the following sections.

The MIMIC model consists of an ordered probit component and relates socio-demographic information to perceived / experienced[3] benefits of and barriers to telework satisfaction and to telework satisfaction itself. Similar to other structural equation models, the presented model consists of two components: 1) *a structural model*, capturing the inter-relationship between different latent variables and the relationship between socio-demographic information and latent variables; 2) *a measurement model*, capturing the relationship between continuous latent variables and their observed indicators (all of which are categorical in this study) [113].

Figure 5.3 presents the structure of the MIMIC model used in this study. The indicators for each of the latent variables were determined following an exploratory factor analysis that allowed for polychoric correlations [161]. In the MIMIC model, the structural equation relates the socio-demographic information with the identified latent variables (i.e., benefits of and barriers to telework), the measurement equations relate each latent variable with their indicators, and the telework satisfaction response propensity is related with the latent variables and the socio-demographic information using an ordered probit type model. All models in this chapter are estimated using the R programming package *lavaan* [162], which uses mean and variance adjusted weighted least square (WLSMV) procedure [163]. WLSMV estimator is the most appropriate estimator for non-normal data and makes minimum assumptions about the distribution of the observed variables [164, 165].

[3]Note here that we use to perceived / experienced terminology here instead of just experienced due to presence of individuals in the data with no telework experience, for example, essential workers. While using the experienced benefits or barriers is more relevant for individuals who had at least some telework experience during the pandemic, for individuals with no experience of telework during the pandemic, our data only reflects their perception of telework which may not be formed by personal experiences.

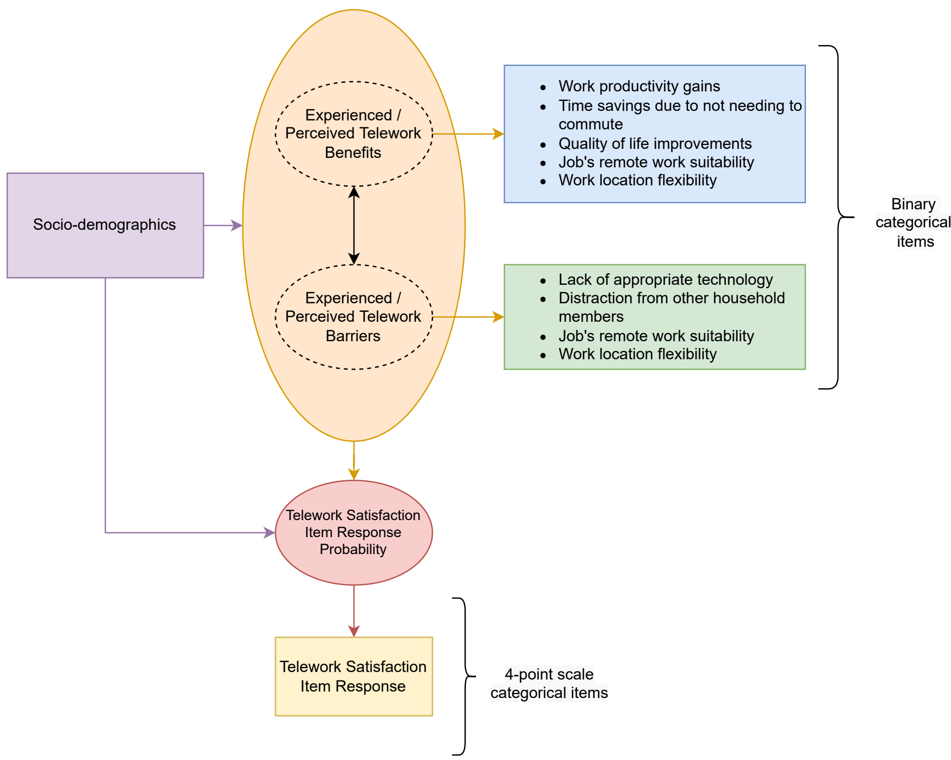


Figure 5.3: Structure of the MIMIC Model

5.4 Estimation results

5.4.1 Exploratory factor analysis

We began the exploratory factor analysis with the Kaiser – Meyer – Olkin (KMO) test [166, 167] of sample adequacy and the Bartlett's test of sphericity [168] using the 8 indicator variables. A KMO value of 0.66 (minimum acceptable value 0.6) and Bartlett's K squared value of 50.371 (degrees of freedom = 7 and p-value = $1.22*10^{-8}$) showed that the data is appropriate for a factor analysis. Table 5.2 presents the results from a 2-factor solution with *varimax* rotation from an exploratory factor analysis (EFA) conducted using the available telework related experience, perception, and contextual variables. The COVID-19 related concern variable has been excluded from the presented solution since it had a small loading value on the 2-factor and 3-factor solutions attempted. Hence, we include the COVID-19 worry related variable directly into the ordered probit part of the model[4]. Admittedly, some loadings are lower than the generally accepted cutoff values, but we decided to keep the corresponding indicators given that they were extremely important aspects [169, 170]. The two identified latent variables were named as 1) Telework Benefits and 2) Barriers to Telework. Overall, the 2-factor solution explains 52.7% of the common variance in the 7 indicators with 2 cross-loadings across the factors. Given that cross-loadings are reasonably high, we decided to keep these to explicitly account for cross-correlations in the final MIMIC model while defining the latent variables. Given the increasing concerns regarding the use of Cronbach's α for measuring internal consistency reliability in non-continuous data [171], we use ω total measure of composite reliability proposed by McDonald [172, 173]. The ω are estimated using the *psych* R programing package [174] and were found to be 0.77 and 0.58 for factor 1 and factor 2, respectively, which showcases reasonable reliability for the identified factors.

Table 5.2: Results from the exploratory factor analysis

Indicator	**Factor Loading**	
	Factor 1 (Telework Benefits)	**Factor 2 (Barriers to Telework)**
Work productivity gains	0.816	–
Job's remote work suitability	0.576	-0.815
Time savings due to not needing to commute	0.680	–
Quality of life improvements	0.852	–
Lack of appropriate technology	–	0.454
Distraction from other household members	–	0.267
Work location flexibility	0.319	-0.649
ω total	0.77	0.58

% of common variance explained by two factors = 52.7%
rotation = varimax

[4]Despite the risk of endogeneity, since we do not have the longitudinal measures of both satisfaction and COVID-19 concerns to resolve the complexity of simultaneous effects, we determined that this variable is a relevant factor during the time of the pandemic where individuals with higher COVID-19 concern might feel more satisfied with telework. Notably, removing this variable from the presented models did not change the remaining parameter estimates or their statistical significance. Capturing COVID-19 concerns and related risk-avoidance or tolerance behaviors remains an important avenue for further research.

5.4.2 Estimation Results

Model of socio-demographic determinants of telework satisfaction

Table 5.3 presents the results from the ordered probit model with socio-demographic information but without latent variables. This model helps to gain a fundamental understanding of the distribution of satisfaction across the respondents in the data. According to the R^2 value [175, 176], the presented model explains 21.9% of the variance in the *latent propensity function* of the telework satisfaction equation. Note that the typically reported log-likelihood based fit measures are not available here since the model has been estimated using the WLSMV estimator instead of maximum likelihood estimator.

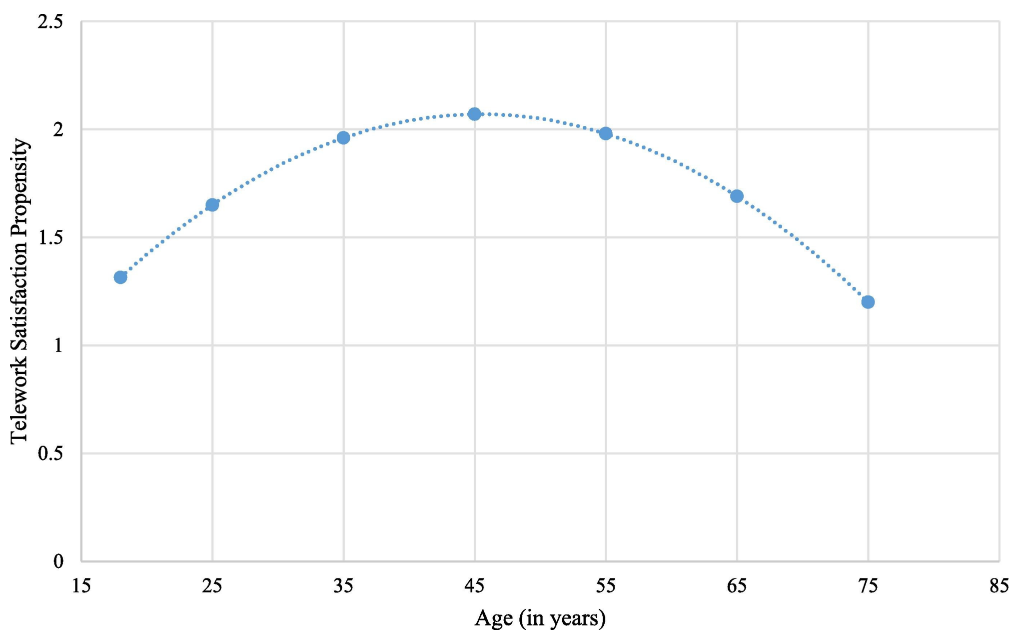


Figure 5.4: Variation of telework satisfaction as a function of respondent's age.

As seen in Figure 5.4, there is a parabolic relationship between telework satisfaction and age. Specifically, results indicate that while middle aged individuals were more satisfied with teleworking, the satisfaction was lower for younger and older individuals. As reported by some news articles [177], this might be related to either loss of networking and mentoring opportunities that younger individuals benefit from in the early stages of their careers or to lack of proper remote working conditions at their homes as many younger individuals often live in shared apartment. For older individuals, the lower satisfaction may be related to higher position ranks, echoing findings in Carillo et al. [178] where managers adjusted less well to telework than non-managers, related to the difficulty of managing teams in the uncertain environment. Lower satisfaction of older workers may also be associated with challenges to use technology as a primary work tool. Results also suggest that the satisfaction was lower for individuals with at least an undergraduate degree and for households with children attending school virtually from home. A likely reason for presence of children attending school from home impacting satisfaction is that it may strain individual's attention span [179, 180]. Furthermore, telework satisfaction for individuals with a graduate degree was marginally higher than for individuals with just an undergraduate degree, but the corresponding parameter was not highly significant. However, we decided to retain this parameter to control for the effect of having a graduate education, given the consistent importance of this variable in past research.

Hispanic or Latino respondents reported higher satisfaction with teleworking compared to other ethnic groups. A conjecture is that Hispanic or Latino respondents tend to be over-represented in work requiring in-person activities, which are less telework friendly, even before the pandemic [181]. Hence, their reported satisfaction is higher when they were given a hypothetical situation of teleworking being an available option or when their employers were forced to give telework as an option. Individuals living in suburban areas also reported higher satisfaction with teleworking compared to both rural and urban residents, potentially related to several factors including relocating to suburban areas since telework was possible[5] or to not needing to commute to work anymore

[5]Several independent data sources point out to a significant relocation across regions in the U.S. during the pandemic. For example, a study by Zillow, which is a major online real estate marketplace company in the U.S., reported

Table 5.3: Ordered probit model of telework satisfaction with only socio-demographic information

Variable	Parameter Estimate	t-statistics
Age (in years)	0.091	3.800
Age^2 (in years squared)	-0.001	-3.128
Hispanic or Latino indicator	0.653	1.991
Suburban household indicator	0.324	2.462
At least an undergrad degree indicator	-0.334	-2.215
Graduate degree indicator	0.214	1.185
Presence of at least one child attending school from home indicator	-0.594	-3.812
Worried about contracting COVID indicator	0.291	2.059
Thresholds		
τ_1	0.990	1.881
τ_2	1.454	2.747
τ_3	2.429	4.458
Fit Measures		
No. of estimated parameters in the entire model		11
No. of observations		318
R2 (for ordered probit component)		0.219

[182–184]. Lastly, the model also suggests higher satisfaction amongst individuals who were more worried about contracting the COVID-19 virus. This result suggests that satisfaction with remote work can also be driven by factors external to the nature of the work and household environment, to encompass concerns about viral exposure.

MIMIC model

Table 5.4 presents the ordered probit component of the MIMIC model, which is an extension of the model presented in the previous subsection. This model now includes latent variables which were not included in the previous model. To provide a more causal structure to the model and capture heterogeneity in the latent variables, socio-demographic information was included in both the ordered probit component as well as the structural model where significant, as presented in

about 11% of American moved during the pandemic of which about 75% did so due to reasons like moving closer to family. Another two studies that use data from United States Postal Service (USPS) found a significant increase movement for individuals from big cities to suburban areas. The studies also found a 27% increase in temporary movers in 2020 compared to the same time-period in 2019. Even in our own data where we asked some of the respondents whether they moved since the beginning of the pandemic, 69 out of 418 (~16.5%) reported doing so.

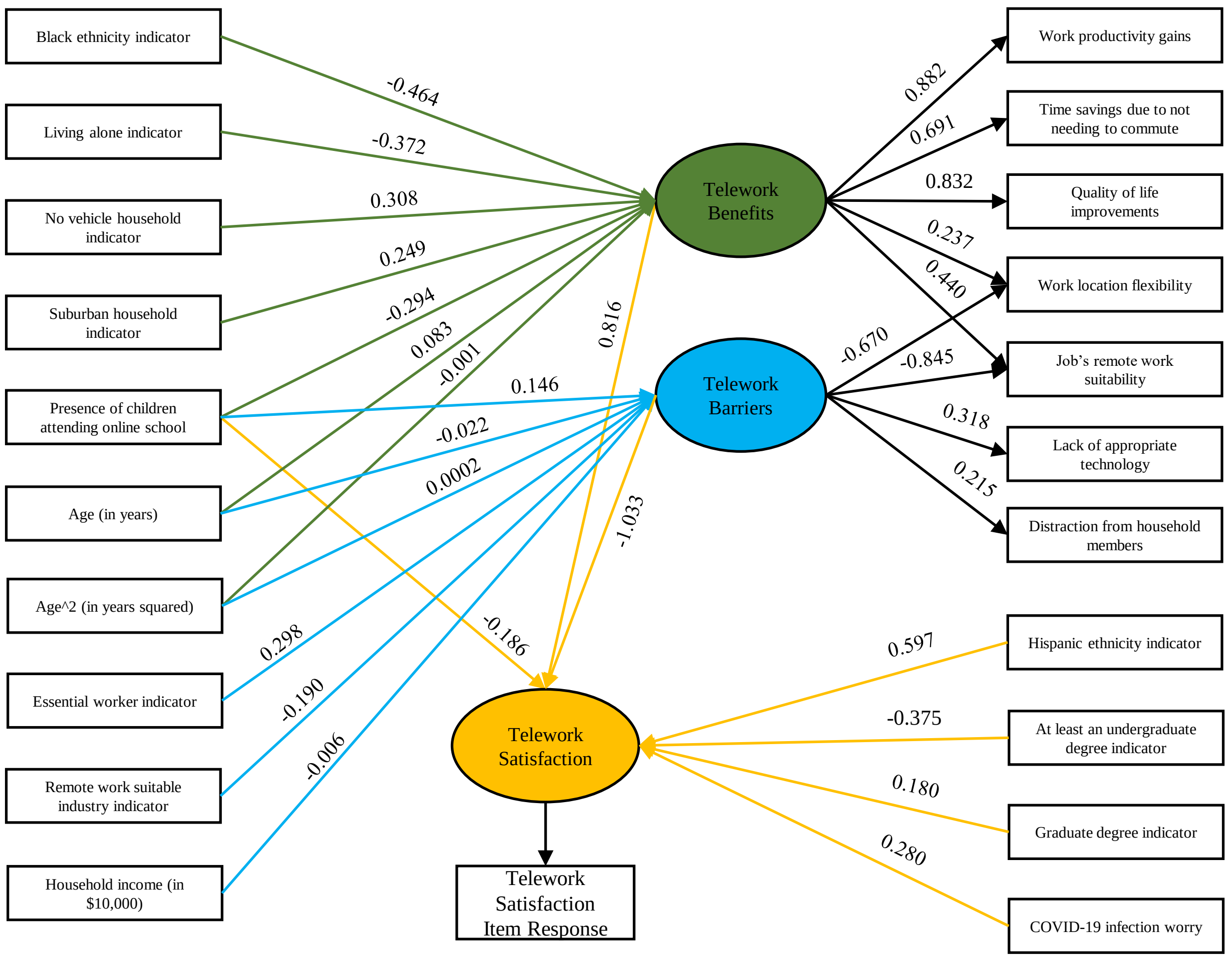
Table 5.5. However, preference was given to include socio-demographic information in the structural model when a parameter was significant in only one model components. Hence some of the socio-demographic variables – like age – do not appear in the ordered probit component of the MIMIC model but rather have an indirect impact on satisfaction via the latent variables. Table 5.5 presents the results from the structural model and Table 5.6 presents the results from the measurement model. Furthermore, Figure 5.5 presents a path diagram with all statistically significant paths, as well as various model fit measures typically reported in the structural equation models.

Model fit

As can be seen from Table 5.4, the R^2 value of the ordered probit model with latent variables is 0.648, which is a significant improvement from the value of 0.219 reported earlier in the model without latent variables. Moreover, the typically reported structural equation based fit measures (see Figure 5.5) are within the acceptable ranges except SRMR. For example, the acceptable range for TLI and CFI is of greater than 0.95 and both satisfy this criterion. The model is acceptable if the upper bound of 90% confidence interval of RMSEA is below 0.08, which is satisfied in our model as well. While SRMR is slightly above the acceptable threshold of 0.08, SRMR tends to be higher in models with smaller sample sizes and with greater complexity [185] . Given that the inclusion of latent variables significantly improves the R^2 in the ordered probit component and that the typically reported structural equation model fit measures are all within the acceptable ranges, the presented model's results are believed to be trustworthy.

Ordered probit model of telework satisfaction

As can be seen from Table 5.4, there is an intuitive link between satisfaction and the latent variables. Namely, individuals which rank higher on telework benefits also report higher satisfaction,



FIT INDICES (robust values)

chi-squared test statistic = 138.952
degrees of freedom = 111
relative chi-squared = 1.252

comparative fit index (CFI) = 0.955
Tucker-Lewis index (TLI) = 0.989
root mean square error of approximation (RMSEA)
90 % confidence interval = 0.043

standardized root mean square residual (SRMR) = 0.084

Figure 5.5: Path diagram for the MIMIC model.

and vice versa for barriers. Furthermore, the results related to COVID-19 related worry, level of education and Hispanic or Latino ethnicity remained the same as in the earlier model. It is noted that a few of the variables, like age, which were earlier present in the ordered probit model, are now more appropriately included in the structural component of the overall model, suggesting an indirect effect on telework satisfaction. This indicates that age was structurally correlated with benefits of and barriers to telework variables rather than being a direct causal factor driving telework satisfaction.

Table 5.4: Ordered Probit Component of the MIMIC Model

Variable	**Parameter Estimate**	**t-statistics**
Hispanic or Latino indicator	0.597	1.926
At least an undergraduate degree indicator	-0.375	-2.300
Graduate education indicator	0.180	0.960
Presence of at least one child attending school from home indicator	-0.186	-1.338
Worried about contracting COVID indicator	0.280	1.924
Latent Variables		
Experienced/perceived telework benefits	0.816	10.958
Experienced/perceived barriers to telework	-1.033	-2.023
Thresholds		
τ_1	0.721	1.278
τ_2	1.205	2.118
τ_3	2.202	3.766
Fit Measures		
No. of estimated parameters in the entire model		39
No. of observations [6]		308
R^2 (for ordered probit component)		0.648

Structural model

Table 5.5 presents the estimation results from the structural model that captures the heterogeneity in the latent variables included in the ordered probit component. For the *telework benefits*, we found that these were higher for individuals living in suburban areas and individuals without

[6] Income information was missing for 10 individuals in the data, hence the number of observations dropped to 308 instead of 318 in this model. However, this did not alter the results significantly

access to a vehicle. Further, the experienced/perceived benefits were lower for Black individuals, individuals living alone, and individuals with children attending school from home. Lastly, age had a non-linear impact on the experienced/perceived benefits as shown for the satisfaction probit model. Regarding households without a vehicle, higher telework satisfaction is expected since many of these individuals are potentially transit users, pedestrians, bicyclists, carpoolers etc. for whom telework potentially is a way to save commute time and to reduce COVID-19 exposure by not using transit or other shared modes [186]. Furthermore, lower satisfaction for individuals living alone is likely associated with the issue of social isolation and emotional well-being [187]. Interestingly, we found that individuals with Black ethnicity perceived/experienced lower benefits of telework. This is potentially due to several factors including individuals with Black ethnicity being disproportionately employed in less telework friendly job sectors [181], or not experiencing much productivity gains or quality of life improvements as a results of the telework due to lack of access to necessary resources and environment at home.

For the barriers to telework[7], we found that the barriers were higher for essential workers and lower for individuals in remote work friendly industries. This highlights that the nature of the work tasks/telework friendliness of the job is a highly important factor driving barriers to telework. Additionally, the barriers were higher for individuals with presence of a child attending school from home and were lower for higher income households (who potentially are in higher ranks in their jobs). Lastly, perceived/experienced telework barriers varied parabolically with age, with higher barriers for younger and older individuals and lower barriers for middle-aged individuals.

[7]In earlier drafts of this work, it was suggested to us to incorporate a dummy or interaction variable representing whether an individual was given a potentially hypothetical situation on telework or not so that differences in satisfaction levels or benefits and/or barrier latent variables or the two groups can be captures. However, since almost all individuals in the hypothetical group were working on-site due to employer set mandates (i.e. had no work location flexibility) and large portion of them were essential workers or from non-telework friendly industries, this variable was highly correlated the variables already present in the barriers structural model and hence was dropped from presented model. However, our analysis suggests that the respondents who were given a hypothetical situation regarding telework perceived/experienced higher barriers, which makes sense since they didn't have work location flexibility.

Table 5.5: Structural component of the MIMIC model

Variable	Parameter Estimate	t-statistic
Experienced/perceived telework benefits		
Black ethnicity	-0.464	-2.429
Living alone	-0.372	-2.049
Presence of at least one child attending school from home	-0.294	-1.918
No vehicle household	0.308	1.370
Age (in years)	0.083	3.397
Age^2 (in years squared)	-0.001	-3.191
Suburban household	0.249	1.961
Experienced/perceived barriers to telework		
Essential worker	0.298	2.225
Remote work suitable industry	-0.190	-2.048
Presence of at least one child attending school from home	0.146	1.811
Age (in years)	-0.022	-1.734
Age^2 (in years squared)	0.0002	1.396
Household Income (in $10,000)	-0.006	-1.171

Measurement model

Table 5.6 presents the results from the measurement model with standardized parameters estimated to measure the two latent variables. The signs of all the parameters are intuitively correct, providing more confidence in the results. For *benefits* our results echo the importance of saving commute time, which was a leading factor supporting remote work productivity in Shamshiripour et al. [188]. Considering barriers, the importance of remote work suitability reflects earlier telework research [11] while location flexibility is likely a new feature shaped by the notable professional and personal uncertainty surrounding the pandemic work policies [178]. As previously discussed, although some loadings are smaller in magnitude than the generally acceptable values, they were retained in the model because they captured important information and had intuitively plausible signs.

