UNIVERSITY OF CALIFORNIA,
IRVINE

Modeling Commute Behavior Dynamics in Response to Policy Changes: A Case Study from the COVID-19 Pandemic

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Civil and Environmental Engineering

by

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2023

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ACKNOWLEDGEMENTS

I extend my heartfelt gratitude to a number of individuals whose support was invaluable in the completion of this dissertation.

Foremost, I would like to express my deepest appreciation to my dear husband, whose unwavering support and assistance were instrumental throughout this journey. His dedication to helping with all aspects of editing and result collection was not only a professional boon but also a personal source of strength and encouragement.

I am immensely thankful to Professor Michael G. McNally and Rezwana Rafiq for their help with my dissertation committee.

My sincere thanks go to Professor Stephen G. Ritchie and Assistant Professor Michael Hyland for their time and valuable contributions, particularly in attending my defense. Their presence and feedback were greatly appreciated and added substantial value to my work.

Additionally, I am grateful to Professor Jean-Daniel Saphores for his valuable advice and expertise. His suggestions have been extremely beneficial in refining my research and conclusions.

This dissertation stands as a testament to the collective effort and support of these remarkable individuals, to whom I am deeply indebted. Thank you for being part of this academic journey and for contributing to its successful completion.

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FIELD OF STUDY

Transportation Systems and Human Behavior, COVID-19 Pandemic Impacts on Telecommuting

ABSTRACT OF THE DISSERTATION

Modeling Commute Behavior Dynamics in Response to Policy Changes:
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Doctor of Philosophy in Civil and Environmental Engineering

University of California, Irvine, 2023

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This dissertation introduces a novel model intended for integration within an Agent-Based Model (ABM) framework to dynamically estimate and predict workers' commuting behaviors under various policy scenarios. The model is designed to aid policy-making by providing insight into commuting patterns and their potential responsiveness to policy interventions. In particular, the focus is on changes in Working from Home behavior due to the COVID-19 pandemic.

The methodology encompasses a three-step process, starting with the identification of worker commuting preference classes. Employing an unconditional latent class analysis model, the study categorizes workers into distinct groups based on their telecommuting preferences and behaviors. This classification is foundational for understanding diverse work-related travel patterns. The second step is predicting class membership. Post-classification, the study considers demographic features to determine their association with class membership. This analysis is critical for predicting shifts in commuting behavior in relation to demographic changes. Third, estimating commuter type within each commuter type class: This concluding step uses logistic regression to estimate the likelihood of an individual being a commuter, a hybrid commuter, or a telecommuter, with adaptability to policy changes for exploring varied outcomes.

The study produced several key findings. First, diverse worker classes were identified: The analysis of the ASU Covid Future Panel Survey data revealed several distinct worker classes based on telecommuting experiences and preferences. These include a telecommuter class, a regular commuter class, pre-Covid home remote worker class, and a class exhibiting significant demographic changes during the pandemic. Particularly noteworthy is a class that shows a strong propensity to shift to high-frequency telecommuting under supportive policies, despite an initial preference for hybrid or regular commuting. Distinct class characteristics and predictors were identified within each class, serving as predictors for class membership. This finding is essential for understanding and predicting changes in commuting behaviors. The study also included an intra-class commuter type estimation and factor analysis to identify the factors influencing these classifications. This provides deeper insights into the motivations and constraints affecting commuting choices.

CHAPTER 1

INTRODUCTION

Telecommuting has long been recognized as a potential substitute for traditional commuting. The conceptualization of telecommuting can be traced back to foundational works by Salomon and Salomon (1984), Nilles (1988), and Hall (1989). Nilles (1988), in particular, was instrumental in envisioning telecommuting as a viable alternative to physical commuting. Further studies by Kitamura et al. (1990) and Mokhtarian (1991) offer a detailed analysis of the multifaceted aspects of telecommuting and how the emerging trends in remote working could impact social interactions, work-life balance, and offer benefits like time management flexibility and reduced traffic congestion. These early investigations laid the groundwork for subsequent research in transportation, exploring various factors influencing telecommuting adoption, as evidenced in the works of Mokhtarian et al. (1998), Choo et al. (2005), Fu et al. (2012), and Caulfield (2015).

To reduce greenhouse gas emissions, telecommuting has emerged as a potential solution. Studies like those by Shemer et al. (2022) have shown that telecommuting and flexible work schedules can significantly reduce VMT and vehicle hours traveled (VHT). This study provides a scenario-based analysis of the long-term impacts of increased work-from-home practices based on the trip-based Maryland statewide model. According to this research, by 2045, total VMT reduction could range between 3% and 12%, highlighting the substantial potential of WFH combining with other policies to reduce travel demands and associated environmental impacts.

Additionally, telecommuting addresses the equity aspect of commuting by providing advantages to demographics with limited access to transportation or household responsibilities (Mokhtarian et al., 2005; Bloom et al., 2015). A study by Vanderstukken et al. (2022) specifically considered indicators such as individuals with disabilities who may benefit significantly from the option to work from home. This research adds to the understanding that telecommuting can provide more equitable work opportunities, particularly for those who may face challenges in traditional commuting scenarios (Mokhtarian et al., 2005; Bloom et al., 2015).

Prior to the COVID-19 pandemic, however, the prevalence of telecommuting was relatively low. The Bureau of Labor Statistics (2019) reported that only about 7% of U.S. civilian workers had access to telework, a statistic further highlighted by the Pew Research Center (2021). This scenario drastically changed with the onset of the pandemic in March 2020. The American Community Survey (ACS) data, as analyzed by the U.S. Government Accountability Office (2021) and the U.S. Census Bureau (2022), indicated a significant rise in teleworking, jumping from 5.7% in 2019 to 17.9% in 2021. This shift was a result of government-enforced policy measures, including the transition to online education, adoption of Work from Home (WFH) practices, decreased business travel, and limitations on social interactions, as Ahmed et al. (2021) observed in their study on organizational and individual adjustments to the pandemic.

The pandemic also catalyzed a re-evaluation of the necessity of traditional commuting, as noted by Ecke et al (2022). This re-evaluation has implications for both employers, who must balance in-person and remote work (Hynes, 2020), and for urban and transport policy development, as Bhat & Koppelman (1999) emphasize. Understanding the dynamics between telecommuting and traditional commuting is vital in this regard.

To further this understanding, this research utilizes the ASU COVID Future Panel Data to analyze societal adaptations to telecommuting during the pandemic. It proposes a conceptual framework for telecommuting implementation, characterizes various telecommuters and commuters, and outlines a methodology to update current activity-based models (ABM) to reflect policy-induced changes in work modalities.

A Repeat Measurement Latent Class Analysis (RMLCA) model is employed to identify diverse teleworking preference classes and analyze the commuting characteristics and demographic features of each class. The study also includes an intra-class commuter type estimation and factor analysis to identify factors influencing these classifications, incorporating policy changes at the class level. The findings offer insights into potential post-pandemic shifts in worker commute status, contributing to the development of more accurate pattern choice sets in ABMs (Barrero et al., 2020).

The structure of this dissertation is delineated across seven chapters. Chapter 2 presents the conceptual framework, detailing the prerequisites for telecommuting, including work capability thresholds and limitations in opportunities. Chapter 3 outlines the methodology employed, focusing on estimating commute statuses and developing scenarios for policy changes. Chapter 4 offers a comprehensive overview of the ASU future panel survey, including the selection of a representative sample and justification for the chosen time-period. This chapter also summarizes changes in telecommuting and commuting behaviors among the sample population and elucidates the categorization of commuter types. In Chapter 5, the RMLCA model is introduced along with its corresponding class membership predictors and the results of the within-class worker/telecommuter type model. Chapter 6 advances the discussion to within-class behavioral changes, influenced by factors such as worker opportunities, capabilities, and experiences that evolved during the pandemic. This chapter also explores policy variables in relation to scenario changes and delves deeper into workplace-related insights. The dissertation concludes in Chapter

7 with a summary of the findings, an acknowledgment of the study's limitations, and suggestions for future research directions.

CHAPTER 2

CONCEPTUAL FRAMEWORK AND THEORY

2.1 Introduction

Telecommuting, akin to conventional commuting, is a distinctive activity within the realm of transportation demand. Traditional travel demand is often seen as a derivative of the need to engage in various activities. However, telecommuting emerges uniquely, predominantly driven by a desire to avoid certain aspects rather than to seek them. This avoidance could be of the costs associated with commuting, or the preference to remain close to family, thereby maximizing personal or family time (U.S. Bureau of Labor Statistics, 2022).

The dynamics of telecommuting can be dissected into supply and demand components. On the supply side, telecommuting is contingent upon employer authorization, which can be influenced by policy measures. The demand side represents individuals' inclination to minimize commuting. However, not all preferences for reduced commuting are feasible or can be satisfied. The realistic portion of this demand respects constraints such as the nature of one's work being conducive to remote execution and the degree of employer support for telecommuting. A confluence of supply and demand factors determines the feasible extent of telecommuting, thereby influencing individuals' decisions regarding their commuting status.

The COVID-19 pandemic catalyzed a paradigm shift in telecommute dynamics, propelling demand to unprecedented levels. Researchers estimate that telework accounted for about 50 percent of paid work hours between April and December 2020, compared with 5 percent before the pandemic (Barrero, Bloom, & Davis, 2020). This shift was not merely a temporary adjustment but rather a transformative experience for many workers, leading to a reevaluation of their work-life balance preferences. The pandemic, in this sense, functioned akin to introducing someone to automobile ownership; it opened new possibilities and preferences, potentially leading to a persistent increase in the demand for telecommuting, akin to an induced demand in transportation terminology.

2.2 Conceptual Framework

The pivotal research question examines how, post widespread adoption of hybrid commuting, individuals reassess telecommute demand and make future commute decisions. Telecommuting's occurrence is contingent on two principal dimensions: the supply side, encompassing employer permission and policy regulation; and the demand side, reflecting employee preference.

Telecommuting typically requires employer permission, contrasting with traditional commuting, which generally does not. However, this can be viewed reciprocally, where workers might need permission for an assigned office space. Employer permission is influenced by policy and organizational benefits. For instance, during the pandemic, stay-at-home mandates substantially increased telecommuting, offering employers cost savings by reducing the need for permanent office spaces (Armour et al., 2020).

Employees' decisions hinge on the nature of their work, determining the feasibility of telecommuting, and personal preferences influenced by individual and household factors. The alignment of supply and demand is critical for telecommuting to occur, influencing the scheduling of both telework and commuting.

However, the challenge remains in accurately measuring the demand and supply for telecommuting. This measurement is vital for understanding the evolving dynamics of work arrangements, particularly in the aftermath of the COVID-19 pandemic, which has altered the landscape of telecommuting and traditional work environments (Armour et al., 2020).

The research question is: after society experiences the heavy hybrid commute, how will people re-evaluate telecommute demand and make their future commute decisions?

Telework happens on two sides: the supply side, which refers to an employer's permission and is under policy control; and the demand side, which refers to an employee's preference.

Usually, telecommuting needs permission; commuting does not. Of course, things could be seen on the other side; workers may need permission to own an assigned office from their supervisor so that they could own a working space. The employer's permission could be influenced by policy and the employer's own benefit. For example, during the pandemic, stay-at-home policies enforced telecommuting at the highest level historically; the employer may benefit from not renting a permanent working office location to save on expenses.

The employee's decision would be highly dependent on the nature of the work, which refers to the work's eligibility to be telecommute work, and their own preference, which is a comprehensive outcome related to their personal characteristics and their household-level needs. The eligibility of the nature of work to be able to telecommute is a key element.

The supply and demand must meet, so telecommuting will happen, and worker can decide on schedule of teleworking so that commuting schedule is fixed.

The question left is how we measure the demand and supply for telecommuting.

2.3 Telecommuting Theoretical Framework

In this study, the focus is on a distinct social experiment: the ongoing pandemic period. The analysis centers on workers' expectations rather than their actual behavior during this time, investigating the concept of expectation and its influence on future work behavior. The perspective is exclusively from the workers' viewpoint, owing to survey limitations. Here, 'opportunity' is defined as the chance to work from home, shaped by employer policies and pandemic-specific regulations, representing the supply side. 'Capability', on the demand side, refers to the extent to which a worker's job can be performed remotely, independent of employer approval.

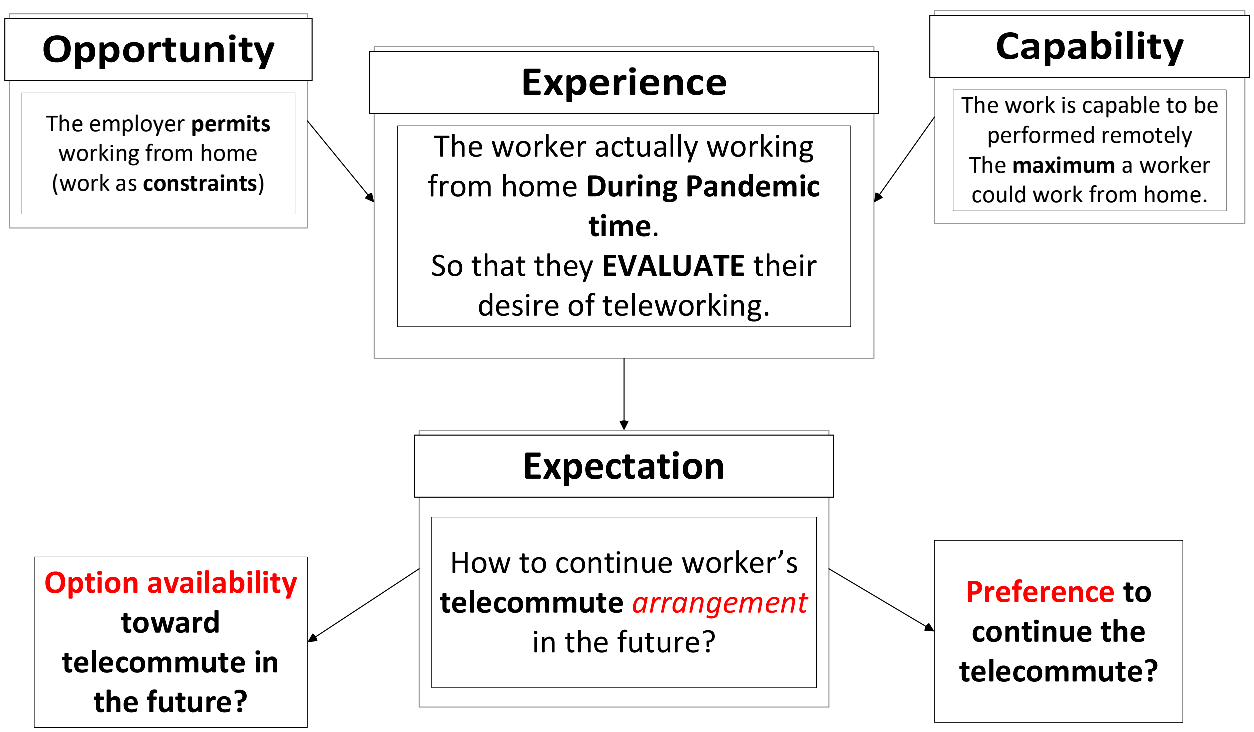

Figure 2.1 – Exposition of conceptual framework

From the employee perspective, decisions regarding telecommuting are significantly influenced by the nature of their work, determining the feasibility of telecommuting, 'Capability' is a measurement to this aspect. This feasibility varies based on several factors, including the physical and manual intensity of the job, the necessity for face-to-face interaction, and the availability of information and communication technology (ICT) and internet connectivity at home. Adding to this, a study by Dingel and Neiman (2020) finds that in the U.S., about 37% of jobs can be performed entirely from home, with these jobs typically paying more than those that cannot be done from home, accounting for 46% of all U.S. wages.

During the pandemic, workers were compelled to telecommute, providing them with firsthand experience in this mode of working. This period serves as a reliable gauge for predicting future work decisions. A worker's opportunity to telework largely depends on their employer, but it's also shaped by policy, especially during the pandemic. Capability, in contrast, is determined by the nature of their work and how much of it can be done remotely.

Opportunity and capability act as constraints and thresholds, shaping the extent of telecommuting experience a worker could gain during the pandemic. This experience enables workers to assess and reassess their preferences for telecommuting and commute arrangements. It encompasses not only the practical aspects of work but also personal factors like household needs and individual preferences.

The pandemic-induced stay-at-home policies expanded teleworking opportunities to unprecedented levels, allowing nearly all capable workers to experience telecommuting. Without this enforced shift, telecommuting would remain a theoretical concept without practical validation. Only through this experience can workers form firm and reliable expectations for future work arrangements.

At this stage, workers can more accurately determine their preferences for new commuting arrangements, considering their attitudes towards telecommuting and its suitability for their family needs. However, these preferences can only manifest within the scope of the opportunities provided.

Therefore, the ultimate expectation regarding work commute arrangements should be assessed by considering both the realistic expectation of opportunity and individual preferences for working from home. The harmonization of supply (opportunity) and demand (capability, experience, and expectation) elements ultimately influences the structuring of workers' telecommuting and commuting patterns in the post-pandemic landscape.

CHAPTER 3

METHODOLOGY

3.1 Introduction

This study presents a structured methodology to enhance existing regional models through the integration of an Activity-Based Model (ABM), particularly focusing on telecommuting and commute behaviors. The method is exhibited in this method along with the case study during Covid-19.

The methodology encompasses four key steps: definitions, latent class analysis, predictor integration, and analysis.

<u>Defining Telecommute-Commute Dynamics</u> – This foundational step involves delineating the interplay between telecommuting and commuting, including the substitution patterns and scheduling aspects. The design of this stage is critical for subsequent survey development, aligning the survey objectives with the model's parameters. This alignment often poses challenges, as traditionally, surveys are conducted prior to finalizing modeling approaches, necessitating retrospective adjustments.

<u>Latent Class Analysis for Worker Classification</u> – The second stage employs latent class analysis to categorize workers based on projected telecommuting and commute patterns. This anticipatory approach accounts not only for current behaviors but also for expected changes in response to potential policy shifts. Worker expectations are integrated into the model, providing a forward-looking perspective.

Predictor Integration for Worker Class Estimation – In this stage, predictors are selected based on the demographic distribution across worker classes. Notably, the application of a Latent Class Analysis (LCA) mirrors that of a multinomial regression, focusing solely on predictors and excluding other indicators.

Analysis and Calibration of Worker Classes – The final stage involves a detailed examination of telecommuting and commuting behaviors within each worker class, recognizing that not all behavior types are present across all classes. The model is then calibrated to respect various work-related demands and constraints, exemplified using capability variables in this case study.

Each step in this methodology is crucial for accurately adjusting the ABM within regional modeling frameworks, offering a systematic approach to understanding and predicting telecommute and commute behaviors in the context of policy changes and societal shifts.

3.2 Research Questions and Research Gap

As of the present, telecommuting has significantly increased to 28% of full paid working days, up from a mere 7.2% prior to the pandemic, as per the U.S. Survey of Working Arrangements and Attitudes (SWAA) data. This fourfold increase has revolutionized the nature of commuting. Commuting, once seen as an obligatory aspect of work life, has evolved into a more flexible option, particularly for those eligible for hybrid work models. This surge, analyzed by Barrero, Bloom, and Davis (2021), was driven by various factors, including improved WFH experiences, new investments in enabling technologies, reduced stigma around WFH, persistent concerns about crowds and contagion, and a surge in technological innovations supporting WFH.

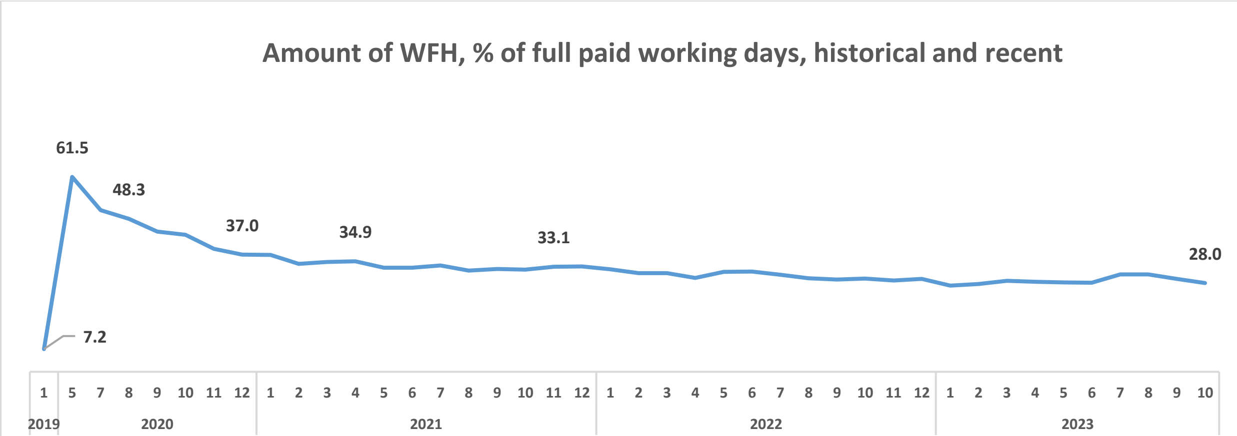

Figure 3.1 – Amount of work-from-home as percent of full paid working days

Barrero, Jose Maria, Nicholas Bloom, and Steven J. Davis, 2021. "Why working from home will stick," National Bureau of Economic Research Working Paper 28731.

These changes in telecommuting habits have dramatically altered time expenditure and behavioral patterns during and after the pandemic. Before these societal shifts, commuting was deemed a fixed and essential part of employment. However, the rise of telecommuting options has led people to reconsider their commuting habits, seeking to reduce the time and costs associated with commuting while expecting more flexible schedules and daily activities. The impact of these changes extends beyond the binary status of commuting (to commute or not) and includes alterations in the associated commute tour patterns and the daily trip patterns of non-commute workers. Estimating and incorporating these changes into activity-based models for future travel pattern simulations has become a pressing need.

Therefore, this study calls for the creation of new worker classes based on telecommute/commute preferences to guide pattern estimations. While the current study lacks sufficient information about corresponding tour patterns, this gap must be acknowledged and addressed in the model's development.

In addition, the study explores how policy changes can influence these behaviors. Given the importance of realistic policy implementation, the study focuses on setting boundaries based on pre-surveyed expectations rather than using arbitrary measures to influence demand. Identifying these boundaries and understanding the maximum potential for policy change is crucial for generating useful policy insights and aiding policy decisions. This exploration is essential for assessing the capability of a policy to influence choice changes under different scenarios, aligned with overall worker preference classes.

3.3 Research Challenges

This research was conducted during the COVID-19 pandemic, offering an exceptional opportunity to evaluate how telecommuting alters global travel patterns and attitudes towards remote work. Yet, this period posed unique challenges, introducing potential biases linked to policy measures and public health concerns that could skew individuals' decision-making and future expectations. To mitigate these effects, the study carefully selected and justified the timeframe, examining worker behavior and expectations across different stages of the pandemic and correlating them with national COVID-19 trends.

A key challenge was the ambiguous definition of telecommuting in the survey. Telecommuting often overlaps with or complements commuting, complicating the distinction from an Activity-Based Modeling (ABM) perspective. The survey's telecommuting frequency categories were not directly linked to commuting patterns, leading to the development of a translation mechanism in the modeling process to represent the relationship more accurately between telecommuting and commuting frequencies. This adaptation was crucial for understanding the true nature of telecommuting and its impact on commuting behaviors.

3.4 Research Methods

Latent Class Analysis (LCA) is conceptualized as a mixture model, positing the existence of inherent, unobserved subgroups within a population. This hypothesis is derived from observed variable responses, introducing a categorical latent variable that segments the population into distinct, non-overlapping, and comprehensive latent classes. This model construct is rooted in the foundational work of Lanza and Rhoades (2013), who provided a detailed exploration of this concept. Additionally, the formal structure of the model is further articulated by Linzer and Lewis (2011), offering a more structured framework for LCA implementation.

The likelihood of observing a specific respondent in Latent Class Analysis (LCA) is determined by the probability model underlying the technique. This likelihood is essentially the probability of observing the respondent's pattern of responses, given the latent class structure of the population. In LCA, this is calculated by summing the products of two probabilities for each latent class: the probability of a respondent belonging to a particular latent class, and the conditional probability of their observed responses, given their membership in that latent class.

Maximum log-likelihood estimation (MLE) target function is here:

$$f\ (Y_i|\pi,\ \rho) = \sum_{r=1}^{R} \rho_r \prod_{j=1}^{J} \prod_{K=1}^{K_j} K_j (\pi_{jrk})^{Y_{ijk}}$$

Let Y_{ijk} = 1 if respondent i takes k-th outcome for its j-th categorical variable, and Y_{ijk} = 0 otherwise, where j = 1,…, J and k = 1,…, K_j. Let ρ_r denote the probability that a respondent falls into a certain class r (called the class membership probability) and π_{jrk} denote the probability that observation in class r produces the k-th outcome on the j-th variable (called the class-conditional probability). The parameters that the LCA model estimates are ρ_r and π_{jrk}, which are found via maximum log-likelihood estimation (MLE).

3.4.1 Repeat Measurement Latent Classification Analysis (RMLCA)

Repeat Measurement Latent Class Analysis (RMLCA), an advanced form of traditional Latent Class Analysis (LCA), is adept at handling multi-temporal data to identify hidden subgroups within a population based on their trajectory patterns. This technique is particularly valuable for analyzing the dynamics of individual behaviors or attributes over time, crucial in travel behavior research. RMLCA facilitates the identification of distinct groups that exhibit similar development patterns in their characteristics across various time points.

RMLCA is especially relevant for longitudinal surveys, like the ASU COVID future survey, to understand changes in individual preferences over time. Although RMLCA and LCA are technically similar in their estimation methods, RMLCA's capacity to handle longitudinal data makes it preferable for such surveys. In the first phase of our analysis using RMLCA, we process indicator variables from repeated measurements across different waves of the survey. This approach allows us to categorize workers into specific classes with shared commuting preferences and to analyze each worker's preference within their class, providing a nuanced understanding of the evolving telecommuting and commute behaviors.

Repeated measures latent class analysis (RMLCA) models were fit using Mplus v.8.0 (Collins LM, Lanza, 2010), employing full information maximum likelihood estimation with robust standard errors. These models used six binary indicators, one for each follow-up survey. They did two things: they cut down on the amount of data they needed to find key longitudinal patterns and they made sure that measurement error was taken into account. The assumption underlying this approach is that missing data on indicators were missing at random and were handled using Mplus' full information maximum likelihood estimation procedure (Muthén LK, Muthén BO, 2017). Cases with missing data on covariates were excluded. The identification of the maximum likelihood solution was confirmed using 2000 initial stage random starts and 200 final stage optimizations.

Due to the nature of dichotomous indicators, the bootstrap likelihood ratio test could not be applied for determining the optimal number of classes. Instead, a variety of fit criteria were employed, including the Bayesian Information Criterion (BIC), sample size-adjusted BIC (a-BIC), and the Consistent Akaike Information Criterion (CAIC). These criteria, along with the Vuong-Lo-Mendell-Rubin LRT, an adjusted test for the necessity of additional classes, have been shown in simulations to be effective for determining the enumeration of latent class models (Dziak JJ, Lanza ST, Tan X, 2014).

3.4.2 Latent Class Analysis (LCA) with Predictors

In the second phase, the analysis evolved into Latent Class Analysis (LCA), with demographic variables introduced as predictors. We used Vermunt's 3-Step Approach (R3STEP command in Mplus) (Bakk et al. 2013) to do this. We made the most likely class variable using the latent class posterior distribution and took measurement error into account. Subsequently, auxiliary variables were included (Dziak JJ, Lanza ST, Tan X, 2014) as baseline-category variables in multinomial logistic regression models that included all cases. Prevalence estimates of unadjusted covariates across latent classes were obtained using the BCH command in Mplus. This design allows covariates not to affect latent class formation in both the R3STEP and BCH methods (Asparouhov T., Muthén B., 2015).

The BCH (Bolck, Croon, and Hagenaars) method, as described in Vermunt (2010) and Bakk et al. (2013), is a statistical approach used for analyzing outcomes in mixture modeling. This method has been shown to substantially outperform other methods like Lanza's method and the 3-step method, especially in scenarios where the latent class variable is associated with a continuous distal outcome. The BCH method is particularly effective because it avoids shifts in latent class identification in the final stage of analysis, a common issue with the 3-step method.

In the final stage, the BCH method employs a weighted multiple group analysis, where the groups correspond to the latent classes. This ensures that a class shift is not possible since the classes are already known. An important aspect of the BCH method is its use of weights, which reflect the measurement error of the latent class variable. Each observation in a class or group is assigned a weight, so each observation will obtain k weights for each class, and the auxiliary model is estimated as a multiple-group model using these weights.

A critical consideration with the BCH method is that it relies on weights that can take negative values. This can happen, particularly when the entropy is low or when the latent class variable is measured with error. Negative weights can lead to inadmissible estimates for the auxiliary model. For instance, the variance of the distal outcome might be estimated as a negative value, or the frequency table of a categorical auxiliary variable might have negative values. In such scenarios, utilizing the BCH method becomes challenging beyond the basic model for comparing mean outcomes across classes. However, Bakk and Vermunt (2014) demonstrated that the means of continuous distal outcomes can be accurately estimated with the BCH method even when group-specific variances are negative, provided the variances are held equal across groups or classes. This equal variance assumption ensures that the variance estimates do not affect the mean estimates.

3.4.3 Within-Class Analysis and Estimation of Future Commuter Status

The final part of the methodology is centered around within-class analysis and the estimation of future commuter statuses. models were fit using Stata 17.0. This is achieved through the application of Logistic Regression, which is a statistical method used for modeling the probability of a binary outcome based on one or more predictor variables.

Dayton, C. M. (1992) states logistic regression model, $\{X\} = \beta_0 + \sum \beta_i \cdot X_i$ where Y is a binary outcome variable (0 or 1), β_0 is an intercept, β_i denotes the logistic regression coefficients for the design matrix X of covariables i.

In the proposed model, the outcome is a predicted probability ranging from 0 to 1. To forecast outcomes for n-1 commuter types, I am incorporating the BCH weight as an "importation weight" in Stata (iweights). This weighting approach in Stata signifies the relative significance of each observation in the Logistic Regression model calibration, as suggested by StataCorp (2023). It's important to note that during the calibration of the Logistic Regression model, proportional assignment is employed, which includes all 870 samples in the process. The BCH weight plays a crucial role here, as it filters out negative values, ensuring only positive value cases are considered in the model calibration.

When applying the model, it's essential to adhere to the defined capability threshold. The resultant probabilities will be ranked and selected in alignment with the proportion of a specific commuter type. This approach is consistent with the "rule" used in the California statewide model as described by Cambridge Systematics Inc (2014). The rule specific for this model framework is, after all model applied, each observation would obtain a probability to belong to each eligible commuter type. The Regular commuter would be selected first, then home remote worker, the rest would be split between high frequency and low frequency commuter. In the study case the selected commuter type to calibrate is Home remote worker, regular commuter, and low frequency commuter.

The primary objective of this phase is to accurately estimate and apply the model for updating each worker's commuting status (yes or no). This updated status is subsequently integrated into an activity-based model, which provides a framework for guiding future commuting pattern choices.

To introduce the policy test variable, the new set of outcome commuter type variables for each class needs to be prepared, the application process is the same.

Overall, this three-part methodology offers a robust framework for analyzing and predicting commuting preferences, combining statistical techniques and demographic insights to provide a detailed and actionable understanding of commuter behaviors.

CHAPTER 4

DATA OVERVIEW

4.1 Introduction

This chapter presents an overview of the ASU COVID Future Panel Data and the process of selecting the worker sample for the study. We will discuss the criteria used for this selection. The next section will introduce the method for classifying workers as telecommuters or commuters, setting the stage for later discussions about the results of the model and its findings.

The study is further refined by justifying the choice of time periods for the Latent Class Analysis indicators and considering future expectations for telecommuter and commuter behaviors.

To conclude, the chapter will provide a summary that encapsulates the changes in commuting behaviors observed before, during, and after the pandemic, along with a discussion on the expected behaviors and the capability threshold of the individuals involved.

4.2 ASU Covid Future Panel Data Overview

The ASU COVID Future Panel Survey, whose protocol was approved by both Arizona State University (ASU) and University of Illinois at Chicago (UIC) Institutional Review Board offices (Chauhan et al., 2021), serves as a crucial study in evaluating the COVID-19 pandemic's effects on travel behavior and work-from-home practices in the United States. This extensive survey aims to understand the evolving attitudes and choices regarding travel and telecommuting during and after the pandemic, thereby offering valuable insights into the long-term shifts in behavior (Salon et al., 2022; Javadinasr et al., 2022).

The survey's initiation, Wave 1A, from April to June 2020, coincided with the peak of stay-at-home orders, offering initial insights into the immediate responses to the pandemic. This early phase gathered 1110 responses through a convenience sampling method using various channels. The survey then progressed to Wave 1B, from late June to October 2020, extending its reach through survey invitations sent to a random email list of 450,000 addresses across the U.S. and additional addresses from the Phoenix metropolitan area. Despite challenges like email spam filters, Wave 1B achieved 1116 responses from the email list, 782 from the Phoenix area, and an additional 5250 via the Qualtrics Online Panel, employing quota sampling for demographic representation. Wave 1 survey data collection, encompassing both 1A and 1B, thus totaled 8,723 responses (Salon et al., 2021; Salon et al., 2022; Javadinasr et al., 2022).

Table 4.1: Wave responses and collection time

ASU future data collection	# of responds	Total	Data collect time-period
wave 1a	1113	9265	2020.4-2020.6
wave 1b	8152		2020.7-2020.10
Wave 2	311/1a	2877	2020.11-2021.8
	2566/1b		
Wave 3	304/1a	2728	2021.10-11
	2424/1b		

The subsequent waves, Wave 2, and Wave 3, continued to build on this foundation. Wave 2, running from November 2020 to June 2021, gathered 2,877 responses, with 311 from Wave 1A participants and 2,566 from Wave 1B respondents. Wave 3, conducted in October and November 2021, further expanded the survey's depth, amassing 2,728 responses, comprising 304 from Wave 1A and 2,424 from Wave 1B respondents. These subsequent waves ensured continuity and depth in the survey's findings, with approximately one-third of the initial respondents continuing their participation, thus offering a rich longitudinal perspective (Salon et al., 2021; Salon et al., 2022; Javadinasr et al., 2022).

Covering over 120 questions across various categories, the survey provided insights into pre-COVID commuting habits, travel choices during the pandemic, work-related queries, and anticipated lifestyle changes in the post-pandemic era. This extensive range of questions was crucial for a detailed understanding of the pandemic's multifaceted impacts (Chauhan et al., 2021).

The ASU COVID Future Panel Survey dataset is a significant resource for researchers and policymakers. It facilitates an in-depth analysis of the long-term effects of the COVID-19 pandemic on travel behavior and telecommuting practices. This dataset is available at the ASU Dataverse, offering an extensive range of information for further research and policy development (ASU Dataverse: COVID Future Panel Survey).

4.3 Outcome Commuter Type Variable Construction

Table 4.2: Variable derivation logic

Telecommuter/ commuter type	Before COVID	During COVID	Telecommute Expectation in WAVE 3	Capability
Non-commuter/ Home remote Worker Commute status: Always NOT commute	Has telework option and **commute frequency is 0**	Has telework option and **commute frequency is 0**	Report their expected *commute mode* is **Work only from home and *not commute***	**All** of the work could be done remotely. Upper threshold for Non-commuter
Hybrid Commuter: low frequency commuter / High frequency teleworker	Has telework option, telework **more than few time a week or every day**	Has telework option, telework **at least 5 days a week**	Has telework option, expect to telework **more than few time a week or every day**	At least some of worker's work could be done remotely.
Hybrid Commuter: high frequency commuter/ low frequency teleworker	Has telework option, but only telework **less than once a week**	Has telework option, but only telework **less than 4 days a week**	Has telework option, but only expect to telework **less than once a week**	
Regular Commuter Commute status: Always commute	No option to telecommute /Telecommute frequency is 0	Not able to telecommute /Telecommute frequency is 0	**None** of the worker's work could be done remotely	**None** of work could be done remotely. Lower threshold

4.3.1 Capability variable

The capability variable serves as a threshold in the theory as well as in the model and is derived from a question trying to identify if the nature of work can let workers telecommute or not. The question is phrased "How much of your job could be done remotely (telecommuting), if your employer allowed it? Do not consider your employer's current remote work policies when answering this question.". The original survey has 4 answering options, "All of it", "Some of it, and I could work entirely from home some days" , "Some of it, but I would need to be at my workplace for at least part of most workdays", and "None of it". I combined the middle two answers to form "worker has *some* work that could be done remotely" since the two options do not facilitate identifying the high or low telecommute frequency.

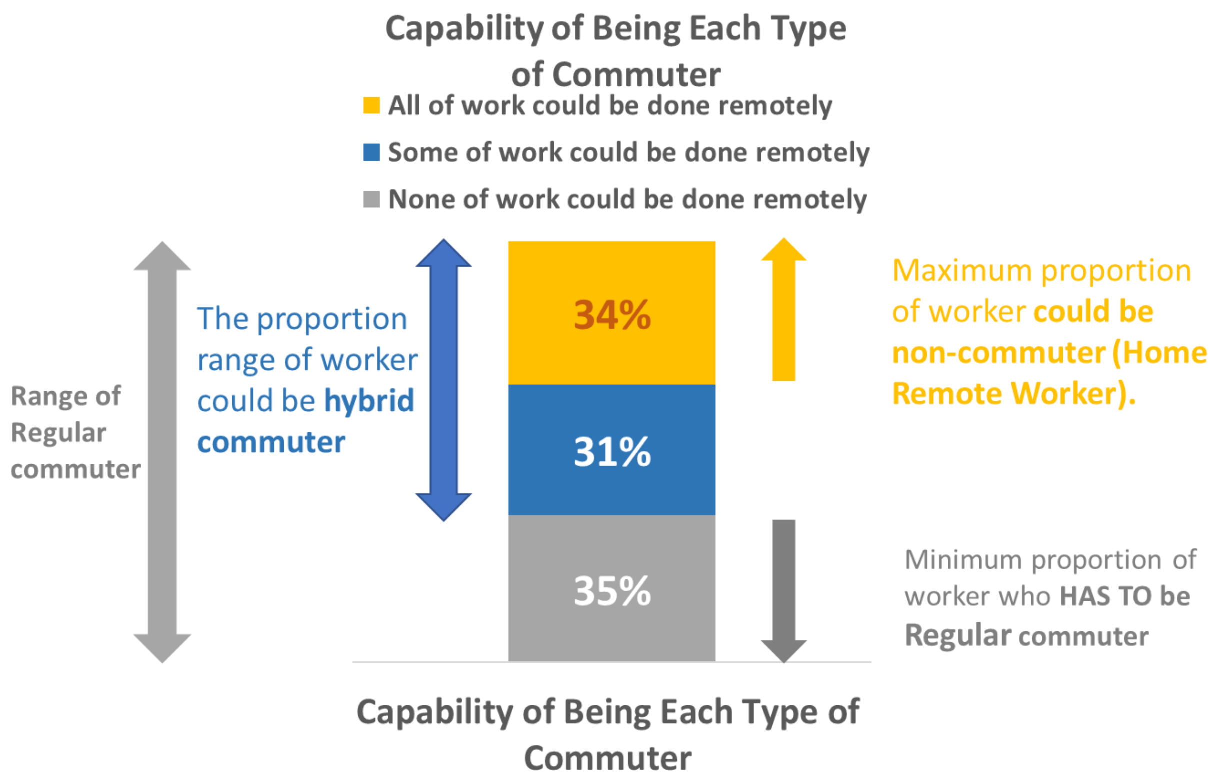

Figure 4.1 – Capability of being each type of commuter

A worker who reported "all" work could be done remotely is eligible to be a home remote worker (non-commuter). Thus, the proportion of workers reporting "all" work could be done remotely is serving as a maximum boundary for home remote working. Similarly, the worker who reported "none" of their work could be done remotely must be a regular commuter, and the proportion of workers reporting “none” of the work could be done remotely serves as the minimum boundary of regular commuting. It is also important to note that the “None of it” response is used as a logical criteria to define those respondents’ commute expectation, to be discussed shortly.

Workers who ever have any work that could be done remotely are eligible to be a hybrid commuter, which includes workers reporting “some” or “all” work could be done remotely. And it is important to recognize that any worker could be a regular commuter if they choose to be, regardless of their work’s capability to be performed remotely.

4.3.2 Before and During Pandemic Variable Definition

I define 3 types of commuters, regular commuter, non-commuter, and hybrid commuter, and 2 levels of commute frequency within the hybrid category, high frequency commuters and low frequency commuters. The scale is derived from several questions.

The first category, regular commuters, were defined as having no option to telecommute before the pandemic. During pandemic wave 1 and wave 2, they reported not “Able” to work from home. In wave 3, the expectation question was reworked and a more clear answer, “expect not to have the option to work from home”, indicates workers whose employer is not going to provide the opportunity to them, as well as people who were not able to do it.

For non-commuters also referred to here as home remote workers, the definition for pre-pandemic or during pandemic time is that they have a work from home option and the commute frequency is 0-day days per week.

For hybrid commuters, the definition is more complicated due to intricacies of the survey instrument. Due to the survey questions, we use the telecommuting frequency to define the hybrid commuter: the low frequency telecommuter is referring to high frequency commuter, the high frequency telecommuter is referring to low frequency commuter.

When asking about the time before the pandemic, the responses regarding telecommute frequency categories were: “Never”, “a few times/year,” “a few times/month,” “once/week,” “a few times/week,” and “Every day”. If the worker’s pre-pandemic telecommuter frequency is less than “a few times/week,”, they are classified as low frequency telecommuter, aka high frequency commuter. Otherwise, they are placed in the high frequency telecommuters, or low frequency commuters.

When asking about the current wave’s pandemic frequency, wave 1 and wave 2 were using the number of telecommuting days *in the past 7 days* before the survey took place. Unfortunately, the survey administrators failed to collect a response in wave 3. If the worker’s during-pandemic telecommuter frequency is at least “5 times/week”, they are classified as high frequency telecommuter, aka low frequency commuter. Otherwise, they are placed in the low frequency telecommuters, or high frequency commuters.

The Hybrid commuter type by expectation is consistent with the pre-covid time-period, which is good so that we could compare the result with pre-Covid time.

4.3.3 Construction of Expectation Categories of Commuter Type

<u>Regular commuters</u>: The expected regular commuters are defined by capability threshold, which is “None” of their work could be done remotely. The decision is being made because the people who do not have that capability to work from home are different from people who think they are not going to have this option. The wording in wave 3 expectation question is not clearly identified. The other consideration is that the capability variable is clearly defined and leads to

assumptions of the work nature which should be more stable. In fact, it should be noted that workers who are "not capable" to work from home and workers who "don't have the option" to work from home are two types of workers. The former is constrained by their own capability, the second is constrained by the employer. If a worker really wants a WFH option they could seek employment elsewhere *unless* the nature of their skills/trade means they cannot move "horizontally" to open WFH options. Assuming these constraints are fixed leads to the conclusion that regular commuters are workers that "always commute" and do not expect that to change.

<u>Home remote workers</u>: Workers reporting that they expected to be Non-Commuters/ Home remote worker, was identified from another question about post-covid time commute mode: "When society reaches a post-COVID new normal, which mode do you expect to use most frequently to go to work?" and the answer is "work only from home and not commute". This is a very clear definition about commute status, which is what I'm looking for in this study. Non-Commuters/ Home remote workers are workers that do not commute at all, their commute status is "always not commute".

4.3.4 Construction of Hybrid Commuter - Current Opportunity

The expectation for hybrid commuters has a complicated construction process. The question "How much do you expect to be able to work from home when society reaches a post-COVID new normal?" was asked first to separate worker into 4 groups:

A "I expect to have to work from home whenever I am working."
B "I expect to be able to choose to work from home as much as I want."
C "I expect to be able to choose to work from home, but only on some days."
D "I expect not to have the option to work from home."

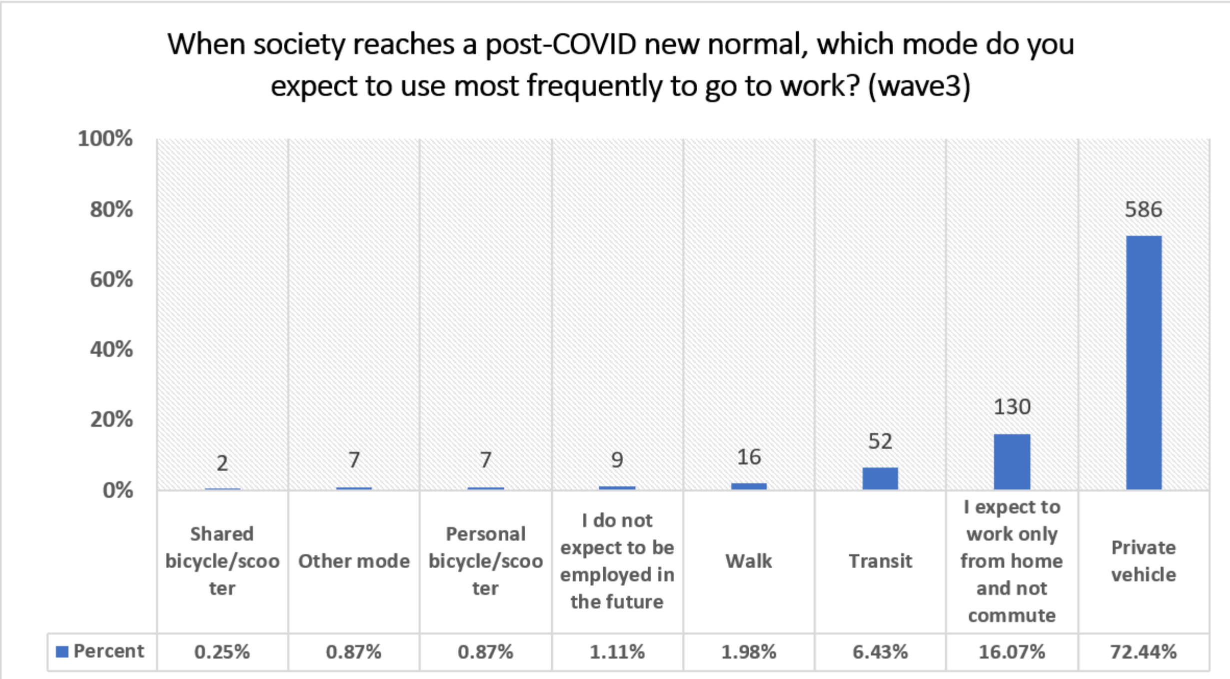

Figure 4.2 – New normal (wave 3) most frequent expected commute mode

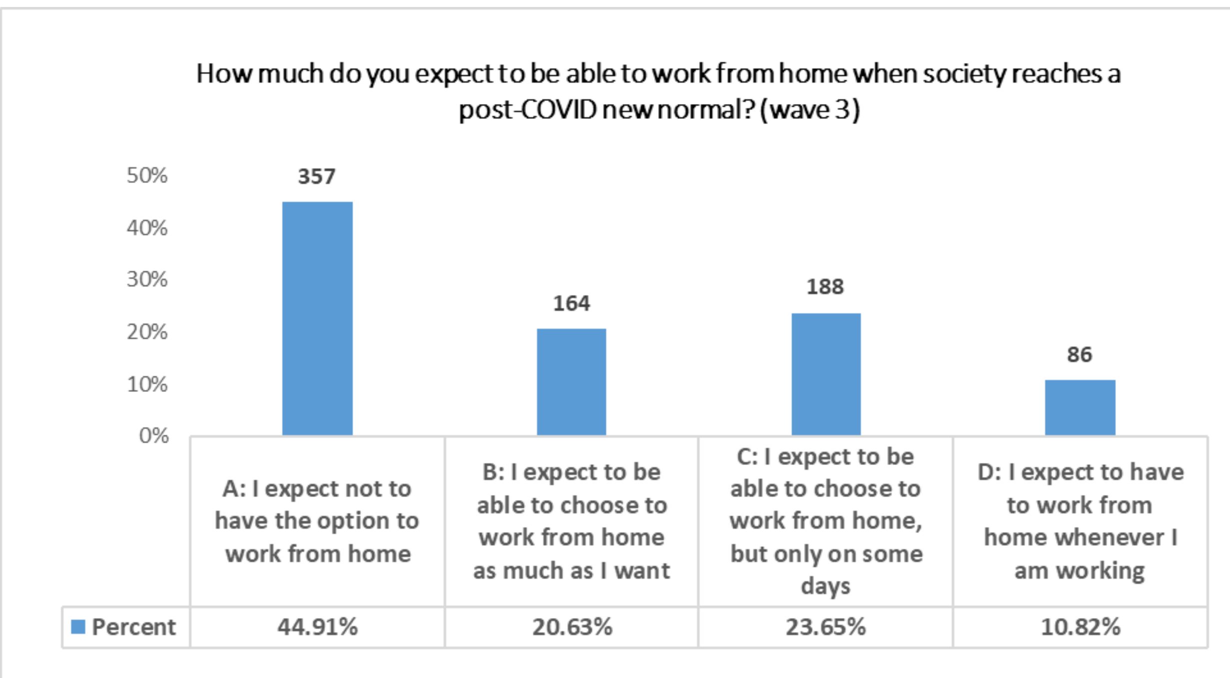

Figure 4.3 – New normal (wave 3) expectation to work from home

Only group B and C continued with the question to answer their desired telecommuting frequency once society reaches a post-COVID new normal. A and D group was not surveyed, originally, they were missing value. Thus, based on the meaning of A and D, I put A in high frequency telecommuter type temporarily, and D in low frequency telecommuter type temporarily. So far, all workers have been assigned as either high frequency or low frequency status.

Then, regular commuter and home remote worker was split out from the current high frequency telecommuter and low frequency telecommuter, the remaining population fixed in as the high and low frequency telecommuter. For a visual representation, please refer to the flow chart.

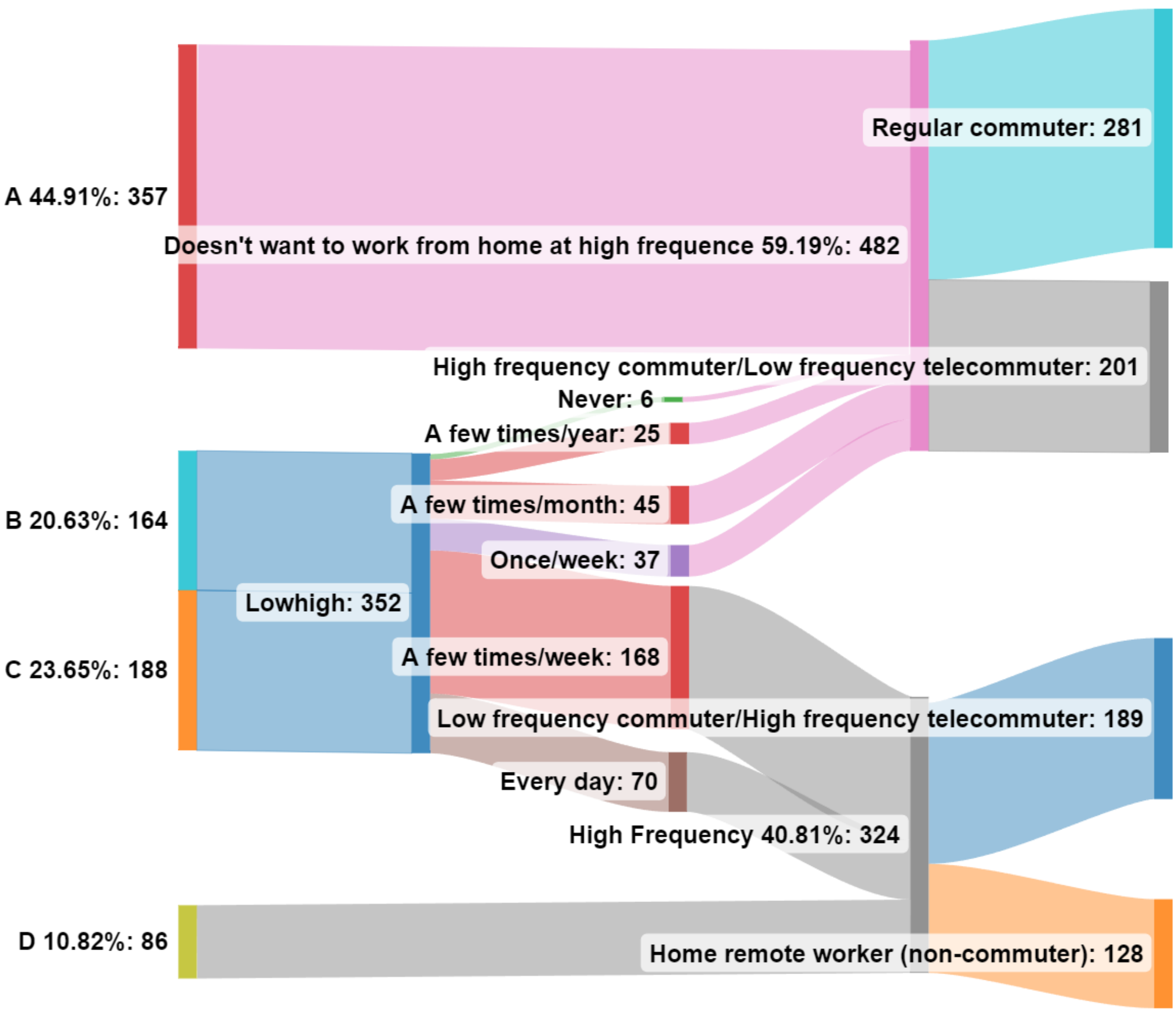

Figure 4.4 – Sankey chart of commuter type derivation flow

4.3.5 The Bridge Between Commute and Telecommute

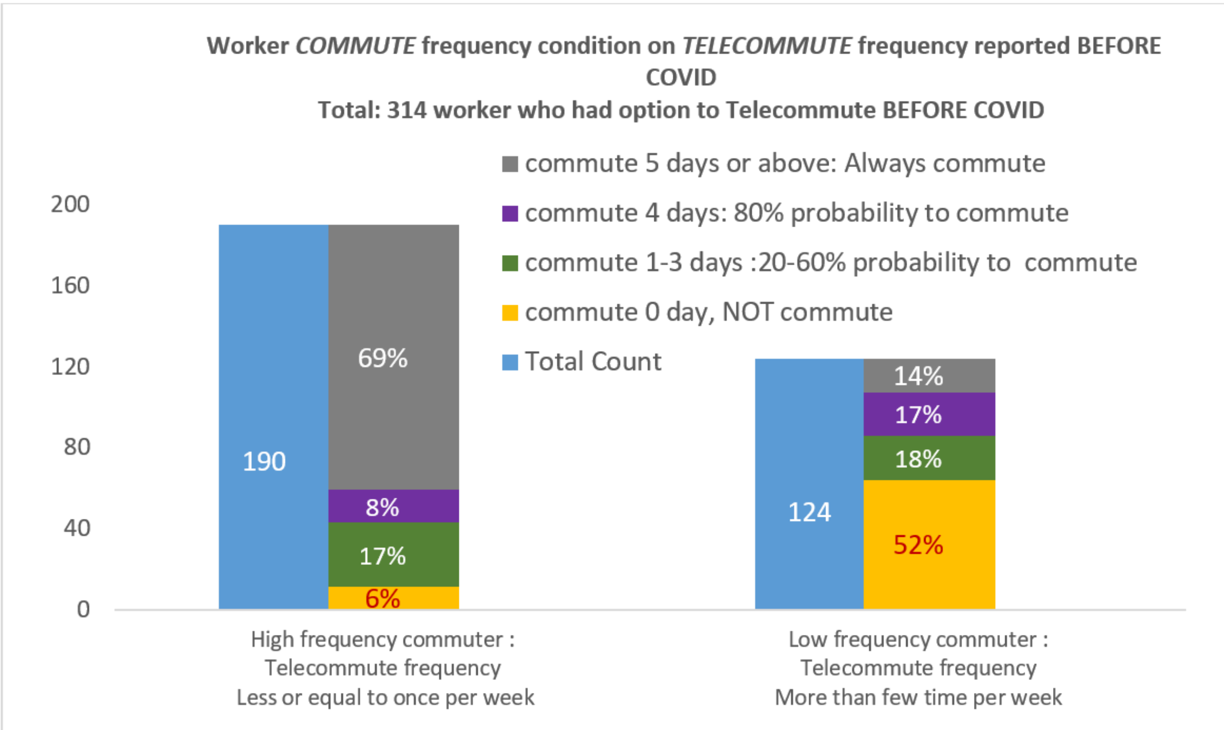

Figure 4.5 – Worker commute frequency proportions given they are telecommuters

In this investigation, distinct queries were posed to assess the separate occurrences of telecommuting and commuting. However, the interplay between these two modalities remains ambiguous. It is imperative to establish a connection between their respective frequencies to accurately reflect commuting patterns in relation to telecommuting frequencies. It is crucial to recognize that telecommuting does not preclude physical commuting; individuals may report daily telecommuting yet still engage in physical commuting. Additionally, telecommuting activities can occur within office environments, such as conducting international calls or participating in remote meetings with colleagues who are telecommuting.