[8] t-statistics not available since the parameter was fixed for identification
[9] τ_1: first threshold for binary indicator measurement model

Table 5.6: Measurement component of the MIMIC model (standardized parameters)

Variable	Parameter Estimate	t-statistic
Experienced/perceived telework benefits		
Work productivity gains	0.882	— [8]
Time savings due to not needing to commute	0.691	8.905
Quality of life improvements	0.832	11.537
Job's remote work suitability	0.440	7.416
Work location flexibility	0.237	3.155
Experienced/perceived barriers to telework		
Lack of appropriate technology	0.318	—
Distraction from other household members	0.215	1.550
Job's remote work suitability	-0.845	-2.301
Work location flexibility	-0.670	-2.214
Thresholds		
Work productivity gains | τ_1 [9]	1.636	2.675
Time savings due to not needing to commute | τ_1	0.879	1.342
Quality of life improvements | τ_1	1.298	2.109
Job's remote work suitability | τ_1	3.306	4.197
Work location flexibility | τ_1	1.842	2.558
Lack of appropriate technology | τ_1	0.552	0.639
Distraction from other household members | τ_1	-0.195	-0.271

5.5 Summary, Key Takeaways, Policy Implications and Limitations

Summary and Key Takeaways

Using data from a U.S. representative sample (based on gender, age and ethnicity variables) of 318 working adults, this study uses a multiple indicator multiple cause model (MIMIC) to understand individual's satisfaction with telework. The study also presents an ordered probit model without the latent variables, which reveals systematic heterogeneity in telework satisfaction. The MIMIC model consists of an ordered probit component relating socio-demographic information and perceived/experienced telework benefits and barriers to telework satisfaction. Additionally, we anchor the modeling on personal, work, and household environment factors that help disentangle structural differences in how people experienced remote work.

The results from the ordered probit model without latent variables suggests that the telework satisfaction was higher for middle aged individuals compared to younger and older individuals, Hispanic or Latino respondents, respondents with less than an undergraduate degree, and respondents with higher levels of concern about contracting the COVID-19 virus. On the other hand, satisfaction was found to be lower for individuals with children attending school virtually from home. The results from the MIMIC model confirms the ordered probit reference findings, namely that Hispanic or Latino ethnicity, education level, presence of an online-schooling child and worry related to contracting the COVID-19 virus are the main factors to drive satisfaction. Age, however, is now included in the structural component of the MIMIC model, revealing instead an indirect impact on satisfaction. The model also suggests a positive impact of telework related benefits and negative impact of barriers to telework. Epidemic-induced telework *benefits* can be associated with several demographic and household factors, namely: it is lower for individuals with Black ethnicity, those living alone or with presence of at least one child attending online school from home. The benefits were found to be higher for individuals without a vehicle and those who are suburban dwellers. Lastly, the barriers to telework were found to be most pronounced for essential workers and those with a remote-schooled child in the household. On the other hand, barriers were found to be lower for individuals employed in remote work suitable jobs and those with higher household income. A non-linear impact of age was also found to be a significant factor for both benefits and barriers latent variables.

Overall, three important takeaways emerged from the presented analysis. First, benefits and barriers to telework are disproportionately distributed across age groups. For younger individuals, this may be related to loss of networking opportunities that they need to advance in their careers or maybe related to the younger individuals mostly being employed in jobs that are not suitable for telework. For older individuals, the issue might be related to workplace anchoring, difficulty of managing their teams in more senior positions, and possible technology limitations in performing usual work activities. A second important finding is the evidence for inequity along the lines of racial/ethnic identity. Our findings are in line with other reports that Black and Hispanic or Latino individuals are disproportionately impacted in term of not being able to telework [181]. Third, the presence of children attending online school is a consistently important factor impacting telework satisfaction. This is not surprising since several recent studies have pointed to negative impact of the pandemic on working parents with younger children [189, 190].

Policy Implications

From a policy standpoint, our results suggest several implications for employers and policy makers in planning for the pandemic and post-pandemic periods. For employers who plan to adopt a hybrid or remote workplace in the long run, our study highlights several core factors that shape barriers and benefits of telework that can be used for communication and promotion of future efforts (e.g., the benefits of commute time savings). Furthermore, the causal structure of the model reveals the diverse experiences of different employer segments with regard to barriers and benefits. These insights can be used to design worker support strategies (e.g., on-site school/day-care pods assisting with challenges of inconsistent schooling access). If remote work were to become a norm at least for positions or tasks where physical presence is not necessary, employers must ensure support that is mindful of the diverse experiences and circumstances of workers, including the more complex non-linear effects such as those related to worker age. For younger employees, a hypothesis is that higher barriers or lower benefits are perceived due to lack of networking opportunities that they need to excel and advance in their careers. Employers could alleviate these by creating an environment to facilitate networking opportunities like organizing mandatory on-site days at regular intervals or hosting online networking hours. For older individuals who might perceive high barriers and lower benefits to teleworking potentially due to difficulty with technology, employers must invest in providing technology support. Concerns about social isolation, especially for workers for whom work provides an important environment for social interaction may also need to be addressed.

On the other end, if employers opt to have an in-person/office-centric plan for the future, creating a safe working environment will be important to phase in the return to the office since our results indicates a positive relationship between telework satisfaction and COVID-19 related worry. This could potentially be achieved by clear policies on social distancing, masking, and vaccination. As employers seek to determine the appropriate mix of telework and in-person presence, the factors identified in this study could assist in bringing out the positive features of each mode while mitigating some of the negative aspects. As a broader implication for public agencies planning for transportation and other infrastructure, it is important to thoroughly gauge the extent to teleworking in the post pandemic era, since basing future policies solely on trends during the pandemic could be erroneous [191].

Limitations

Some limitations of this study are worth mentioning here. First, for at least for some of the respondents, the satisfaction data was related to a hypothetical scenario of teleworking, and results could potentially be impact by the hypothetical bias [192]. Second, our study uses a relatively small sample size and additional insights could potentially be derived from a larger sample. Third, our study provides only a snapshot in time in an otherwise dynamic process; it would be important to examine the longer-term impacts of telework on both employees and employers, particularly with regard to factors such as productivity, creativity and worker retention, as well as personal satisfaction, work-life balance and happiness.

CHAPTER 6

TRAJECTORIES OF TELEWORK THROUGH AND BEYOND THE PANDEMIC

6.1 Introduction

More than 3 years since the beginning of the pandemic, the remote work landscape is still evolving and the extent to which the pandemic accelerated trends in telework will remain is still unclear. However, evidence is growing that at least some of these trends are going to stick well beyond the pandemic. Data from several sources suggest a significant retention of the pandemic accelerated telework trends (even as of early 2023) [80–82, 84, 193–195]. This retention could be attributed to several factors including a largely positive experience of working from home (in terms of productivity or effectiveness to get the job done) [80]; and well-being and cost savings related aspects of telework for the employees [90]. On the employer's end, employee push back against return to work, telework being good for organization's public image or it being an important perk to retain and recruit employees are some of the aspects that are driving this change [196].

While teleworking has significant benefits for the employees and potentially for employers too, if the teleworking trends are to continue at the rates similar to the current ones, this will have strong implications for the future of our cities since urban systems (e.g. transit systems and coffee shops, restaurants etc.) are often located and optimized taking the historic demand patterns into consideration [43–45]. On top of this, services like transit systems in many situations are only feasible due to demand concentration, and if a significant proportion of it is eliminated, it will likely lead to significantly reduced revenue for the transit agencies, potentially leading to budget deficits and deterioration of transit services in future. Individuals commuting to downtown for work also support a large number of individuals in the third sector of the economy including transportation sector workers, restaurant workers, and retailers. The spending by commuters in urban core is also a source of a significant share of tax revenue (e.g. commercial real estate taxes from the third places or sales tax) for the cities, which eventually gets reinvested in the urban communities in some form. In a situation where a large portion of employees are teleworking (all the time or even if a few times a week), it could have a cascading impact on urban systems at several levels and a large extent of this impact is already evident on aspects like significant decline in transit ridership across the nation, increased commercial real estate vacancy rates, and reduction in activity in urban cores [46–49]. Depending upon the extent to which these trends recover over time, at some point, cities will have to reconfigure the urban systems in light of the changing demand patterns and generated revenue. However, it is important for cities to do this in a way that it best caters to the changing societal needs while also minimizing the adverse impact on the vulnerable sections of the society.

Geography of future of work will be a function of several factors [80, 88, 90, 95, 180, 197–200] but a thorough characterization of its evolution through the pandemic, the factors that impacted this evolution and will shape its future is still missing from the literature. If the cities have to plan for this changing geography of work and related activity participation behavior, it is important for them to gain a thorough understanding of how telework evolved through the pandemic, how it will look like in the future, how it is distributed across various industry sectors and across various cities, and what factors will likely shape the extent to which employees telework in the future. Under this evolving telework landscape and its potential impact on the future of cities, our study has three underlying goals: 1) to understand how the telework patterns have evolved over time since the beginning of the pandemic and how socio-demographic and occupational factors are associated with this evolution; 2) to understand how these trends are expected to look like in the future (to be specific, in April 2024, about 4 years since the beginning of the pandemic) and the factors that will govern the shaping of this future; 3) to understand the implications that these changing trends may have for the future of our cities.

To achieve these goals, we utilize data from a sample of *915 working adults* from across United States collected in April/May 2022 and weighted to represent the U.S. population distribution by gender, age, ethnicity and education attainment to conduct the following sets of analyses:

- Using individual level retrospectively collected data on *trajectories of work location* at 7 different time points (between 2019 (pre-pandemic) to March 2022 (2 years since the pandemic began)), we present a *hierarchical agglomerative clustering-based sequence analysis* focused at identifying clusters of telework trajectories through the pandemic. With this analysis, we identify four clusters of trajectories with differing levels of telework adoption, ranging from a group that maintained significantly high in-person work participation even at the height of the pandemic, to a group that worked exclusively from home for an extended period in the pandemic and shows little sign of rebounding back to their pre-pandemic behavior.

- With the identified clusters, we estimate a *multinomial logit-based cluster membership model* focused at understanding the systematic heterogeneity in clusters of telework trajectories. Specifically, we identify how different occupational sectors, and individuals in different age, gender, ethnic, educational, or other socio-economic groups followed distinct trajectories.

- Using data on respondent's attitudes regarding the impact (positive, neutral, negative) of a hypothetical 2-days a week remote work program on 12 different response items including their productivity, creativity, ability to innovate and effectiveness to get the job done, we present a *latent class analysis*, where six latent classes of respondents with varying degrees of positivity towards the impact of remote work on various work aspects is identified.

- We present a set of comprehensive predictive models to understand how telework landscape is expected to look like in *April 2024*, about four years since the beginning of the pandemic, when we expect any COVID-19 related concerns to be resolved. Specifically, we present predictive models for two different outcome variables: 1) a binary logit model for predicting who is still unsure about their April 2024 work location; and 2) a set of ordered logit models to understand who is more likely to work in-person in April 2024. We present three different versions for the ordered model: a) a model with only socio-demographic information focused at understanding the distribution of telework across the population going forward; b) a model with socio-demographic information as well as trajectory clusters identified earlier as indicator variables (with the motivation that these clusters capture a mixture of information on changing employee preferences (due to their own experiences of working from home) as well as employer side decisions requiring workers to return back to the offices; and c) a model that builds upon the previous two models by adding identified attitude classes as indicator variables in order to capture the impact of individual attitudes regarding remote work on the likelihood of working remotely in the future.

The structure of the remaining chapter is as follows. Section 2 presents the data available for this study along with some descriptive statistics. Section 3 presents the analysis framework adopted for analyzing the data. Section 4 presents the results from various models and identifies the implications of the these results for the future of cities. Finally, section 5 presents summary, key takeaways, policy implications from the study and identifies the limitations of this work.

6.2 Data and descriptive statistics

6.2.1 Data

The data used here comes from Wave 7 of the 7-wave longitudinal tracking survey conducted between April and May 2022, where 972 individuals who participated at least once in the previous 6 waves of the tracking survey were re-invited to participate in this wave and data from an additional U.S. population representative sample (by gender, age, and ethnicity) of 905 individuals was also collected. In the combined dataset from wave 7, 1290 complete responses were available for this study (386 respondents from the re-invitations, 39.7% return rate) [1]. To correct for the sampling bias, we weigh our data using raking technique with age, gender, ethnicity and education attainment variables with the help of the American Community Survey's Public Use MicroData Sample (PUMS) [201]. While the sample weights were derived for the entire sample of 1290 individuals, in this study, we restrict ourselves to 915 working adults or students (810 sample size after weighing, about 62% of 1290 individuals) at the time of the survey.

To characterize the trajectories of telework through the pandemic and to understand the future of (remote) work, each respondent working full time, part time or a student *at the time of the survey* (915 out of 1290) was asked to retrospectively report their work location during the following time points:

- During 2019 (before the COVID-19 pandemic)
- April 2020 (start of lockdown period, 1^{st} peak in COVID-19 cases)
- August 2020 (2^{nd} peak in COVID-19 cases)

[1]Note here that while the new sample of 905 individuals was U.S. population representative, the combined sample of 1290 individuals was not, due to respondent attrition during re-invitations. Hence, to account for sampling bias, we weigh our sample to derive the population level statistics where necessary.

- April 2021 (vaccine available for all adults)
- July 2021 (COVID-19 cases at an all-time low)
- December 2021 (surge in cases due to Omicron variant)
- March 2022 (month prior the survey was conducted)

The possible responses included: *Exclusively on-site/at the office, Mostly on-site/at the office, Sometimes at home and sometimes on-site/at the office (or About 50/50), Mostly at home, Exclusively at home and Not applicable*. The "Not Applicable" would be chosen if the respondent (who was employed at the time of the survey) was not employed at a particular time point (either by choice or due to layoffs). Further, data for two additional *future time points* were also collected to understand the expected future work location behavior: *October 2022 and April 2024*. For these two time points, the respondents were also given an option of "Don't Know" to indicate work location uncertainty during the future time points, i.e. the respondent does not know where they will work from in the future.

Other information that we used in this study include respondents' *socio-demographic* information and respondents' *attitudes* regarding the impact (positive, neutral, negative, or not applicable) of a hypothetical 2-days a week remote work program on 12 different response items including their productivity, creativity, ability to innovate, effectiveness to get the job done. Socio-demographic information included respondents' age, gender, level of education, employment status (at the time of the survey), ethnicity, household size, number of children under 12 years old in the household, location of residence, and vehicle ownership status.

Regarding respondent's attitudes towards the impact of 2-days a week remote work policy at their organization, respondents were asked: *"Imagine that your employer has committed to a future work program allowing a hybrid workforce with an option of remote work for 2 days a* *week. In your opinion, what effects will such a program have on the following 12 aspects related to work?"* The respondents were asked to report their response on a 5-point Likert scale varying from Very Negative to Very Positive with "Not Applicable" as a possible option to choose from for cases where a particular response item was not relevant for an individual. The 12 aspects included [respondent's]:

- Productivity
- Creativity
- Ability to innovate
- Effectiveness to get the job done
- Ability to receiving / delivering appropriate mentoring
- Ability to receiving / delivering appropriate feedback
- Teamwork and ability to collaborate
- Career Advancement
- Social interaction with colleagues
- Employer's ability to accomplish its goals
- Employer's profit
- Employer's public image

6.2.2 Descriptive statistics

Telework trajectories

Figure 6.1 [2] presents a color-coded snapshot of work location trajectories of all 915 respondents in the data between 2019 (pre-pandemic) and April 2024. The color coding presented can be used

[2] Note here that the individual trajectories in this figure cannot be weighed. Instead, the proportions presented in Figure 6.2 have been weighted

to determine whether a respondent worked exclusively at home (**dark maroon**) or exclusively on site (**dark green**) during a time point. Colors (**light green**), (**light maroon**) and (**yellow**) represent mostly at office, mostly at home and about 50/50, respectively. The (**grey color**) represents whether this question was not relevant for a respondent at a particular time point and is potentially indicating that the respondent is not employed during that particular time point (by choice or by market conditions) or if the question for working from home/office is not relevant for them (e.g. for someone who is self employed and does not have a particular office site). The last two time points (October 2022 and April 2024) also have (**red color**) representing someone with uncertainty about their work location in the future. A different version of this data as cross-sectional proportions (weighted) across different work locations and at different time points is presented in Figure 6.2. A number of important observations can be made from these two figures, which acts as a sanity check for the quality of the data as well as builds a comprehensive picture regarding the evolution of telework through the pandemic.

Our data captures several intuitive trends. First, many individuals lost their jobs at the height of the pandemic ((**dark green**) to (**grey**) transition between 2019 and April 2020) and that those who did so were working exclusively in person pre-pandemic. This is in line with other data sources where it was found that majority of jobs lost due to the pandemic were low paying jobs (which generally tend to be exclusively in person) [202]. The trends of economic recovery over time can also be seen as COVID-19 cases reduced and economy was slowly re-opened. Second, as seen from Figure 6.2, the number of individuals working exclusively from on-site/office reduced from 47.8% in 2019 to 21.3% in April 2020 and then is slowly increasing since then with 32.6% in March 2022 and 29.4% (expected) in April 2024. The data also captures the expected trend of higher uncertainty at farther time point than at a time point only a few months away (4.6% don't know response in October 2022 and 15.3% in April 2024). Other interesting trends include an

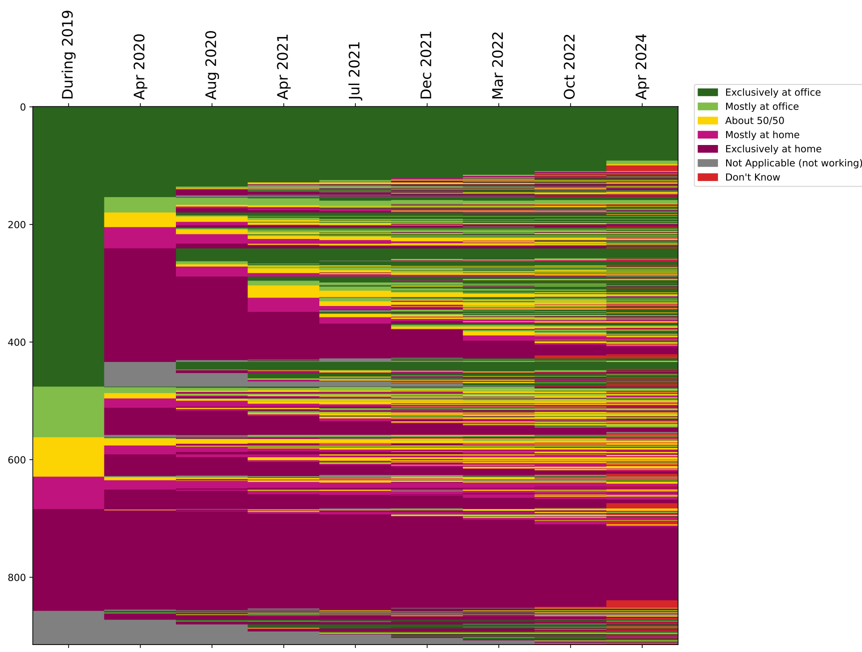


Figure 6.1: Telework trajectories of 915 respondents in the survey

increase in exclusively at home work from 21.8% in 2019 to 50.4% in April 2020, 35.3% in March 2022 and 26.9% (expected) in April 2024. Comparing 2019 and April 2024, even if everyone with a don't know response switches to exclusively working from office, there is a clear expected shift toward exclusively at home and hybrid work arrangements going forward.

The presented trajectories have been used later to identify clusters of telework trajectories through the pandemic, followed by estimation of a cluster membership model. Later, cluster indicators have been used as predictors in the April 2024 work location model where they capture a joint effect of employees' own decision to continue teleworking as well as the employer side policies on teleworking.

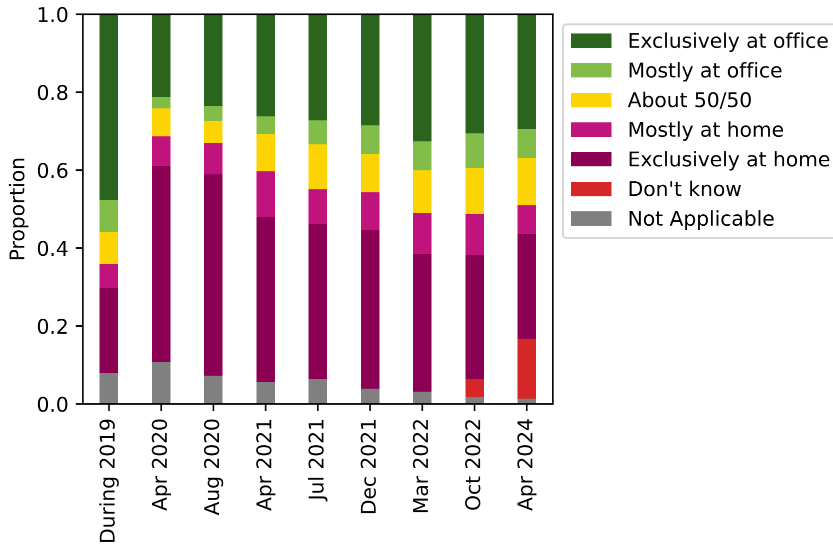


Figure 6.2: Work location proportions before, during and post-pandemic (weighted)

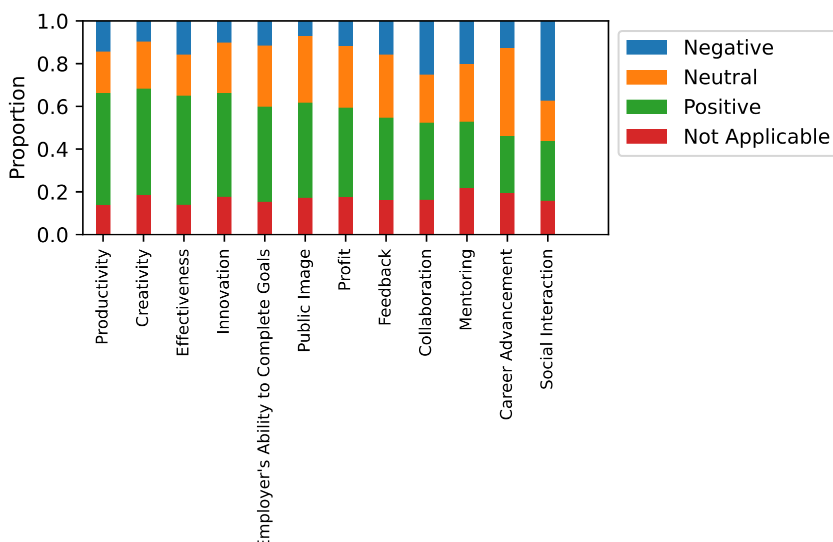


Figure 6.3: Respondents' attitudes regarding the impact of 2-days a week remote work on various aspects of work (weighted)

Attitudes regarding impact of 2-days a week remote work

Figure 6.3 presents distribution (weighted) of respondent's attitudes regarding the impact of 2-days a week remote work program on 12 different aspects of work. The original 5-point scale response has been converted to a 3-point scale to reduce complexity, while a 'not applicable' option also exists to denote respondents for whom these questions were not relevant. On the positive end, a large number of respondents expect a largely positive impact on productivity, creativity and the effectiveness to get the job done. Our results align with other studies and dataset regarding a positive impact (at least from the employee's own perspective) of remote work during the pandemic on employee productivity [80, 89, 91, 193]. On the negative end, an impact on social interaction with colleagues is the aspect where most respondents reported having a negative impact. Other aspects with negative to neutral impact included career advancement, mentoring, and collaborations. A negative impact of remote work on collaborations, mentoring and career advancements has also been pointed out by other studies [193, 203]. We use this data to conduct a latent class analysis and later use the latent classes as indicator variables in April 2024 expected work location prediction models.

Socio-demographics

Table 6.1 presents the descriptive statistics (weighted) of various socio-demographic information for the 915 respondents from whom the data is used in this study. Note here that these descriptives are only for the individuals who were working full-time, part-time or were students at the time of the survey and may not match with the U.S population level statistics. However, the overall dataset with 1290 respondents matches closely with the population distribution (after weighting). We use these socio-demographic variables as covariates in several models that we estimate in this study.

Table 6.1: Distribution of socio-demographic information of the 915 working adults in the data (weighted)

Variable	**Percent (%)**
Respondent's occupational sector	
Transportation, Warehousing and Manufacturing	8.51
Health Care	7.76
Information	11.58
Educational Services	9.85
Finance and Insurance	3.03
Professional, Scientific, and Technical Services	10.92
Retail Trade	14.17
Arts, Entertainment, and Recreation	11.17
Others	20.01
Respondent is *essential* workers or have been asked to work in-person	29.06
Ethnicity	
White	56.37
Black or African American	7.70
Asian	10.66
Hispanic or Latino	20.85
Others	4.42
Age	
Less than or equal to 44 years	56.50
Between 45 and 64 years	35.52
More than 65 years	7.98
Household location	
Urban	30.16
Rural	18.36
Suburban	51.48
Highest education level	
Less than undergraduate degree	61.50
Undergraduate degree	24.00
Graduate or professional degree	14.50
Household income	
Less than or equal to $49,999	42.7
Between $50,000 and $99,999	37.92
More than or equal to $100,000	19.38
Household with at least one kid under the age of 12 years	17.13
Respondent is female	45.81
Respondent is a student	8.68
Household size	
1	21.44
2	36.70
3	17.93
4	13.13
5	7.58
6 or more	3.23
Household without access to a vehicle	9.95

6.3 Analysis framework

Figure 6.4 presents the analysis framework adopted in this study to characterize the evolution of telework through the pandemic and the expected trends in work location in April 2024. We organize our analysis in four parts.

First, we begin with a hierarchical agglomerative clustering of telework trajectories for seven time points starting September 2019 to March 2022, where we identify four distinct clusters with varying level of telework adoption pre-pandemic, at the beginning of the pandemic and the rebound (or lack thereof) back to in-person work as economy opened and COVID-19 vaccines were introduced. Second, keeping the identified cluster labels as an outcome variable, we estimate a multinomial logit-based cluster membership model with the respondent's occupation and socio-demographic information as covariates. This analysis helps us understand the factors associated with various clusters of telework trajectories that we observed in our data. Third, we present results from an unconditional (i.e. without covariates) latent class model using responses regarding the impact of 2-days a week remote work program on various aspects of work. Using the latent class analysis, we identify six latent classes with varying degree of positivity towards the impact of 2-days a week remote work on various aspects. We use the latent class model to assign individuals into latent classes using a modal assignment procedure (i.e. assigning them in the latent classes with highest probability) and then use assigned latent class as indicator variable in the April 2024 work location model in order to capture the impact of individual attitudes on the future remote work behavior.

Lastly, we present two models to characterize the expected April 2024 work location of the respondents. In the first model, we use a binary logit model characterizing the factors impacting work location uncertainty given that about 15.3% respondents (weighted) in our data are not sure

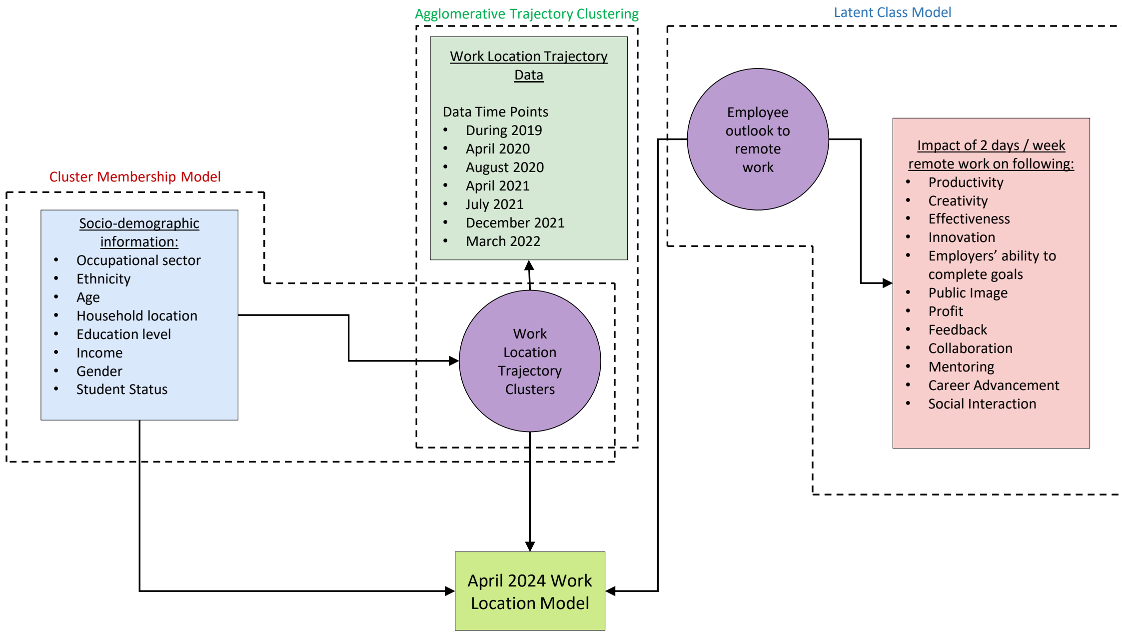


Figure 6.4: Analysis Framework

about their work location in April 2024. In the second model, we present an ordered logit model (for those with no uncertainty in their April 2024 work location) to understand the factors associated with the level of expected in-personness in April 2024. We present three different versions of the second model:

1. a model with only socio-demographic information focused at understanding the expected distribution of telework across the population.

2. a model with socio-demographic information as well clusters identified in the previous step as indicator variables (with the motivation that these clusters capture a mixture of information on changing employee preferences as well as employer side remote work decisions requiring workers to return back to the office.

3. a model that builds upon the previous two models by adding the information on the latent

class an individual belongs to using the data on attitudes towards the impact of telework on various aspects of work.

Clustering of telework trajectories was done using Agglomerative Hierarchical Clustering [116–118] with Levenshtein or Edit distance [119] as a similarity metric (calculated using *TraMineR* [120]) and with *agnes* [121] package in R programming language. Note here that we only use data up to March 2022 for the clustering and April 2024 data is used as the prediction time point. The clustering analysis revealed 4 distinct trajectory clusters with differing telework adoption levels through the pandemic.

Based on the four trajectory clusters identified in the previous step, we estimate a multinomial logit [111] based cluster membership model to understand the factors associated with various trajectories of telework through the pandemic. We estimate this model using maximum likelihood estimation with the *apollo* package in R programming language [204]. The dependent variable in our model is the discrete cluster variable to which a respondent belongs, and the independent covariates are the socio-demographics information of the respondent including their industry of occupation, age, ethnicity, household income, and education status.

To analyze the data on the employee attitude towards the impact of a hypothetical 2-days a week remote work policy at their workplace on various work aspects, we utilize a latent class model that stochastically divides individuals into various latent classes based on their responses to the 12 response items available to us. In the latent class model [205], we used the 12 available indicators (with 4 response options each, positive, neutral, negative, not applicable) as indicator variables to define the latent classes. We estimate the model in R using the *poLCA* package [206] and determine the optimal number of latent classes using model fit measures like Bayesian Information Criteria (BIC) as well as interpretability of the results. Note here that while the model estimation was done using unweighted data, we update the class proportions using the sample weights. We utilize the individual level probabilities of belonging to a latent class for assigning individuals into class with highest probabilities and then use this information as exploratory variables in the April 2024 work location model to understand the impact of respondent's attitudes toward remote work on their future work location decisions.

The April 2024 work location response variable consisted of 6 possible responses. Since the response scale is partly ordered (for Exclusively at home to Exclusively at office) and partly unordered discrete (for don't know), we estimate two separate models here: 1) a binary logit model to understand the factors associated with work location uncertainty in April 2024; 2) an ordered logit model to understand the factors associated with April 2024 work location preferences, only for those who do not have any uncertainly (i.e. they chose one of 5 ordered responses as their future work location). For both the binary and ordered model, we also include trajectory clusters as an indicator variable to capture impact of a mixture of employee preferences as well as employer side decisions on remote work. The binary logit setup in our study is similar to the cluster membership model presented earlier but with only 2 possible discrete outcomes (don't know and know). We estimate these models using *apollo* [204] and include socio-demographic information and trajectory cluster indicators as covariates.

6.4 Results

6.4.1 Clusters of telework trajectories

Figure 6.5 presents the mean trajectories (weighted) for 4 identified telework trajectory clusters with error bars corresponding to the standard deviation from the mean trajectory in each cluster. To generate Figure 6.5, individual response regarding work location was assigned a value between 1 to 5 (1 = exclusively at home, 5 = exclusively at office, excluding not applicable cases). Figure 6.6 presents a color-coded trajectory plot as in Figure 6.1 but now for each cluster separately. In

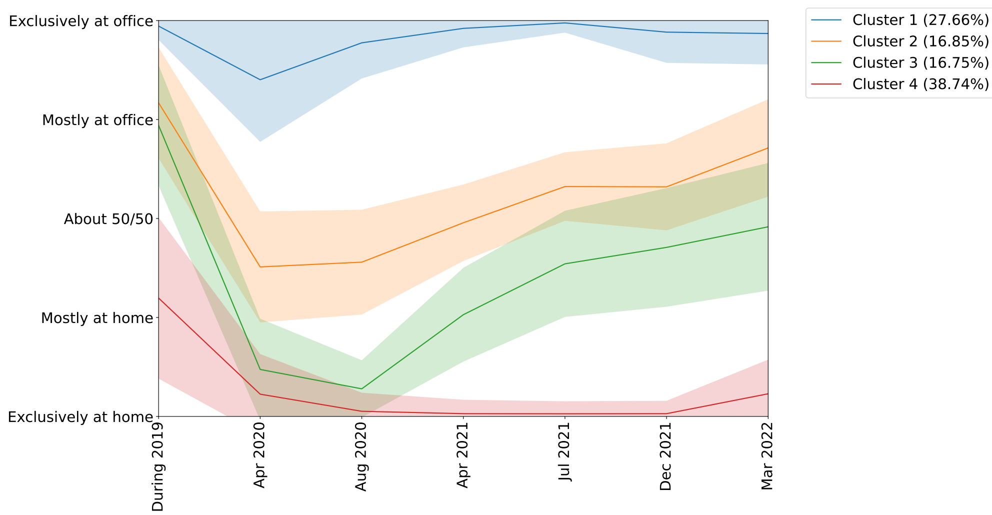


Figure 6.5: Mean telework trajectories for each cluster (weighted)

Figure 6.6, note that data for October 2022 and April 2024 was not used for clustering but is shown to describe how individuals in different clusters expect to work in the future. Below, we name these clusters taking into consideration the general teleworking trends these clusters denote. Several interesting insights can be derived from each cluster:

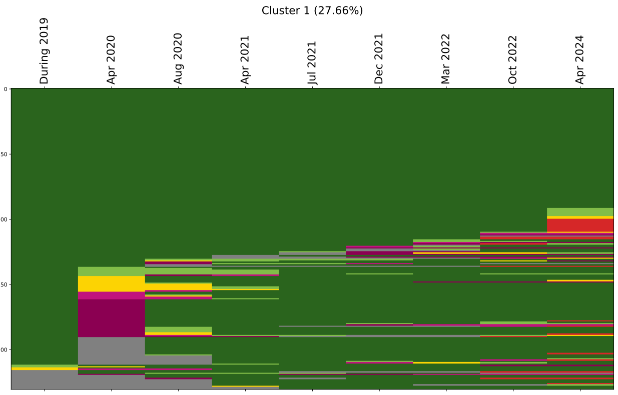
1. **In-person workers (Cluster 1, 27.66%)** – Most respondents in this cluster worked exclusively at office pre-pandemic and continued doing so at the height of pandemic. Even for cases where a set of respondents were able to shift to full or partial remote work, there was a significant rebound back to exclusively at office work in later stages of the pandemic. Most of the respondents in this cluster expect to work in person in April 2024, with some uncertainty for a small number of respondents. We name this cluster as the in-person workers cluster given the high prevalence of exclusively at office work throughout the pandemic and similar expected behavior in April 2024.

2. **Level 1 hybrid workers (Cluster 2, 16.85%)** – Most respondents in this cluster worked either exclusively at office or mostly at office pre-pandemic but a majority of them moved

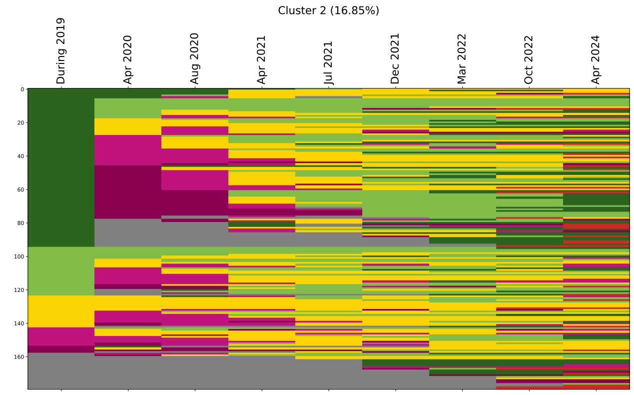
to some form of telework at the height of the pandemic in April 2020 (exclusively at home and mostly at home being more common). However, as the pandemic progressed, most respondents rebounded back to higher in-person activity and appears to have settled around mostly at office or about 50/50 at office / at home work. We name this cluster as Level 1 hybrid workers given their potential for at least some telework but perhaps also an employer side requirement for higher in person presence.

3. **Level 2 hybrid workers (Cluster 3, 16.75%) –** Most respondents in this cluster worked either exclusively at office or mostly at office pre-pandemic (similar to as in cluster 2) but made a drastic shift to exclusively at home work at the height of the pandemic. This cluster showed slower rebound back to workplace and also showed much higher levels of telework adoption compared to cluster 2. In April 2024, the respondents in this cluster are expected to showcase higher at home work adoption compared to cluster 2. Given that this cluster showed higher at home presence compared to cluster 2 (and is also expected to maintain this behavior going forward), we name this cluster as Level 2 hybrid workers.

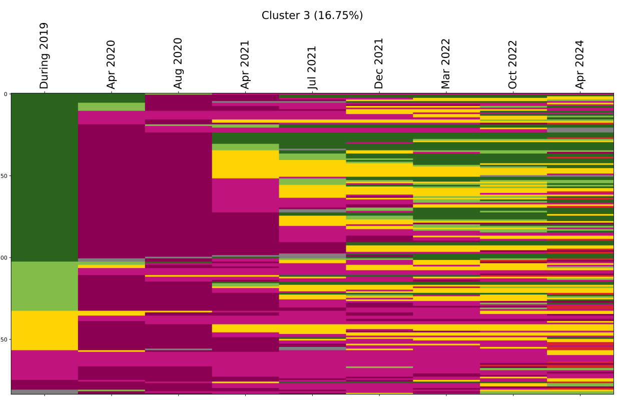
4. **At home workers (Cluster 4, 38.74%) –** A majority of respondents in this cluster worked exclusively or mostly at home pre-pandemic and continued doing so for a long time during the pandemic. For those who were working hybrid or exclusively at office, they too shifted to exclusively at home worker with a minor rebound to some in person work in 2022. This cluster shows higher uncertainty in April 2024 work location preferences but still is expected to maintain a much higher at home work arrangement compared to other clusters. We name this cluster as at home workers due to high prevalence of remote work throughout the pandemic and a similar expected behavior going forward.



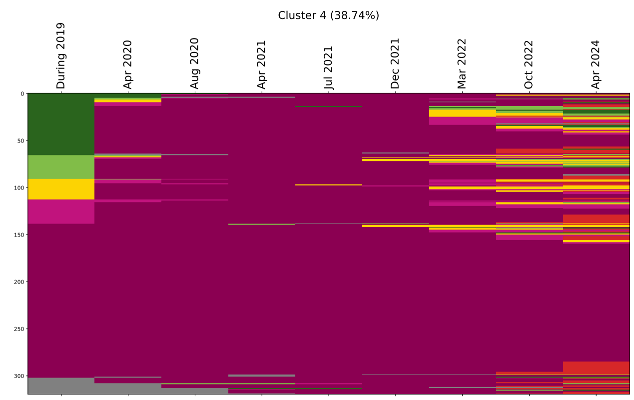
(a) Color coded telework trajectories for cluster 1



(b) Color coded telework trajectories for cluster 2



(c) Color coded telework trajectories for cluster 3



(d) Color coded telework trajectories for cluster 4

Figure 6.6: Color coded telework trajectories for various clusters

It is important to note here that for the last three clusters (which is about 72% of the data) some form of remote work is expected going forward, suggesting a high level of hybrid work arrangement in th future. Albeit, the level of uncertainty is also higher in these three clusters, potentially indicating the importance of the role that employers will play in determining the future of remote work. We investigate these trends further in the next few sections with the help of membership model and with April 2024 work location prediction models.

6.4.2 Cluster membership model

Table 6.2 presents the results from the cluster membership model aimed at understanding the factors associated with the identified telework trajectory clusters. A visual representation of these results is presented in Figure 6.7. Note that the clusters show an ordered pattern of telework adoption through the pandemic with cluster 1 showcasing most in-person presence at work location, cluster 4 with least in-person presence at work location and clusters 2 and 3 being hybrid work location clusters with increasing level of at home presence. In the presented model, cluster 1 is kept as the reference cluster, so the estimated parameters are interpreted with reference to cluster 1. Since the parameters corresponding to cluster 1 are fixed to zero, Figure 6.7 only includes three columns of parameters, corresponding to clusters 2, 3 and 4. The colored circles in Figure 6.7 correspond to the mean value of the estimated parameters and the horizontal bars correspond to 90% confidence interval, however, most parameters are also significant at 95% confidence interval.

Several important insights can be derived from this model. On the end of job related factors, our results capture a significant systematic trends in the adoption of telework through the pandemic and the occupational sector in which the respondents work. On the in-person end, our results indicate that those in *transportation and manufacturing* sectors were a lot less likely to be present in cluster 2, 3 and 4 (i.e. very high likelihood for in-person work), those in the *healthcare* sector were less likely to be present in cluster 4 while those in the *education* sector were more likely to be present in clusters 2 and 3 but less likely to be present in cluster 4. On the end of remote work, our results indicate a high likelihood for presence in cluster 2, 3 and 4 for those in *professional, scientific and technical services* and *information* sector and higher likelihood for cluster 4 for those in *finance/insurance* sector. Lastly, our results also indicate a significantly lower likelihood of presence in clusters 2, 3 and 4 for those who are essential workers. Our finding with regards to occupational sectors align with findings of Barrero et al. [80] and Eisenberg [97]. These results highlight the strong interaction between industry sector / nature of work and remote work adoption. An important insight from these results is that various cities across the United States may be impacted deferentially from the changed remote work landscape based on the composition of the city's economy. This is also evident from the mobility recovery trends from across United States where recovery to pre-pandemic mobility / activity levels is higher for New York city and Chicago compared to San Francisco since the former two have a lot less presence of information sector companies than later [49].

On the end of the respondent's household characteristics, some of the key significant variables include household vehicle ownership, presence of young child in the household, location of the household (urban or not), household income and household size. On the end of vehicle ownership, results suggest that households without a vehicle (who also tend to be more likely to be transit riders) were more likely to be in clusters 2, 3 and 4, i.e. more likely to adopt some form of remote work. This potentially highlights the commute elimination aspect of remote work, which has been highlighted in Chapter 5. Another important aspect here is related to the COVID-19 exposure risk while using transit and that the individuals who were transit dependent potentially used remote work as a way to avoid exposure to the virus by working from home more frequently. While the pandemic exposure risk issue has been resolved, it would be interesting to see how the commute

Table 6.2: Cluster Membership Model

Variables	**Cluster 1**	**Cluster 2**	**Cluster 3**	**Cluster 4**
Constant	--	-0.248 (-1.529)	0.104 (0.803)	1.387 (14.828)
Socio-Demographics				
Ethnicity				
Asian Ethnicity Indicator	--	0.962 (5.956)	--	--
Black or African American Ethnicity Indicator	--	0.630 (4.021)	0.343 (2.049)	--
Hispanic Ethnicity Indicator	--	-0.674 (-4.488)	--	-0.627 (-5.193)
Level of Education				
Highest Degree as Undergraduate Indicator	--	0.583 (4.848)	0.934 (7.671)	--
Highest Degree as Graduate Indicator	--	0.296 (1.825)	0.937 (6.217)	--
Household Income				
Income less than $50k Indicator	--	--	-0.435 (-3.831)	--
Income $50k to $100k Indicator	--	-0.200 (-1.863)	--	--
Age more than 65 years Indicator	--	--	--	0.744 (4.689)
Urban Household Location Indicator	--	0.486 (4.372)	-0.247 (-2.055)	--
Household with at least one child under age 12 years indicator	--	0.365 (2.111)	0.311 (1.879)	0.734 (4.689)
Female Respondent Indicator	--	-0.521 (-4.810)	-0.274 (-2.563)	--
Full Time Student Respondent Indicator	--	--	-0.828 (-4.474)	-1.506 (-9.161)
Natural log of Household Size	--	0.227 (2.113)	--	--
Household without a vehicle Indicator	--	1.241 (4.772)	1.840 (6.958)	1.635 (6.725)
Job Related Factors				
Essential Worker Indicator	--	-1.614 (-12.348)	-2.474 (-16.680)	-3.719 (-23.553)
Sector of Occupation				
Transportation and Manufacturing	--	-1.004 (-4.683)	-0.491 (-2.513)	-2.313 (-9.790)
Information	--	0.456 (2.375)	--	0.885 (5.701)
Health Care	--	--	--	-1.310 (-6.247)
Educational Services	--	0.484 (2.411)	0.701 (3.533)	-0.439 (-2.111)
Finance and Insurance	--	--	--	0.276 (1.574)
Professional, Scientific and Technical Services	--	1.246 (4.957)	1.464 (5.783)	1.296 (5.312)
Model Fit				
Number of observations	915			
ρ_c^2	0.2534			
Adjusted ρ_c^2	0.2437			

elimination aspect of remote work evolves since this will have important implications for the future of transit ridership going forward. On the end of presence of young children in the household, our results suggest that these households were more likely to be in clusters 2, 3 and 4 (i.e. high remote work) and highlights that households potentially used remote work as a way to cater to childcare responsibilities. This is interesting since in the results in Chapter 5, we found out that those with a young child at home were less satisfied with their telework experiences during the pandemic, however, despite this, our results here suggest a higher remote work amongst them during the pandemic. A potential reason is the closure of or high exposure risks at daycare centers for the respondents, forcing them to work remotely for an extended period of time. It would be interesting to see the extent to which remote work continues amongst these households since the exposure risks have been mostly alleviated and the daycare centers are open too. However, it may also be true that households may use remote work as a way to save on the daycare cost, and if true, remote work may continue to be high amongst these households.

Our results also suggest that urban households were more likely to be in cluster 2 but less likely to be in cluster 3. While a detailed characterisation of why this is the case maybe difficult with the data we have available for this study, a potential interaction with residential self-selection may be at play here, where households that decided to continue to live in the urban areas may have done so taking their commute frequency in consideration — however, a deeper investigation is needed to fully characteristics this aspects.