The frequency cross-tabulation was developed utilizing pre-pandemic data from individuals who had the option to telecommute, reporting both their telecommuting and commuting frequencies. The categorization of telecommuting frequency was harmonized with the study's criteria. Specifically, individuals classified as high-frequency commuters/low-frequency telecommuters are those who reported telecommuting no more than once weekly.

It is noteworthy that post-pandemic frequency distributions are anticipated to diverge, reflecting changes in telecommuting habits. This necessitates gathering contemporary data and integrating geographic factors. For the interim, however, this study employs pre-pandemic frequency tables as a provisional framework for analysis.

4.4 Construction of Hybrid Commuter - Maximum Opportunity

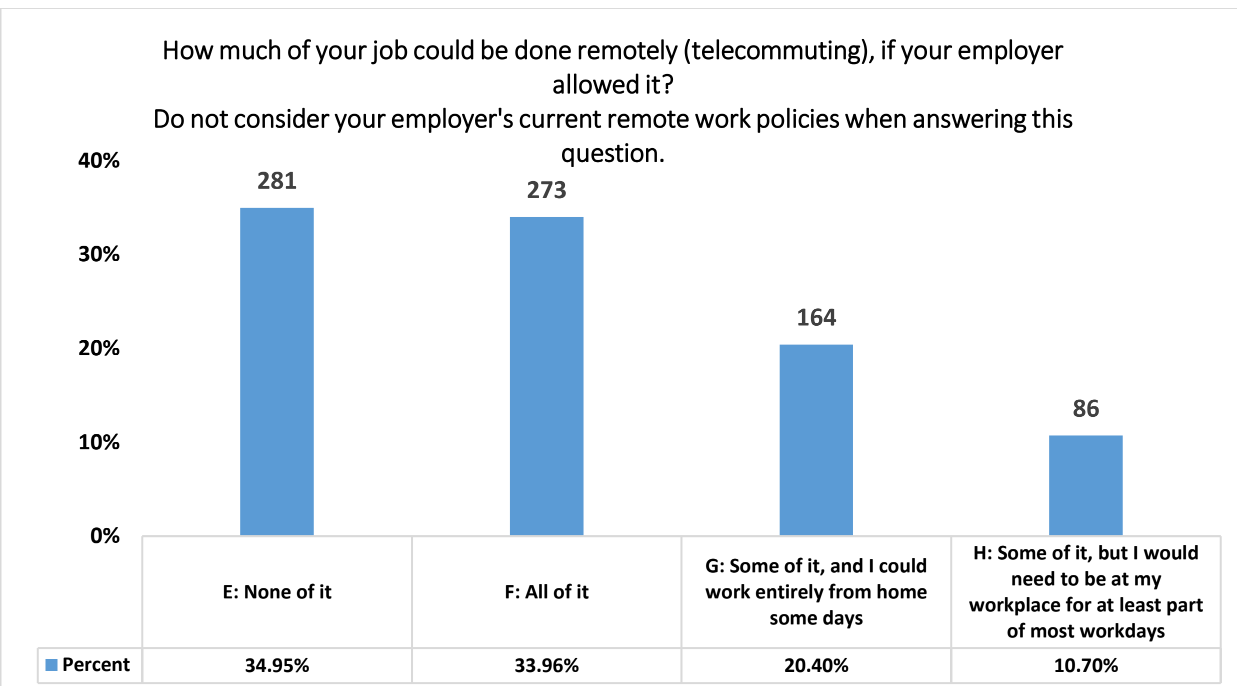

Figure 4.6 – Response fractions for how much work could be done remotely

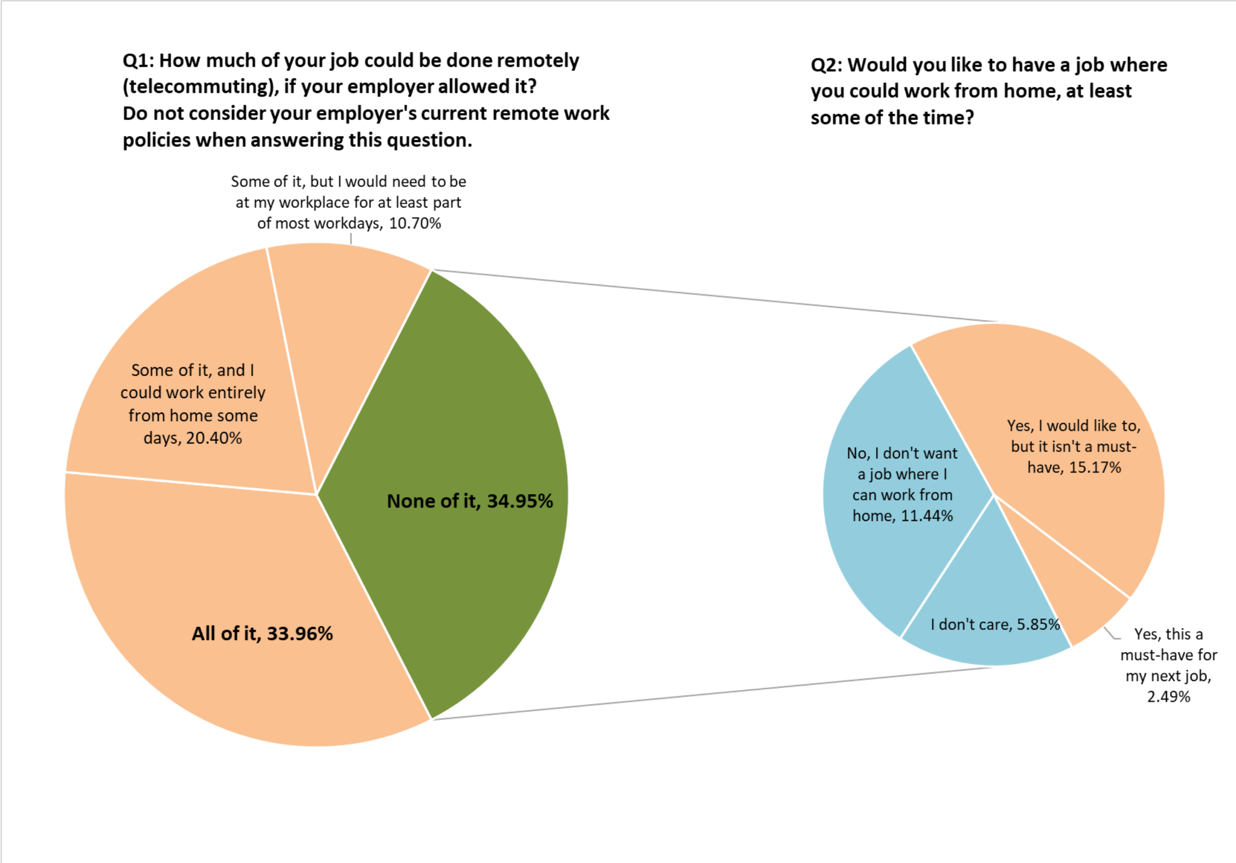

Figure 4.7 – Worker preference for remote work options

The candidate variable is employed to delineate the prospective alteration achievable when an employer permits telecommuting to the extent desired by the employee. This serves the purpose of approximating the maximum potential for telecommuting that an employee could access. At this juncture, we can investigate the uppermost threshold of telecommuting that could transpire if the policy were introduced while simultaneously accommodating the preferences of the workforce.

The query regarding telecommute frequency was exclusively directed at a specific subset of individuals. This subset comprises employees who responded to the capability question with answers F, "All of it," G, "Some of it, and I could work entirely from home some days," and H, "Some of it, but I would need to be at my workplace for at least part of most workdays." Additionally, it encompasses those who answered E, "None of it," and in response to the subsequent question, "Would you like to have a job where you could work from home, at least some of the time?" replied with either "Yes, I would like to, but it isn't a must-have" or "Yes, this is a must-have for my next job." This categorization was cross-referenced with the responses to other questions, with individuals answering B, "I expect to be able to choose to work from home as much as I want," being excluded from this particular query.

Subsequently, individuals who responded with "I don't care" and "No, I don't want a job where I can work from home" to the question, "Would you like to have a job where you could work from home, at least some of the time?" were temporarily classified as low-frequency telecommuter types. Conversely, those who answered B were temporarily considered high-frequency telecommuters. Finally, the regular commuters and remote home workers were segregated from the existing high-frequency and low-frequency telecommuters, while the remaining population was designated as the high and low-frequency telecommuter groups.

4.5 Construction of Hybrid Commuter - Trade-off Office Workspace for Higher Frequency of Telecommuting

The variable under consideration is also deduced from a series of two sequential questions. The initial inquiry seeks to determine, "Do you have your own designated office or workspace at your workplace?" Among the selected sample, 52% of workers reported having an assigned office.

The subsequent question inquired, "If you could work from home a few times per week, how would you feel about relinquishing your designated office or workspace at your workplace?" The responses encompassed three categories: "I wouldn't mind," "I would decide not to work from home. This is a tradeoff I am not willing to make," and "I would be upset, but I would still choose to work from home."

Workers who responded with "I wouldn't mind" and "I would be upset, but I would still choose to work from home" were reclassified as "high-frequency telecommuters." Only those initially categorized as "low-frequency telecommuters" underwent a transition to the high-frequency telecommuter classification, while individuals designated as home remote workers and regular commuters remained in their respective categories.

4.6 Sample Selection and Time-Period Justification for LCA Indicators

After examining the data, I began with 3 waves of data chained together. Since the purpose of this study is to study an individual's commute status change, only workers who worked for at least 1 wave, participated in wave1 phase B but not A, and responded continuously for 3 waves were kept. Overall, 870 workers were repeatedly surveyed 3 times during Pandemic. The data collection time frame can be found in the figure.

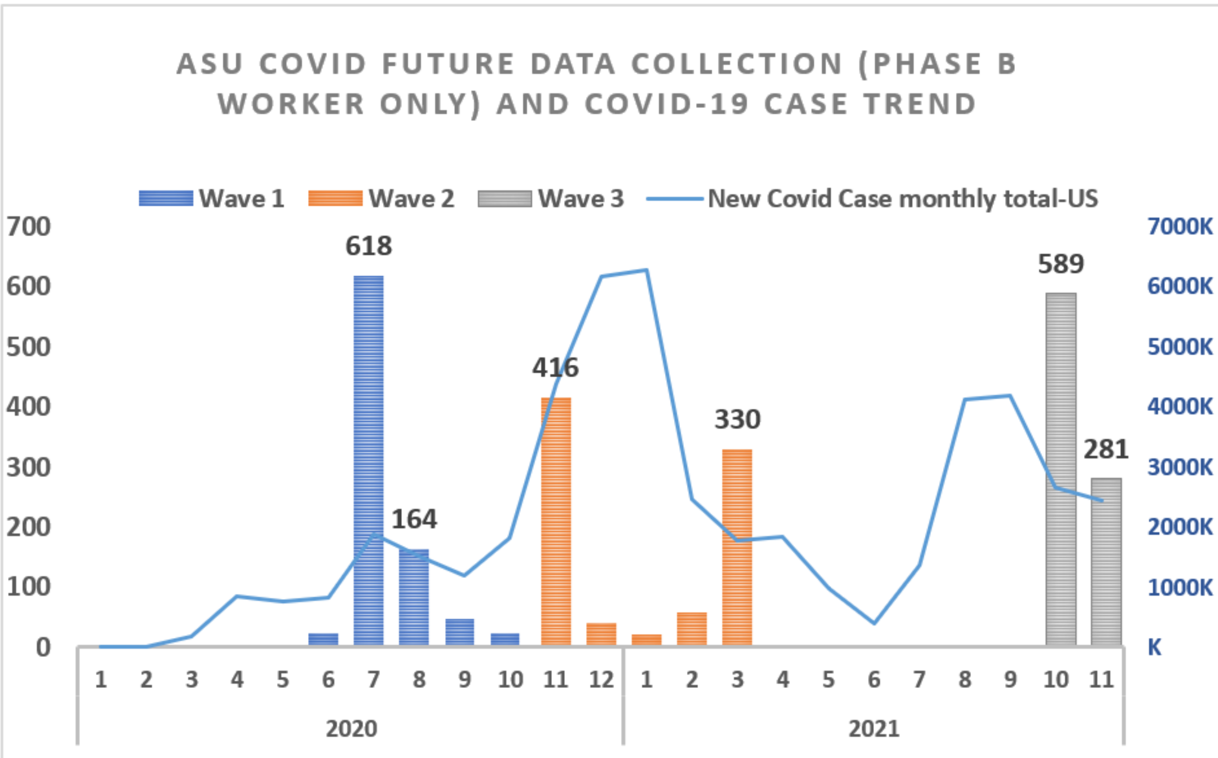

Figure 4.8 – ASU Covid Future data collection counts and US National Covid-19 case rate

The first wave sample data was concentrated in July 2020, the third wave data was concentrated in October and November 2021. However, the second wave data collected on two peaks, which happened to be distributed on each side of the covid wave in between 2020 and 2021. This brings the attention that if the covid case serge would influence worker's behavior and attitude that would bring in the undesired effect to the study, thus, wave 2 data was not included in the indicator pick.

4.6.1 Justification of Time-Period Selection

Justification of time-period selection of expectation study by 3 aspects: 1) overall national activities. 2) selected sample employment change and expectation change. 3) selected sample behavior change.

4.6.1.1 National Activities Change During Pandemic

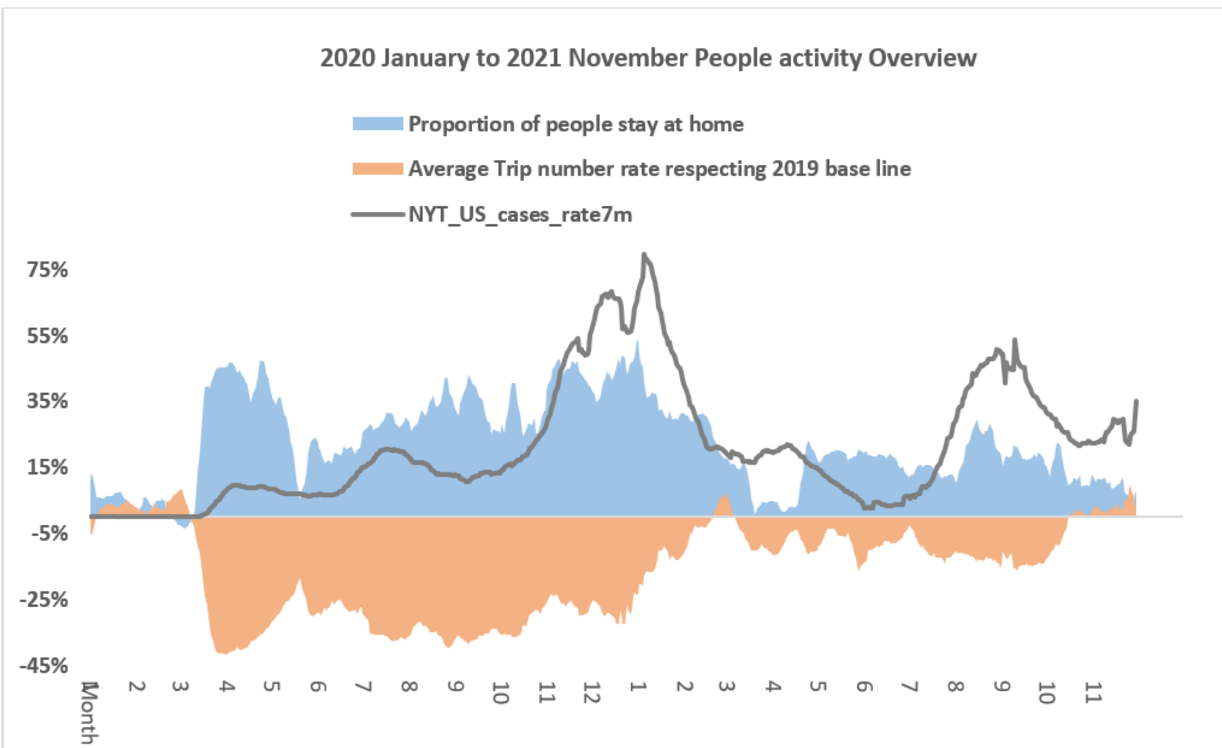

Figure 4.9 – Pandemic activity disturbance

Changes in the number of trips with respect to baseline travel and change in the fraction of people staying at home (light blue shaded area), average trip number (orange shaded area) and total case number. Data Source Bureau of Transportation Statistics, The New York Times (2020) Coronavirus (COVID-19) data in the United States. Note Changes in trips are shown as a seven-day moving average.

The graph under analysis, drawing on data from the Bureau of Transportation Statistics, demonstrates a marked increase in the rate of individuals staying at home, contrasting sharply with figures since COVID-19 pandemic started on March 2019. This rise correlates with a notable decrease in average trip numbers respecting 2019 same data as base line. The negative of this value provides that the measurement of trip number decreased as people's stay-at-home increased. Concurrently, the representation, especially the black line on a different scale, captures an exponential surge in COVID-19 case rates, as reported by The New York Times (2020) Coronavirus (COVID-19) data in the United States, with significant spikes in regions such as New York and various Western States.

The critical period of November, December in 2020, and January 2021 marks when a substantial portion of the U.S. population contracted COVID-19. The graph continues to show increased stay-at-home behaviors and reduced trip occurrences, extending beyond this period, until April 2021, which matches the end of wave 2 of ASU data collection. Post the relaxation of state-mandated stay-at-home orders, a decrease in home-staying behavior is noted, followed by a resurgence influenced by vaccine rollout and state reopening strategies.

This shift in pandemic attitudes, inferred from the data, is crucial in the decision to exclude 'wave 2' data from analysis, aiming for uniform assessment of pandemic-related policy impacts and avoiding skewed results due to the unique circumstances of this phase.

The attitude towards the pandemic, as inferred from the data, seems to have undergone a transformation.

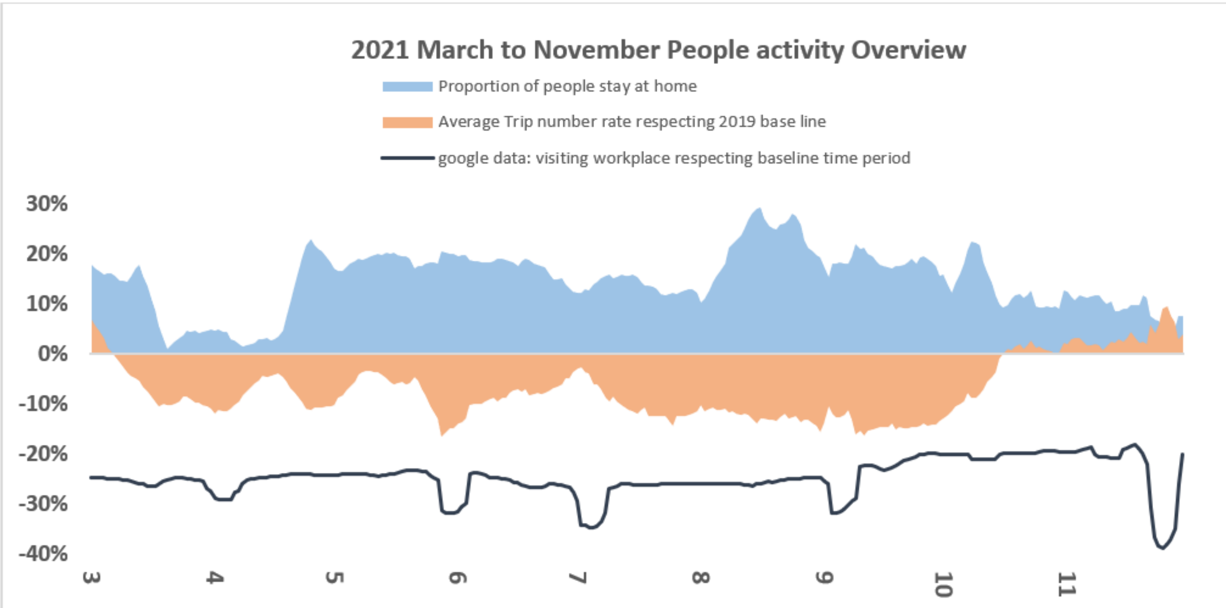

Figure 4.10 – 2021 pandemic activity overview

Changes in the number of trips with respect to baseline travel and change in the fraction of people staying at home (light blue shaded area), average trip number (orange shaded area) and total case number. Data Source Bureau of Transportation Statistics, The New York Times (2020) Coronavirus (COVID-19) data in the United States. Note Changes in trips are shown as a seven-day moving average. Google COVID-19 Community Mobility reports, the baseline day is the median value from the 5-week period Jan 3 – Feb 6, 2020.

During the transition from wave 2 to wave 3, the analysis is centered on commuting patterns, particularly informed by Google COVID-19 Community Mobility reports. Notably, around mid-October, the average trip rate not only recovered but turned positive, suggesting that people were venturing out at levels comparable to the same period in 2019. Despite this increase in general mobility, the data indicates that commuting rates continued to stay low, implying a sustained preference for teleworking. This contrasts with the return to more typical daily activities, as evidenced by the reduction in stay-at-home rates and increased general outings, which make wave 3 a good candidate for study expectations.

4.6.1.2 Sample Employment and Expectation Change

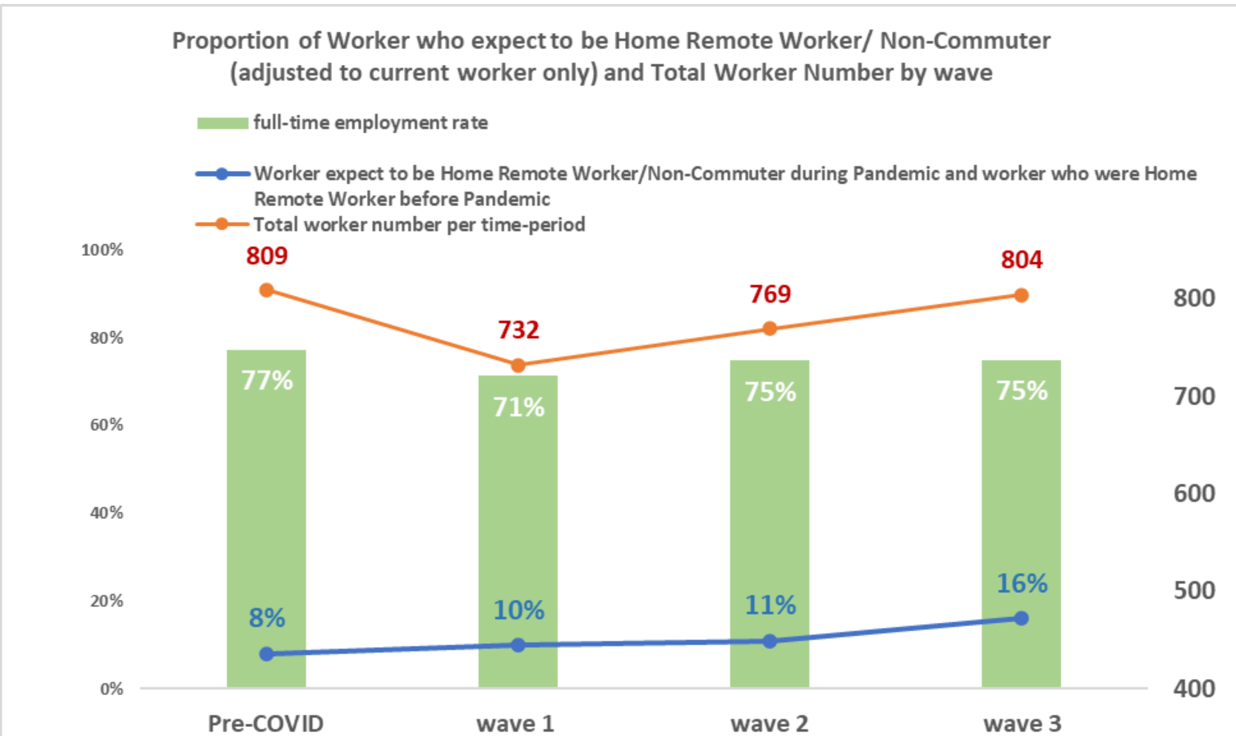

Figure 4.11 – Surveyed workforce and employment status

The graph presents an intriguing narrative on the evolution of work modalities during different phases of the pandemic. The total number of workers, represented by the orange line, initially dips from 809 (units unspecified) pre-COVID to 732 during wave 1, then oscillates and rises to 804 by wave 3, nearing the pre-pandemic figure. The full-time employment rate, shown by green bars, falls from a pre-COVID 77% to 71% in wave 1, subsequently recovering to 75% in waves

2 and 3, which is consistent with pre-COVID rates. Notably, the percentage of workers anticipating exclusive home-based work, depicted by the blue line, starts at 8% pre-COVID and climbs to 16% by wave 3, after lower rates in waves 1 and 2. This distinct increase in wave 3 suggests a considerable shift in work-from-home expectations, despite environmental conditions being similar to earlier waves. The disparity in telecommuting expectations in wave 3 from previous waves underscores its importance as a focal point for study.

4.6.1.3 Sample Behavior Change

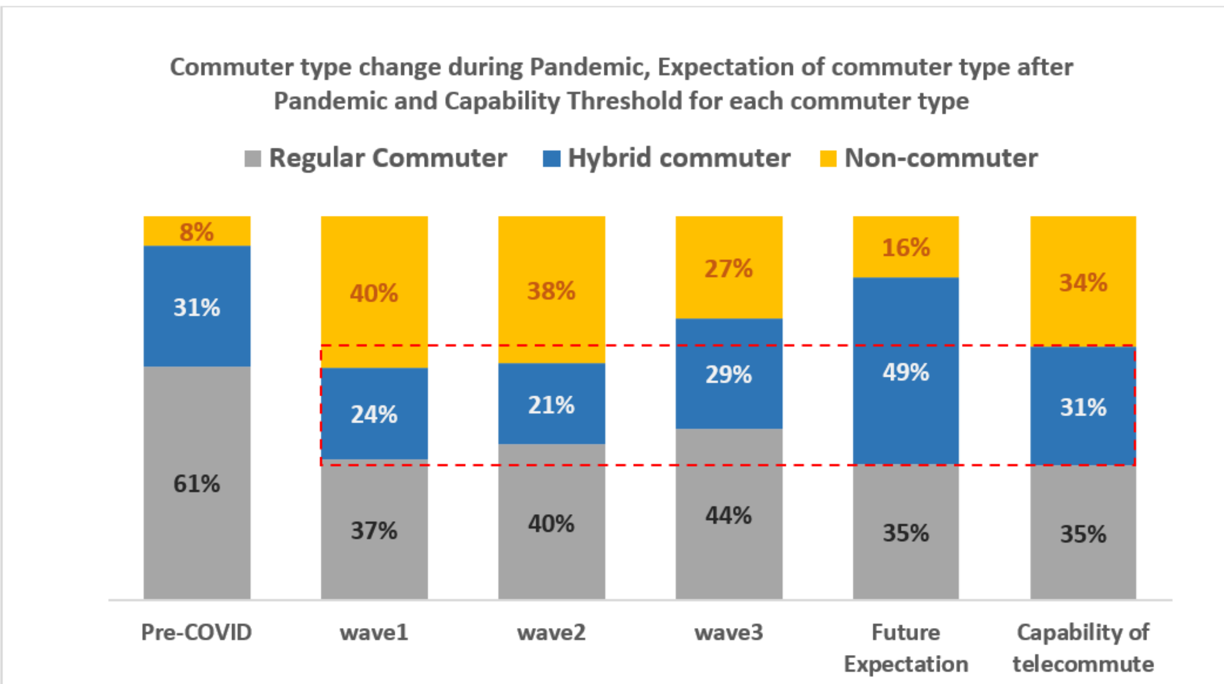

Figure 4.12 – Trends in commuter type, expectation, and capability

The gray box in the graph delineates the proportion of workers who are regular commuters both pre-COVID and during the pandemic (waves 1-3). This group is characterized by the capability of telecommuting, signifying that they have "none" of their work that could be done remotely, as per future expectations and capability variables. Conversely, the yellow box signifies the proportion of workers identified as non-commuters before and during the pandemic, and also in terms of future expectations. These individuals, according to the capability variable, could perform all their work from home. The red dashed box defines the scope within which workers might fluctuate between being non-commuters and needing to be regular commuters, respecting the capabilities and expectations regarding telecommuting. The implementation of stay-at-home policies during wave 1 and wave 2 appears to have led to an elevated level of telecommuting, which may not align with actual work capabilities, thus there was a proportion of worker fully telecommute that passed the red dash line. This discrepancy suggests that the extent of telecommuting was not solely determined by the nature of the work but was influenced by the policies in place. Therefore, the behavioral responses in waves 1 and 2 may not accurately reflect normal telecommuting patterns, rendering these periods less suitable for inclusion in studies aimed at understanding standard telecommuting behaviors.

Thus, we justified that the objective expectation is using wave 3 expectation only since wave 1 and 2 are under heavily impact of stay-at-home policy influence.

Summary of Sample telecommuting behavior change based on selected sample before during pandemic and expectation.

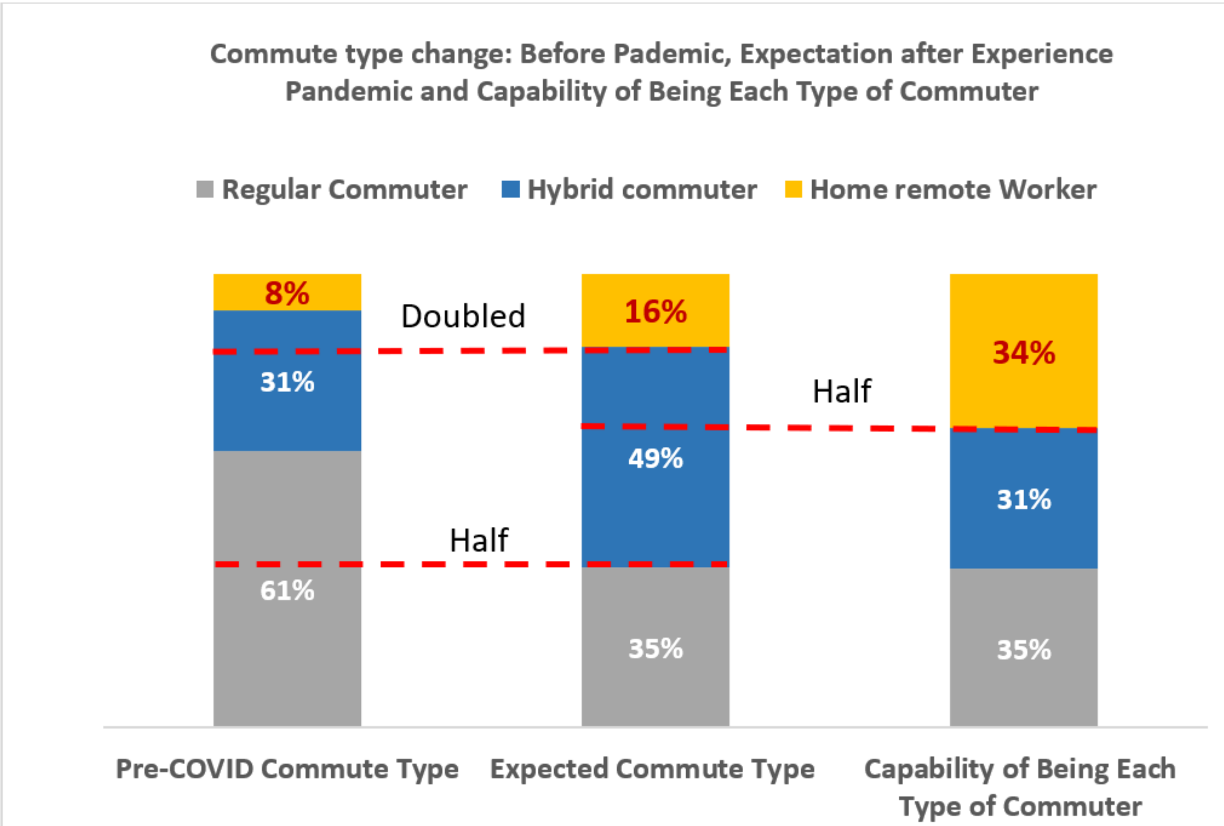

Figure 4.13 – Summary of respondent pre- and post-Covid commuting and capability

During Waves 1 and 2, the stay-at-home policy significantly influenced the commuting patterns of workers, noticeably shifting behaviors towards telecommuting. In Wave 3, as the impact of the pandemic lessened, a gradual return to pre-pandemic life was observed. However, the frequency of workplace visits remained subdued, indicating a sustained preference for teleworking, alongside a resumption of some regular activities.

Notably, in Wave 3, approximately 50% of those who had the capability to work from home classified themselves as Home Remote Workers, a figure that is twice as high as the proportion observed prior to the pandemic. Furthermore, the number of workers anticipating a high frequency of telecommuting in the future showed a significant increase, with over three times as many workers expecting to telecommute frequently compared to the pre-pandemic era.

Identify the hybrid proportion: biggest change is on low frequency commuter.

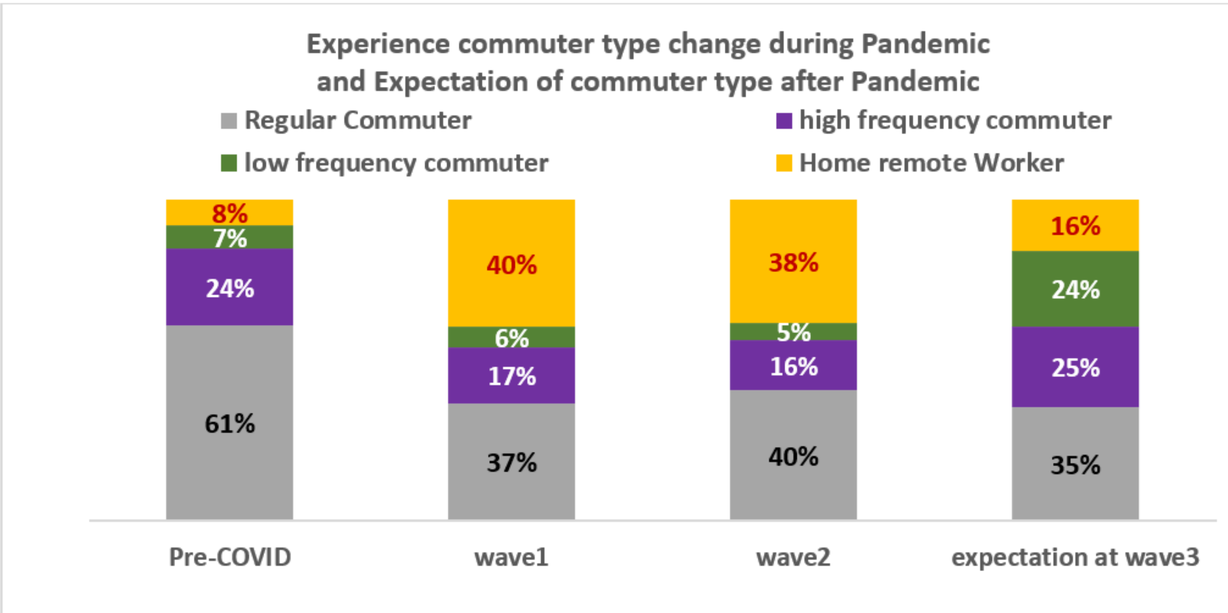

Figure 4.14 – Respondent pre-, mid-, and end-of-survey commuter type

To Break down the proportion of hybrid commuter, we can see that the low frequency commuter took only 7% of pre-pandemic worker proportion, however, the proportion of expectation at wave 3 expanded to 24%, which is more than 3 times of before. This observation is indicating that we should pay extra attention to the following pattern of low frequency commuter if any travel survey could provide an travel pattern scale.

CHAPTER 5

RESULTS

5.1 Introduction

The primary objective underlying the development of the Latent Class Analysis (LCA) model is to enhance our understanding of worker preferences concerning telecommuting, with a specific emphasis on post-pandemic telework dynamics. Our central goal is to seamlessly integrate this model into Activity-based Models (ABM) to identify a subset of workers who display a distinct preference for telecommuting as their primary mode of work. This integration aims to measure an "expectation" based on "opportunity" from the supply side and "preference" from the demand side, aligning with the concept of measuring expectations as well as the actual outcome variables such as "expectation of telecommuter/commuter" type.

Utilizing a set of discriminating indicators, our objective is to determine whether factors related to telework result in qualitatively distinct subtypes among workers and to investigate whether these subtypes, when identified, exhibit significant associations with demographic predictors, especially regarding "expectation of telecommuter/commuter" type outcomes. This approach ensures that we not only assess preferences but also align them with expectations.

This research initiative is primarily motivated by the necessity to gain insights into the potential evolution of workers' attitudes toward telecommuting following their experiences with remote work during the pandemic. Furthermore, we seek to analyze how individuals are likely to respond to future teleworking options within a post-pandemic context. This comprehensive analysis encompasses the measurement of expectations, aligning them with the evolving preferences of workers as they adapt to changing circumstances.

A critical aspect of this inquiry involves precisely defining the demand for telecommuting and determining whether it will increase, remain static, or diminish over time. This analysis of demand aligns with our overarching objective to utilize LCA as a tool for categorizing distinct teleworker groups characterized by their diverse preferences for teleworking in the post-COVID era. We also aim to estimate, wherever feasible, the likelihood of a worker selecting telecommuting as their primary work mode based on their individual demand perspective, thereby linking expectations to actual choices.

In our pursuit of suitable variables, we prioritize the inclusion of measurements that capture teleworking expectations, preferences, and an appreciation of the relative benefits it offers. While these measurements may not serve a direct role-modeling function, they play a pivotal role in guiding the identification and understanding of subgroups within the telecommuting landscape, particularly regarding the "expectation of telecommuter/commuter" type outcomes.

5.2 Unconditional RMLCA

5.2.1 Indicator Selection

5.2.1.1 Supply Side Indicator

The methodology employed for this assessment remained consistent in Wave 1 and 2 but underwent modification in Wave 3.

In Wave 1, the question was posed to both individuals who were employed prior to the pandemic and those who were currently working. However, in Wave 3, the scope of the question was narrowed, exclusively targeting current employees who anticipate continued employment in the post-COVID era. It is worth noting that among the 841 current employees surveyed in Wave 3 as part of the selected sample, there were 36 individuals (4.28%) who did not expect to remain employed afterward, resulting in missing data within the selected group. Additional details regarding this variable's evolution between Wave 1 and Wave 3 can be found in the provided flow chart.

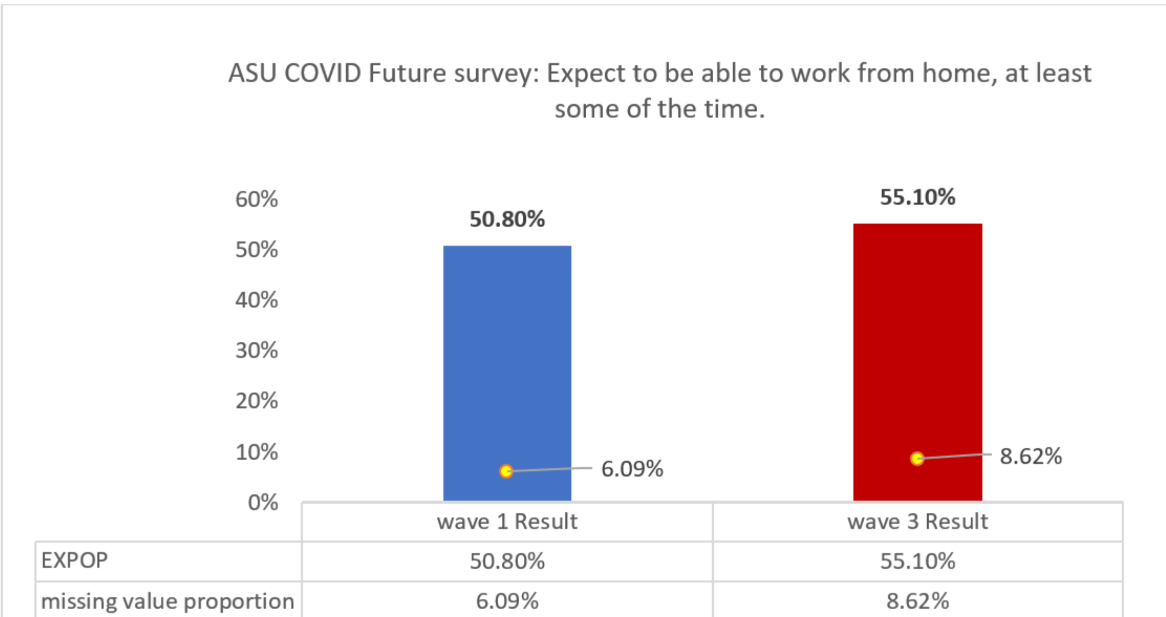

Figure 5.1 – Respondent pre-, mid-, and end-of-survey commuter type

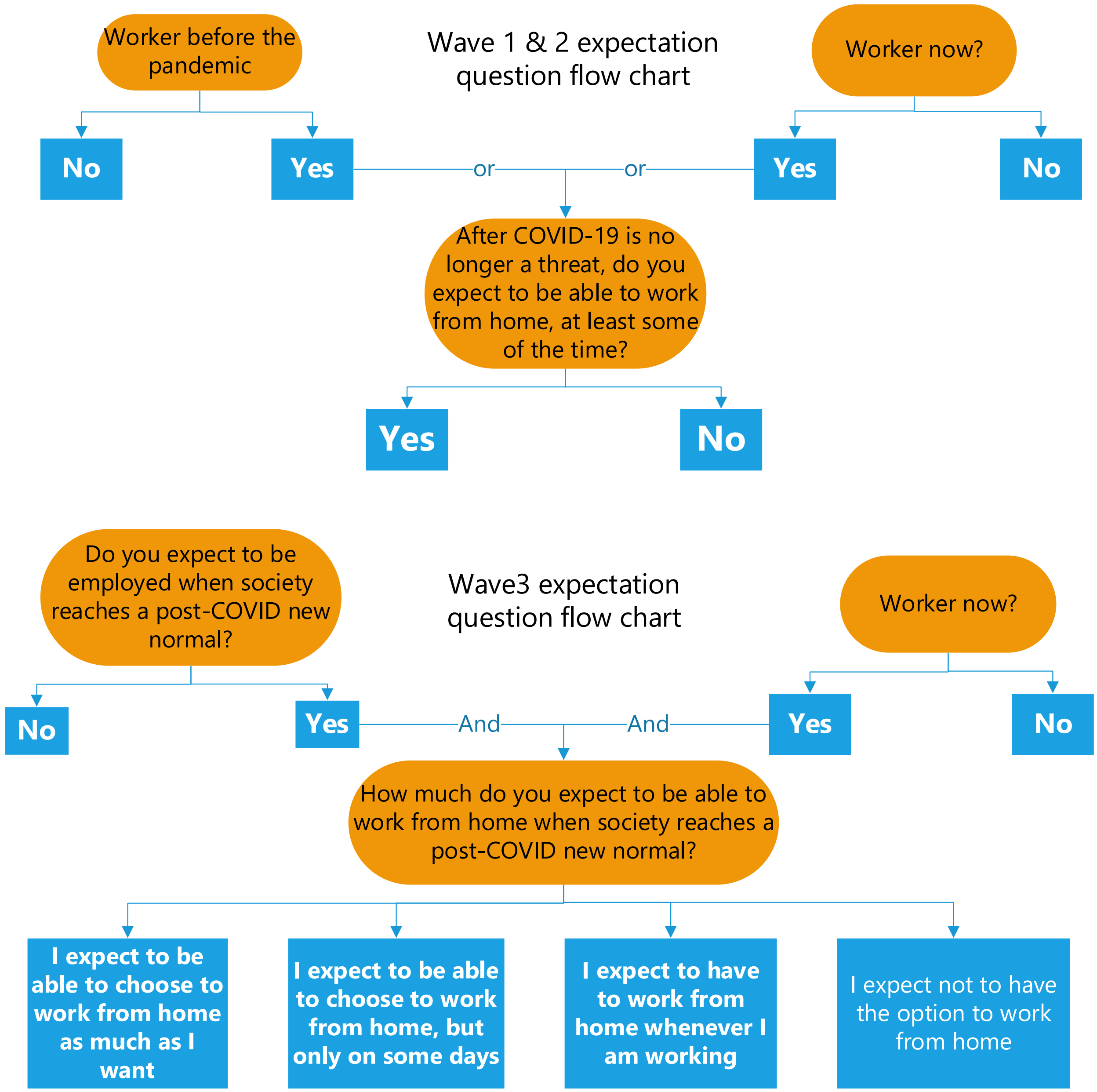

Figure 5.2 – Wave 1 and 2 expectation derivation from survey

The question asking wording is changed which bring more attention:

It is worth notice that the slight difference of wording may introducing the misleading result: worker who was not “able” to work from home only constrained by their own capability, however, the “option” was given by employer, thus, worker who was not “able” to do it and not having “option” to work from home are different people. The wave 1 question was asking in the wording of “able” to work from home, while wave 3 the question is asking in “able” to work from home, but the answer is “option”. At this point, the indicator was both employed but the problem was noticed.

5.2.1.2 Demand Side Indicator

The inquiry posed is as follows: "COVID-19 has necessitated significant alterations in our daily routines. Would you like to continue any of these newfound lifestyles even after COVID-19 is no longer a threat?" The response options encompass "yes," "maybe," and "no." This query is directed at the entire population under study.

In the initial phase of Wave 1, referred to as Phase A, the question was posed without subsequent follow-up questions. However, in Wave 1 Phase B, as well as in the ongoing Wave 2 and 3, respondents who answered either "Yes" or "Maybe" were presented with an additional question. This subsequent query invited participants to select, without a specific order, up to three "change items" they would like to perpetuate. In Wave 1, among the 870 workers surveyed, 78.16% responded with either "Yes" or "Maybe." By Wave 3, this percentage had increased to 84.14%, signifying that approximately 6% more workers expressed a desire to maintain the changes implemented during the pandemic.

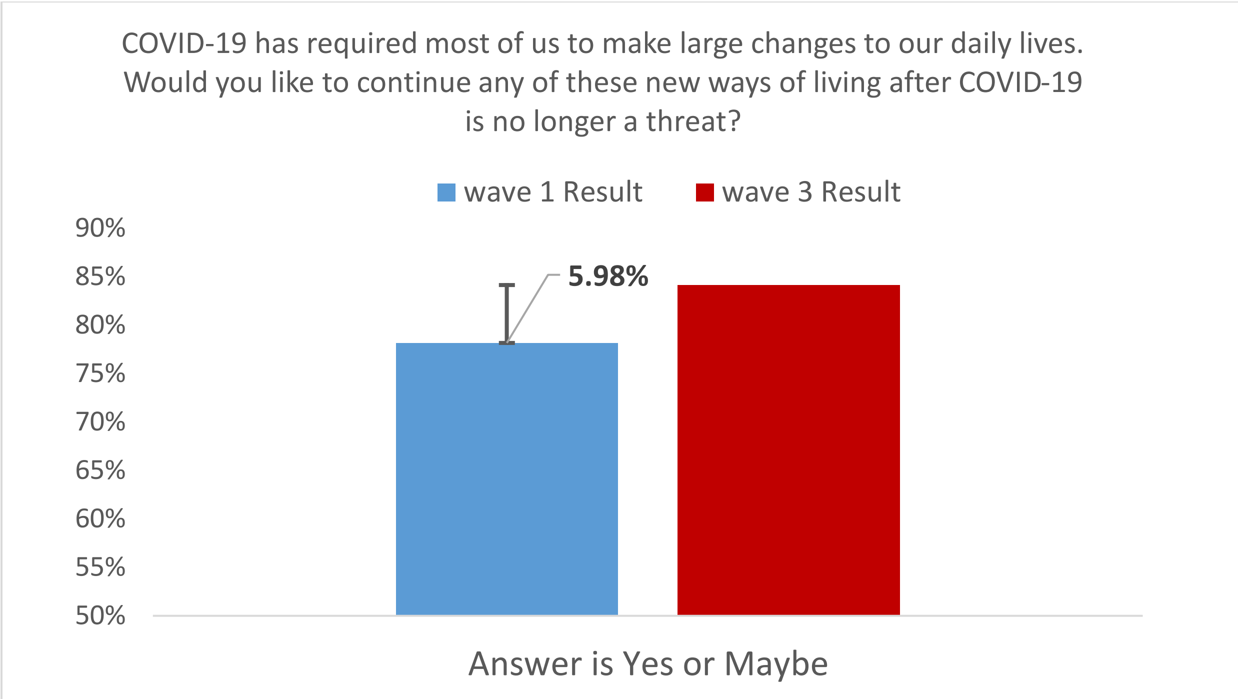

Figure 5.3 – Frequency of respondents indicating yes or maybe like certain impacts of COVID on daily life

Subsequently, participants were presented with the following question: "Which of the following experiences have you had during the pandemic and would most like to continue when society reaches a post-COVID new normal?" In response, participants were instructed to select three out of thirteen items. All responses to these items were recorded as binary variables. The items in the figure are arranged in descending order based on the outcomes from Wave 3, with the highest percentage choosing "working from home, at least some of the time," and the lowest preference being "traveling less."

While this group of variables appears to be the most promising indicator(s), it is essential to consider the potential limitation. There exists the possibility that certain workers had been telecommuting on a frequent basis even before the pandemic. For these individuals, working

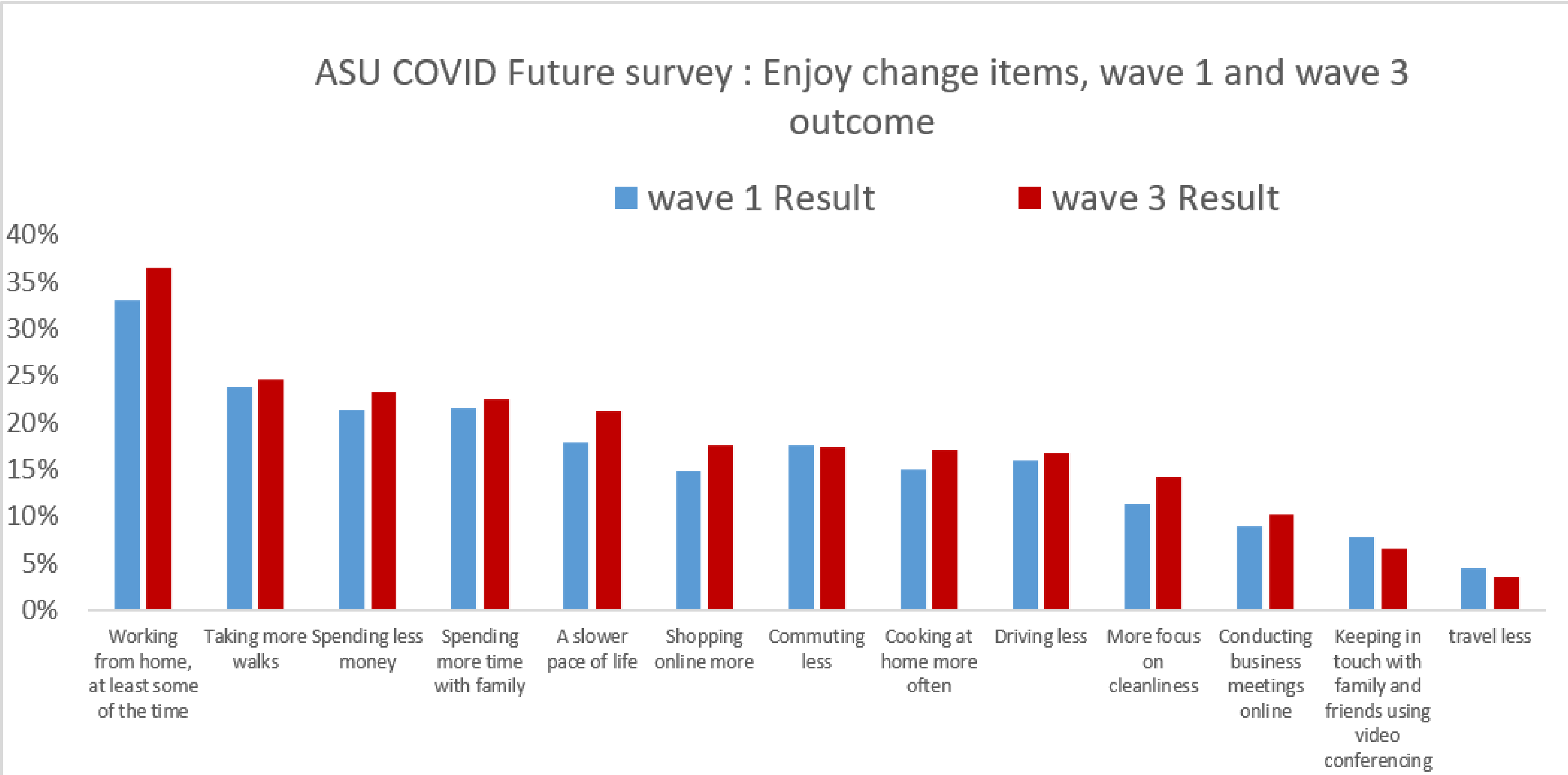

Figure 5.4 – Frequencies of 13 enjoyed changes

from home during the pandemic may not constitute a significant "change," which could lead to a substantial portion of this group being omitted from the analysis. Alternatively, these individuals might not select "work from home" or "reduce commuting" because such practices were not new to them. This asp ect must be carefully weighed in our evaluation of these variables.

The final pick of the preference indicators is "working from home, at least some of the time," and “Commute less” since the two aspects are directly connected to “tele-commute”.

5.2.1.3 Final indicator overview

In this study, we conducted an in-depth analysis of the indicators collected in both wave one and wave three of our survey. The aggregated levels of each binary variable were examined to assess the proportion of respondents who answered in the affirmative ("yes").

For the initial item, which inquired about the expectation of being able to work from home, approximately 50% of respondents provided an affirmative response in wave one. Notably, this figure exhibited a modest increase of 4.3% in wave three.

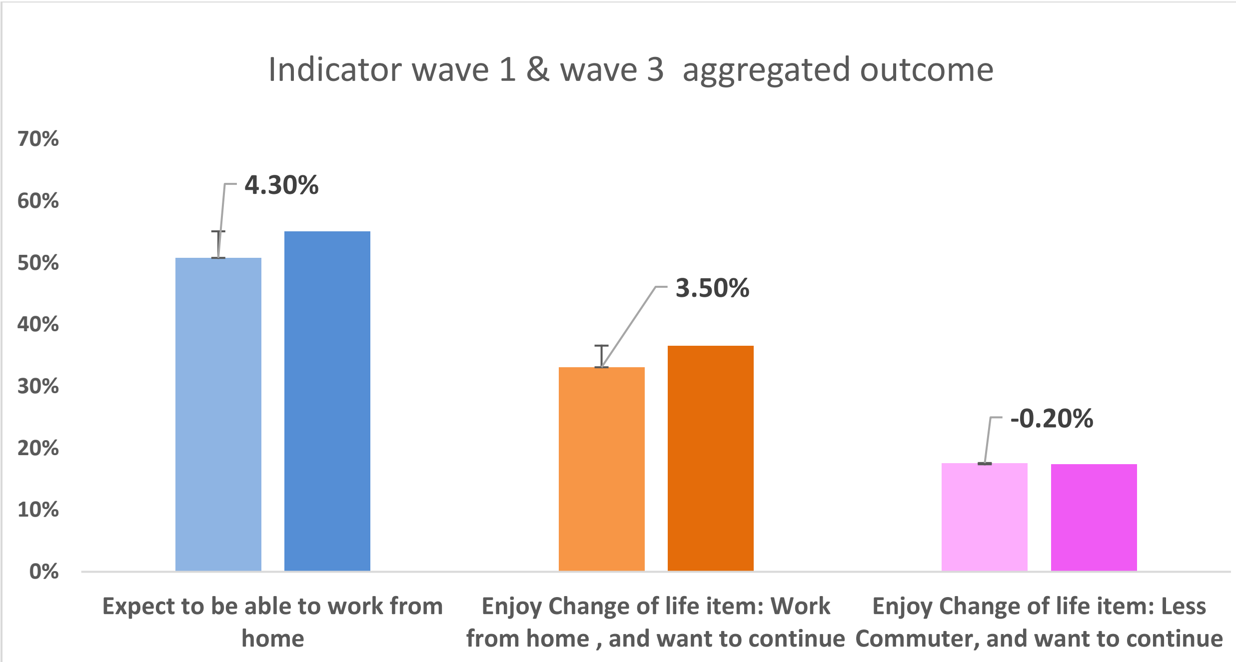

Figure 5.5 – Aggregated indicators for wave 1 and wave 3

The second item delved into respondents' enjoyment of working from home and their desire to continue this practice once the threat of Covid-19 had subsided. Here, around 35% of respondents reported a positive stance in wave one, with a slight uptick of 3.5% observed in wave three.