With regards to household size, our results capture a small positive but significant relationship between larger household size and likelihood of belonging to cluster 2 (level 1 hybrid). This may potentially be related to the distraction / disturbance aspect from other household members in the household, forcing an individuals to work from a non-home location a few days a week [198]. This aspect also has important implications from mobility standpoint depending upon the location at which this out of home work takes place. For example, it is possible that teleworkers may use third places like a coffee shop or local libraries for work instead of commuting to workplaces, since the third places may serve the same purpose for most, while also reducing the commute time. If true, there may potentially be an increase in demand for shorter trips to these third places around places of residence. Lastly, our results also capture variation of telework trajectories by household income where the most significant effect was lower likelihood of being in cluster 3 for those with income $50,000 or under and lower likelihood of being in clusters 2 for households between $50,000 and $100,000.

On the end of individual characteristics of the respondents, our results include gender, age, education attainment, ethnicity and student status as significant variables. Key results include a lower likelihood of being in cluster 3 and 4 for students (i.e. high in-person presence), lower likelihood of being in clusters 2 and 3 for females, higher likelihood for being in cluster 4 for those with age 65 years or older. Further, our results also indicate a higher likelihood being in hybrid clusters (cluster 2 and 3) for those with a bachelor's degree or higher. Lastly, our results also capture a significant variation of remote work adoption by ethnic groups as well where individuals with African American ethnicity were more likely to be in clusters 2, and 3, those with Asian ethnicity were more likely to be in cluster 2 while those with Hispanic ethnicity were less likely to be in cluster 2 or cluster 4.

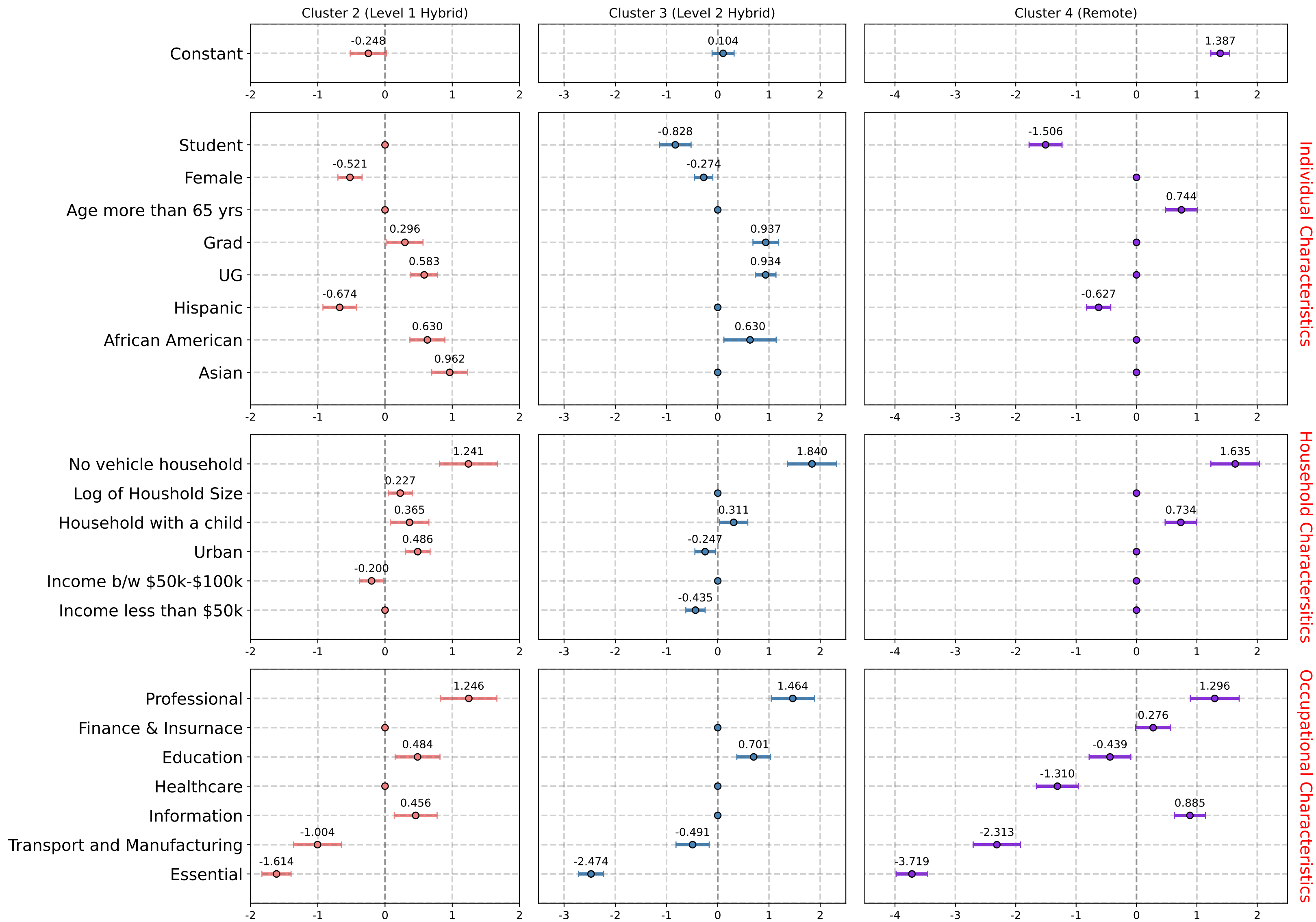


Figure 6.7: Estimated parameters and 90% confidence intervals for the cluster membership model

6.4.3 Latent class analysis

Figure 6.8 presents the results from the latent class analysis where we identify 6 different latent classes with varying degree of positivity towards the impact of remote work on various work aspects. All six clusters have been named based on the patterns in estimated conditional response probability values (ρ parameters) as shown in the collection of twelve bar plots, one for each response item. The proportions presented in orange color at the top are weighted and represent the proportion of individuals belonging to a particular latent class. For example, our model suggests that about 16.4% individuals have relatively negative outlook towards the impact of remote work on their productivity or creativity. The latent classes have been ordered from negative to positive, with the last class denoting individuals to whom these questions were not‘ relevant. Important insight from this analysis include that the perceived impact of remote work on various work aspects is mixed and this will have important implications for the future of remote work going forward. Based on the latent class model, we estimate the class probability of each individual in the data and assign them to a cluster based on modal assignment (i.e., assigning them into cluster with the highest probability) and then use these cluster indicators as independent indicator variables in the April 2024 work location model to capture the impact of individuals attitudes on future remote work decision.

6.4.4 Predictive model for April 2024 work location

Binary logit model characterizing work location uncertainty

Table 6.3 presents results from a binary logit model for understanding the uncertainty in work location in April 2024. A visual representation of these results is presented in Figure 6.9. Note here that the number of observations used for this model decreased from 915 to 905 due a missing

Class Labels	Negative	Neutral	Positive to Neutral	Mixed	Positive	NA
Proportions	16.4%	11.50%	9.50%	21.9%	27.3%	13.4%
Productivity						
Not Applicable	0.02	0.01	0.05	0.00	0.00	0.97
Positive	0.08	0.06	0.44	0.92	0.98	0.01
Neutral	0.19	0.79	0.28	0.06	0.02	0.01
Negative	0.72	0.14	0.23	0.03	0.01	0.01
Creativity						
Not Applicable	0.04	0.03	0.17	0.00	0.01	0.99
Positive	0.20	0.07	0.37	0.81	0.94	0.01
Neutral	0.25	0.80	0.29	0.18	0.04	0.00
Negative	0.51	0.10	0.17	0.01	0.00	0.00
Ability to innovate						
Not Applicable	0.03	0.02	0.20	0.00	0.02	0.99
Positive	0.20	0.05	0.34	0.77	0.93	0.01
Neutral	0.24	0.84	0.28	0.22	0.05	0.00
Negative	0.53	0.10	0.18	0.02	0.00	0.00
Effectiveness to get the job done						
Not Applicable	0.02	0.01	0.03	0.00	0.00	0.97
Positive	0.04	0.00	0.49	0.88	0.98	0.00
Neutral	0.15	0.89	0.26	0.09	0.02	0.01
Negative	0.79	0.10	0.21	0.02	0.00	0.02
Receiving / delivering mentoring						
Not Applicable	0.03	0.06	0.41	0.03	0.04	1.00
Positive	0.05	0.04	0.45	0.11	0.91	0.00
Neutral	0.19	0.88	0.11	0.49	0.05	0.00
Negative	0.73	0.02	0.03	0.38	0.00	0.00
Receiving / delivering feedback						
Not Applicable	0.01	0.00	0.21	0.00	0.00	0.98
Positive	0.06	0.07	0.59	0.19	0.96	0.00
Neutral	0.24	0.93	0.20	0.55	0.03	0.02
Negative	0.69	0.00	0.00	0.26	0.00	0.00

Class Labels	Negative	Neutral	Positive to Neutral	Mixed	Positive	NA
Proportions	16.4%	11.50%	9.50%	21.9%	27.3%	13.4%
Ability to collaborate						
Not Applicable	0.02	0.02	0.25	0.00	0.01	0.96
Positive	0.07	0.17	0.47	0.19	0.89	0.00
Neutral	0.11	0.72	0.17	0.44	0.09	0.00
Negative	0.79	0.09	0.11	0.37	0.02	0.04
Career Advancement						
Not Applicable	0.01	0.05	0.31	0.00	0.04	0.99
Positive	0.05	0.00	0.31	0.22	0.73	0.00
Neutral	0.43	0.92	0.29	0.65	0.21	0.01
Negative	0.52	0.03	0.09	0.13	0.02	0.00
Social Interaction with collegues						
Not Applicable	0.02	0.02	0.21	0.00	0.01	0.97
Positive	0.09	0.25	0.44	0.06	0.64	0.00
Neutral	0.09	0.51	0.19	0.21	0.20	0.00
Negative	0.80	0.23	0.17	0.73	0.15	0.03
Employer's ability to accomplish goals						
Not Applicable	0.00	0.00	0.14	0.01	0.00	0.97
Positive	0.03	0.06	0.43	0.62	0.98	0.01
Neutral	0.29	0.90	0.38	0.35	0.02	0.02
Negative	0.68	0.04	0.06	0.01	0.00	0.00
Employer's profit						
Not Applicable	0.03	0.01	0.28	0.03	0.03	0.96
Positive	0.11	0.12	0.22	0.57	0.88	0.01
Neutral	0.33	0.81	0.37	0.36	0.08	0.02
Negative	0.53	0.06	0.13	0.04	0.01	0.01
Employer's public image						
Not Applicable	0.01	0.00	0.30	0.03	0.01	0.95
Positive	0.21	0.16	0.27	0.57	0.92	0.02
Neutral	0.43	0.82	0.34	0.39	0.07	0.03
Negative	0.35	0.02	0.09	0.02	0.00	0.00

Figure 6.8: Respondents' attitudes regarding the impact of 2-days a week remote work on various aspects of work

values in a few covariates used for estimating the models.

Several important findings are revealed from this analysis. On the positive end of uncertainty, we found it to be higher for female respondents, those who are students and those in the information sector. On the other end of the spectrum, we found it to be lower for those with a graduate degree as their highest level of education attainment. Higher uncertainty for student respondents is intuitive since they might be unsure about their job situation 2 years down the line after graduation. For respondents with highest education as a graduate degree, lower uncertainty may be potentially related to either the nature of the work or higher leverage viz. their employers since individuals with a graduate degree are typically in more specialized jobs and hence are able to negotiate their

Table 6.3: Binary logit model of work location uncertainty in April 2024

Variable	Parameter Estimate	t-stat
Intercept	-1.9863	-17.867
Female respondent indicator	0.4275	3.054
Information sector occupation	0.4217	2.136
Student	0.6412	3.025
Graduate	-0.2772	-1.308
Model Fit		
Number of observations	905	
ρ_c^2	0.3864	
Adjusted	0.3819	

work location. Higher uncertainty for individuals in the information sector is likely associated with employer side uncertainty in reaching a work location policy for the future. Lastly, higher uncertainty for female respondents is potentially related to higher job switching rates or potentially higher rate of burnout amongst women during the pandemic [207].

One important implication of these results for cities is that there is still a significant level of uncertainty in the future of work location and how the landscape evolves from here will determine the true nature of the impact on cities. However, the fact that the uncertainty is higher amongst in the information sector, it is likely that the employers will play an important role in determining the ultimate trajectory of remote for the future. Some existing and ongoing efforts in understanding the employer perspective might provide important information in this regard for the cities [93, 94, 96, 97, 197]

Ordered logit model characterizing work location for those without uncertainty

Table 6.4 presents results from three different ordered models focused at understanding the relationship between April 2024 work location (for those who are certain about it) and socio-economic factors, attitudes regarding remote work's impact on various aspects determined using the latent

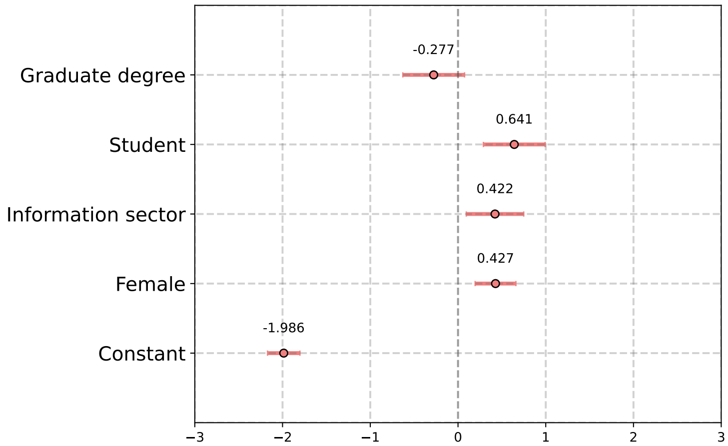


Figure 6.9: Estimated parameters and 90% confidence intervals for the april 2024 work location uncertainty

class analysis and the impact of a mixture of changing personal preferences and employer side decision on remote work. A visual representation of these results is presented in Figure 6.10. A positive parameter estimate represents a higher likelihood for in-person work in April 2024 and a negative parameter represents a lower likelihood for in-person work.

Several important insights can be derived from the presented results. First, following the results from the model with just socio-demographic information, our results indicate a continuation of higher in-person work for transportation/manufacturing, healthcare and education sectors, while lower in-person work is expected for those in the information sector. Surprisingly, finance/insurance and professional / scientific / technical services sectors were no longer significant in this model. These results align with those presented in the membership model earlier, providing more evidence on how remote work is distributed across various sectors as well as how the recovery of mobility patterns across cities depending upon the composition of jobs in various sectors in a city.

On the end of household characteristics, results indicate a lower likelihood for in-person work

Table 6.4: Ordered logit model for work location in April 2024

Variable	Without clustering info	With clustering info	With trajectory info + attitude latent class
Socio-demographics			
Highest level of education			
Highest degree is Undergraduate	0.482 (2.785)	0.428 (2.218)	0.432 (2.145)
Highest degree is graduate	0.482 (2.218)	0.704 (2.830)	0.695 (2.798)
Age more than 65 years	-0.934 (-3.714)	-0.718 (-2.473)	-0.693 (-2.382)
Respondent is a student	0.923 (3.470)	--	--
Zero vehicle household	-0.611 (-2.585)	--	--
Occupational Sector			
Transportation and manufacturing	1.094 (4.019)	--	--
Information	-0.770 (-3.341)	--	--
Health Care	0.825 (3.127)	--	--
Education Sector	1.172 (4.283)	1.628 (5.333)	1.620 (5.283)
Trajectory Info			
Cluster 2 indicator	--	-2.262 (-8.560)	-2.240 (-8.479)
Cluster 3 indicator	--	-3.039 (-10.954)	-2.979 (-10.647)
Cluster 4 indicator	--	-5.460 (-18.789)	-5.428 (-18.635)
Negative attitude towards remote work class indicator	--	--	0.355 (1.513)
Thresholds			
1|2	-0.757 (-4.030)	-4.236 (-14.383)	-4.139 (-13.872)
2|3	-0.271 (-1.454)	-3.422 (-12.107)	-3.326 (-1.602)
3|4	0.455 (2.436)	-2.248 (-8.353)	-2.145 (-7.833)
4|5	0.976 (5.169)	-1.387 (-5.379)	-1.276 (-4.838)
Model Fit			
ℒℒ	-1,063.28	-823.96	-821.95

zero vehicle households. With regards to individual characteristics, we found out that students, or those with at least an undergraduate degree are more likely to be in-person, while those with age 65 years or older are less likely to be in-person. In the model with clustering information, the results suggest lower in-person work likelihood for clusters 2, 3 and 4 (in increasing order of magnitude), potentially indicating a continuation of the trends captured in the clustering analysis. Note here that some of the occupation sector related variables have been removed from this model since the corresponding parameters are now insignificant due to potential correlation between trajectory clusters and these variables. Lastly, the model with both the trajectory cluster and attitude latent class variable suggests that those with negative attitudes regarding the impact of remote work on job related factors are more likely to be in-person.

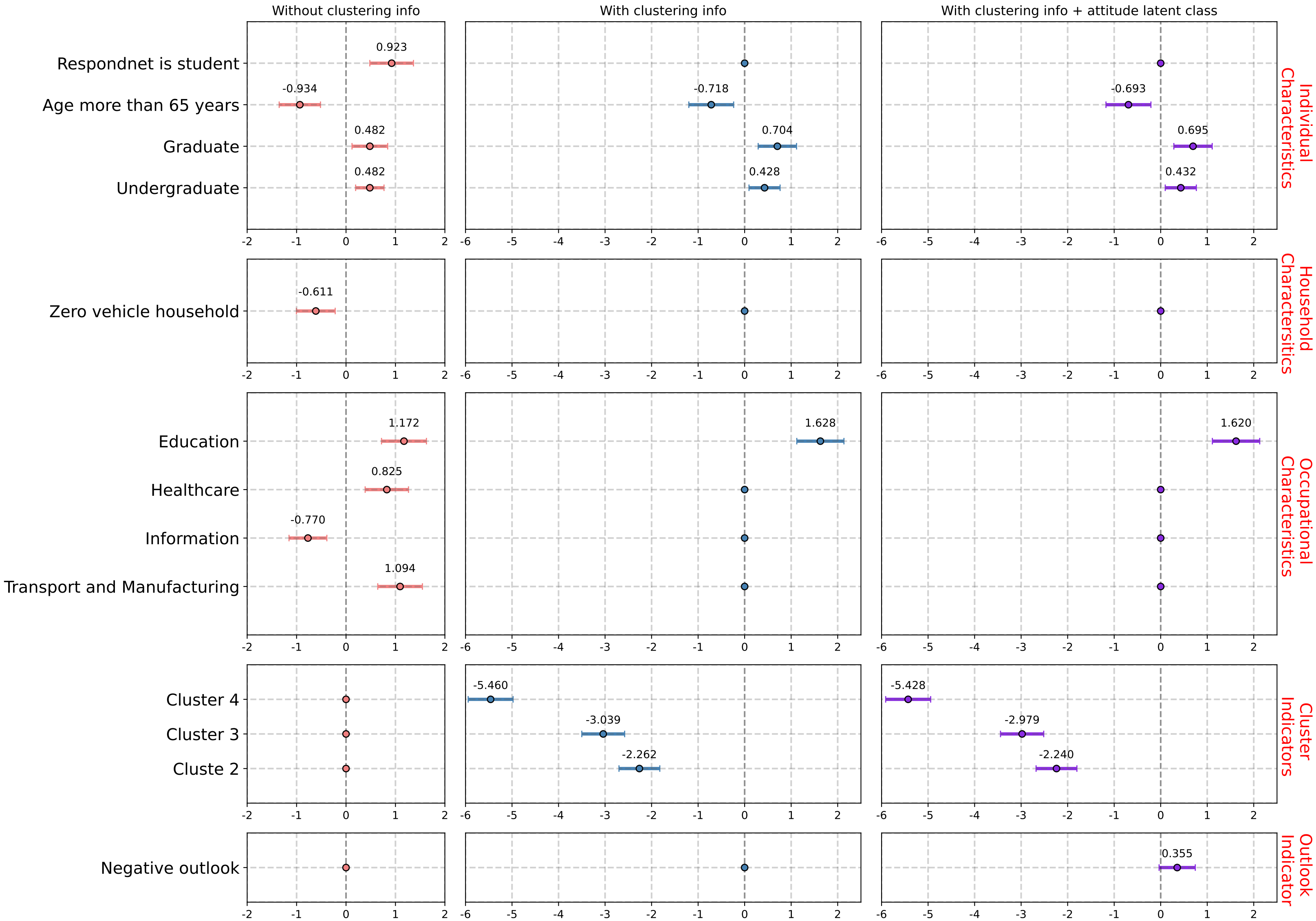


Figure 6.10: Estimated parameters and 90% confidence intervals for the April 2024 work location model

6.5 Summary, Key Takeaways, Policy Implications and Limitations

Summary and Key Takeaways

Using data from U.S representative sample of 915 respondents, this study presents a trajectory-based clustering analysis of work location trajectories through the pandemic. We identified 4 distinct clusters of telework trajectories with distinct levels of telework adoption patterns. Following the clustering analysis, the study presented results from a cluster membership model focused at understanding the factors associated with various telework trajectories including sector of occupation and socio-economic factors. This was followed by a two-part model focused at understanding the April 2024 expected work location, four years since the beginning of the pandemic.

Several key insights emerged from our analysis. First, at aggregate level, our data suggests that for three out of four clusters (72%) of respondents, some form of remote work is expected going forward, suggesting a high level of hybrid work arrangement in the future.

Using these clusters as a dependent variable, a multinomial logit based membership model suggested that the telework trajectories through the pandemic were highly associated with nature of job in which one is employed, where higher in-person work was seen for transportation / manufacturing, logistics, healthcare sectors but higher remote work was seen for professional services, finance and insurance and information sectors. Other important insights included a higher level of remote presence by those with age 65 years or more, those without a vehicle and those with a young child at home. On the other end, results suggest lower remote presence for those who are students; while a hybrid presence was maintained by female respondents, those with at least an undergraduate degree, those with non-white ethnicity, those with a large household and those with income less than $100,000.

On the end of expected work location trends in April 2024, about 4 years since the beginning of the pandemic, our results indicate work location to be uncertain for about 15% of the respondents, who were more likely to be a female, a student or information sector employee but less likely to have a graduate degree. Amongst those that are certain regarding their work location in April 2024, higher in-person work is expected from those who are in education, healthcare and transportation / manufacturing sectors, those who are students or those with at least an undergraduate degree. On the opposite end, higher remote work is expected amongst those in the information sector, those without a vehicle or those with age less than 65 years. Results also suggest a high interaction between past telework behavior through the pandemic and the expected future behavior, along with a strong interaction between a respondent's outlook towards the impact of remote work on various work aspects like productivity and supervisions, and their future work location decisions.

Policy Implications

There are several important policy takeaways from these results. First, our results suggest that those without are vehicle (who also tend to be transit users) are more likely to continue to work remotely — potentially indicating a slower rebound of transit ridership. Second, a strong interaction between the occupational sector and remote work adoption level highlights that the impact of remote work on different cities across the United States may be different — dependent on the composition of the economy of a city. Third, a reduced level of commuting may hurt individuals employed in the third sector of the economy (especially in urban cores) — who largely rely on spending by commuters. Lastly, an increased flexibility may also motivate teleworkers to move away from urban cores in search of better value for their money — potentially changing the mobility landscape in urban cores, as well as where the location where teleworker may move.