The final item investigated whether individuals derived satisfaction from reduced commute times and expressed a desire to continue such arrangements post-Covid-19. Strikingly, this item garnered the lowest proportion of affirmative responses, standing at less than 20%. Moreover, there was a marginal decrease of -0.2% observed from wave one to wave three.

While the aggregate statistics between the two waves remained relatively stable, with changes not exceeding 5%, a closer examination of individual responses revealed a noteworthy trend. Specifically, we observed substantial shifts in respondents' preferences between wave one and wave three.

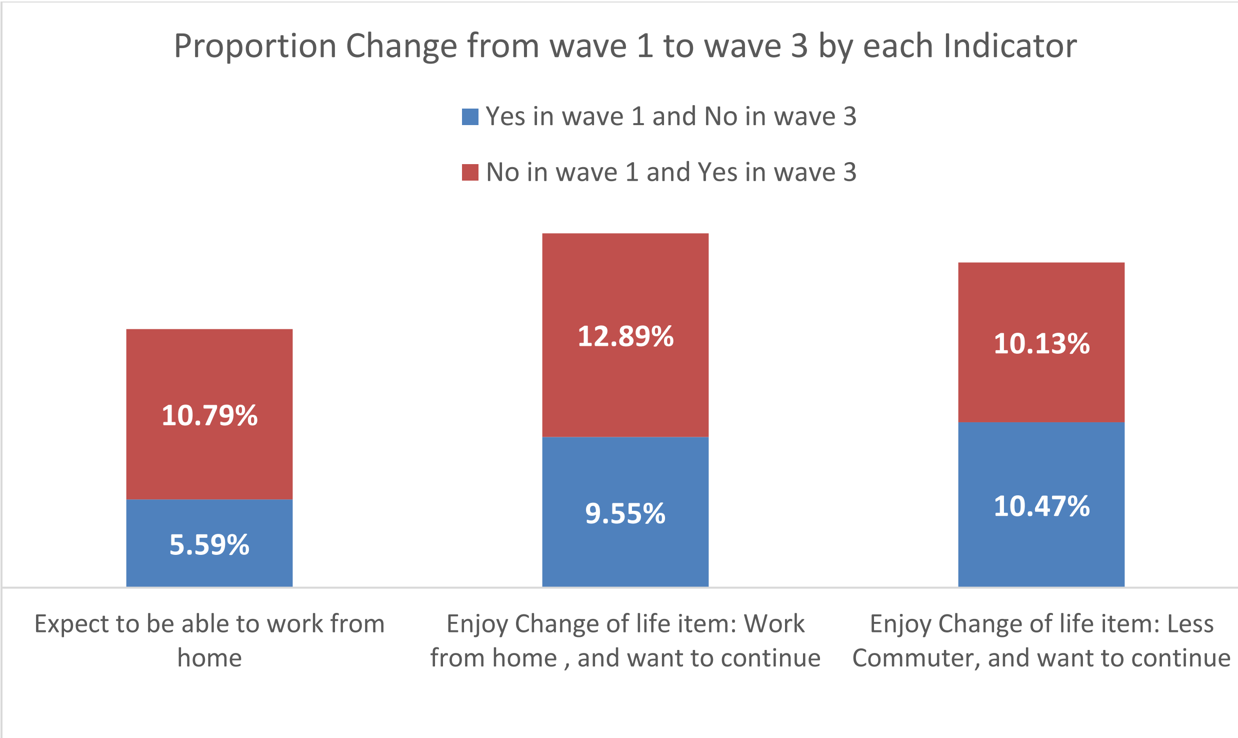

Figure 5.6 – Changes in respondent indicator reporting between wave 1 and wave 3

To decode this transition, we scrutinized instances where respondents changed their answers between waves. Remarkably, more than 15% demonstrated a change in stance regarding the first question, over 20% for the second, and similarly, about 20% for the third. These shifts are pivotal, highlighting a considerable evolution in opinions and preferences during the pandemic.

Employing these six indicators as vital inputs, we conducted a Repeat Measurement Latent Class Analysis (RMLCA) to classify worker expectations effectively. The dynamic nature of these responses emphasizes the importance of incorporating evolving preferences in our modeling and policy development endeavors.

While the impact of stay-at-home policies was considered, our primary focus was on capturing the in-person changes, which may lead to subsequent class mergers in our analysis. This approach ensures the elimination of factors not central to our study's objectives, enhancing the precision and relevance of our findings.

5.2.2 Class Enumeration

Class enumeration is the choice of how many K latent classes to estimate. The choice might be based on a number of factors including but not limited to:

1. K (Classes): Number of latent groups in the data.
2. LL (Loglikelihood): Indicates model's fit to the data; higher values are better.
3. Parms (Parameters): Total number of model parameters.
4. AIC (Akaike Information Criterion)
5. BIC (Bayesian Information Criterion): Goodness of fit measure with penalty for more parameters, suitable for large datasets.
6. ssBIC (Sample-Size Adjusted BIC): BIC variant adjusted for sample size, often used for smaller samples.
7. p-value: Significance level of model improvement tests.
8. Entropy: Measures classification certainty; higher values indicate clearer class separation.
9. VUONG-LO-MENDELL-RUBIN -LRT: Adjusted test for the necessity of additional classes.

In the realm of Latent Class Analysis (LCA), choosing the appropriate number of classes is pivotal. Collins and Lanza's seminal work on LCA suggests considering an array of statistical criteria for class enumeration, such as the Bayesian Information Criterion (BIC) and the Integrated Completed Likelihood (ICL) with BIC approximation. These measures often yield divergent recommendations, a common conundrum in mixture modeling.

The data examined suggests varying worker options and preferences during the pandemic. Notably, a subset of workers with no remote work capability likely constitutes a distinct class, exhibiting regular commute patterns. Conversely, a class with both high capability and preference for WFH is anticipated. The surge in telecommuting implies the existence of at least one class with a notable increase in this option. The possibility of further subclassification based on preference in response to increased telecommute options is reserved for further scrutiny.

The following figure and tables indicate these criteria as calculated for a number of estimations, each with a different K parameter.

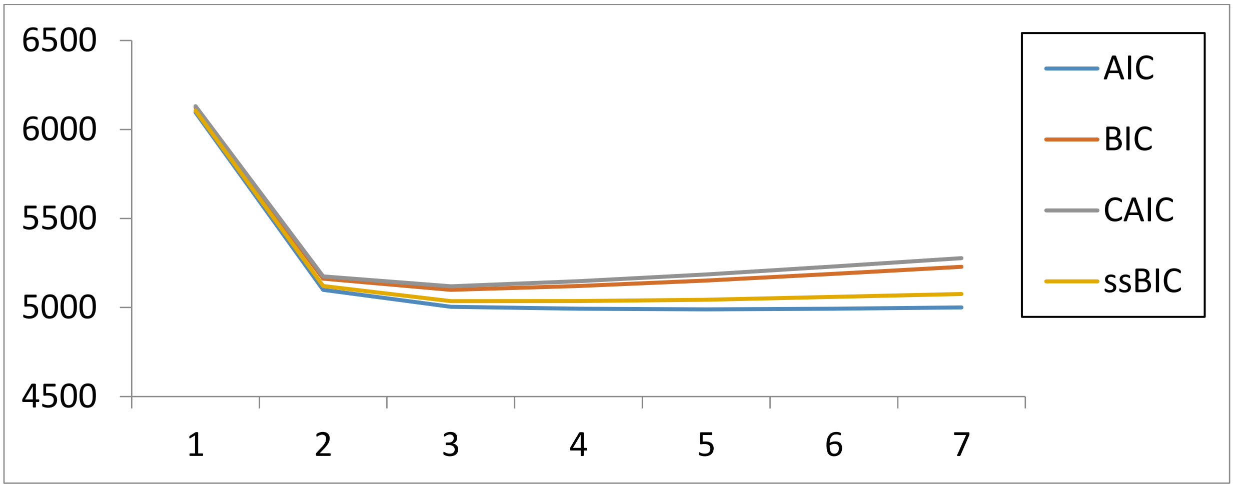

Figure 5.7 – Graphical representation of "parsimony criteria" by K (1 through 7)

Table 5.1a: Class enumeration statistics by several K estimations

Classes (K)	N	parms	LL	Entropy	AIC	BIC	CAIC	ssBIC	Entropy
					Parsimony Criteria				
1	870	6	3042.170	0.00	6096.34	6124.95	6130.95	6105.90	*NA*
2	870	13	2537.146	103.12	5100.29	5162.28	5175.28	5121.00	0.829
3	870	20	2482.051	250.42	5004.10	5099.47	5119.47	5035.96	0.738
4	870	27	2469.527	184.53	4993.05	5121.80	5148.80	5036.06	0.847
5	870	34	2460.918	200.23	4989.84	5151.96	5185.96	5043.99	0.857
6	870	41	2456.083	246.30	4994.17	5189.67	5230.67	5059.47	0.842
7	870	48	2451.877	259.02	4999.75	5228.64	5276.64	5076.21	0.847

Table 5.1b: Class enumeration statistics by several K estimations (cont)

VUONG-LO-MENDELL-RUBIN					
Classes	**N**	**parms**	**LL**	**p-value**	**class preference**
1	870	6	3042.170	NA	NA
2	870	13	2537.146	0.00	prefer 2 classes model
3	870	20	2482.051	0.00	prefer 3 classes model
4	870	27	2469.527	0.00	prefer 4 classes model
5	870	34	2460.918	0.05	kind of prefer 4 classes
6	870	41	2456.083	0.33	prefer 5 classes
7	870	48	2451.877	0.07	prefer 5 classes

The figure presented captures the item-response rates across various latent class models, delineating the changing preferences and options for work-from-home (WFH) scenarios among respondents throughout two survey waves (W1 and W3). The analysis includes 3-, 4-, 5-, and 6-class models, with a total of 870 cases.

Upon analyzing the classes, continuity in naming is maintained for clarity, with Class "6" consistently representing the same membership across models. The key decision points in LCA estimation include separation—how distinct the classes are based on indicator values—and class sample proportion, avoiding classes with less than 5% representation to maintain statistical power.

The 3-class model shows even distribution and adequate class separation, aligning with theoretical expectations. Class 6, with low indicator values, represents workers without remote work capability. Class 2, with high indicator values, is consistent with those preferring reduced commuting. Class 4 shows an increase in both WFH options and enjoyment, which aligns with expectations but fails to delineate decreases in indicators.

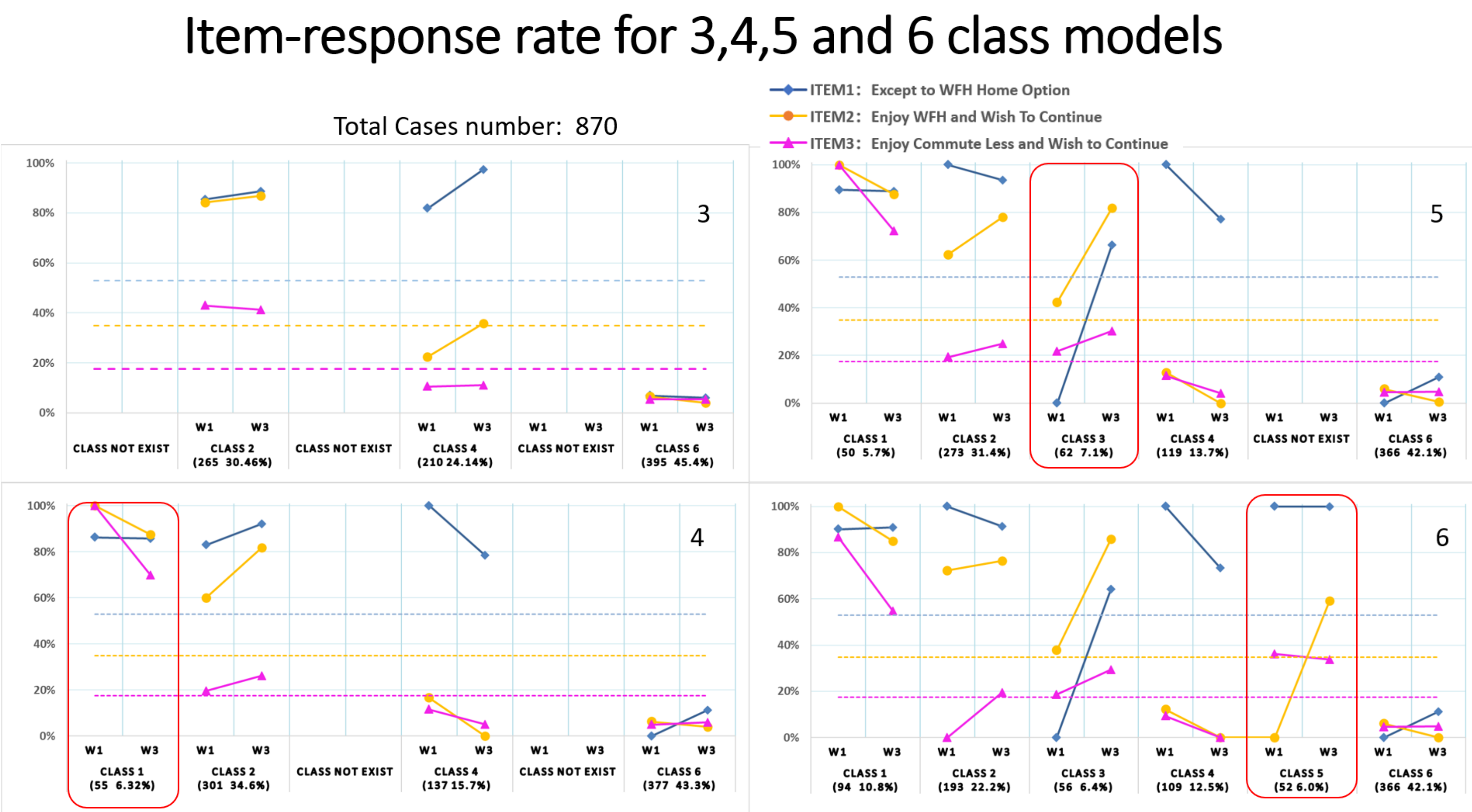

Figure 5.8 – summary of indicators by wave by class for K= 3, 4, 5, 6

The 4-class model reveals a new dynamic. A marked increase in the option indicator is evident in wave three, suggesting a shift in some respondents' preferences. The reconfiguration into Classes 1, 2, and 4 reveals distinct patterns: Class 1 as the extreme case of high WFH preference, Class 2 exhibiting mid-to-high levels of all indicators, and Class 4 with high WFH options but low preference.

The 5-class model introduces Class 3, capturing respondents with a significant increase in the WFH option, akin to Class 2 in preference trends but with a distinct pandemic-induced shift towards WFH.

The 6-class model adds Class 5, characterized by a strong preference for WFH and stable enjoyment of reduced commuting, representing the most dynamic and interesting segment from both research and policy-making perspectives. Class 6 remains the largest and least dynamic, underscoring the strength of the classification and supporting the decision for a 6-class estimation.

7-class model split a small class with 17 workers which only count as 1.7% over total cases, which is not meeting the criteria, the test was stopped at this point and the 7-class model is not under consideration as a result.

These classifications are integral for understanding the multifaceted impacts of the pandemic on work arrangements and for informing nuanced policy responses. The selected 6-class model effectively captures the diversity of worker experiences during the pandemic, facilitating targeted policy formulation.

5.2.2.1 Final decision: 6-classes model result demonstration

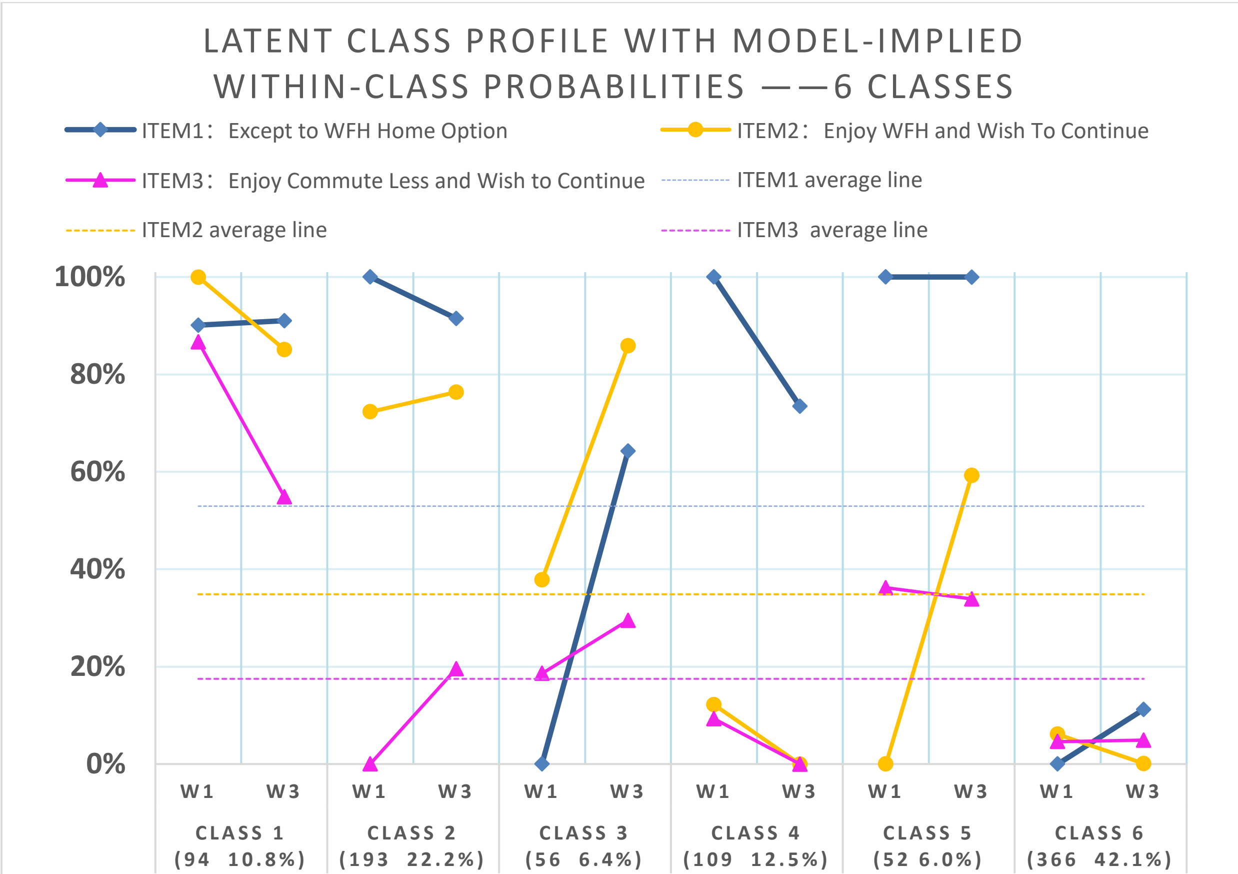

Figure 5.9 – Latent class profiles of indicators by class

The figure provided represents the results of a Latent Class Analysis (LCA) model with six distinct classes, based on individual preferences and behaviors related to work-from-home (WFH) policies and commuting. The analysis categorizes respondents into classes based on their responses to three items:

- ITEM1: Exception to Work from Home Option
- ITEM2: Enjoy Work from Home and Wish to Continue
- ITEM3: Enjoy Commute Less and Wish to Continue

The average lines are the average of each indicator for wave 1 and wave 3 each for the sample. This is fine because the overall change between waves was very small.

Class 6, being the largest and showing the least amount of change, suggests a significant portion of the population remains ambivalent or neutral towards WFH and commute preferences, or they are constrained by their job nature to not have a WFH option. The lack of dynamism could imply that these individuals are less influenced by preference and more by necessity or lack of alternatives. They might represent a traditional work mindset, structural job requirements that necessitate physical presence, or a lack of resources to effectively work from home.

In the 6-class LCA framework, Classes 1, 2, and 5 display congruent responses to ITEM 1 (Expectation for Telework Option) and ITEM 2 (Satisfaction with WFH) in Wave 3, yet they manifest a clear divergence in their stance on ITEM 3 (Preference for Less Commuting). This disparity in ITEM 3 responses implies that while these groups generally accept and appreciate the opportunity to WFH, their commuting preferences contrast sharply, likely influenced by the commute burdens they bore before the pandemic. Specifically, Class 5 shows an intensified preference for WFH between Wave 1 and Wave 3, with a notable increase in their aversion to commuting, hinting at a substantial pre-pandemic commuting burden. Conversely, Class 2's proclivity for WFH and aversion to commuting may be a reflection of previously lesser commute-related strains, which have guided their transition in work preferences.

Class 3's responses underwent a significant transformation regarding both ITEM 1 and ITEM 2, signaling a newfound acknowledgment and enjoyment of telework capabilities by Wave 3, raising questions about their prior exposure to WFH. This pivot calls for a deeper inquiry into Class 3's historical interaction with remote working modalities.

Class 4's high expectation for the availability of telework contrasts with their low satisfaction in such arrangements. This dichotomy could suggest a preference within this group for social interaction and an aversion to isolation, which telework may exacerbate. However, the survey design—particularly the ordering of ITEM 2 and ITEM 3—raises the possibility that pre-pandemic teleworkers might not identify with these items if their working conditions have remained unchanged by the shift to telework. Therefore, relying solely on these indicators may not suffice to fully comprehend the work dynamics of Class 4. A comprehensive analysis of their teleworking experiences, anticipated future work modalities, and demographic profiles is imperative for a thorough understanding.

5.2.3 Class Comparison and research finding:

5.2.3.1 Class behavioral outcomes (commuter type) characteristics

This chart presents the distribution of commute behaviors and corresponding expectations for telework options across six distinct classes. Classes 1, 5, and 2 are grouped due to their analogous outcome distributions. Conversely, Classes 3, 4, and 6 are examined together because of their differing outcome profiles. The outcome variable categorizes commute arrangements into four levels:

- Regular Commuter: Always commutes, never teleworks.
- High Frequency Commuter: Primarily commutes, with occasional telework (less than a few times a week).
- Low Frequency Commuter: Primarily teleworks, with occasional commuting (more than a few times a week).
- Home Office Worker: Exclusively teleworks, does not commute.

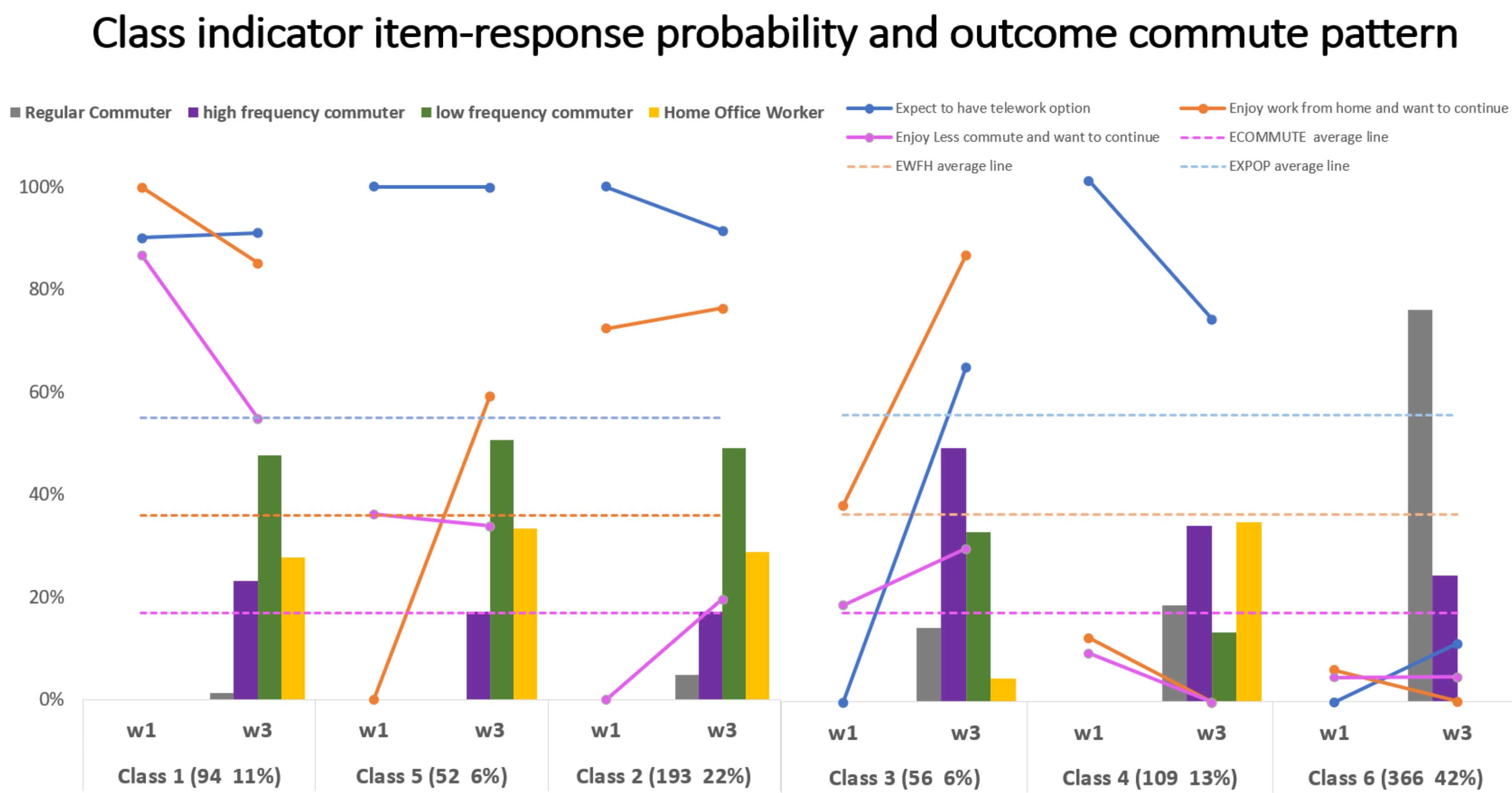

Figure 5.10 – Indicator item-repsponse probability and outcome (commute type) pattern

In Wave 3, Classes 1, 5, and 2 each demonstrate higher-than-average responses for all indicators, indicating a prevalent expectation to be provided with telework options. A notable uptick is observed in Class 5's enjoyment of WFH from Wave 1 to Wave 3, with Class 2 also showing an initial lower enjoyment of reduced commuting. Despite these variations, their overall outcome distributions are remarkably akin, with a minority as regular commuters and the majority as low frequency commuters. Additionally, a substantial fraction of each class, about 30%—compared to the 16% average across the entire sample—comprises home office workers, indicating that remote work is not confined to a single class.

Classes 3, 4, and 6 diverge substantially in their outcome distributions, both from the first grouping and from each other. Class 3 aligns with Classes 1, 5, and 2 regarding high indicator values in Wave 3, but this is a significant increase from Wave 1, particularly for the telework option indicator, which rose from 0%. This suggests that Class 3 members previously lacked the telework option, potentially due to reasons other than job suitability for remote work. Their outcome distribution is skewed towards high frequency commuting, with a negligible presence of exclusive home office workers, implying that their WFH engagement is restricted despite a reported enjoyment comparable to Classes 1, 5, and 2.

Class 4 presents a unique trajectory with a noticeable decline in the telework option indicator, ending above average but paired with low enjoyment levels of WFH and commuting less. This class's outcome distribution is characterized by a significant presence of both high frequency commuters and home office workers.

Finally, Class 6 is the most pronounced case, with consistently low indicator values across waves, and predominantly identified as regular commuters. Notably, this class lacks both low frequency commuters and home office workers, reinforcing its distinction from the other classes.

5.2.3.2 Class Demographic Features

Class 1 - Telecommute Embracer (94 members, 11%)

Class 1 is characterized by individuals with the highest education and income levels, primarily full-time workers who had the highest commute costs before the pandemic. They show a very high capability and enjoyment of telecommuting, with many owning their homes and having designated workspaces, although they are open to flexibility in their work environment. Members of this class are predominantly younger, suggesting agility and a willingness to adapt to remote work. This demographic's significant resources and space to accommodate WFH likely contribute to their strong preference for telecommuting over traditional commuting.

Class 2 - Typical Hybrid Telecommuter (193 members, 22%)

Members of Class 2 echo many attributes of Class 1 but with less extremity. They are younger on average, with a high proportion under 45 years old, and they were more likely to have been remote workers even before the pandemic. This class has a high level of education, with many holding graduate degrees, indicating that their jobs may be more conducive to remote work. Their demographic profile points to a modern, flexible workforce that had already been transitioning toward telecommuting before the pandemic accelerated this trend.

Class 3 - Lower Telecommute Opportunity (56 members, 6%)

Class 3 consists of younger workers, more diverse in race, living in densely populated urban areas, and likely relying on public transit for commuting. They have middle-income levels and are predominantly rent payers with bachelor's degrees. Despite their potential capability for remote work, they were not given ample opportunities to telecommute, which might reflect organizational policies or job nature. Their increased desire for telework options in Wave 3 indicates a shift in either the opportunity available to them or a change in their personal preferences due to the pandemic.

Class 4 - Pre-Covid Home Remote Worker (109 members, 13%)

Class 4 encompasses the highest level of pre-pandemic home remote workers, a status that has largely been maintained. These individuals are generally older, and more than half have at least one unemployed adult in their household, potentially influencing their need or ability to work from home. The demographic profile of this class suggests stability in their work arrangement that was less disrupted by the pandemic, accompanied by a solid foundation that supports telecommuting.

Class 5 - Exhibited Changes during Pandemic (52 members, 6%)

Class 5 members predominantly comprise full-time workers who faced the longest commute distances or costs, and the highest proportion of transit users. This class saw a significant shift during the pandemic, with a marked increase in WFH enjoyment. The members of this class likely experienced the greatest relief from transitioning out of their commute, which may have been particularly onerous due to distance or reliance on public transit.

Class 6 - Regular Commuter (366 members, 42%)

Class 6 is the largest class and is predominantly made up of older white workers in the sales/service job category, with lower education levels and income. They exhibit the lowest capability for remote work, with only a small fraction stating that their work could be done remotely. Job security was also a concern, as a significant percentage reported job changes during the pandemic. Despite having the lowest average commute time and transit use, this class had almost no expectation or capability for WFH, indicating a strong inclination towards or necessity for on-site work.

Table 5.2 – Summary of indicator and outcome levels for LCA K=6

	Survey question	**Survey answer**	**w1**	**w3**	**w1**	**w3**	**w1**	**w3**	**w1**	**w3**	**w1**	**w3**	**w1**	**w3**
Mixture Model Indicators	After COVID-19 is no longer a threat, do you expect to be able to work from home, at least some of the time?	Yes	**High**	**High**	**High**	**High**	**High**	**High**	**Middle**	**High**	**High**	**High**	**Low**	**Low**
	Enjoy change Question: COVID-19 has required most of us to make large changes to our daily lives.Would you like to continue any of these new ways of living when society reaches a post-COVID new normal? ---Yes or Maybe ---select up to three	Working from home, at least some of the time	**High**	**High**	**Low**	**High**	**High**	**High**	**Low**	**High**	**Low**	**Low**	**Low**	**Low**
		Commuting less	**High**	**High**	**Middle**	**Middle**	**Low**	**Low**	**Middle**	**Middle**	**Low**	**Low**	**Low**	**Low**
Outcomes	**Commute type**	**Description**	**Class 1 (94 10.8%)**		**Class 5 (52 0.60%)**		**Class 2 (193 22.2%)**		**Class 3 (56 6.4%)**		**Class 4 (109 12.5%)**		**Class 6 (366 42.1%)**	
	Regular Commuter	100% chance commuting to work location on a typical workday	0%		0%		0%		20%		20%		80%	
	High frequency commuter	higher chance to commute on a typical work day.	20%		20%		20%		50%		30%		20%	
	Low frequency commuter	lower chance to commute on a typical workday.	50%		50%		50%		30%		10%		0%	
	Home Office Worker	100% chance not going to commute on a typical workday.	30%		30%		30%		0%		30%		0%	

5.3 RMLCA with Predictors

5.3.1 Background

The contemporary body of literature extensively explores various facets of telework, also known as telecommuting and is afforded a review prior to variable choice. This exploration encompasses the benefits and drawbacks of telework (Tavares, 2017; Gálvez et al., 2020; Beno, 2021; Brînzea & Secară, 2017), predictive modeling and forecasting of its adoption (Mokhtarian & Salomon, 1994, 1996a, 1996b, 1997; Mokhtarian et al., 1998; Popuri & Bhat, 2003; Haddad et al., 2009; Sener & Bhat, 2011; Singh et al., 2012; Asgari et al., 2014, 2015; Paleti, 2016; Shabanpour et al., 2018), and the analysis of teleworking's travel-related consequences (Mokhtarian, 2003; Mokhtarian et al., 2004; Zhu, 2012; Asgari et al., 2016, 2017; Asgari & Jin, 2018; De Abreu e Silva & Melo, 2018a, 2018b; Elldér, 2020). The progression of information and communication technologies, along with evolving workplace concepts, have propelled telework into a subject of increased consideration among planners and researchers.

Research efforts have concentrated on identifying and assessing factors influencing the adoption of teleworking by employees. The literature indicates that telework adoption can be evaluated through various methodologies, including options, stated preferences, revealed choices, and frequency. It points towards certain personal, household, and job-related characteristics as predictors of telework propensity. Demographic variables, such as age (Singh et al., 2012; Sener & Reeder, 2012), gender (Singh et al., 2012; Loo & Wang, 2018; Peters et al., 2004), education (Loo & Wang, 2018; de Graaf & Rietveld, 2007; Peters et al., 2004), income (Loo & Wang, 2018; Yen, 2000; Mannering & Mokhtarian, 1995; He & Hu, 2015), and job-related aspects like commute distance (Loo & Wang, 2018; Helminen & Ristimäki, 2007; Iscan & Naktiyok, 2005), have been identified as significant determinants in telework adoption.

In-depth quantitative analyses have been conducted to understand telework behavior, particularly during the pandemic. Brynjolfsson et al. (2020) highlighted the variability in telework adoption across different socioeconomic groups during this period. The study revealed a higher tendency for telework among individuals with advanced degrees, higher incomes, and within white demographic groups, compared to people of color, lower income groups, and those with less than a high school education (Bick et al., 2020). Dingel and Neiman (2020) introduced an algorithm for predicting telework feasibility across various occupations, based on work context and generalized work activities. This algorithm effectively predicted the feasibility of telework for ten distinct occupations. Additionally, the feasibility of teleworking showed a positive correlation with median household income and the percentage of people holding college degrees at the metropolitan level, but a negative correlation with home ownership rates and the percentage of white residents. Mongey et al. (2021) conducted a statistical examination using work-from-home and physical-proximity metrics, observing lower telework rates among less educated workers, those with lower incomes, fewer liquid assets relative to income, and a lower likelihood of home ownership.

During the pandemic, several studies focused on telework dynamics. Morilla-Luchena et al. (2021) surveyed social workers in Spain, finding higher telework prevalence among older individuals, those with marital experience, parents, and public sector employees. Sostero et al. (2020) reported that in Europe, telework during the pandemic was predominantly observed in high-income and white-collar jobs, although the compulsory nature of telework increased its adoption among lower- and middle-income office and administrative workers. Raiien et al. (2020) identified three distinct teleworker attitudes through an exploratory study: the most satisfied teleworkers were highly educated female millennials in management or administrative roles with some prior teleworking experience, while less satisfied teleworkers tended to be older, educated males with extensive professional experience but no prior teleworking experience. Papageorge et al. (2021) explored various self-protective behaviors during the pandemic, noting a tendency among younger individuals and those with higher incomes to transition teleworking.

5.3.2 Variable Choice for Predictors

The selection of demographic variables as predictors for estimating class membership in a multinomial logit model is strategic and grounded in the understanding that these factors are influential in determining telecommuting behaviors and preferences. I briefly describe why each variable is a pertinent choice:

Age: Age is often correlated with flexibility, technological adaptability, and work-life priorities. Younger individuals may be more open to and capable of adopting new technologies required for telecommuting, while older individuals may have established routines or responsibilities that influence their work preferences.

Race: Racial demographics can reflect cultural, economic, and social factors that impact telecommuting opportunities and preferences. Studies have shown that race can influence job types, sectors of employment, and access to telecommuting-friendly roles.

Commuting Cost Before Pandemic: Pre-pandemic commuting costs are indicative of the burdens faced by individuals when traveling to work. Those with higher commute costs may be more inclined to embrace telecommuting to reduce these expenses. Post-pandemic measurements are less reliable due to the significant changes in commuting patterns during the period.

Population Density Based on ZIP: Population density can affect both the practicality and attractiveness of commuting. In densely populated areas, commuting can be more timeconsuming and stressful, making telecommuting more desirable. Conversely, in less dense areas, commuting might be easier and less of a deterrent to working on-site.

Income Level: Income can dictate the kind of job one has and, by extension, the feasibility of telecommuting. Higher-income individuals may have more jobs that allow telecommuting, while lower-income individuals may have more service-oriented or manual jobs that require physical presence.

Education Level: Education level often correlates with the type of employment, with higher levels of education linked to jobs that are more likely to be telecommuting friendly. Moreover, individuals with higher education may have better access to the resources needed for effective telecommuting.

If Household Has Any Unemployed Adult: The presence of unemployed adults in the household may influence the need and ability to telecommute. Households with unemployed adults may need to share resources, such as computers and internet bandwidth, which could affect the ability of others to telecommute effectively.

If Household Has Extra Space (Bedroom): Having extra space in a household can facilitate a more comfortable and productive telecommuting environment. A dedicated workspace is a significant factor in the viability and attractiveness of WFH arrangements.

These demographic variables provide a comprehensive foundation for understanding the multifaceted influences on telecommuting behavior. By analyzing these predictors, the multinomial logit model can estimate the likelihood of an individual belonging to a particular class, thus offering valuable insights for policy-making and organizational planning in the context of telecommuting trends and preferences.

5.3.3 Model Result

Drawing from the demographic insights delineated in the preceding chapter, alongside established literature, we have curated a set of predictors for classifying individuals into the respective classes. It's important to note that this is a methodological exemplar designed to demonstrate the application of the model for predictive estimations. Typically, regional models might not necessitate incorporating temporal dynamics as a feature, since such models often aim to capture a snapshot of behaviors rather than their evolution over time, the variable selection is documented in the table below.

Table 5.3a – Odds ratio results for RMLCA with predictors

Class	Class 1 (94 10.8%)				Class 5 (52 6.0%)				Class 2 (193 22.2%)			
Variable	Odds ratio	P-Value (Odds ratio)	[95% conf. interval]		Odds ratio	P-Value (Odds ratio)	[95% conf. interval]		Odds ratio	P-Value (Odds ratio)	[95% conf. interval]	
Age above 55	0.34	0.00	0.18	0.63	0.51	0.07	0.54	6.85	0.52	0.00	0.31	0.87
Education level is Graduate or higher	2.31	0.06	1.30	4.13	1.20	0.78	0.47	5.93	1.91	0.08	1.12	3.27
Full time employee	8.75	0.04	3.77	20.28	4.77	0.19	0.53	6.53	1.62	0.13	0.99	2.65
Household Income is above 100K	2.47	0.03	1.43	4.28	1.27	0.69	0.14	9.17	2.22	0.03	1.34	3.68
Living in Urban area (sqmile0>=7000)	0.93	0.84	0.45	1.93	1.49	0.56	0.84	1.94	1.24	0.53	0.68	2.28
Race is white	0.74	0.38	0.33	1.65	0.37	0.00	0.80	2.28	0.49	0.00	0.26	0.94

Class	Class 3 (56 6.4%)				Class 4 (109 12.5%)			
Variable	Odds ratio	P-Value (Odds ratio)	[95% conf. interval]		Odds ratio	P-Value (Odds ratio)	[95% conf. interval]	
Age above 55	0.33	0.00	0.14	0.76	1.15	0.65	0.65	2.04
Education level is Graduate or higher	1.68	0.31	0.77	3.64	1.31	0.51	0.65	2.64
Full time employee	2.06	0.14	1.04	4.06	1.18	0.62	0.64	2.18
Household Income is above 100K	0.58	0.12	0.23	1.44	2.06	0.12	1.07	3.95
Living in Urban area (sqmile0>=7000)	2.26	0.13	1.10	4.62	0.61	0.25	0.21	1.78
Race is white	0.34	0.00	0.15	0.74	0.67	0.30	0.27	1.69

The model works as a Multinominal Logistic regression. The base class choice is Class6 since they are the less preferring any Telecommute. The variable choice is based on the observation of 6 classes demographic features.

Table 5.3b – Coefficient estimates for RMLCA with predictors

Class	Class 1 (94 10.8%)		Class 5 (52 6.0%)		Class 2 (193 22.2%)	
Variable	Coef	P-Value	Coef	P-Value	Coef	P-Value
Age above 55	-1.09	0.00	-0.68	0.20	-0.65	0.01
Education level is Graduate or higher	0.84	0.01	0.18	0.76	0.65	0.02
Full time employee	2.17	0.00	1.56	0.01	0.48	0.05
Household Income is above 100K	0.91	0.00	0.24	0.65	0.80	0.00
Living in Urban area (sqmile0>=7000)	-0.07	0.84	0.40	0.48	0.22	0.49
Race is white	-0.31	0.45	-1.00	0.07	-0.71	0.03
Class	Class 3 (56 6.4%)		Class 4 (109 12.5%)			
Variable	Coef	P-Value	Coef	P-Value		
Age above 55	-1.11	0.01	0.14	0.63		
Education level is Graduate or higher	0.52	0.19	0.27	0.45		
Full time employee	0.72	0.04	0.17	0.59		
Household Income is above 100K	-0.55	0.24	0.72	0.03		
Living in Urban area (sqmile0>=7000)	0.81	0.03	-0.49	0.37		
Race is white	-1.10	0.01	-0.40	0.40		
Intercepts	Estimate	P-Value				
CLASS#1	-2.68	0.00				
CLASS#2	-0.62	0.06				
CLASS#3	-0.99	0.01				
CLASS#4	-1.30	0.01				
CLASS#5	-1.83	0.01				

The model works as a Multinominal Logistic regression.
The base class choice is Class6 since they are the less preferring any Telecommute.
The variable choice is based on the observation of 6 classes demographic features.

5.4 Example of Within Class Analysis with Class 4

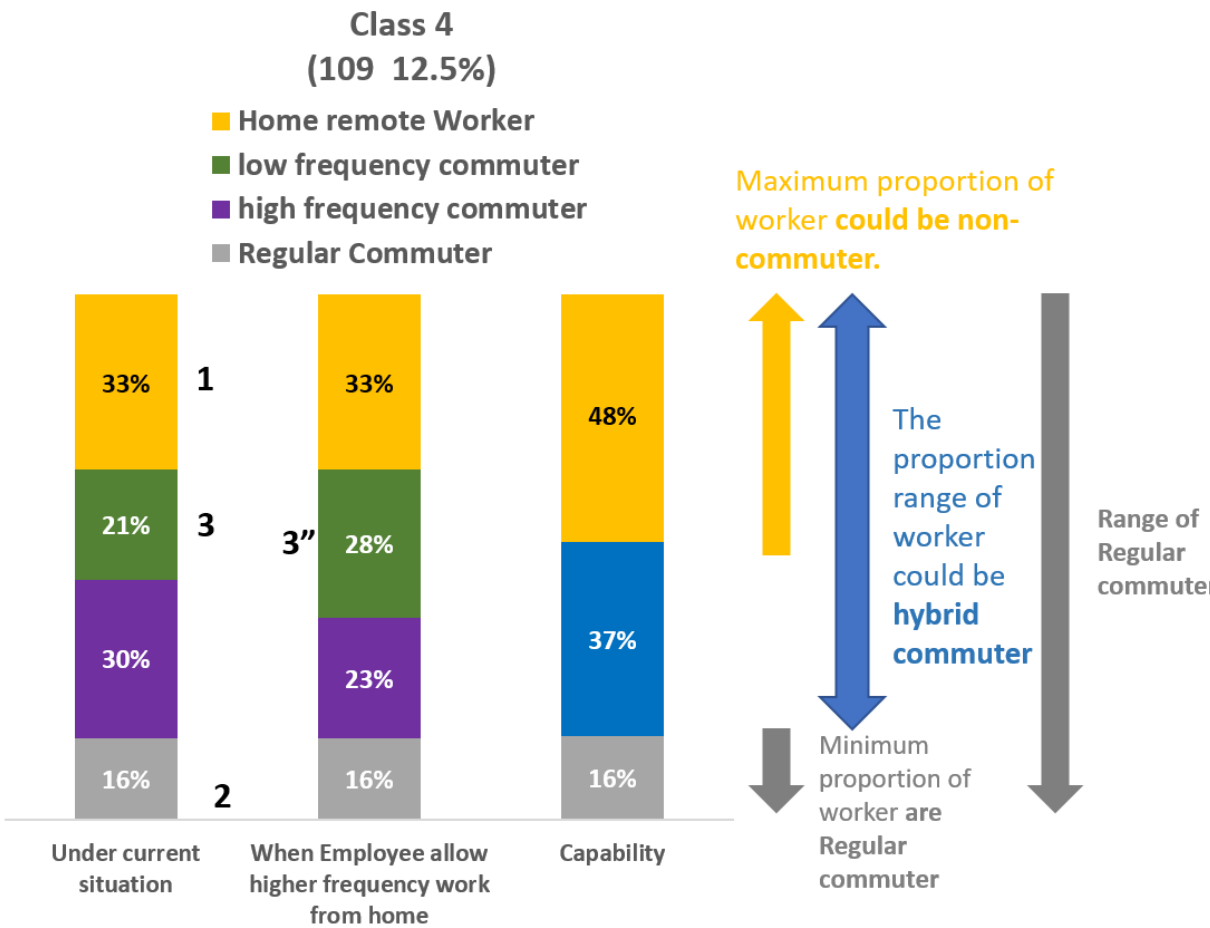

Figure 5.11 – Example application to class 4

To illustrate the application of the logistic model, we take Class 4 as a point of reference. This exercise is dependent on the coefficients and model numbers detailed in the accompanying table.

Given there are four distinct telecommuter/commuter types, our estimation process involves three models, as one category serves as the reference group against which the others are compared. In the calibration phase, we include only those cases that are deemed eligible, meaning they fall within the specified range of the capability variable relevant to each commuter type. For instance, the calibration of the model for the home remote worker category includes only those whose work is entirely conducive to remote execution, excluding all other workers.

Further refinement is made by integrating BCH weights, which allows for a proportional assignment in the estimation process rather than restricting it to the 109 workers strictly categorized under Class 4. This adjustment increases the observation pool to 247 workers for this model. Conversely, the potential for any worker to opt for regular commuting means that all individuals in the sample, totaling 744 observations, are considered in the estimation of model 2.

The third model, which identifies potential low frequency commuters, considers the subset of workers who have at least some capacity for remote work—denoted by the blue range in the figure. This adds up to 480 observations that fall within this category's range.

In practical application, the models run consecutively. We begin with the three models to establish a baseline. Subsequently, we assign workers to the Home Remote Worker category based on the highest probabilities from model 1 results, accounting for 33% of the cases. From the remaining pool, we designate 16% to the Regular Commuter category, proceeding in a similar fashion for the remaining groups. This methodical approach ensures that each worker is categorized in a manner that aligns with their highest probability of fitting into a particular commuting type, based on the predictive strength of the logistic model.

Table 5.4 – Commuting type, based on the logistic model

Class 4 (109 12.5%)									
Model	1 Home Remote Worker				Model	2 Regular commuter			
Variable	Odds ratio	P>|z|	[95% conf. interval]		Variable	Odds ratio	P>|z|	[95% conf. interval]	
gender	0.11	0.01	0.02	0.55	wfh_opt0	0.01	0.00	0.00	0.12
					eduh	22.10	0.02	1.64	298.06
					gender	0.06	0.02	0.01	0.60
					rural13	8.63	0.02	1.37	54.25
cons_	2.77	0.05	1.00	7.70	cons	4.83	0.14	0.59	39.70
	obs	LR chi2(1)	Prob > chi2	Pseudo R2		obs	LR chi2(4)	Prob > chi2	Pseudo R2
	247	0.00	0.00	0.19		744	47.89	0.00	0.55
3 Low frequency commuter 3"									
Model	Current working situation				Model	When ever employer allow as much telework as worker want			
Variable	Odds ratio	P>|z|	[95% conf. interval]		Variable	Odds ratio	P>|z|	[95% conf. interval]	
costtf03	5.42	0.02	1.31	22.35	femp0	0.08	0.01	0.01	0.56
sub0	4.45	0.04	1.06	18.73	costtf03	16.27	0.00	2.81	94.26
					jcserv13	13.35	0.02	1.50	119.15
cons	0.06	0.00	0.02	0.18	cons	0.33	0.07	0.10	1.09
	obs	LR chi2(2)	Prob > chi2	Pseudo R2		obs	LR chi2(3)	Prob > chi2	Pseudo R2
	480	10.30	0.01	0.17		483	25.10	0.00	0.33

5.5 Results of Within Class Analysis for All Classes

In the within-class analysis, the focus is on estimating worker telecommuter/commuter types, prioritizing those with a significant representation in the dataset. The classification of worker types is conducted in a sequential manner: 1 denotes a home remote worker, 2 represents a regular commuter, and 3 characterizes a low-frequency commuter. Consequently, for classes 1 and 5, models are developed to estimate home remote workers and low-frequency commuters. In classes 2 and 4, the analysis extends to include models for home remote workers, regular commuters, and low-frequency commuters. For class 3, the emphasis is on regular commuters and low-frequency commuters. Finally, in class 6, models are constructed for regular and low-frequency commuters, although a selective approach is adopted, applying only one model.

Table 5.5a – Within class analysis for classes 1 and 2

Class 1 (94 10.8%)												
Conditional applied Logit model: Each commute type is a Binary outcome,and the model only applied on worker who are eldigeable to be the commuter/Worker type.	TELE_Commuter4 : Low frequency commuter/High frequency teleworker (Hybrid Commuter) Current Apply for only worker at least has some work could be done remotely				TELE_Commuter E 4 : Low frequency commuter/High frequency teleworker (Hybrid Commuter) When Employer allow more telecommute Apply for only worker at least has some work could be done remotely				TELE_Commuter 5 : Home Remote Worker (None-commute worker) Applied on only worker with Capability "all work could be done remotely"			
Variable	Odds ratio	P>|z|	[95% conf. interval]		Odds ratio	P>|z|	[95% conf. interval]		Odds ratio	P>|z|	[95% conf. interval]	
Being Male	0.23	0.01	0.08	0.65	0.34	0.03	0.12	0.90	4.71	0.01	1.42	15.66
Bachelor's degree(s) or some graduate schoolCompleted					6.43	0.01	1.78	23.28				
Some college or technical school	0.06	0.01	0.01	0.57								
commute time cost (one way commuter time*commute freq per week) above 120 mins per week	2.67	0.05	1.02	7.00								
Race is White					0.09	0.04	0.01	0.87				
Household reported Income above 1000K in 2019	2.96	0.04	1.07	8.18					0.25	0.02	0.08	0.81
Household had equal number of vehicle and worker number					0.27	0.02	0.09	0.78	2.82	0.07	0.93	8.54
_cons	0.64	0.34	0.25	1.61	10.57	0.06	0.93	120.23	0.87	0.79	0.32	2.37
	obs	LR chi2(4)	Prob > chi2	Pseudo R2	obs	LR chi2(4)	Prob > chi2	Pseudo R2	obs	LR chi2(3)	Prob > chi2	Pseudo R2
		441	0.00	0.21	460	19.70	0.00	0.15	243	14.05	0.00	0.16

Class	Class 2																		
Model	TELE_Commuter4 : Low frequency				Model	TELE_Commuter E 4 : Low frequency				Model	TELE_Commuter 5 : Home Remote Worker				Class	TELE_Commuter 1 : Regular commuter			
Variable	Odds ratio	P>|z|	[95% conf. interval]		Variable	Odds ratio	P>|z|	[95% conf. interval]		Variable	Odds ratio	P>|z|	[95% conf. interval]		Variable	Odds ratio	P>|z|	[95% conf. interval]	
Being full-time employee before pandemic	4.38	0.00	1.74	11.05	Age from 31 to 54	3.41	0.00	1.48	7.87	Commute time cost is higher than 120 mins a week one way	0.01	0.01	0.00	0.28	Age equal or under 30	19.35	0.00	2.88	130.15
Having children young est age is 5-17 years old	4.27	0.00	1.65	11.03	Being full-time employee before pandemic	4.12	0.01	1.46	11.65	Living in sub-urban before pandemic	0.06	0.01	0.01	0.48	Before Covid Job category is Professional, managerial, or technical	0.11	0.04	0.01	0.91
					Having more vehicle than worker number	5.20	0.01	1.56	17.27										
					Household income is higher than 100K in 2019	3.11	0.01	1.33	7.29										
_Cons	0.25	0.00	0.11	0.60	_Cons	0.12	0.00	0.04	0.34	_Cons	10.72	0.00	3.01	38.13	_Cons	0.05	0.00	.0159281	.1568414
	obs	LR chi2(2)	Prob > chi2	Pseudo R2		obs	LR chi2(2)	Prob > chi2	Pseudo R2		obs	LR chi2(2)	Prob > chi2	Pseudo R2		obs	LR chi2(2)	Prob > chi2	Pseudo R2
	503	21.83	0.00	0.11		505	43.41	0.00	0.23		253	18.92	0.00	0.39		748	12.09	0.00	0.23

Table 5.5b – Within class analysis for classes 3 and 5

Class	Class 3 (56 6.4%)													
Model	TELE_Commuter4 : Low frequency commuter/High frequency teleworker (Hybrid Commuter) Current Apply for only worker at least has some work				Model	TELE_Commuter E 4 : Low frequency commuter/High frequency teleworker (Hybrid Commuter) When Employer allow more telecommute				Class	TELE_Commuter 1 : Regular commuter (Commute on regular basis) All worker could be regular commuter			
Variable	Odds ratio	P>|z|	[95% conf. interval]		Variable	Odds ratio	P>|z|	[95% conf. interval]		Variable	Odds ratio	P>|z|	[95% conf. interval]	
Job category is Professional, managerial, or technical during pandemic	0.16	0.03	0.03	0.87	Race is white	0.10	0.02	0.01	0.67	Race is white	0.06	0.02	0.00	0.64
Having equal room number and household size	0.18	0.04	0.03	0.95	Age above 60	16.20	0.04	1.09	241.11	Being full-time employee before pandemic	0.03	0.01	0.00	0.36
					Commute time cost is higher than 120 mins a week one way	0.14	0.04	0.02	0.95	Living at rural area during pandemic	6.75	0.06	0.89	51.03
					Having more room number and household size	8.16	0.02	1.33	49.90					
_cons	19.91	0.00	4.38	90.48	_cons						6.23	0.17	0.47	82.57
	obs	LR chi2(4)	Prob > chi2	Pseudo R2		obs	LR chi2(4)	Prob > chi2	Pseudo R2		obs	LR chi2(3)	Prob > chi2	Pseudo R2
	297	8.44	0.01	0.18		285	16.20	0.00	0.24		573	15.70	0.00	0.31

Class	Class 5 (52 6.0%)													
Model	TELE_Commuter4 : Low frequency commuter/High frequency teleworker (Hybrid Commuter) Current Apply for only worker at least has some work could be done remotely				Model	TELE_Commuter E 4 : Low frequency commuter/High frequency teleworker (Hybrid Commuter) When Employer allow more telecommute Apply for only worker at least has some work could be done remotely					TELE_Commuter 5 : Home Remote Worker (None-commute worker) Applied on only worker with Capability "all work could be done remotely"			
Variable	Odds ratio	P>|z|	[95% conf. interval]		Variable	Odds ratio	P>|z|	[95% conf. interval]		Variable	Odds ratio	P>|z|	[95% conf. interval]	
Gender is Male	13.81	0.00	3.05	62.49	Gender is Male	15.95	0.00	3.48	73.04	Race is Asian	0.12	0.03	0.02	0.83
Household Income is lower than 50K during pandemic	0.03	0.02	0.00	0.52	Being Part-time employee before pandemic	0.01	0.02	0.00	0.52	Job category is Professional, managerial, or technical during pandemic	0.18	0.00	0.07	0.47
Having childrenyoungest age is 5-17 years old	0.03	0.01	0.00	0.46										
	0.57	0.23	0.23	1.42		0.61	0.23	0.27	1.38		10.72	0.00	3.01	38.13
	obs	LR chi2(3)	Prob > chi2	Pseudo R2		obs	LR chi2(2)	Prob > chi2	Pseudo R2		obs	LR chi2(2)	Prob > chi2	Pseudo R2
	416	32.600	0.000	0.394		418	30.150	0.000	0.369		253	18.92	0.00	0.39

Table 5.5c – Within class analysis for class 6

Class	Class 6 (366 42.1%)								
Model	TELE_Commuter E4 : Low frequency commuter/High frequency teleworker (Hybrid Commuter) When Employer allow more telecommute Apply for only worker at least has some work could be done remotely				Class	TELE_Commuter 1 : Regular commuter (Commute on regular basis) All worker could be regular commuter			
Variable	Odds ratio	P>|z|	[95% conf. interval]		Variable	Odds ratio	P>|z|	[95% conf. interval]	
Commute time cost is less than 50 mins a week one way	7.97	0.00	2.24	28.45	Having children youngest age under 4 years old	0.14	0.00	0.05	0.45
Household Income is lower than 50K during pandemic	0.15	0.04	0.03	0.94	Being full-time employee before pandemic	0.39	0.01	0.19	0.77
					Job category is Professional, managerial, or technical during pandemic	0.23	0.00	0.13	0.42
	0.21	0.00	0.10	0.46		10.17	0.00	5.21	19.86
	obs	LR chi2(2)	Prob > chi2	Pseudo R2		obs	LR chi2(3)	Prob > chi2	Pseudo R2
	330	14.43	0.00	0.18		583	47.07	0.00	0.14

CHAPTER 6

DISCUSSION AND INTERPRETATION

6.1 Introduction

This chapter presents a comprehensive analysis of telecommuting, examining its evolution before and during the pandemic. We begin by exploring the relationship between telecommuting experience and capability during this period, highlighting how these aspects were influenced by the sudden shift in work dynamics due to the pandemic. This segment is instrumental in understanding the transformation in telecommuting practices under unprecedented circumstances.