Limitations

There are a few limitations to the analysis presented in here. First, the telework landscape is a dynamic process with changing trends and associated attitudes and requires constant monitoring to reveal the expected future trends. Unfortunately, our data ends in March/April 2022 and any future expected trends in our data are based on the learning and decisions at the time of the survey. A more recent data set may reveal updates to the trends that were visible from the dataset we collected. Second, the method of trajectory clustering following by membership model estimation is a two step process that has its limitation which could potentially be corrected using a more robust framework. Agglomerative clustering is deterministic in nature instead of stochastic methods followed in the rest of this dissertation. Further, it does not allow for a joint estimation of the clustering process and the membership model, which potentially may provide better estimates. A possible methodological direction in this regard is the use of a growth mixture modeling, which follows the generalized latent variable modeling framework used in the rest of this dissertation, while allowing for sequential treatment of the trajectory data available to us.

CHAPTER 7
EMPLOYERS' PERSPECTIVE ON THE FUTURE OF WORK POST-PANDEMIC

7.1 Introduction

The changing nature of (remote) work as a result of the COVID-19 pandemic in the United States (and globally) has been studied significantly over the past three years regarding how it evolved through the pandemic; how it may look in the near future and long term; what sort of impact it may have on cities; and how cities may prepare for these changing trends. There is significant emerging evidence from multiple datasets that a large proportion of the pandemic-accelerated telework trends are likely to stick well beyond the pandemic and that this will have major implications for urban mobility and the functioning of cities [43, 49, 80, 104, 193, 194, 208]

Existing studies point to several factors that have and will continue to shape employee preferences regarding the extent to which they will continue to work remotely. On one end, studies point to several benefits for workers. These include travel time savings due to not needing to commute, improved productivity, well-being, and health outcomes, ability to provide care for other household members and dependents, and cost savings like transportation fuel cost of commuting or housing cost in cases where moving to a less expensive area is an option are some factors that employees might consider in evaluating the extent to which to continue to telework. On the other end, telework presents several challenges, such as a fuzziness of boundaries between work and life, lack of appropriate workspace and work environment at home like distraction from others, appropriate furniture and technology at home, and limitations in the ability to coordinate between teammates, opportunity for professional networking or career advancement, to mentoring and supervision opportunities [80, 83–85, 89–91, 104, 209–211].

A major issue with most existing research is that evolving remote work trends are only studied from the perspective of the *employees* even though any future trends are unavoidably a function of both *employee preferences and the employer-side decision* to allow remote work. Emerging literature points to arguments on both ends as to whether employers may continue to provide telework as an option. Evidence exists that productivity while working from home during the pandemic was equal to or better than expected for most [80, 89, 91] and this may be a factor that employers may consider to select remote work strategies. However, there is also evidence of differences between employee-perceived productivity in remote work settings compared to what employers perceive [199]. There is also an argument of cost savings for the employers in terms of reduced office space requirement and not needing a cost of living adjustment to salaries, especially in cases where an employee works fully remotely from a less expensive city [212, 213]. There is also growing evidence that employees are increasingly demanding more flexibility in work location and are even ready to either accept 5-10% pay cuts in order to have more flexibility or are ready to quit and switch to companies that offer better work location flexibility [83, 85, 89, 92]. On the con side, there is evidence that remote work hurts collaborations and innovation; and this may be important for companies that rely on innovation to maintain a competitive edge over others [214]. Similar to the case for productivity, also here there is a gap between the employee and employer expectations for remote work and this difference in expectations at the two ends may decide the eventual remote work adoption [80]. Overall, while there are benefits of remote work for employees and potentially for employers too, there is still disagreement between the two parties on several matters and the result of this power struggle will potentially determine the future remote work landscape.

Even though employers are the ultimate decision-makers in this evolving remote work landscape, only a handful of studies have looked at the employer's perspective to understand the future of work [93, 95, 96]. However, these studies either focus on just the knowledge / information workers and do not present differences across various sectors or have surveyed human resources or mid-level managers only. Since the COVID-19 pandemic potentially proliferated telework beyond knowledge/information sectors and since ultimate company-wide telework policies are going to be driven by top-level executive decisions, we argue that a survey of a diverse set of top-level executives is necessary to gain a thorough understanding of the employers' perspective on telework in the post-pandemic world.

In this chapter, we present results from data collected over a 5-wave longitudinal survey conducted amongst top executives (~90% vice president and chief executive officer level, ~10% director level) of 129 unique employers in North America to understand the evolution and future landscape of remote work through and beyond the pandemic. While our data is neither representative of the population of employers nor it is a large sample, our data is diverse in terms of organizational characteristics captured like annual revenue, number of employees, and sectors of operations, and is rich in terms of the information available and hence provides several interesting insights regarding the potential trajectory of the future of work. We specifically focus on the following four aspects.

First, for those employees for whom telework is possible, we analyze how the employers' approach to remote work varied over time since the beginning of the pandemic and what approach they expect to take in the future. Specifically, we collected data on the employers' approach to remote work at the following time points:

- September 2019 (pre-COVID)
- April 2020 (early phase of the pandemic)

- October 2021
- November 2021
- January 2022
- April 2022
- August 2022
- October 2022 (expected approach)
- April 2024 (expected approach)

We analyze this data to understand how the average work location across organizations varied (or is expected to vary) over time at an aggregate level and also identify differences across various sectors of operations, departments within the same organization, and how it varied for organizations with different remote work approaches pre-COVID (in September 2019) and in the early phase of the pandemic (in April 2020).

Second, we present and analyze data on the employers' opinion regarding the expected impact (positive, negative, or neutral) of remote work on various business aspects in a hypothetical scenario where a 2-days per week remote work policy is adopted by their organization. Business aspects include: the ability to recruit/retain employees, profitability, long-term viability, ability to compete, ability to innovate, public image, employee productivity, creativity, and supervision/mentoring. First, we descriptively present the employers' top concerns and perceived benefits related to the impact of remote work on business aspects, and this is followed by the estimation of a latent class model which divides employers into two latent classes representing their outlook (positive or negative) towards remote work. The latent class analysis is extended with the estimation of a latent class membership model to understand the association between the identified latent classes and the demographic characteristics of the organizations. This analysis helps us understand the important factors that may shape employer policies regarding remote work in the future.

Third, we dive deeper into understanding the remote work landscape in April 2024, four years after the beginning of the pandemic by estimating an ordered probit model that associates an organization's sector of operations, pre-COVID and early pandemic approach to remote work, and the employer's outlook towards the impact of remote work on business aspects with the expected April 2024 remote work approach. The model provides insights regarding which organizations are more likely to showcase higher/lower in-person presence in the future.

Fourth, we present data on the extent of resumption of business travel of over 50 miles and in-person client interactions at the time of various waves of the survey; and how employers have (or plan to) reconfigured their office spaces in light of the expected changes in employee work locations. Collectively, this data provides insights into the extent of the permanency of the altered work location landscape because of the pandemic.

The structure of the chapter is as follows. Section 2 presents the analysis methodology adopted to analyze the available data, which is followed by the presentation of results in Section 3. Last section presents summary, key takeaways, policy implications and limitations from this study.

7.2 Analysis Approach

7.2.1 Employers' approach to employee remote work for whom it is possible

To analyze the data on the employer approach to employee remote work at different time points, we convert the 5-point Likert scale data ranging from fully remote to fully in-person to a numerical value ranging from 1 to 5 (1=fully remote and 5 = fully in-person)[1] and calculate average work

[1]Cases where a respondent reported a 'wait and see' approach for the future time points were removed for this particular analysis since those response do not fit in the ordered scale of 1 to 5. However, in most cases they comprise of less than 10% of total number of observations available for a time point. Specifically, there were 1, 3, 10 and 15

location across the organization for different time points and derive the corresponding confidence intervals using the bootstrapping technique [215]. Specifically, for a time point, we take the available work location approach data to estimate the average work location across organizations and then derive a 90% confidence interval around mean values using 500 resamples and the sample size per sample as the number of observations using the *sur* package in R [216]. We present this data in several different ways:

- aggregate level (where averages are calculated across all organizations),
- across the sector of operations (transportation / manufacturing and others),
- across different departments (IT, sales, HR / admin / legal / finance),
- by different levels of remote work adoption in September 2019 (fully in-person, mostly in-person, and others)
- by different levels of remote work adoption in April 2020 (fully remote, mostly remote, and others).

Given that some employers responded in multiple waves and hence their responses for certain time points are available more than once, we retain their oldest available response for time points which were in the past compared to when the survey was conducted, and retained their newest response in cases a time point was in the future compared to when the survey was conducted. This helps to minimize recall bias [217] and corrects for updating the preferences of the employers. Along with the aggregate level data of work location across time, we also present wave-specific data for future time points, which captures changing employers' preferences regarding remote work, potentially impacted by employee pushback regarding return to office as well as changing pandemic situation since some of our data was collected at the height of the Omicron wave.

responses with a 'wait and see' response for January 2022, April 20222, October 2022 and April 2024 time points, respectively. We elaborate more on these in the results section but these responses have been kept out for this analysis and of modeling due to limited sample size. Of course, the ultimate landscape of remote work will depend on the approach that these employers end up taking.

7.2.2 Employers' opinion on the impact of remote work on business aspects

To analyze the data on the employer's view of the impact of 2-days a week remote work policy on various business aspects, we first analyze the data descriptively to highlight employers' top concerns and perceived benefits related to the impact of remote work on business aspects and later estimate a latent class model to stochastically divide employers into latent classes reflecting their outlook towards remote work. A base latent class model is first estimated without exogenous variables (like the sector of operations) and this is followed by the estimation of a class membership model where latent classes are associated with the sector of operations of the employer's organization[2]. The original data which was on a 5-point Likert scale ranging from Very negative to Very positive was converted to a 3-point scale to reduce complexity given a smaller sample size (positive, neutral, and negative) for both descriptive analysis as well as latent class analysis.

In a latent class model (see Collins and Lanza [205] for more details), we used the 9 available business aspects (which are the ability to recruit / retain employees, profitability, long-term viability, ability to compete, ability to innovate, public image, employee productivity, employee creativity, and employee supervision and mentoring) as indicators to define the latent classes.

Model estimation was done using the *'poLCA'* package [206] in R programming language. We first estimate a model without covariates to determine the number of latent classes, where we varied the number of latent classes from 1 to 8 and then used the Bayesian information criterion (BIC) to pick the best model. To search for a global maximum instead of a local one, we tested 100 different starting values for each number of latent classes and picked the model with the greatest log-likelihood. After determining the number of latent classes, we re-estimated the model incorporating various exogenous variables, establishing that the sector of operations (transport /

[2]Here, we also tried including other exogenous variable like annual revenue and number of employees but did not find them to be statistically significant.

manufacturing or others) was the only significant variable.

7.2.3 The future remote work landscape

To understand the expected future landscape of remote work, we use the data related to the expected work location policy in April 2024 to estimate an Ordered Probit model. Considering the employer's April 2024 work location strategy on a 4-point ordered scale (1=Fully or mostly remote, 2=About 50/50, 3=Mostly in-person, 4=Fully in-person)[3], the model associates an organization's sector of operations, pre-COVID and early pandemic approach to remote work, and the employer's outlook regarding the impact of remote work on business aspects with the expected April 2024 remote work approach.

We estimated this model using the *'lavaan'* package [162] in R programming language. For more information on ordered models, the readers are referred to Washington et al. [111] .

7.2.4 Business travel, in-person client interactions, and office space reorganization

We descriptively analyze the data on the resumption of business travel of over 50 miles and in-person client interactions and office space reorganizations; present bar plots for each. Regarding business travel over 50 miles and in-person client interactions, we calculated the average percentage resumption across data from each wave of the data collection. This is followed by a presentation of data on office space reorganization strategies adopted by the employers.

[3] As mentioned earlier, 15 out of available 121 responses for this question were reported as 'wait and see' and those have been removed from the modeling analysis due to sample size. However, we present descriptive information on these responses in the results section. Further, while the original data available here is on a 5-point scale, we combine the responses from the fully remote and mostly remote responses categories since only one responded reported taking fully remote approach in April 2024.

7.3 Results

Figure 7.1 presents the average work location across organizations for employees for whom remote work is possible at different time points. The red colored line corresponds to a combination of data from all waves, where for respondents who participated in multiple waves, their oldest response was retained for the past points (compared to when the survey was conducted) and the most recent response was retained for the future or current time point. The lines with other colors correspond only to data collected in a particular wave and helps understand the adapting policies for a particular time point.

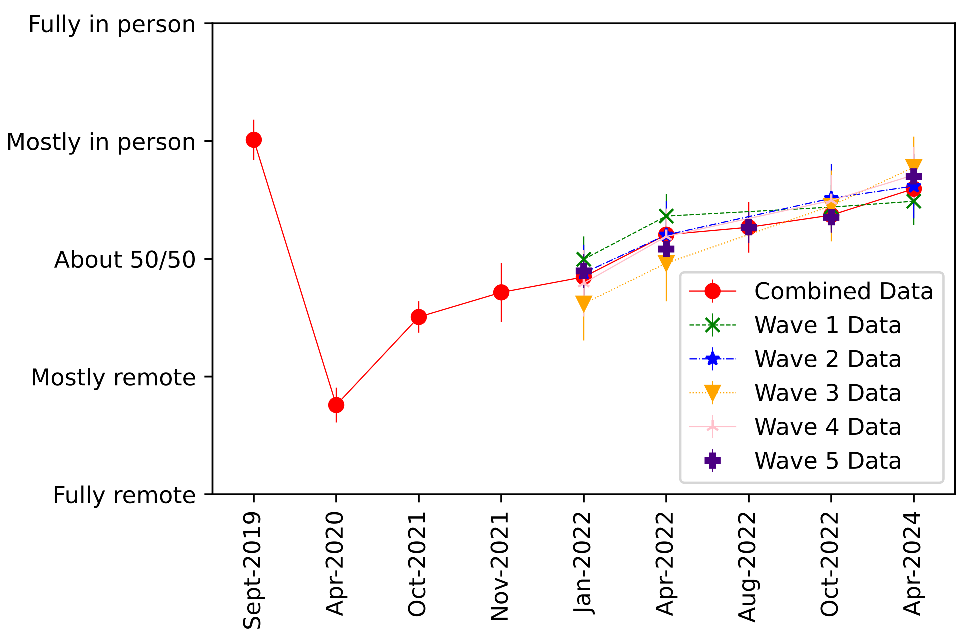


Figure 7.1: Average work location over time

Several interesting insights are immediately visible from this figure. First, as expected, the average work location dropped significantly at the beginning of the pandemic from being somewhere around 'mostly in-person' in September 2019 to being somewhere between 'fully and mostly remote'. This is not surprising given the unprecedented nature of the pandemic situation, which forced employers to adopt remote work at a large scale, at least for whom it is possible. Second, as the economy opened in mid-2020 to early 2021 and mass vaccinations began, a significant rebound to in-person work happened and the average work location has increased since then. Third, despite the increasing average work location over time, in April 2024, about 4 years since the beginning of the pandemic, the average work location is between about 50/50 and mostly in-person and is still not at the pre-pandemic level, suggesting that telework will stay well beyond the pandemic is over. Fourth, our data also captures some trends in employers' policy adjustments potentially due to changing pandemic situation and employee pushback on return-to-work plans. Specifically, our data captures differences between where employers wanted their workforce to be at a future time point versus where the workforce actually was at that time point. For example, the average expected work location for wave 1 data (which was collected in October 2021) in January 2022 and April 2022 are much higher than based on data using wave 2 (collected in December 2021) and wave 3 (collected in January 2022), partly related to in-person presence roll back due to the omicron variant and also potentially related to push back from the employees regarding the return of work plans [92, 196, 218].

A deeper analysis of the April 2024 data seems to suggest that most employers in our data are planning to adopt some form of remote work suggesting hybrid work practices may be the future instead of a fully remote or fully in-person approach. Specifically, only 14.2% of employers in our data reported taking a fully in-person approach, 45.8% reported a mostly in-person approach, 27.4% reported about 50/50, and 13.2% reported taking a mostly or fully remote approach. Within the last group, only one employer reported taking a fully remote approach, reinforcing that most employers will likely adopt some form of hybrid work.

Note here that while we removed the responses where for April 2024 a response of 'wait and see' was recorded for creating Figure 3, we conducted a sensitivity analysis to understand how the mean work location for April 2024 would vary if all those 'wait and see' responses decide to choose a fully in-person or fully remote response. Our analysis shows that the mean average work location would be 3.768 and 3.270 if all the 'wait and see' responses decide to adopt a fully in-person and fully remote approach, respectively. The corresponding mean work location for September 2019 was 4.016 which is higher (more in-person) compared to the extreme case of 3.768, strengthening the case that higher remote work is expected in April 2024.

Figure 7.2 presents the average work location at different time points by the employers' sector of operations. Given the modest sample size and since over 60% of companies in our data are from transportation / manufacturing sectors, we present how the average work location evolved for the organizations which are from the transportation / manufacturing sectors compared to others (which includes sectors like information, consulting, etc.)[4]. Even though average work location was similar across the two sectors in September 2019 as well as in April 2020 (albeit with transportation / manufacturing sectors being slightly more in-person), the rebound across the two sectors has been quite different, where transportation / manufacturing / warehousing sector organizations have rebounded back to much higher in-person work compared to other organizations and these trends seems to continue in April 2024 as well. It must be noted that these trends are only for employees for whom remote work is possible, so higher in-person work in transportation / manufacturing / warehousing sectors is not due to the fact that these sectors employ more individuals that are required to be present in-person. A hypothesis is that higher in-person work in the transportation / manufacturing sector could be due to a requirement of higher coordination between those who are required to be fully in-person and those who can do their jobs remotely. Nevertheless, it is remarkable to see these differences across sectors even though all employees in question are those

[4]For figures 4 to 7, we only present results using the combined data instead of the wave specific data due to sample size constraints.

for whom remote work is possible.

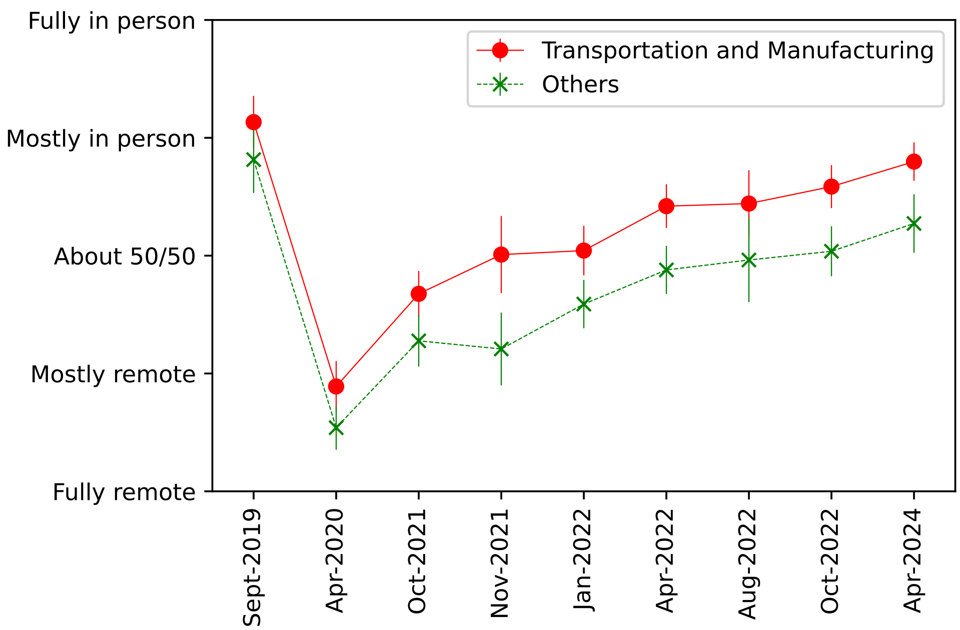


Figure 7.2: Average work location by sector of operations at different time points

Figure 7.3 presents the average work location at different time points for employees in the information technology (IT), Sales, Human Resources, Administration, Legal, and Finance departments of an organization. It is again interesting to see that even though the employers had a similar approach to remote work across the three sets of departments (with HR/Admin/Legal/Finance being slightly more in-person, followed by IT and then Sales), the gap between HR/Admin/Legal/Finance and Sales/IT has increased significantly since the pandemic with HR/Admin/Legal/Finance departments expected to be much more in-person than others. This is not surprising though since sales-related tasks can easily be done using phone or video calls and IT-related tasks also have a potential to be completed through virtual connections to IT infrastructure; and given the pandemic forced acceleration of remote work, potential cost savings for the employers and employee push back on return to work post-pandemic adoption is higher for IT and sales departments. For the

HR/Admin/Legal/Finance departments, since their work potentially requires more in-person coordination, both intra-organizational and with outside parties, this leads to more in-person work. Nevertheless, it must be noted that the average work location in April 2024 is still below the pre-pandemic trends in September 2019 for all three department groups suggesting a companywide increase in remote work adoption.

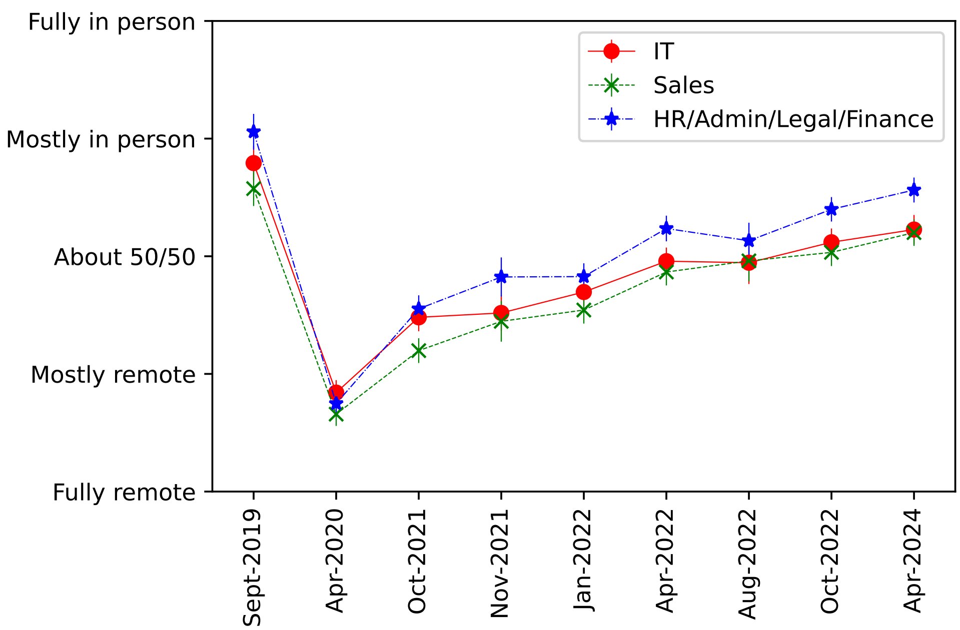


Figure 7.3: Average work location by various departments

Figure 7.4 presents the average work location of various organizations by their pre-COVID work location approach. This data provides several insights into how the remote work landscape has changed for organizations with different remote work approach pre-COVID. First, all organizations irrespective of their pre-COVID approach to remote work heavily adopted remote work during the early period of the pandemic in April 2020. This is understandable since the unprecedented nature of the pandemic forced most employers to adopt remote work. Second, the results also show that the rebound back to higher in-person work was and is expected to be higher for those who were fully in-person pre-COVID compared to others. Third, it is interesting to note that the average work location for those who were in the *others* category pre-COVID has rebounded higher than their pre-COVID average work location indicating that not all organizations have seen an increase in remote work as a result of the pandemic, some have seen a reverse impact as well. A deeper investigation of this data shows that there were 24 organizations in this category with 11 in transportation / manufacturing and 13 in other categories, however, almost all of them were closely related to the transportation sector like railroads, freight, logistics, or transportation-related data-based organizations. Given that these sectors have considerably grown during the pandemic (partly attributable to e-commerce) and also faced higher performance pressure due to global supply chain disruption, an increase in in-person work during and beyond the pandemic for these organizations is potentially due to these factors.