Subsequently, the chapter investigates the differential impacts of stay-at-home directives on each class. This section includes an in-depth analysis of the disparities in the ability to work remotely across different classes, examining factors such as the proportion of individuals in each class who are capable of remote work. We also explore how employment patterns shifted across these classes during the pandemic, highlighting the variations in job security and adaptability to remote work. Furthermore, we scrutinize the diverse experiences of telecommuting within each class, aiming to uncover how the transition to remote work varied based on socioeconomic standing. This analysis is pivotal in understanding the heterogeneous effects of the pandemic on different classes and how these variations have reshaped the landscape of telecommuting and employment.

The next section of the chapter focuses on how policy changes influence workers' expectations and preferences for telecommuting versus commuting. We present two scenarios to illustrate this: the first scenario considers a worker with maximum telecommuting opportunities, and the second explores the implications if a worker could trade their assigned physical workspace for more frequent telecommuting. These scenarios help in understanding the potential outcomes of policy shifts on worker preferences and organizational structures.

Furthermore, we provide insights into the evolving nature of the workplace. This includes an analysis of how changes in telecommuting practices have reshaped employee expectations, workplace dynamics, and overall organizational culture.

Lastly, we address the critical issue of equity in telecommuting, specifically focusing on a special class identified in the study. This section examines how disparities in access to telecommuting opportunities can perpetuate existing socioeconomic inequalities and discusses potential strategies to mitigate these issues. This comprehensive analysis not only sheds light on the current state of telecommuting but also provides valuable insights for policymakers and organizations aiming to navigate the post-pandemic work environment effectively.

6.2 Relationship of Telecommuting Experience and Capability

The telecommunication capabilities across 6 classes, aiming to ascertain if opportunities for telework are equitably distributed was systematically examined. The result is represented through a color-coded framework: yellow area is the proportion of worker reporting “All” of their work could be done remotely, indicating within the block worker are eligible to be home remote worker, blue denotes partial remote work feasibility, and gray indicates no remote work potential. The analysis encompasses six distinct classes, with an emphasis on average samples depicted in a consolidated graphical representation.

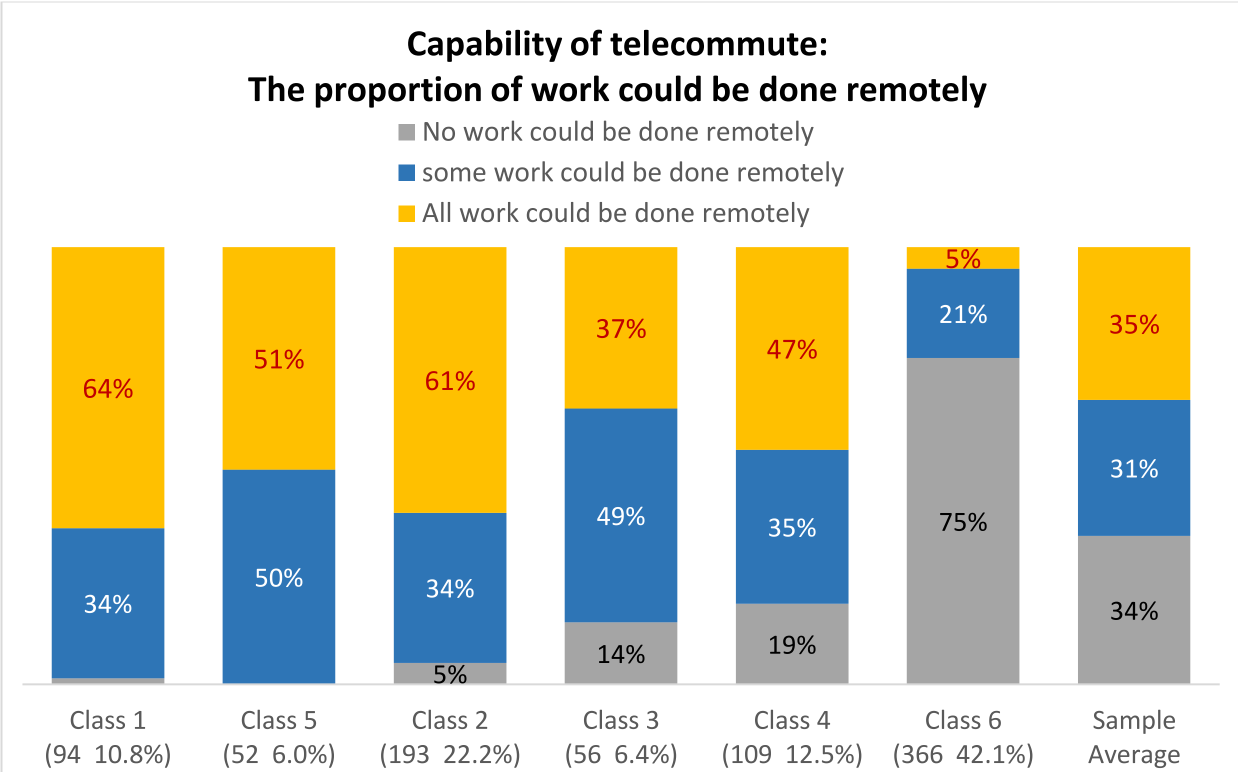

Figure 6.1 – Capability to telecommute by class

Upon reviewing the data, it becomes evident that individuals in classes 1, 5, and 2 exhibit a pronounced likelihood of engaging in at least some form of hybrid work arrangement. Conversely, classes 3 and 4, despite a substantial segment reporting an inability to telework, predominantly affirm the possibility of partial remote work. Class 6 stands out, with a staggering 75% indicating an absolute non-feasibility of remote work.

The study also delves into the dynamics of stay-at-home policies and their impact on remote work adoption. Here, the yellow segment highlights those who can fully work remotely. Notably, the red curve represents the proportion of individuals transitioning to remote work over successive waves of data collection. A striking observation is that in the initial two waves, even members of class 6, who are least likely to work remotely, show higher participation rates than their theoretical telework capacity suggests. This indicates an external impetus, possibly policy-driven, encouraging remote work beyond inherent capabilities.

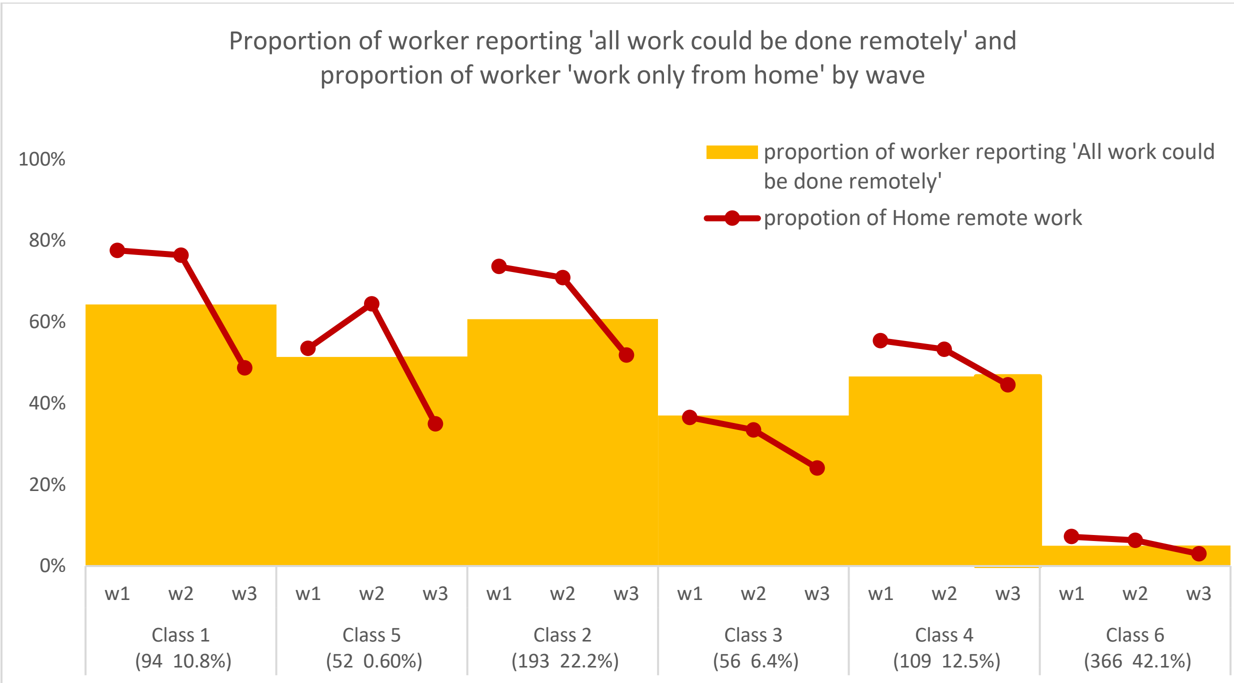

Figure 6.2 – Capability vs. actual proportion of home remote working

The above figure shows the proportion of workers within each class who were working only from home for 3 waves. The yellow block again represents workers who are capable of being home remote workers. According to the analysis based on all samples, we know that stay-at-home policy pushed all workers toward telecommuting over the line in wave 1 and 2, we can observe the same within the class, but with some special findings.

Class 5 presents a unique case, with its peak remote work adoption occurring during the second wave, unlike other classes where the peak is observed in the first wave. This variance underscores a potential shift in work preferences post-exposure to remote work modalities, lending credence to the hypothesis that experiential factors significantly influence telework adoption. This could be the reason that class 5 has a low start on appreciating telecommute but the enjoy telecommute picked up later.

Class 3, however, exhibits a consistent pattern of telework adoption that never surpasses their theoretical remote work capacity, even at the pandemic's peak. This anomaly raises pertinent questions about the characteristics of this group and its implications for future research and model applications. The apparent disparity between their desire for remote work and the actual opportunities available necessitates a focused investigation, as it highlights a critical gap in telework accessibility and preferences.

Lastly, we observe a cross-sectional analysis of remote work proportions across different classes over various waves. This analysis reveals that all classes, including class 6, which has limited eligibility for complete remote work, reported higher than expected participation in telework during the initial stages of the pandemic. However, class 3 remains an outlier, consistently falling below the threshold, indicative of a missed opportunity for hybrid or complete remote work, despite apparent eligibility. This unique position of class 3 underscores the need for a deeper understanding of the barriers and opportunities within this group, shaping future research directions and policy interventions in telecommuting and commute substitution studies.

6.3 Employment Status Change Before and During Pandemic

In this section, we dissect the intricacies of the employment rate in relation to the pandemic's impact, partitioning it into three distinct components: unemployment rate, full-time employment proportion, and part-time employment proportion. The analysis employs a dotted line to denote individual classes and a black dashed line to represent the survey average.

In our analysis of the employment trends among classes 1, 5, and 2 during the pandemic, a distinct pattern emerges. The unemployment rates in these classes consistently fall below the overall survey average. The implication is a relatively muted impact of the pandemic on their employment status compared to other groups.

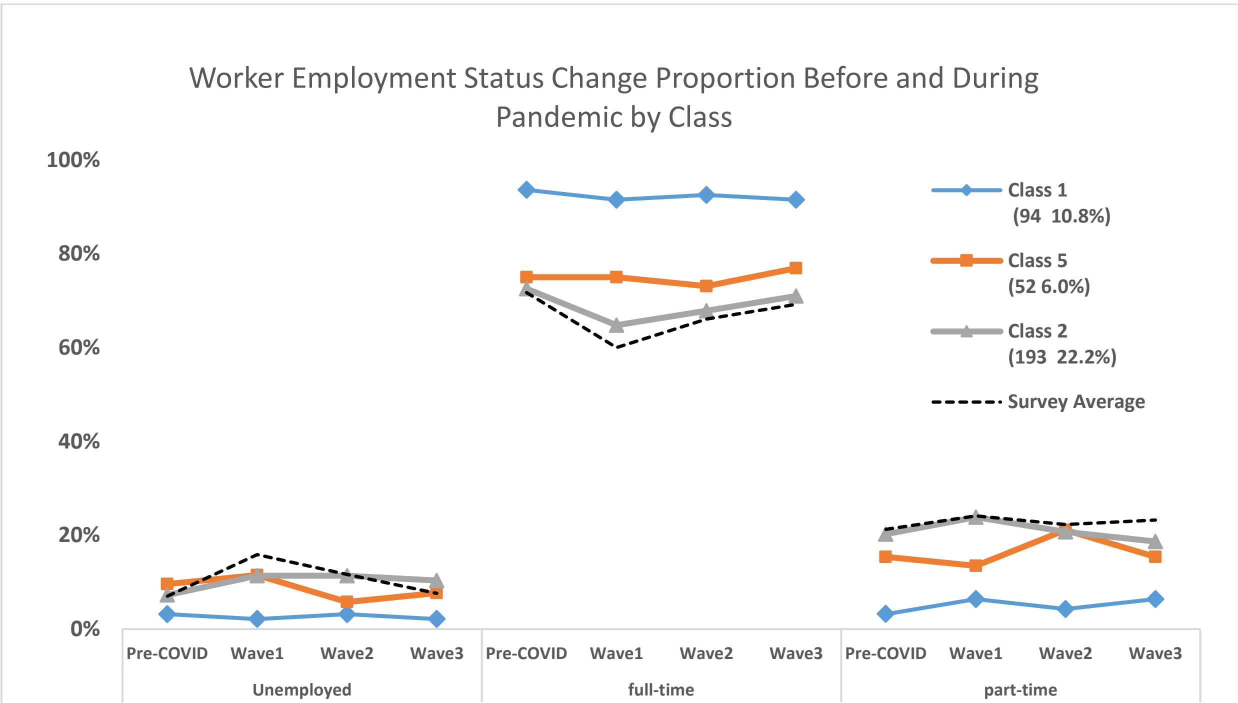

Figure 6.3a – Employment trends before and during the pandemic classes 1, 5, & 2

Delving deeper into full-time employment trends, we generally observe a significant decline across the board, reflecting the broader impact of the pandemic on employment. However, this trend is not uniform across all classes. Class 1, for instance, exhibits exceptional resilience, maintaining a stable rate of full-time employment throughout the pandemic. This stability suggests a seamless adaptation to remote work, mitigating potential employment losses.

Class 5 mirrors the trend seen in class 1, displaying a stable employment trajectory. This parallel indicates that class 5, similar to class 1, was less vulnerable to the fluctuations in employment triggered by the pandemic. Their ability to maintain a steady employment rate underscores a successful adjustment to the remote work environment and a resilience against pandemic-induced job market disruptions.

Class 2 presents a slightly different scenario. Although it is a larger class, its alignment with the full employment rate trend is less pronounced. However, it's important to note that the average unemployment rate in class 2 remains below the significant dip seen in the general trend. This indicates that while class 2 did contribute to the overall decrease in employment to some extent, its members fared better than many others in maintaining employment during the pandemic.

In summary, classes 1, 5, and 2 exhibit varying degrees of resilience in the face of pandemic-induced employment challenges. Class 1 stands out for its robust adaptation to remote work and sustained full-time employment, while class 5 shows similar stability. Class 2, despite being larger and contributing to the employment dip, still maintains a lower-than-average unemployment rate, indicating a better-than-expected performance in retaining jobs during the pandemic.

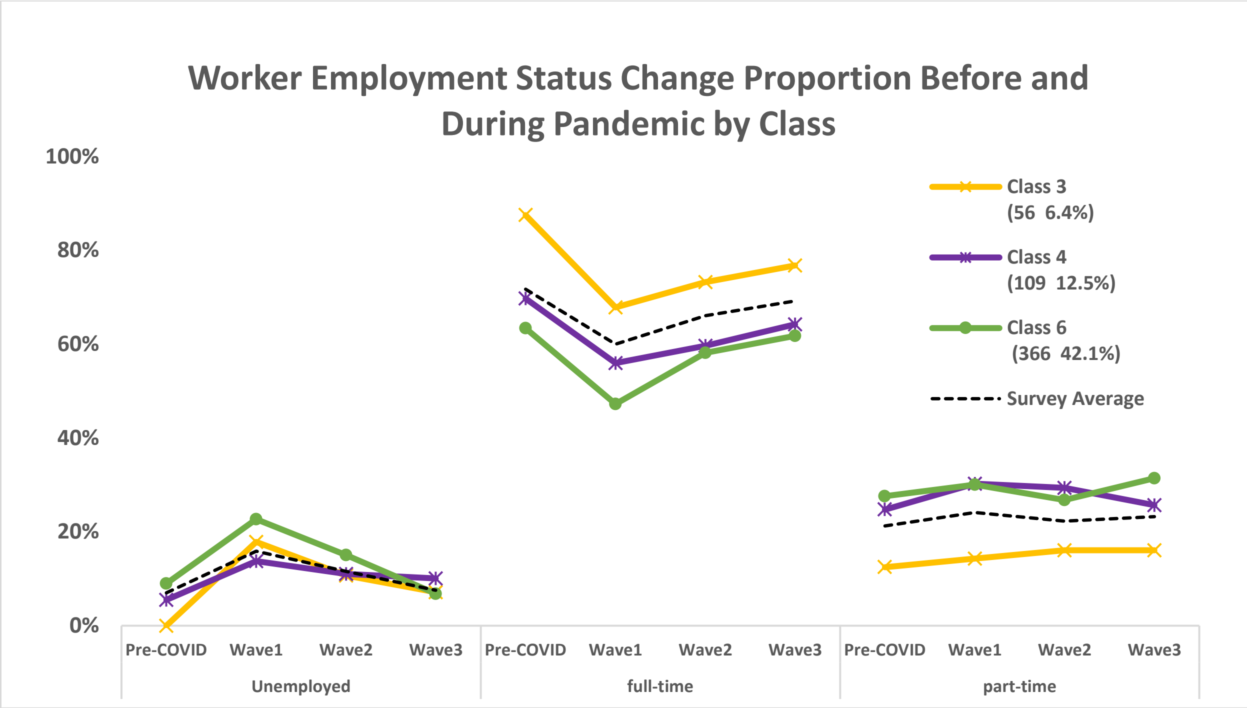

Figure 6.3b – Employment trends before and during the pandemic classes 3, 4, & 6

Turning to classes 3, 4, and 6, we discern a different pattern. Notably, class 3 exhibits a full-time employment rate significantly above the average, whereas class 6 is markedly below. These classes also display a pronounced dip, indicative of a higher impact from the pandemic. Despite the challenges, these classes show a positive outlook towards remote work, valuing reduced commuting. Interestingly, class 3 maintains a high full-time employment rate, resilient in the face of pandemic challenges.

A critical observation emerges when considering classes 3, 4, and 6 in relation to full-time employment rates. All three fall below the survey average, with their unemployment rates corresponding to this trend. This pattern particularly accentuates the challenges faced by class 6, which not only had a lower pre-pandemic proportion of full-time employment but also significantly contributed to the observed employment dip. Class 3, the smallest in terms of membership, also displays a marked contribution to this trend. Intriguingly, they hold a predominantly negative view towards remote work and do not adjust to telecommute very well, categorizing them as a disadvantaged group in the context of the pandemic's impact on employment.

In conclusion, the analysis reveals varied responses across different classes to the shift towards remote work, influenced by the pandemic. While some classes adapted and even thrived in this new work environment, others faced significant challenges, underscoring the need for nuanced policy interventions and support mechanisms tailored to the specific needs and preferences of each class.

6.4 Opportunity of Work from Home

In analyzing the variation in work-from-home opportunities among different classes, we focus on how these opportunities evolved during the pandemic and how they differ across classes. The analysis reveals that classes 1, 5, and 2 share similar trajectories, characterized by a high level of opportunity for remote work. This trend is evident across all waves of data collection, indicating a consistent and robust capacity for telecommuting within these groups.

On the other hand, class 4 exhibits a notable decrease in telecommuting opportunities, particularly from wave two onwards. This decline suggests that members of class 4, who were not telecommuting prior to the pandemic, continued to have limited opportunities to shift to remote work during the pandemic. In contrast, those who were already telecommuting before the pandemic generally maintained this mode of work.

Further, when we assess the actual realization of work-from-home opportunities in each wave, a disparity becomes apparent.

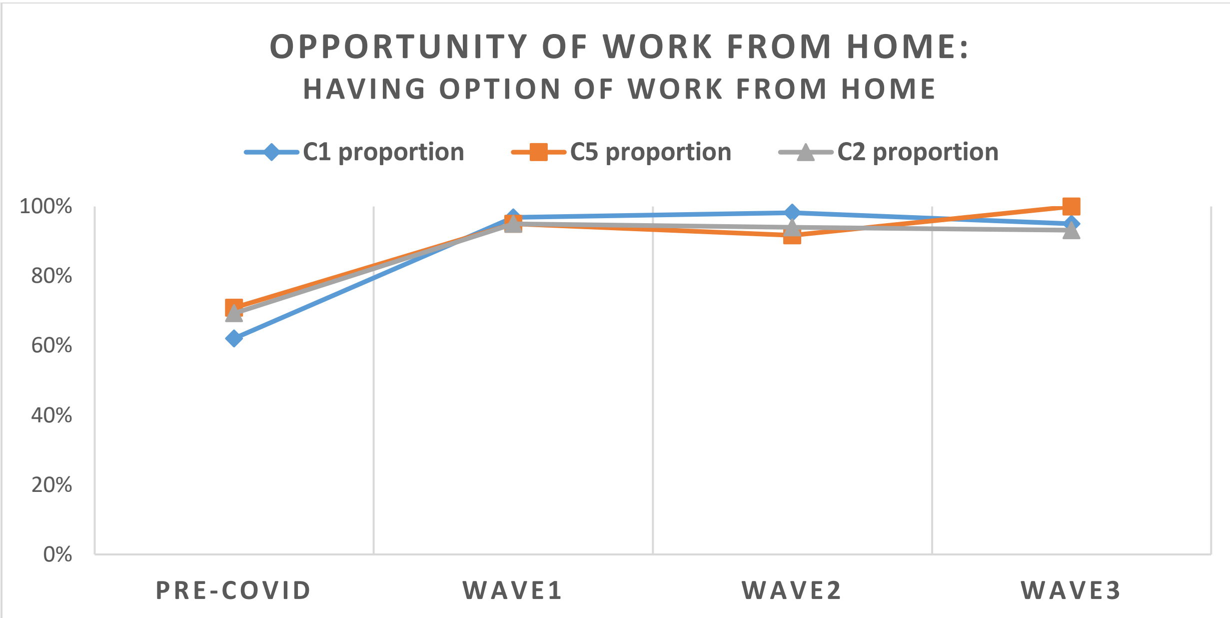

Figure 6.4a – Opportunity of work from home before and during the pandemic for classes 1, 5, & 2

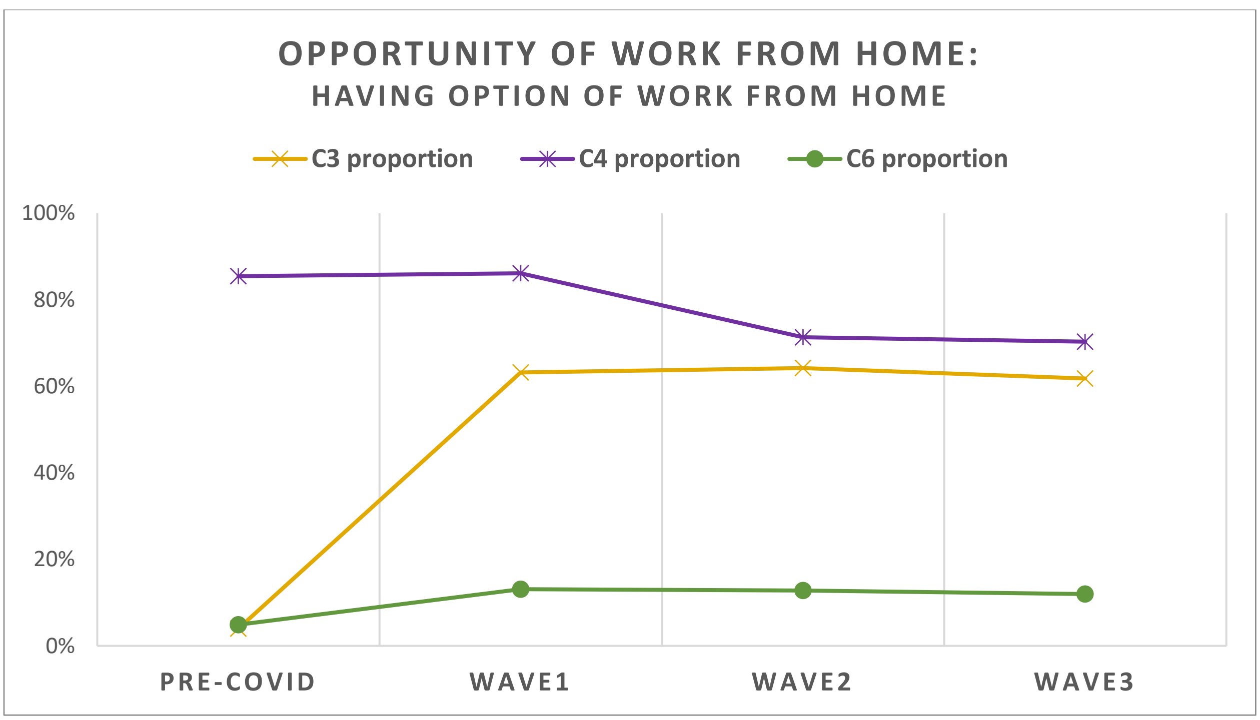

Figure 6.4b – Opportunity of work from home before and during the pandemic for classes 3, 4, & 6

A critical observation is made for class 3, where only 60% of individuals had the opportunity to work from home during the pandemic, despite having a capability rate as high as 86% for telecommuting. This significant gap between capability and actual opportunity indicates a unique challenge faced by class 3 compared to other groups.

The distinction between these classes becomes increasingly clear when considering all measured indicators.

In summary, this analysis reveals significant differences in the changes and realization of telecommuting opportunities among different classes during the pandemic. While classes 1, 5, and 2 consistently experienced high levels of telecommuting opportunities, classes 3, 4, and 6 faced distinct challenges, with class 3 notably underutilizing its telecommuting potential.