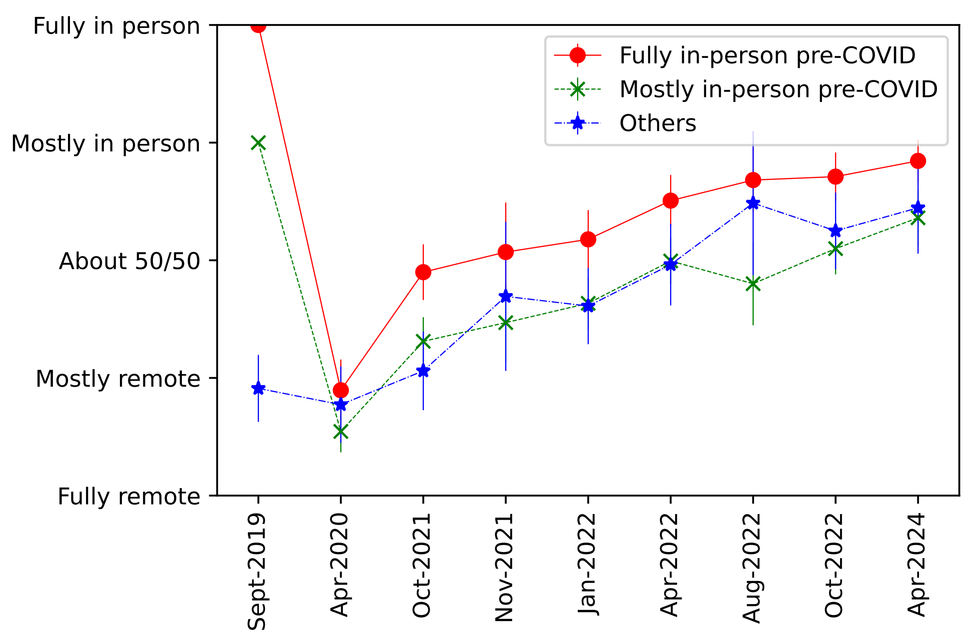


Figure 7.4: Average work location by pre-COVID remote work policies

Lastly, Figure 7.5 presents the average work location of various organizations by their April

2020 work location approach. This data helps us understand whether a pandemic-forced shift in work location policies impacted the organizations' long-term policies. In this regard, a key finding is that those with higher remote work adoption in April 2020 maintained higher remote work throughout the pandemic than others and are also likely to maintain these trends in April 2024 (though the difference is perhaps not significant). An interesting observation here is that those who were fully remote in April 2020 were slightly more in-person pre-COVID than those with a mostly remote approach during April 2020. This potentially indicates a sort of cultural shift in some organizations who shifted to fully remote work at the height of the pandemic and maintained a higher remote work through the pandemic compared to others.

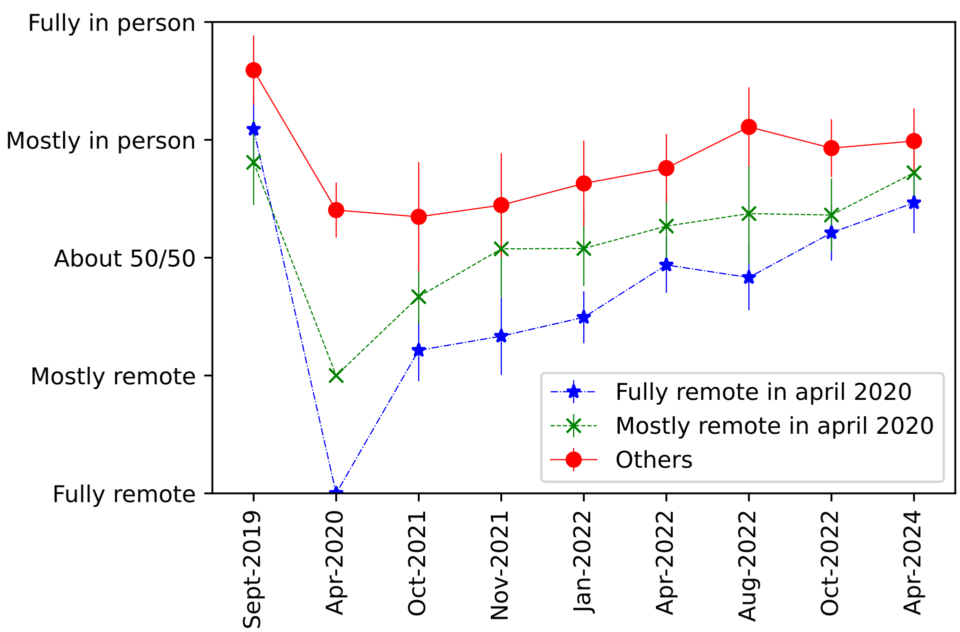


Figure 7.5: Average work location by April 2020 work location policies

Overall, several key insights emerged from this analysis. First, our data suggest that the pandemic accelerated remote work adoption is likely to stick well beyond the pandemic with some form of hybrid work likely to be the norm for most organizations. Second, there is a significantly higher remote work adoption pattern between transportation / manufacturing sectors compared to others; and it is also higher for sales and IT departments, compared to those in HR / Legal / Administration / Finance departments. This is interesting since all this data correspond to those for whom remote work is possible, indicating a potential requirement for coordination between employees for whom remote work is possible and those who are required to work in-person. Third, the post-pandemic in-person work extent is expected to be higher for those working fully in-person work pre-COVID. However, not all organizations have seen an increase in remote work as a result of the pandemic, some have seen a reverse impact as well, potentially related to business growth during the pandemic.

7.3.1 Employer opinion regarding the impact of remote work on various business aspects

Top benefits and concerns related to remote work. Figure 7.6 presents descriptive statistics from the 9 response items related to employer opinion regarding the impact of 2-days a week remote work program on various business aspects. Several interesting insights can be derived from this figure. First, the ability to supervise/mentor, the effect on creativity and innovation are the aspects where employers see the most negative impact of remote work. On the other hand, a majority of employers agree that a 2-days a week remote work policy will have a positive impact on their ability to recruit and retain employees, their public image, and their ability to compete. Lastly, business viability and profit and employee productivity are in the middle. Regarding the aspects with the most negative impact, our results align with existing research that remote work may lead to an adverse impact on innovation and creativity [214], so, naturally, it is an important factor that employers are considering. Our results on the positive impact of remote work on the ability to recruit / retain also aligned with the emerging literature regarding employees demanding more flexibility [83, 85, 89, 92]. It is interesting to see most employers reporting a neutral impact on profit, while the employers seem to be divided on the aspect of employee productivity.

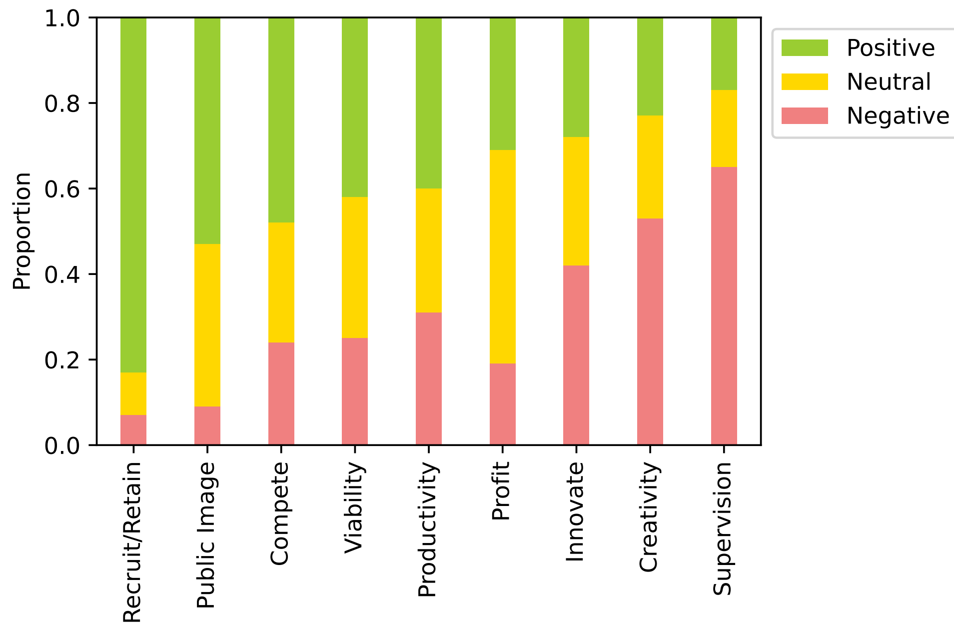


Figure 7.6: Employer opinion of the impact of 2-days a week remote work policy on various business aspects

Latent Class Analysis. To gain a deeper understanding of these results, we use this data to estimate a latent class model with and without covariates. Figure 7.7 presents the item response probabilities (ρ) for the two latent classes we found and for 9 items and three response categories. Table 7.1 presents the results from the membership model and the estimated population shares (γ) for each latent class. Several insights emerge from this analysis. First, we name the two latent classes as employers with a positive (class 1) or negative (class 2) outlook towards remote work based on the item response probability values for each item. Specifically, for class 1, the probability of a positive response is higher than for class 2, for most response items, hence it makes sense for these employers to be termed as those with a positive outlook towards remote work. Similarly, for class 2, the probability of a negative response is higher than for class 1 for most responses, hence it makes sense for these employers to be terms as those with a negative outlook towards remote work.

In our data, 52.5% of employers belong to the positive outlook class and 47.5% belong to the negative outlook class. Based on the item response probabilities, variables where the employers are most divided include the ability to supervise / mentor, impact on innovation and creativity (where employers in class 2 see remote work to have a highly negative impact while those in class 1 are almost equally likely to report positive, neutral or negative impact). Further, employers in both classes seem to agree that remote work policies have a positive impact on the ability to recruit / retain. The results from the membership model estimation suggest that those in Transportation / Manufacturing sectors were more likely to have a negative outlook toward the impact of remote work on various business aspects compared to other sectors potentially suggesting a large interaction between the nature of work, level of coordination required between in-person employees and those who can work remotely and the employers' perception of the impact of remote work.

Table 7.1: Latent Class Membership Model and Population Shares

Variable	Parameter Estimate	t-stat
Constant	-0.262	-1.045
Transportation and Manufacturing sector indicator	0.958	2.152
Model Fit		
Number of observations	129	
Log-Likelihood	-867.952	
Estimated population shares (γ)		
Class 1: Positive Outlook	0.525	
Class 2: Negative Outlook	0.475	

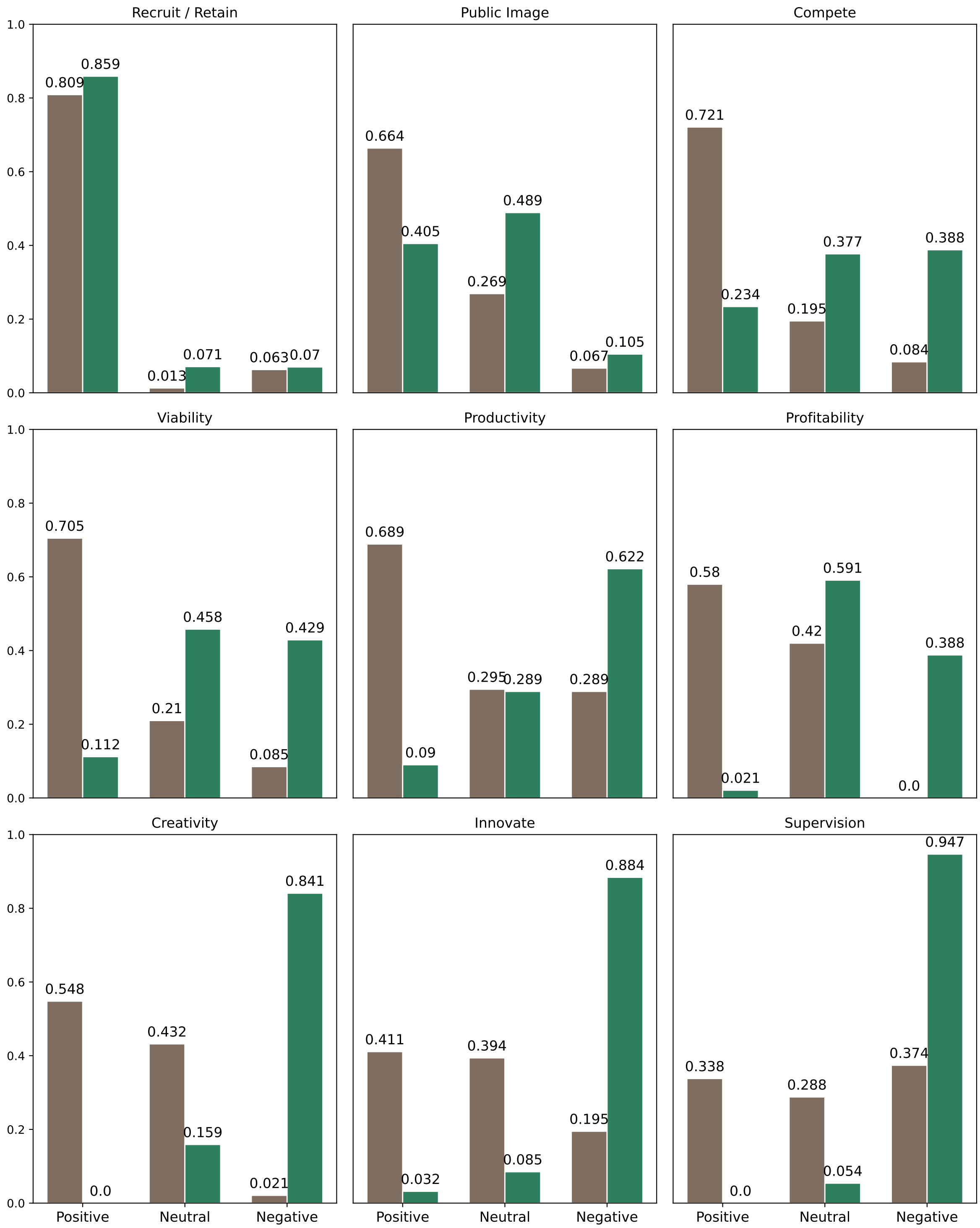


Figure 7.7: Item response probabilities for various business aspects for the two identified clusters

7.3.2 Future Landscape of Remote Work

Table 7.2 presents the results from the ordered probit model of the April 2024 work location approach, with the dependent variable on a 4-point ordered scale (1 = fully or mostly remote, 2 = about 50/50, 3 = mostly in-person, 4 = fully in-person). Here a positive parameter corresponds to a higher likelihood of in-person work in April 2024 compared to the base group. We determined the final specification for this model after extensive testing and retained only four variables in the final specification. Admittedly, two less significant variables were also retained due to their intuitive interpretation and the smaller size of our sample.

Table 7.2: Ordered probit model of April 2024 work location

Variable	**Parameter Estimate**	**T-Statistic**
Transportation, Warehousing, and Manufacturing sector indicator	0.492	1.916
Fully in-person approach pre-covid indicator	0.525	2.352
Fully remote approach in April 2020 indicator	-0.281	-1.248
Probability of being in the negative outlook class	0.302	1.126
Thresholds		
1|2	-0.637	-2.637
2|3	0.343	1.558
3|4	1.769	7.852
Fit Measure	0.170	
No. of observations	105	

Four key insights emerged from this analysis. First, those in the transportation / manufacturing / warehousing sectors are significantly more likely to maintain a higher in-person presence than those in the other sectors. This aligns with the results presented earlier and potentially relates to the nature of the work, which required higher coordination between those who work fully in-person and those who have the option to work remotely. Second, our results also show that those who were fully in-person pre-COVID are more likely to be in-person in April 2024. Interestingly, this variable was significant even after controlling for the sector of operations, indicating that past remote work approach in an indicator of future approach in the other sectors, again potentially related to the nature of work done by an organization. The organizations in this segment (other sectors with a fully in-person approach pre-COVID) in our data included a few public agencies and some engineering consulting firms. Given that such organizations typically have tasks that requires interactions with other involved parties like clients, public officials, construction sites crews, etc., it is intuitive that these organizations are expected to take a higher in-person work approach in April 2024. Third, those who were fully remote in April 2020 are marginally less likely to be in person in April 2024. This could potentially be related to a cultural shift in the remote work approach within on organization where an employer decided to continue a higher remote work approach after a positive experience in the early phase of the pandemic; or could also be a result of employee pushback to return to work. Lastly, our results show that those with a negative outlook toward remote work are more likely to be in-person in the future. Note here that this variable is insignificant in this model potentially due to a strong association with the sector of operation variable as revealed by the membership model presented earlier. However, when we re-estimated this model without the sector of operations variable, the parameter corresponding to the probability of being in the negative outlook class was significant.

Overall, a key takeaway here includes a high interaction between the nature of work, sector of operations and potential impact remote work may have on business as leading factors impacting future remote work policies.

7.3.3 Business travel, in-person client interactions, office space reorganization and work arrangements employers are willing to consider

Business travel and in-person client resumption compared to pre-pandemic

Figure 10 presents the percentage of business travel of over 50 miles and in-person client interaction that has returned compared to the pre-pandemic levels at the time of different waves of data collection. Regarding business travel, our data suggests that the business travel trends were at 32% in October 2021, 40% in December 2021, 36% in January 2022, 48% in April 2022, and 55% in August 2022 compared to pre-pandemic levels. It is interesting to note that the trends in August 2022 were still well below the pre-pandemic levels and potentially indicating a slower rebound. Our numbers on business travel are also close to the estimates from a survey by the Global Business Travel Association which found out that the domestic business was at about 63% of pre-pandemic levels in early October 2022 [219]. It would be interesting to see how business travel recovers from here, especially given that there are growing concerns regarding a slowing economy amongst employers [220] . Regarding in-person client interaction, the trends were at 30% in October 2021, 43% in December 2021, 32% in January 2022, 51% in April 2022 and 61% in August 2022 compared to pre-pandemic trends. It is not surprising that the recovery of local in-person client interactions is slightly faster than business travel, potentially due to the involved cost as well as higher (perceived) contagion risk when flying. Another interesting trend in our data is the reduced business travel and in-person client interactions around January 2022 compared to the previous month, potentially due to the changing pandemic landscape due to the omicron variant.

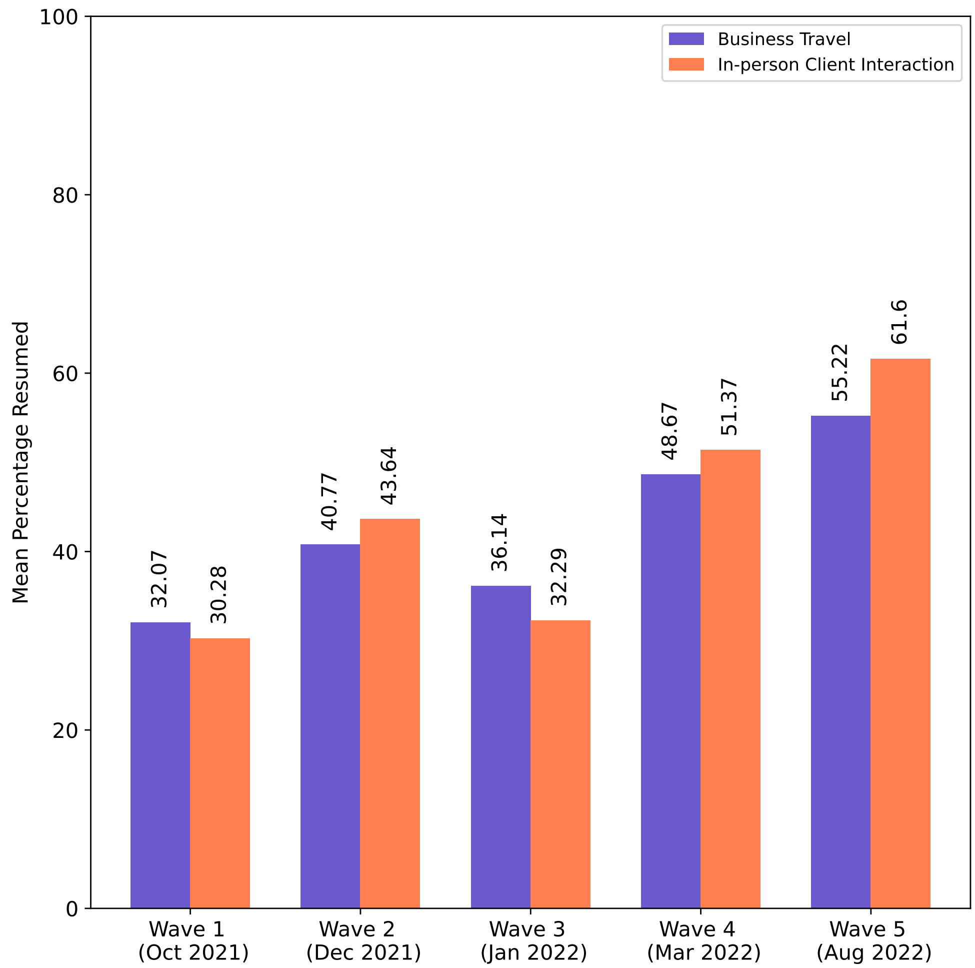


Figure 7.8: Percent of business travel and in-person client interactions returned during various waves of data collection

Office space reorganization

To gain a better understanding of the permanency of changes in the work location landscape, we also asked the employers whether they have or plan to relocate, expanded, or reduced office spaces since the beginning of the pandemic. Figure 7.9 shows the number of employers with various office space reorganizations adopted (or to be adopted) by them. This question was only asked in Wave 5 (August 2022) where 38 out of 56 respondents reported making some changes to their office space (i.e. ~32% made no changes). The most reported response was a reconfiguration of office space to cater to changing nature of the work environment (21/38), followed by reduced office space (10/38). For others, there seems to be mixed response of either increase or decrease in office space in same the same or different building or area. We also asked the respondents to self-describe the nature of their office same reorganization in a few words. Based on these open-ended responses, a general trend was that those who expanded or are planning to expand soon are growing companies, however, their growth in office space has been slower than expected due to changing work location landscape.

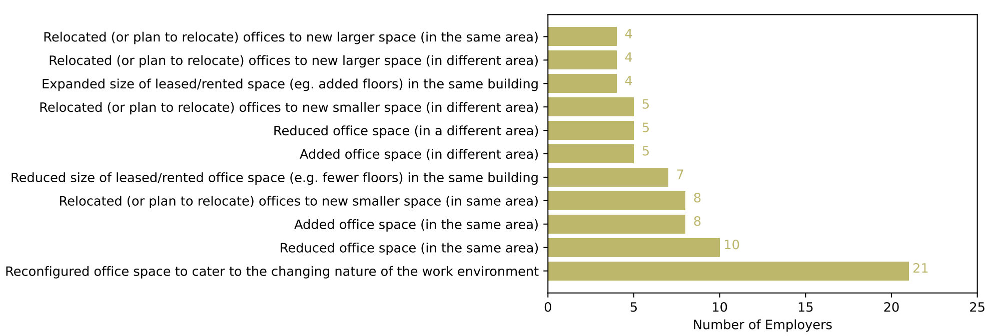


Figure 7.9: Office space reorganization made by the employers since the beginning of the pandemic

7.4 Summary, Key Takeaways, Policy Implications and Limitations

Summary and Key Takeaways

Using data from top executives from 129 employers in North America from a 5-wave longitudinal survey, this study presents an employer-side perspective on telework through and beyond the pandemic. Specifically, we present data on how employer approach to remote work evolved over time and what is expected in April 2024, four years since the beginning of the pandemic. We also identify employers' top concerns and expected benefits related to remote work, which will potentially shape their future remote work policies. To dig a little deeper, we conduct a latent class analysis which divides the employers into latent classes based on their outlook towards remote work. Next, we present results from an ordered probit model to understand the factors that may shape employers' April 2024 remote work approach and then present results on resumption of business travel of over 50 miles and in-person client interactions at the time of the 5 waves of data collection, followed by how employers' have or expect to reconfigure their office spaces in the future.

The following key insights emerged from the above analyses. First, our data suggests that the pandemic accelerated remote work adoption is likely to stick well beyond the pandemic with some form of hybrid work likely to be the norm for most organizations. We also found out that there is a much higher rebound to in-person work in the transportation / manufacturing / warehousing sectors, compared to other sectors; and this trend also exists for employees in HR / Legal / Administration / Finance departments compared to Sales / IT departments. This is interesting since all this data correspond to those for whom remote work is possible, indicating a potential requirement for coordination between employees for whom remote work is possible and those who are required to work in-person. Our results also show that the post-pandemic in-person work extent is expected to be higher for those working fully in-person work pre-COVID. However, not all organizations have seen an increase in remote work as a result of the pandemic, some have seen a reverse impact as well, potentially related to business growth during the pandemic.

Second, on the end of employers' opinion regarding impact of remote work on various business aspects, the ability to supervise and mentor, and the effect on creativity and innovation are the aspects where employers see the most negative impact of remote work. On the other hand, a majority of employers agree that a 2-days a week remote work policy will have a positive impact on their ability to recruit and retain employees, their public image, and their ability to compete. Lastly, business viability and profit and employee productivity are in the middle. Most employers report a neutral impact on profit, while employers seem to be divided on the aspect of employee productivity. Based on a Latent Class analysis, we divide the employers into two latent classes: those with a positive outlook on the impact of remote work on business and those with a negative impact of remote work on business. variables where the employers are most divided include the ability to supervise / mentor, the impact on innovation and creativity (where employers in class 2 see remote work to have highly negative impact while those in class 1 are almost equally likely to report positive, neutral or negative impact). Further, employers in the both classes seem to agree that remote work policies have a positive impact on ability to recruit / retain. The results from the membership model estimation suggest that those in Transportation / Manufacturing sectors were more likely to have a negative outlook towards the impact of remote work on various business aspects compared to other sectors potentially suggesting a large interaction between the nature of work, level of coordination required between in-person employees and those who can work remotely and the employers' perception of the impact of remote work.

Third, based on the results from the estimated ordered probit model of April 2024 work location approach, our results indicate that those in transportation /warehousing / manufacturing sectors, those with a fully in-person approach to remote work, and those with a negative outlook towards the impact of remote work on business are likely to be more in-person going forward and those with fully remote work in April 2020 are less likely to be fully in-person.

Lastly, we also found out that as of August 2022, about 55% business travel of over 50 miles and 61% of in-person client interaction has resumed compared to pre-COVID level, indicating a slower rebound to pre-pandemic level of work-related in-person travel. On the end of office space reconfiguration, we find mixed results with over 30% of employers reporting no changes to their office spaces. Amongst those who made some form of changes, a reconfiguration of the office space to cater to changing nature of work was the most popular approach with some employers also reporting an expansion due to a business growth. However, those who grew reported the office space expansion to be less than expected due to changing work location landscape.

Policy Implications

A key implication of the results from the employer end is that the pandemic accelerated trends in remote work adoption may be long lasting since their seems to be a strong support from the employer end too. This opens up several questions for cities to around the changes to activity geography as a results of these changes - which cities need to understand better in order to cater to changing societal needs.

Limitations

A few limitations are worth mentioning here. First, our sample size is admittedly small and a future study with a larger sample size would be of great value to gain a thorough understanding of changing remote work landscape. Second, our data over-represents the transportation / warehousing / manufacturing sector, which prevented us from gaining a deeper understanding of the difference between work location practices in the other sectors. Third, the work location landscape continues to evolve and the true future of work is potentially going be a function of several factors and thus required continued monitoring of the situation.

CHAPTER 8

CONSUMER SPENDING BEHAVIOR AND ADAPTATION ACROSS ONLINE AND IN-PERSON CHANNELS THROUGH THE PANDEMIC

8.1 Introduction

Another dimension of telemobility that was significantly impacted by the pandemic was that of how our everyday need for food and non-food items is fulfilled. While the option to shop online did exist pre-pandemic, the pandemic clearly accelerated the growth of these options — reaching new set of users as well as new set of product categories [98, 221]. An important question in this regard is the extent to which this pandemic supported growth sustained over time and to what extent it varied across product categories. Further, from urban mobility perspective, the answer to the question of substitution versus complementarity effect of e-commerce is also not clear.

A majority of existing literature is this regard analyzes consumer spending data in parts where spending for a particular product category like grocery or restaurant food or for a particular acquisition channel like in-person shopping or online delivery is studied in isolation. However, it is not inconceivable that consumer spending behavior across product categories and across acquisition channels may be or may not be related since the consumption of one product type through a channel may reduce the consumption of another product through the same channel or the same product type through a different channel in some cases, or it may not have such impact in other cases. Hence, to thoroughly uncover the complexity in consumer spending behavior an integrated analysis is needed where data from multiple spending categories and acquisition channels is analyzed together.

In this chapter, using data from 785 individuals from across United States, weighted to represent the U.S. population by age, gender, ethnicity and education attainment, at 4 different time points since the beginning of the pandemic and across 10 different product categories and acquisition channels, I present a latent transition analysis with a random intercept to characterize the consumer spending behavior through the pandemic across different product and acquisition channel categories over time. The joint framework:

- allows for the identification of latent classes of spending behavior across various acquisition channels and product categories
- allows estimation of changes in the proportion of individuals in the data across different latent classes over time
- allows estimation of transition probabilities across latent classes across various time points
- controls for additional correlation (that is not explained using the latent classes) across spending data indicators using random intercept that allow for separating of time-invariant between-subject variation from within-subject variability over time - which is of main interest - leading to better estimates for the measurement models and the transition matrices.
- allows inclusion of covariates in time-invariant latent trait / intercept that helps capture systematic heterogeneity in time-invariant between-subject variability; in initial latent class statuses as well as latent transitions to understand the impact of socio-demographics variables on various aspects of the model

The study uses data from four time points: pre-COVID (collected retrospectively during wave 3 of the 7 wave survey), December 2020 (Wave 1), March 2021 (Wave 6) and March 2022 (Wave 7), where we asked the respondents to report their past week's spending in the following three categories: grocery, cooked food from restaurants, and non-foods items - across three channel: in-person, pick-up and delivery. For cooked food category, the pick-up option was separated in take-out and order online then pick-up – leading to a total of 10 indicators on food categories and acquisition channels. The pre-COVID data was collected by asking the respondents to report their usual weekly spending in the same categories as above. While the original data has spending amount, we utilize a binary version of the data instead to separate the spending amount (which is significantly impacted by income) from whether or not someone spends in a particular category — making model interpretation easier.

The estimated model has several features including: 1) use of sample weights to make the data representative of U.S. population, derived using the 2021 American Community Survey Public Use MicroData Sample [201]; 2) use of full information maximum likelihood estimation to account for missing data due to non-response by the respondents; 3) a measurement invariance structure that allows for latent class definitions to remain consistent over time — making it easier to both estimate and interpret the model - especially with a smaller sample size; and 4) a factor loading restriction on the random intercepts that makes the impact of latent trait to remain same for all in-person channels and same for all delivery channels but different between in-person and delivery channels.

The structure of rest of this chapter is as follows. The next section discusses the data used in this study. The third section discusses the analysis procedure followed. Results are presented next and key insights are identified. The last section summarizes the findings and discusses the policy implication of this study.

8.2 Data

For this study, I utilize data from four time points: 1) pre-COVID (collected retrospectively during Wave 3); 2) December 2020 (Wave 1) 3) March 2021 (Wave 6); and 4) March 2022 (Wave 7).

The respondent pool for this study included those who appeared at once during the first 6 waves - which corresponded to 785 unique respondent. Those who joined only in wave 7 were not included since their pre-COVID data (which was collected in wave 3) was not available. Two sets of data sets were available for this study - spending behavior data, which is the basis of the latent classes defined in this study; and socio-demographic information, which are used as covariates in various parts of the model.

During each wave of the survey, respondents were asked (on a 6-point scale) about the amount their household spent in the *past week* in the following categories:

- Groceries (including uncooked meal kits and alcoholic beverages) using the following channels:
  - In-store
  - Ordered online and picked-up
  - Ordered online and delivered
- Cooked / Prepared meals (such as cooked meal kits or food from a restaurant) using following channels
  - At restaurant or in-store for dine-in
  - At restaurant or in-store for take-out
  - Ordered online and picked-up
  - Ordered online and delivered
- Purchases other than groceries or cooked meals (such as electronics, books, or clothing) using following channels:
  - In-store
  - Ordered online and picked-up
  - Ordered online and delivered

The 6-point scale used for the above three spending categories are as given below:

- Groceries: Nothing at all ($0), $1-$49, $50-$99, $100-$199, $200-$299, $300 or more
- Cooked / Prepared meals: Nothing at all ($0), $1-$49, $50-$99, $100-$199, $200-$299, $300 or more
- Purchases other than groceries or cooked meals: Nothing at all ($0), $1-$99, $100-$249, $250-$499, $500-$999, $1000 or more

Further, in wave 3, the respondents were also asked, on the same scale, to report their household's typical spending behavior before the beginning of the COVID-19 pandemic. For this study, given the small available sample and potential difficulty in the interpretation of results if too many categories are used, we simplify the analysis by converting the 6-point scale to a binary scale representing whether a household reported spending greater than $0 on a spending category. Another theoretical motivation for converting the data to dichotomous in nature was to focus on likelihood of spending money in a particular category instead of 'how much" is being spent. The three spending categories with their acquisition channels correspond to a total of 10 binary behavioral indicators used in this study.

Apart from the spending indicators, we also have access to several socio-demographic variables for the respondents including age, gender, household size, household income, whether there are children present in the household, household location type (rural, urban, or suburban), vehicle ownership status etc. Note here that the socio-demographic information is not used in the LTA to define the latent classes, but only to understand the association between socio-demographic groups and the latent classes generated using the spending behavior data.

8.3 Analysis approach

8.3.1 Unconditional Model

I take a two step approach to estimating a latent transition analysis with random intercepts, where an unconditional model without covariates is estimated to determine the optimal number of latent classes, followed by including covariates in a model with the number of latent classes as determined in the unconditional model.

To determine the optimal number of latent classes, I extensively tested models with and without measurement invariance and decided to retain a model with measurement invariance based on both model fit as well as interpretation. Another feature of our model is a restriction in the factor loading values (λ_k, see Chapter 4 that captures the impact of the latent trait corresponding to the time-invariant between subject variation, where I allow for only two possible values (one for items corresponding to in-person and pick-up channels, i.e. those with physical mobility component; and one for items corresponding to delivery channel) instead of the 10 different values - one for each indicator - as suggested by Muthén and Asparouhov [115]. While I tried a model with 10 unrestricted factor loading values too, the estimated values were close to each other delivery and physical mobility modes, respectively. This restriction was also supported using the model fit information where the restricted model was not significantly worse compared to an unrestricted model. This choice also has behavioral under-pinning since the shared unobserved effects for similar modes may be similar to each other and hence their manifestation on the spending behavior may be same.

Using the unconditional model, I present estimation results in terms of measurement and factor model as well as the transition matrices. I also present the estimated proportions for the top 10 pathways in the model to understand which behaviors pathway dominated the spending dynamics over time. Lastly, I present how estimated proportion for the top 10 pathways vary for different socio-demographic groups - which descriptively help in improving the understanding the interaction between socio-demographics and spending behavior dynamics.

8.3.2 Incorporating socio-demographics as covariates

I incorporate covariates in the model at three different locations: 1) the latent factors that captures socio-demographics impacting the time-invariant propensity in spending; 2) the latent class variable at the initial time point that which captures the factors impacting various spending behaviors pre-COVID; 3) latent transitions - that capture the factors impacting transitions to different classes at time point t from a particular class at time point $t-1$.

Given that the latent class models are well known for class reshuffling in between consecutive re-estimation — making it difficult to test multiple specifications to decide upon a specification of interest, I take a two step estimation procedure for incorporating covariates. Fixing the parameters of the measurement model and the factor loading to same as the values obtained from the unconditional model earlier, several specifications were first tested to decide upon specification of interest. Next, removing the covariates that were not significant in any of the classes in the relevant submodels where they were added, a joint model for both the covariates and the measurement / factors model was estimated to obtain the new estimates for the measurement and factor models. Next, the model with the specification determined earlier was re-estimated with the new measurement and factor model estimates and this is the model whose results are presented in the chapter.

8.4 Results

8.4.1 Unconditional model

Figure 8.1 presents the estimated ρ parameters (or the item response probabilities) on the probability scale and the δ parameters (or the class proportions at various time points). Figure 8.1 also shows the λ factor loading parameters. The ρ and δ parameters have been used to create a Sankey visualization in Figure 8.3. I interpret these parameters one by one below. The estimated transition probabilities are presented in Figure 8.2.

Latent Classes and Item Response Probabilities

Looking at the results presented in Figure 8.1, 5 latent classes corresponding to different spending styles with differing levels of likelihood of spending in different product categories and acquisition channels are identified. For example, the probability of spending more than zero dollars for individuals in class 1 is 0.995. Similarly, for class 3, the probability of spending more than zero dollars on cooked food via takeout is 0.715. Based on these values, the 5 identified classes have been named and their key behavioral patterns are presented below:

- *Class 1: I primarily shop in-person but love amazon too*: Households in this class have high probability of spending in-person for various products. However, the probability of spending in delivery for non-food items is also moderate. On the end of grocery, the households in this class have high probability of spending on grocery in-person but low probability of spending on grocery delivery and pick-up. On the end of cooked food, households in this class have moderately high probability of spending on dine-in and take-out but moderate probability of delivery and pick-up. On the end of non-food items, the households in this class have high probability of spending through in-person channel and moderately high probability of

	I primarily shop in-person but love amazon too	I eat at home	Why pay for delivery	I trust you with my delivery	I pick-up when I can
Class Proportions					
Pre-COVID	55.07%	8.89%	23.03%	5.55%	7.46%
Wave 1 (Dec 2020)	8.40%	42.93%	15.98%	14.39%	18.30%
Wave 6 (Mar 2021)	7.03%	44.30%	18.73%	14.05%	15.90%
Wave 7 (Mar 2022)	14.75%	31.68%	22.96%	17.03%	13.58%
Item Response Probability					
Grocery - In-person	0.995	0.999	0.971	0.622	0.603
Grocery - Pick-up	0.212	0.137	0	0.057	0.953
Grocery - Delivery	0.213	0.098	0.025	0.94	0.322
Food - Dine-in	0.789	0.052	0.345	0.184	0.233
Food - Takeout	0.63	0.368	0.715	0.297	0.585
Food Pick-up	0.404	0.315	0.053	0.189	0.479
Food - Delivery	0.362	0.138	0.016	0.529	0.329
Other - In-person	0.901	0.599	0.604	0.37	0.451
Other - Pick-up	0.174	0.144	0.029	0.024	0.347
Other - Delivery	0.736	0.572	0.283	0.749	0.715
Factor Loadings: For channels with physical travel: 1.181; For channels with no physical travel: 0.529					

Figure 8.1: Measurement model and proportions

spending through delivery channel.

- *Class 2: I eat at home* : Households in this class have low probabilities of spending on outside food. On the end of grocery, the probability of in-person spending is the very high, with extremely low probability of spending through other channels. On the end of cooked food, the probability of spending is low overall, but highest for takeout, followed by pick-up and delivery and lowest for dine-in. For non-food items, the probability is moderate for in-person and delivery but low for pick-up.

- *Class 3: Why pay for delivery* : Households in this class rarely use pick-up and delivery services and rely mainly on in-person shopping. On the end of grocery, the probability of spending is very high for in-person spending but closed to zero for other channels. On the end of cooked food, probability is highest for takeout, followed by dine-in but very low for delivery and pick-up services. On the end of non-food items, the probability of spending is moderate to moderately high for in-person and delivery, but low for pick-up.

- *Class 4: I trust you with my delivery* : Households in this class have high to moderately high probability of using delivery channels for all category of items. On the end of grocery, the probability is highest for grocery delivery, followed by moderate value for in-person. On the end of food, the probability is again highest for delivery but still non-zero for dine-in, takeout or pick-up. On the end of non-food items, the probability is highest for delivery and medium for in-person. An important point to note here is that the high probability of spending on delivery does not significantly reduce the probability of spending in-person channels, especially for grocery - potentially highlighting some form of complementarity instead of complete substitution.

- *Class 5: I pick-up when I can* : Households in this class have a high probability of spending on pick-up through various channels. On the end of grocery, the probability is highest for pick-up, followed by in-person and then delivery. On the end of cooked food, take-out and pick-up is more popular, followed by delivery and dine-in. Lastly, on the end of non-food items, delivery more popular, followed by in-person and delivery.

Class Proportions over Time

The top portion of Figure 8.1 shows how the percentage of respondents in the data belonging to different latent classes changed over time. These trends highlight the changing consumption patterns of time potentially taking into consideration the risk related to the pandemic as well as changing habit and supply of the e-services. Key highlights from these include that the pandemic resulted significant reduction in size of class 1 from about 55% pre-COVID to 8% in December

2020 and 7% in March 2021, but this class increase to 14% in size during the last wave of the data in March 2022. Class 2, which was about 8% pre-COVID increased to 42% during December 2020 and 44% during March 2021 but decreased to about 31% in March 2022. Individuals in this class had a lower likelihood of spending on outside food and since the pandemic restrictions and risks potentially led to households eating more at home, an increase in the size of this class is intuitive. Class 3, which was about 23% pre-pandemic reduced to 15% during December 2020, but increased to 18% and 22% during March 2021 and 2022, respectively. Since this class included eating out for dine-in and take-out, both of which were potentially high risk activities as well as additional discretionary spending that individuals may have been trying to cut down on given inflation and financial hardship for some households, the decrease in this class's proportion and then some rebound makes sense. Class 4, which was only 5% pre-COVID increased to 14% during December 2020 and March 2021 and was about 17% during March 2022. A key feature of this class was shopping using delivery and an increase in this class' size and stability over time potentially indicates some long-term behavioral changes. Lastly, class 5 was about 7% pre-COVID but increased to 18% and 15% in December 2020 and March 2021, respectively but was about 13% during March 2022. This shows that the use of delivery services also grew during the pandemic - but has been declining since its peak. However, it was still significantly higher than the pre-pandemic proportion.

Transition Probabilities

The transition probabilities presented in Figure 8.2 and class proportions presented in Figure 8.1 have been combined in Figure 8.3 to create a sankey visualization. While the class proportions tell us about how the class proportions changed over time, this figure helps us understand a detailed dynamics between classes of time.

Between pre-COVID and December 2020, key transitions include from class 1 to classes 2, 4, and 5; and class 3 to class 2. Other small transitions also exist (e.g. from class 3 to 4 and 5) but they have not been interpreted for brevity.

Looking at class 1 (pre-COVID) to class 2 (Dec 2020), it seems that the biggest impact of the pandemic was in terms of a suppression of spending on restaurant food, where a large portion those who were spending on dine-in and take-out food options restricted their spending as a results of the pandemic - potentially either due to it being a high risk activity or due to lock downs which restricted these activities even if one was willing to do them.

		1	**2**	**3**	**5**	**4**
		Wave 1 (Dec 2020)				
Pre-COVID	1	0.14	0.56	0.00	0.12	0.19
	2	0.00	0.91	0.00	0.09	0.00
	3	0.00	0.18	0.69	0.06	0.06
	4	0.00	0.00	0.00	1.00	0.00
	5	0.09	0.00	0.00	0.04	0.88
		Wave 6 (Mar 2021)				
Wave 1 (Dec 2020)	**1**	0.83	0.00	0.09	0.09	0.00
	2	0.00	0.95	0.02	0.03	0.00
	3	0.00	0.00	1.00	0.00	0.00
	4	0.00	0.12	0.07	0.81	0.00
	5	0.00	0.10	0.00	0.03	0.87
		Wave 7 (Mar 2022)				
Wave 6 (Mar 2021)	**1**	0.78	0.04	0.10	0.03	0.06
	2	0.21	0.62	0.05	0.10	0.01
	3	0.00	0.00	1.00	0.00	0.00
	4	0.00	0.26	0.00	0.74	0.00
	5	0.00	0.00	0.07	0.13	0.79

Figure 8.2: Transition across classes over time

The second significant behavioral transition was from class 1 (pre-COVID) to class 4 (Dec 2020) consisting of those who moved to the use of delivery services - specifically for groceries, though an increase in the use of delivery services for cooked food and non-food items is also evident. For this transition, an increase in the use of delivery was accompanied by a decrease in the probability of usage in-person and pick-up channels for grocery, dine-in, takeout and pick-up for cooked food as well as in-person and pick-up channels for non-food items. The increase in the size of class 4 was mostly due to this transition from class 1 at pre-COVID, suggesting that household moved to the use of delivery services as a result of the pandemic related disruption of in-person channel of spending.

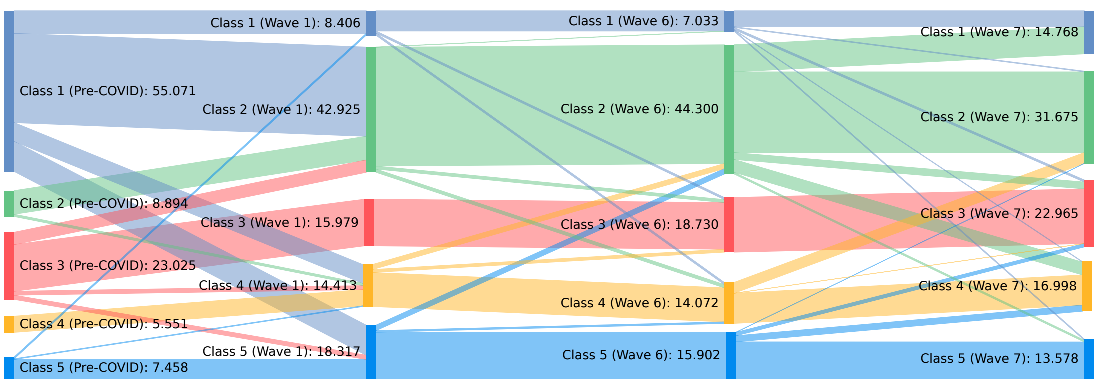


Figure 8.3: Transition across classes over time

The third significant behavioral transition was from class 1 (pre-COVID) to class 5 (Dec 2020) consisting of those who to the use of pick-up channel of product acquisition - specifically for groceries, though an increase in the use of pick-up channel for food and non-food items is also visible. For this transitions, other effects include a decrease probability of spending on in-person grocery, cooked food dine-in and in-person non-food items.

Moving to the transition from class 3 (pre-COVID) to class 2 (Dec 2020), this mostly consists of individuals who restricted their spending on dine-on and take-out of cooked food, with some increase in pick-up and delivery usage. Here, an increase delivery of non-food items is also seen, however, this has not come at the expense of reduction in probability of spending in in-person non-food items.

Between December 2020 and March 2021, our results suggest a remarkable stability in spending behavior with marginal movements across classes - potentially the pandemic still being of significant importance at the time and vaccine distribution only at an initial phase. Two of the biggest transitions between these two time periods included class 4 (Dec 2020) and Class 5 (Dec 2020) to Class 2 (Mar 2021) suggest at least a small movement to in-person behavior spending where the use of delivery and pick-up services is being abandoned to move towards an in-person spending behavior. However, the overall spending landscape during these time periods is remarkably stable.

Lastly, between March 2021 and March 2022, significantly less stability of behavior is seen - potentially due to a one year gap between two time periods as well as the pandemic being of a significant lesser risk given a large-scale vaccination efforts as well as removable to restrictions. However, this time period also saw a significant increase in inflation in the United States – too may have impacted spending behavior too some extent. Some significant transitions between these two time periods include class 2 to classes 1, 3, and 4; class 4 to class 2 and class 5 to class 4.

Most significant transition during this time period was from class 2 to Class 1 — potentially a reversal of trends from reduced spending on outside food at the height of the pandemic to an increase in spending at this time period. Another key transition here is movement from class 5 to class 4 and others - potentially related to some reversal of trends in the use of pick-up services. However, an interesting set of transitions here are that of from class 2 and class 5 to class 4 — leading to an increase in the use of delivery services, which gets balanced out due to movement out from class 4 to class 2.

Pathway Analysis

Figure 8.4 presents the top 10 pathways (based on the estimated posterior pathway probabilities) followed by the respondents in the data over 4 time periods. Note here that there are $5^4 = 625$

possible pathways corresponding to 5 classes at each time point and 4 time points in total. These top 10 pathways (out of 625) correspond to about 65% of the respondents. In this figure, a pathway 1222 corresponds to being in class 1 pre-COVID, transitioning to class 2 at December 2020 and then staying in the same class 2 for the remaining two time periods. Other latent classes are interpreted similar here. Based on these pathways, the most common pathway in the data was 1222 and corresponded to about 23% of the individuals in the data. Other pathways where there was a switching in latent classes included 1555 (9.2%), 1221 (8.8%), 1444 (5.4%), 1224 (3.8%). Clearly, some of the pathways (related to pick-up and delivery usage) included here correspond to sticking to a spending behavior after an initial transition inn December 2020. A deeper investigation of these pathways is done and presented in Figure 8.5 where the estimation proportion of individuals in the top 10 pathways is presented for various socio-demographic groups. Several key insights are visible from this figure.

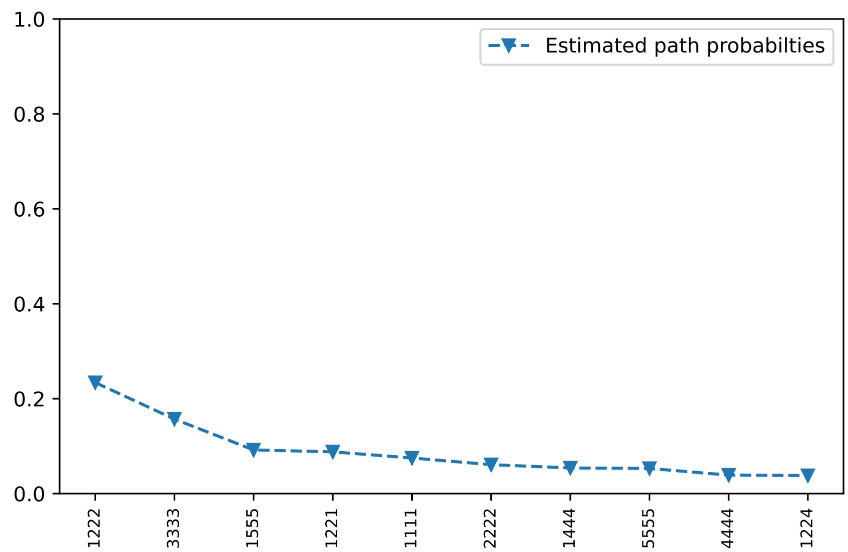
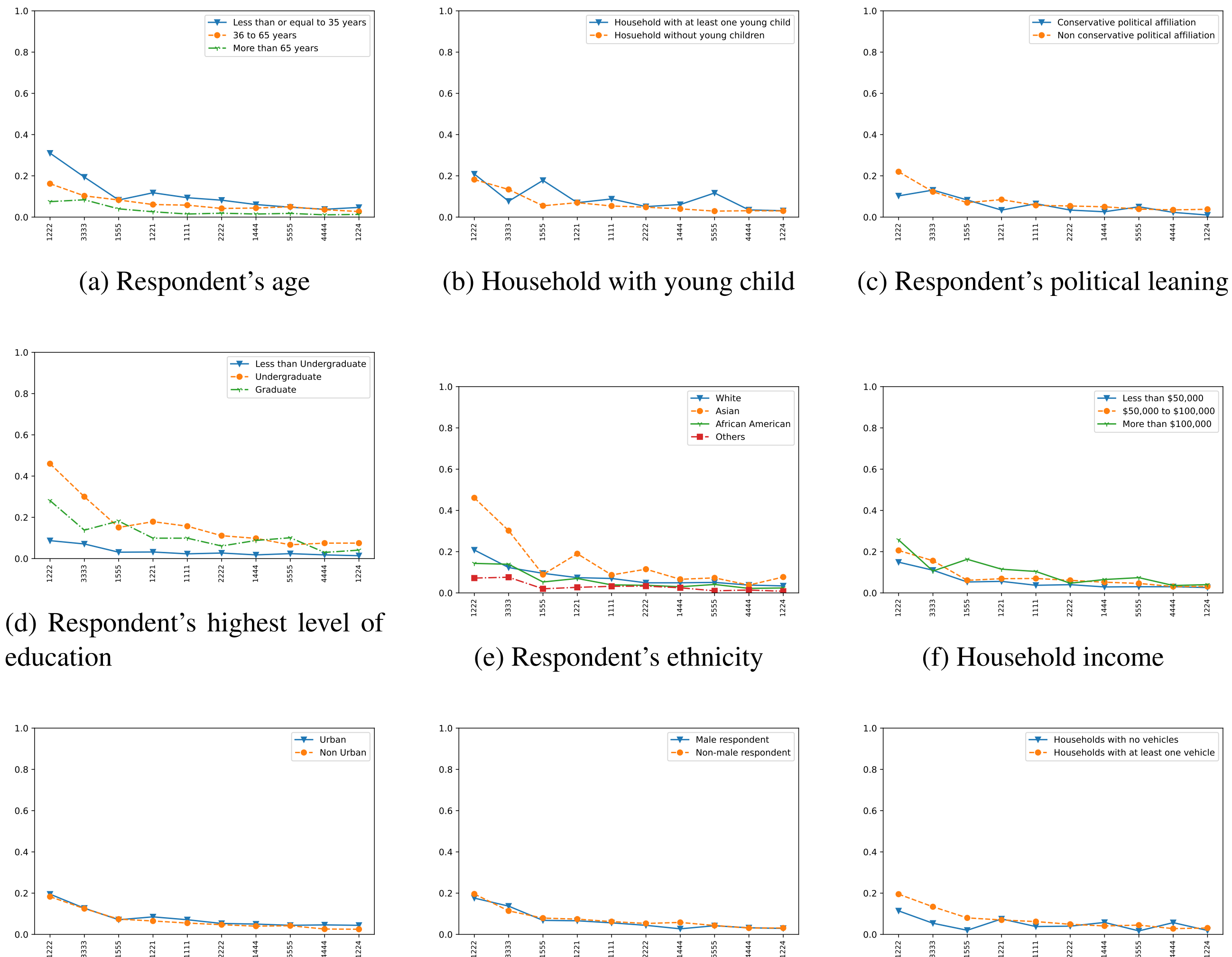


Figure 8.4: Top 10 pathways with estimated path probabilities



(a) Respondent's age

(b) Household with young child

(c) Respondent's political leaning

(d) Respondent's highest level of education

(e) Respondent's ethnicity

(f) Household income

(g) Household location type

(h) Respondent's gender

(i) Vehicle ownership status

Figure 8.5: Estimated path probabilities for top 10 pathways for various socio-demographic groups

8.4.2 Incorporating socio-demographics as covariates

Table 8.1 presents the results from the inclusion of covariates in the latent trait factor f_i, while Table 8.2 presents the results from the inclusion of covariates in initial latent classes as well transitions. Lastly, Table 8.3 presents various intercepts included in the model — which have not been interpreted here for brevity.

Table 8.1: Factor Membership Model

Variable	**Parameter Estimate**	**T-stat**
Household with at least one child under 12 years age	0.873	5.584
Household location is urban	0.531	3.313
Households without a car	-0.529	-2.073
Respondent's ethnicity is white	-0.251	-2.649
Household income less than $50,000	-0.379	-3.078
Respondent's highest education level is graduate	0.199	1.822
Respondent's age is less than 35 years	0.412	2.898

With reference to covariates in time-invariant latent factor (Table 8.1) , a positive parameter in results corresponds to a high likelihood of spending (across all categories and channels) by a socio-demographic group compared to others. Note here that were values are further multiplied by the factor loading values — so the net likelihood is different for physical and delivery acquisition channels. The results here indicate a high likelihood of spending in a given week by those with young child, those who live in urban areas, those with a graduate education and those with age less than or equal to 35 years. Similarly, our results indicators a lower likelihood of spending for households without a car, those who are of white ethnicity and those with income less than $50,000. These result are intuitively correct and help capture for additional heterogeneity in the data that is not captured otherwise.

With reference to Table 8.2, we included covariates to the pre-COVID latent classes as well as transitions. However, in the transitions, we only included covariates where there was a big enough transition between classes, otherwise only an intercept was estimated (see Table 8.3). First part of Table 8.2 corresponds to a pre-COVID membership model where covariates were included to the latent classes at initial time period. Our results here suggest that who were in class 1 were more likely to have a graduate or undergraduate degree; and those in class 2 and 3 were less likely to be of white ethnicity.

Table 8.2: Membership and Transition Model

Variable	Class 1	Class 2	Class 3	Class 4
Pre-COVID Membership Model				
Respondent's highest education level is graduate	2.16 (3.34)	--	--	--
Respondent's highest education level is undergraduate	1.06 (2.66)	--	--	--
Respondent's ethnicity is white	--	-2.61 (-2.76)	-1.33 (-2.75)	--
From Pre-COVID Class 1				
Household with at least one child under 12 years age	-1.63 (-1.66)	-1.07 (-2.30)	--	--
Respondent's highest education level is graduate	--	-1.10 (-2.67)	--	--
Households without a car	--	--	--	3.09 (3.83)
Respondent's age is less than 35 years	--	--	8.03 (2.56)	--
From March 2021 Class 1 to March 2022				
Respondent's highest education level is graduate	6.91 (5.72)	--	--	--

More important here are the results from the transitions, which are presented in the part two (titled *From Pre-COVID Class 1*) and part three (Titled *From March 2021 Class 1 to March 2022*. In the part two, covariates were included in Class 1 (pre-COVID) to Class 1, 2, and 4 transitions with Class 5 as base class. The results here indicate that those with a young child were less likely to stay in class 1 or move to class 2; those with graduate education were less likely to move to class

2; while those without a vehicle were more likely to move to class 4. These results suggest that socio-economic status like education (potentially correlated with income) and vehicle ownership played a key role in these transitions. In part three of the results, our results suggest that those with a graduate degree were more likely to stay in class 1 between March 2021 and March 2022 — potentially related to spending capacity of highly educated individuals given inflation being an important phenomenon during that time period.

Table 8.3: Constants

	Class 1	**Class 2**	**Class 3**	**Class 4**
Pre-COVID Membership Model				
Pre-COVID	1.68 (4.83)	1.79 (3.35)	2.05 (4.67)	-0.39 (-0.94)
Dec 2020	-1.81 (-1.96)	-20.38 (-4.74)	-33.83 (-25.39)	-3.33 (-2.06)
Mar 2021	-4.17 (-2.42)	-2.22 (-3.82)	-28.01 (-16.50)	-3.46 (-2.68)
Mar 2022	-15.93 (-69.62)	-2.88 (-2.53)	-4.13 (-1.54)	-1.70 (-2.20)
Pre-COVID to December 2020				
Class 1	1.29 (1.19)	10.97 (5.07)	-10.14 (-5.90)	-18.46 (--)
Class 2	21.74 (4.90)	47.88 (6.64)	21.77 (8.42)	5.68 (--)
Class 3	24.26 (7.54)	23.56 (--)	36.58 (--)	13.63 (--)
Class 4	2.17 (1.26)	29.40 (--)	3.67 (1.61)	11.38 (2.31)
December 2021 to March 2021				
Class 1	15.44 (7.02)	27.82 (7.11)	26.48 (4.15)	17.15 (7.73)
Class 2	-8.68 (--)	31.23 (16.65)	9.14 (4.91)	28.13 (14.82)
Class 3	37.15 (15.11)	52.57 (13.54)	55.12 (--)	53.87 (--)
Class 4	12.76 (6.20)	28.89 (--)	-1.22 (--)	31.28 (--)
March 2021 to March 2022				
Class 1	18.12 (13.22)	18.63 (17.13)	19.11 (6.92)	28.62 (27.61)
Class 2	2.33 (0.57)	6.70 (4.28)	16.68 (4.91)	24.87 (17.92)
Class 3	-0.56 (-0.17)	5.99 (1.98)	29.10 (--)	20.50 (3.59)
Class 4	0.65 (0.26)	3.69 (2.70)	-4.94 (--)	24.66 (--)

8.5 Summary, Key Takeaways, Policy Implications and Limitations

Summary and Key Takeaways

Using data from 785 individuals regarding their spending across in the last week across various product categories and through various acquisition channels across four time periods, a latent transition model with random intercepts is presented in this study that revealed five different behavioral classes of consumer spending and the dynamics of movement between classes as a results of the pandemic. The five classes revealed included: 1) a class with high probability of spending in-person across various product categories but at the same time a high probability of use of e-commerce for non-food items; 2) a class with low probability of spending on outside cooked food; 3) a class that rarely make of the pick-up and delivery services , with the exception of some probability of use of delivery for non-food items; 4) a class with moderately high probability of the use of delivery services for all product categories; and 5) a class with high probability of use of pick-up services for all product categories. The results from the model also revealed that the pandemic's single biggest impact was in terms of suppression of demand for dine-in and take-out of food - potentially due to it being a high risk activity. However, over time a reversal of this behavior is seen, back to an increase dine-in and take-out activity. The second significant behavioral transition was of movement towards delivery and pick-up services where about 2-3 fold increase in their usage is visible — a large portion of which appears to be stable over time, more so in the case of delivery than pick-up.

Policy Implications

On the policy end, the biggest implication of these results is along the lines of a potential increase in use of last mile delivery services — leading to higher congestion due to these additionally generated trips. This is especially true since the use of delivery services is not completely replacing the in-person trips. Cities could deploy better management strategies to cater to this additional traffic — some form of congestion pricing or promotion of sustainable modes of last mile delivery like cargo bikes. In the future, upcoming autonomous delivery technologies with a small footprint may also be an avenue that cities could explore.

Limitations

A few limitations are worth mentioning here. First, our sample size is relatively small for a complex model like RI-LTA. While given the nature of the data (i.e. with binary indicators), while the unconditional model is known to perform well with the available sample size, simulation studies show that the inclusion of covariates may not result in trustworthy parameters in some cases. Another limitation of this study is the presence of missing data due to non-response, which may have impacted some results. Lastly, our data end at March 2022 even though the landscape on spending continues of evolves. A future update to this study using a recent data may provide additional insights on the evolution of consumer spending behavior in the future.

CHAPTER 9
SUMMARY, IMPLICATIONS AND FUTURE RESEARCH

9.1 Summary

This dissertation focuses on understanding the extent to which the COVID-19 pandemic altered the remote work and e-commerce landscape in the United States and the associated implications for the future of cities. To address this, I collected two longitudinal data sets: 1) a 7 wave data set of employees and consumers; and 2) a 5 wave dataset of employers. The two data sets were used to undertake a set of four studies: 1) to understand telework satisfaction during the pandemic using a MIMIC model; 2) to analyze the trajectories of telework through the pandemic; 3) to understand the employer side perspective on remote work; and 4) to understand the evolving consumer spending behavior across online and in-person channels using a random intercept latent transition analysis framework.

From the first study on analyzing data on telework satisfaction, our results highlight diverse experiences of individuals with telework which will potentially shape the future of remote work landscape. An investigation of the data using an ordered model and a MIMIC model revealed several important insights. First, our results suggested that the satisfaction was higher for middle aged individuals compared to younger and older individuals, Hispanic or Latino respondents, and respondents with less than undergraduate degree, and those with higher levels of concerns about contracting the COVID-19 pandemic. On the other end, satisfaction was found to be lower for individuals with children attending school virtually from home.

Analysis using the MIMIC model confirmed several findings from the ordered model but also provided a more enriched structure to the model — through the inclusion of perceived / experienced benefits and barriers to telework latent variables. This enriched model suggests that the benefits and barrier to telework are disproportionately distributed across age groups, where higher barriers and lower benefits are experienced by those who are young or old compared to those in the middle aged group.

In the second study where I analyze the trajectories of telework at various time points before, during and beyond the pandemic, the results indicate presence of four clusters of telework trajectories with varying levels of remote work adoption over time — ranging from a group that maintained high in-person work even at the height of the pandemic; to a group that continued working from home for an extended period of time. An important insight through this data is that for three out of four clusters (72%) respondents, some form of remote work is expected going forward, suggesting a high level of hybrid work arrangement in the future.

Using these clusters as a dependent variable, a multinomial logit based membership model suggested that the telework trajectories through the pandemic were highly associated with nature of job in which one was employed, where higher in-person work was seen for transportation / manufacturing, logistics, healthcare sectors but higher remote work was seen for professional services, finance and insurance and information sectors. Other important insights included a higher level of remote presence by those with age 65 years or more, those without a vehicle and those with a young child at home. On the other end, results suggest lower remote presence for those who are students; while a hybrid presence was maintained by female respondents, those with at least an undergraduate degree, those with non-white ethnicity, those with a large household and those with income less than $100,000.

On the end of expected work location trends in April 2024, about 4 years since the beginning of the pandemic, our results indicate work location to be uncertain for about 15% of the respondents, who were more likely to be a female, a student or information sector employee but less likely to have a graduate degree. Amongst those that are certain regarding their work location in April 2024, higher in-person work is expected from those who are in education, healthcare and transportation / manufacturing sectors, those who are students or those with at least an undergraduate degree. On the opposite end, higher remote work is expected amongst those in the information sector, those without a vehicle or those with age more than 65 years. Results also suggest a high interaction between past telework behavior through the pandemic and the expected future behavior, along with a strong interaction between a respondent's outlook towards the impact of remote work on various work aspects like productivity and supervision, and their future work location decisions.

In the third study, I analyze data from the employer end instead of employees, since they are the ultimate decision makers in the remote work equation — and any pandemic accelerated remote work adoption decisions will not exist if the employers decide to not provide remote work as an option.

Results from the employer end reinforce the results presented earlier from the employee end and are potentially indicative of permanency of trends on the emergence of hybrid form of work. Results from the employer end too suggest an increase in remote work as a results of the pandemic, with some form of hybrid work being the norm going forward. However, a higher rebound to in-person work in transportation / manufacturing / warehousing sectors, compared to other sectors exists and this trend also exists in the HR / Legal / Administration / Finance departments compared to IT / Sales. Some of the key concerns amongst employers include the ability to supervise and mentor, and the impact on creativity and innovation. On the opposite end, employers agree that remote work will have a positive impact on their ability to recruit and retain employees, their public image and their ability to compete. Results also suggest an association between the employers' outlook towards remote work and their sector of operations, where those with a negative outlook where found to be more likely from transportation / warehousing sector.

Lastly, the analysis on the end of e-commerce using the latent transition analysis revealed five different behavioral classes of consumer spending and the dynamics of movement between these classes as a result of the pandemic. The five classes revealed included: 1) a class with high probability of spending in-person across various product categories but at the same time a high probability of use of e-commerce for non-food items; 2) a class with low probability of spending on outside cooked food; 3) a class that rarely make use of the pick-up and delivery services , with the exception of some probability of use of delivery for non-food items; 4) a class with moderately high probability of the use of delivery services for all product categories; and 5) a class with high probability of use of pick-up services for all product categories. The results from the model also revealed that the pandemic's single biggest impact was in terms of suppression of demand for dine-in and take-out of food - potentially due to it being a high risk activity. However, over time a reversal of this behavior is seen, back to an increased dine-in and take-out activity. The second significant behavioral transition was of movement towards delivery and pick-up services where about 2-3 fold increase in their usage is visible — a large portion of which appears to be stable over time, more so in the case of delivery than pick-up.

9.2 Implications for Cities

There are several implications for cities that can be derived from the results of various studies conducted in this dissertation. First, given the presence of a strong interaction between the occupational sector and the adoption patterns in telework, the recovery trajectory of various cities in the United States will likely be different – depending upon the composition of a city's economy. Some of these are already visible through emerging mobility recovery data sets like the study by Chapple et al. [49]. Second, our research suggest that those without a vehicle (who also tend to be transit users) are more likely to continue to work remotely – potentially indicating a slower rebound of transit ridership. Ridership data from several cities provides insights in this regard where the average recovery is currently at about 70%. Third, a reduced level of commuting may hurt individuals employed in the third sector of the economy (especially in urban cores) — who largely rely on spending by commuters. Fourth, there has been potentially a drastic shift in the geography of activity given the changed telework landscape - away from urban cores. Some data sets highlight this [104]. Lastly, there has been a likely increase in the use of last mile delivery traffic in communities that cities need to plan for in the future.

9.3 Future Research

The analysis presented in this dissertation opens up avenues for future research in several directions. In regards to telework, research on the geography of activity participation is needed. Teleworkers are not commuting to work, but they are likely still doing some out of home activities. What is the geography and temporality of this activity? How far they are traveling and what modes they are using? What is the purpose of their trips? Answer to these questions can help transportation agencies better allocate their limited resources. Another direction in this regard is to understand the residential self-selection aspects - where telework select their residential location taking into consideration commute patterns. To what extent did it happen during the pandemic and to what extent is it happening now and its resulting implications for mobility. Third potential direction is along the lines of urban economics and urban re-equilibrium in the light of changed telework landscape. While telework provides greater flexibility, potentially giving an opportunity to some to move away from urban area, factors like fixed housing stock, inflation, changing mortgage rates etc. may eventually prevent everyone from moving out from urban cores and a deeper investigation in this direction may help cities plan for the future better. Fourth direction for future research is along the lines of scenario planning for an uncertain future. Given a continuously changing world, a scenario based approach may help cities design their systems and policies better instead of basing them purely on short-term trends. Some efforts in this direction includes the work by Pan and Shaheen [222] but more work is needed. Lastly, our lives are becoming more and more flexible, making the traditional ways of designing transportation systems around commute hours to be unsustainable. Future work may include devising strategies to design our transportation systems for flexible world where users have better mobility options throughout an average day instead of just the peak commute hours.

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