6.5 Experience of Work from Home at Higher Frequency (at least 5 days per week)

For high-frequency telecommuters, we observe significant variations among different classes. Specifically, the proportion of high-frequency telecommuters in classes 1, 5, and 2 surged notably, ranging between 60 to 80 percent. This increase indicates a strong trend toward sustained or increased telecommuting in these classes. When we broaden our analysis to include those who exclusively work from home without any commuting, we see that classes 1, 5, and 2 continue to exhibit similar trends, with class 5 having a relatively lower proportion of non-commuters. This pattern may suggest why class 5 experienced a significant change in telecommuting behavior. Specifically, class 5 may not have had sufficient opportunities for telecommuting in the initial phase of the pandemic, but as opportunities increased in subsequent

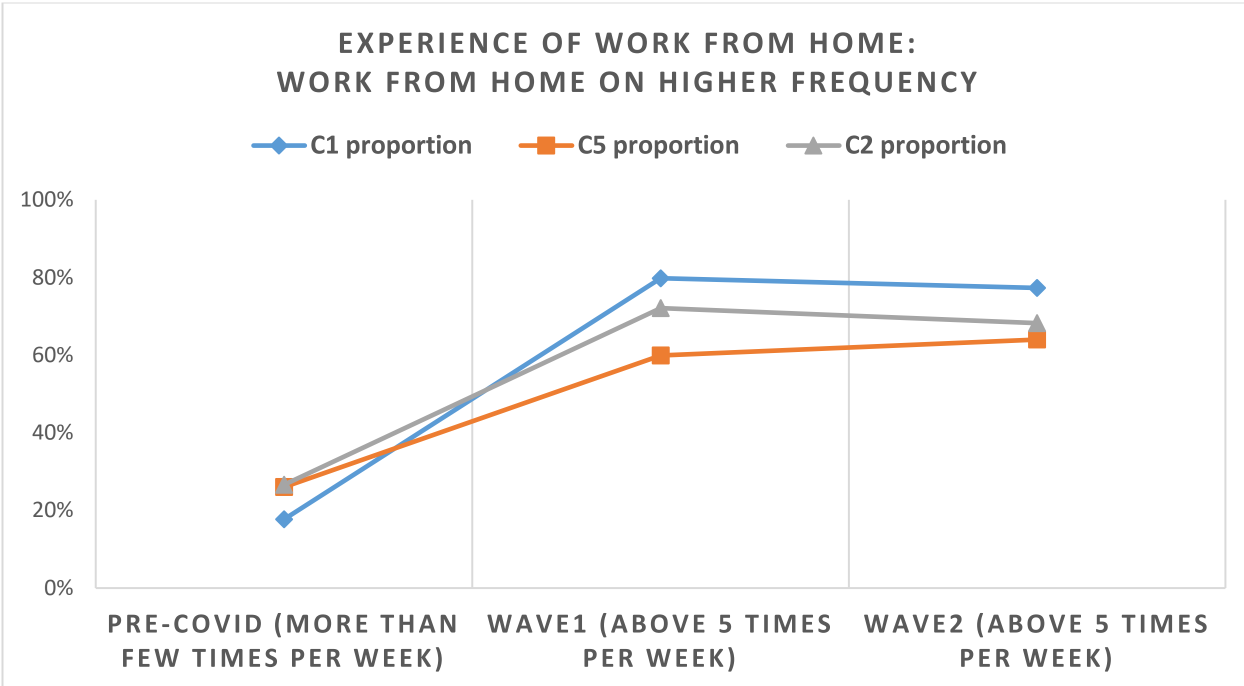

Figure 6.5a – Experience of high frequency work from home before and during the pandemic for classes 1, 5, & 2

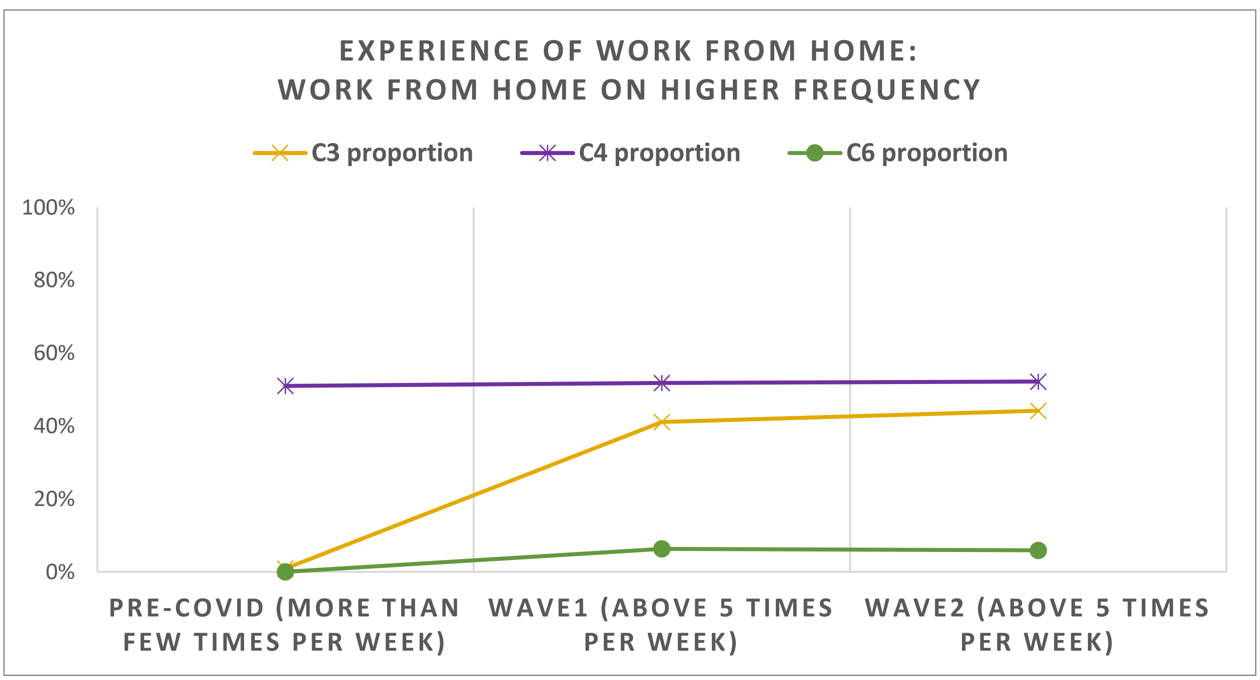

Figure 6.5b – Experience of high frequency work from home before and during the pandemic for classes 3, 4, & 6

waves, their telecommuting rates rose correspondingly. This rise could reflect a latent demand for telecommuting within class 5, which was only fulfilled later in the pandemic.

Conversely, class 4 presents a stark contrast, with its proportion of high-frequency telecommuters remaining remarkably stable. This stability suggests that while individuals in class 4 who were already telecommuting at a high frequency continued to do so, there was little to no transition among the rest of the class to higher telecommuting frequencies. This distinct pattern highlights class 4's unique response to the telecommuting trend.

Class 3, on the other hand, appears to have had insufficient opportunities to engage in high-frequency telecommuting, and class 6 consistently shows the lowest participation in this regard. This observation indicates potential barriers or lack of opportunities for these classes in adapting to a high-frequency telecommuting environment.

Class 4's steady rate of high-frequency telecommuters indicates a consistent pattern, where those accustomed to telecommuting continued while others did not shift their work mode. This steadiness implies a potentially entrenched work culture or external constraints that prevent a shift towards telecommuting.

In terms of the data available for analysis, we note that only wave one and two data are available for high-frequency telecommuters, as wave three lacks necessary variables. This limitation affects our ability to fully understand the telecommuting trends over the entire pandemic period.

Overall, these findings shed light on the differing dynamics of telecommuting across classes. While classes 1, 5, and 2 show high and increasing engagement in telecommuting, classes 4, 3, and 6 display varying levels of engagement, with class 4 maintaining a constant rate and classes 3 and 6 lagging behind. These variations suggest that while telecommuting has become a more prevalent work mode during the pandemic, its adoption and continuity are influenced by class-specific factors and opportunities.

6.6 Equitable Opportunities

The figure shows the worker class proportion of whom had work from home option before or at least one wave during pandemic. The variable aim is to measure if the worker in the class has the minimum exposure of work from home.

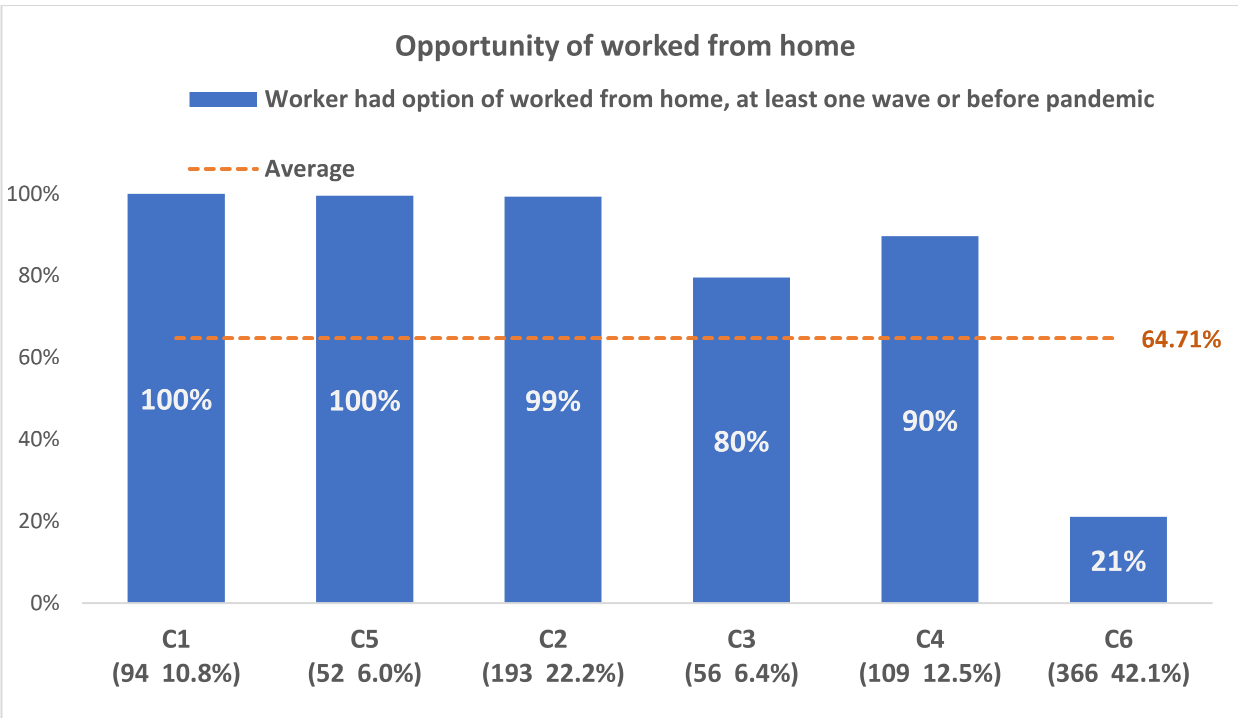

Figure 6.6 – Work from home opportunities

This chart provides a stark visual representation of the opportunities for working from home across various classes, offering insights into the discrepancies in telecommuting accessibility. Notably, classes 1, 5, and 2 exhibit exceptionally high percentages, with classes 1 and 5 reaching a full 100% and class 2 at 99%. These figures suggest that every member of class 1 and 5, and nearly every member of class 2, had the opportunity to work from home at least once during the pandemic or even before it began.

Class 4 also shows a high percentage, with 90% of its members having had the option to telecommute. This nearly aligns with the overall average opportunity rate of 64.71%, as indicated by the dashed orange line. However, the situation is markedly different for class 6, where only 21%—significantly below the average—had the option to work from home. This suggests a severe limitation in telecommuting opportunities for this class, which comprises the largest percentage of the population at 42.1%.

Class 3, while not as constrained as class 6, still sits below the average, with only 80% of its members having had the opportunity to telecommute. This relatively lower percentage indicates that class 3, despite being smaller in representation at 6.4%, faces its own challenges in accessing remote work opportunities.

The disparities highlighted by this chart are telling. They suggest that classes 1, 5, and 2 not only had the highest potential for telecommuting but also that almost all individuals in these classes were given the chance to experience working from home during the pandemic or earlier. In contrast, classes 3 and 6 appear to have been disproportionately disadvantaged in this respect. The low telecommuting option rates for these classes could be attributed to a lack of eligibility or other barriers that prevented them from having equal access to work-from-home opportunities. This differential in telecommuting potential underscores a broader issue of inequality in workplace flexibility and access that merits further investigation, particularly for the disproportionately affected classes 3 and

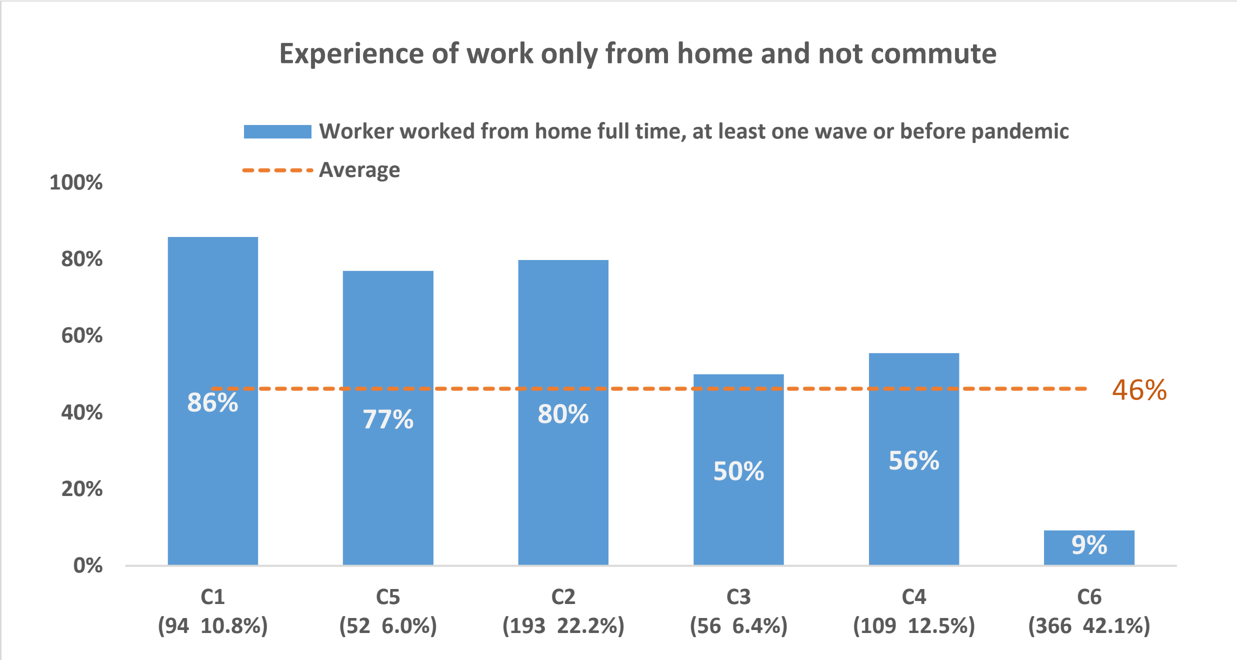

Figure 6.7 – Work from home experiences

The figure shows the worker class proportion of who had experienced being home remote worker before or at least one wave during pandemic. The variable aim is to measure if the worker in the class has the maximum exposure of work from home.

The chart illuminates the disparities in the full-time work-from-home experience across different classes, both during any of the waves of data collection and prior to the pandemic. Class 1 stands out with an 86% rate of workers who worked from home full-time, which is notably above the average of 46%. Classes 5 and 2 also report high percentages, at 77% and 80% respectively, signaling a substantial proportion of their workforce had the opportunity to work exclusively from home.

However, class 3, with only 50% of its workforce having experienced full-time remote work, aligns exactly with the average. This suggests a significant divide within the class itself, where half the group might not have had the same level of access to remote work as their counterparts.

Class 4 is only slightly above this average, with 56% of its members having worked from home full-time, indicating that a notable portion of its workers were not remote workers.

Class 6 presents the most striking figure, with a mere 9% having experienced full-time home working, suggesting that the vast majority of this class was required to commute and could not participate in remote work. This low figure starkly highlights the limited remote work opportunities for class 6, which is particularly concerning given that this class constitutes the largest share of the population at 42.1%.

The implications of these findings are significant. The ability to work from home full-time correlates with a worker's expectations and preferences for future work arrangements. Those who have had the experience of telecommuting full-time during the pandemic, or even before, are more likely to expect and to be able to continue such arrangements in the future. Conversely, those who have not had the opportunity to work remotely are deprived of this experience, potentially affecting their future work expectations and preferences.

These disparities in work-from-home experiences across classes underscore a critical area of concern. The data suggests that there is an uneven distribution of remote work opportunities, with some classes significantly more disadvantaged than others. This uneven access could have long-term implications on workforce dynamics, job satisfaction, and the overall integration of remote work into future employment models.

6.7 Policy Changes Worker's Telecommuter/Commuter Type Expectation Based on Opportunity Change

Under The Current opportunity, workers were asked the question below:

You told us you expect to have the choice to work from home once society reaches a post-COVID new normal. How much do you expect you will work from home?

The high and low frequency commuter splitting with home remote work and regular commuter proportion was given in the figure. This is in use as a based proportion to be compared with the policy change of opportunity Scenarios.

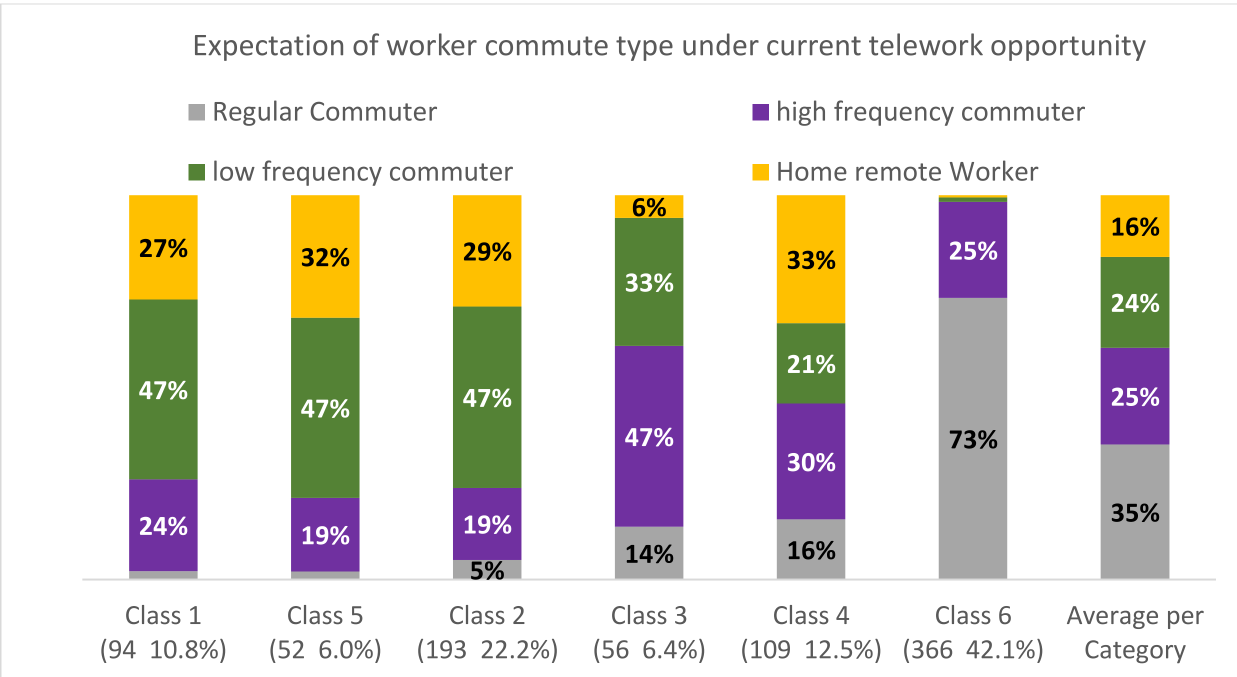

Figure 6.8 – Commute type expectation under current telework opportunity by class

6.7.1 Scenario 1: Worker given Maximum Opportunity

The question for this scenario is “If your employer offered the option to work from home as much as you want after COVID-19 is no longer a threat, how much would you want to?” Answer to Q1 and Q2 are both telecommute frequency.

The provided bar charts depict the expected changes in commuting frequency based on current telework opportunities and potential policy changes that increase these opportunities. The first chart indicates that under the current scenario, 25% of hybrid workers expect to be high-frequency commuters, while 24% expect to be low-frequency commuters. However, when presented with the hypothetical scenario where their employer offers unlimited telecommuting opportunities post-COVID-19, there is a noticeable shift: an additional 10% of workers anticipate moving from high-frequency to low-frequency commuting. This shift suggests that if given more autonomy over their work location, a significant portion of the workforce would opt to telecommute more often, which we can interpret as the upper boundary of a policy's influence on telecommuting behavior.

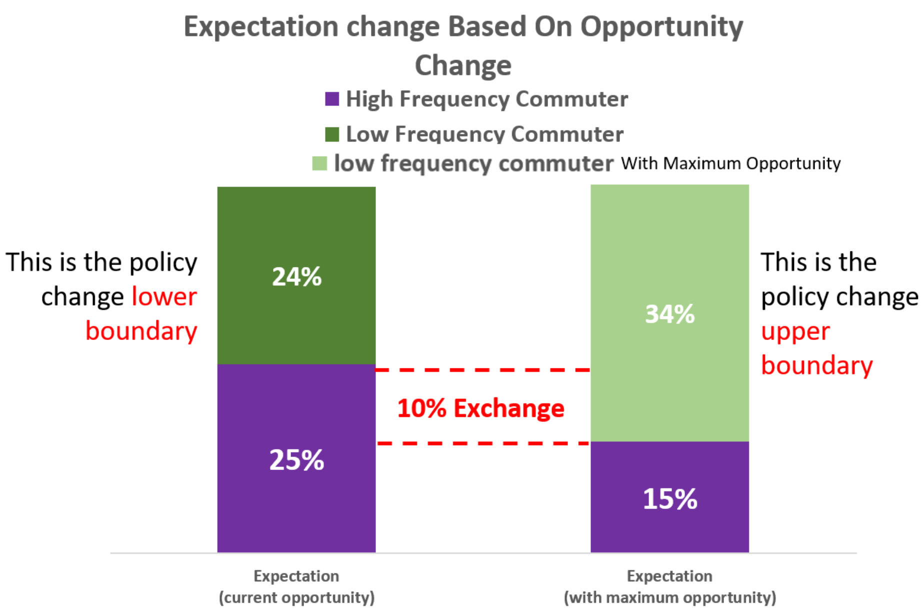

Figure 6.9 – Expectation change based on opportunity change

The subsequent charts compare the expectations of commute types under current telework opportunities and under a scenario of increased opportunities provided by employers. The charts show that, given more telework opportunities, there is a substantial increase in the proportion of workers expecting to become low-frequency commuters and home remote workers across all classes, with the most considerable shifts observed in classes 1, 2, and 5. This indicates that these classes have a higher demand for telecommuting that is not currently being met under existing policies.

By setting up these scenario policy change variables based on the two questions about current and desired telecommuting frequency, we can delineate the boundaries of potential policy impacts. The purple and dark green blocks in the charts represent the proportion of high and low-frequency hybrid commuters, respectively. They highlight the current and potential future states of commuting frequency under different policy scenarios, providing a framework for understanding the elasticity of worker commute preferences in response to policy changes.

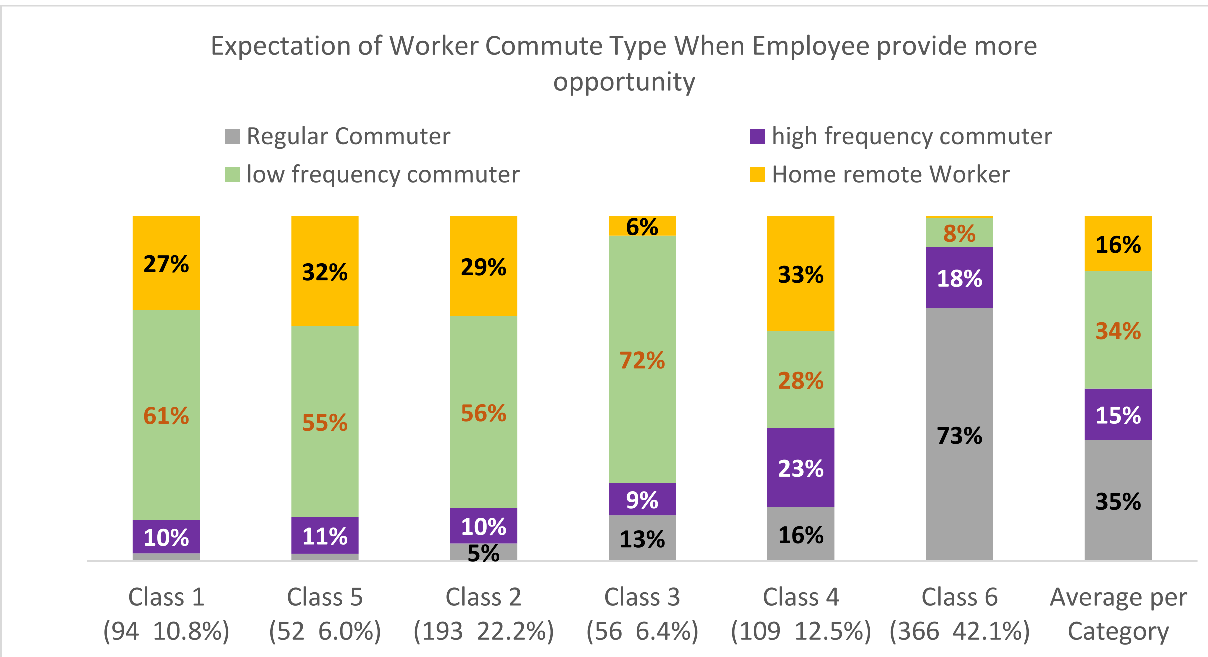

Figure 6.10 – Commute type expectation after opportunity change by class

In summary, these findings illustrate that there is an unmet demand for telecommuting among workers, which could be capitalized on by policy changes. The depicted boundaries serve as a benchmark for policymakers to estimate the maximum potential shift in commuting behavior due to policy interventions, thereby informing the development of future telework and transportation policies.

Analyzing the data by class reveals distinct variations in how each demographic responds to the possibility of increased telecommuting opportunities. Class 3 emerges as particularly noteworthy. Initially, 33% of its members identified as low-frequency commuters, which corresponds to a high rate of telecommuting. However, when presented with the hypothetical of unrestricted telecommuting, this figure soars to 72%. This leap signifies a pronounced sensitivity to policy changes within class 3, marking a stark contrast to other classes, which generally exhibit a more modest increase of 10 to 15 percentage points—even in class 6, where the majority are regular commuters.

The data suggests a shift in mindset across the workforce when additional telecommuting options are introduced. Classes 1, 5, and 2 initially had 47% of their workers commuting at low frequencies. With the prospect of more telecommuting freedom, these classes experience an 8 to 14 percentage point shift towards high-frequency telecommuting, indicating a moderate growth of about 10%.

In the case of class 3, the data underscores a significant behavioral change—a 35 percentage point exchange—where a considerable number of workers transition to low-frequency commuting. This dramatic jump prompts questions regarding the equity of opportunity distribution among the classes. Are the opportunities to telecommute being allocated fairly? The disparity in class 3's response suggests that their current telecommuting needs might not be adequately met under present conditions.

The overall trend indicates a collective inclination towards telecommuting, with a remarkable increase in the preference for low-frequency commuting, particularly when greater flexibility is offered. Even the least responsive group, class 6, shows an increase in low-frequency commuting preferences from 1% to 8%. This indicates a general positive reception towards remote work, underscoring an inherent desire among the workforce to telecommute more if given the chance—with class 3 being the most demonstrative of this sentiment.

6.7.2 Scenario 2: Worker Can Exchange Assigned Job Workspace for Higher Frequency Telecommute

The sequence question is asking "Do you have your own assigned office or workspace at your workplace?" The next question following in a specifically way the next about switching to higher frequency of telecommuter "If you could work from home **a few times/week**, how would you feel about giving up your assigned office or workspace at your workplace?"

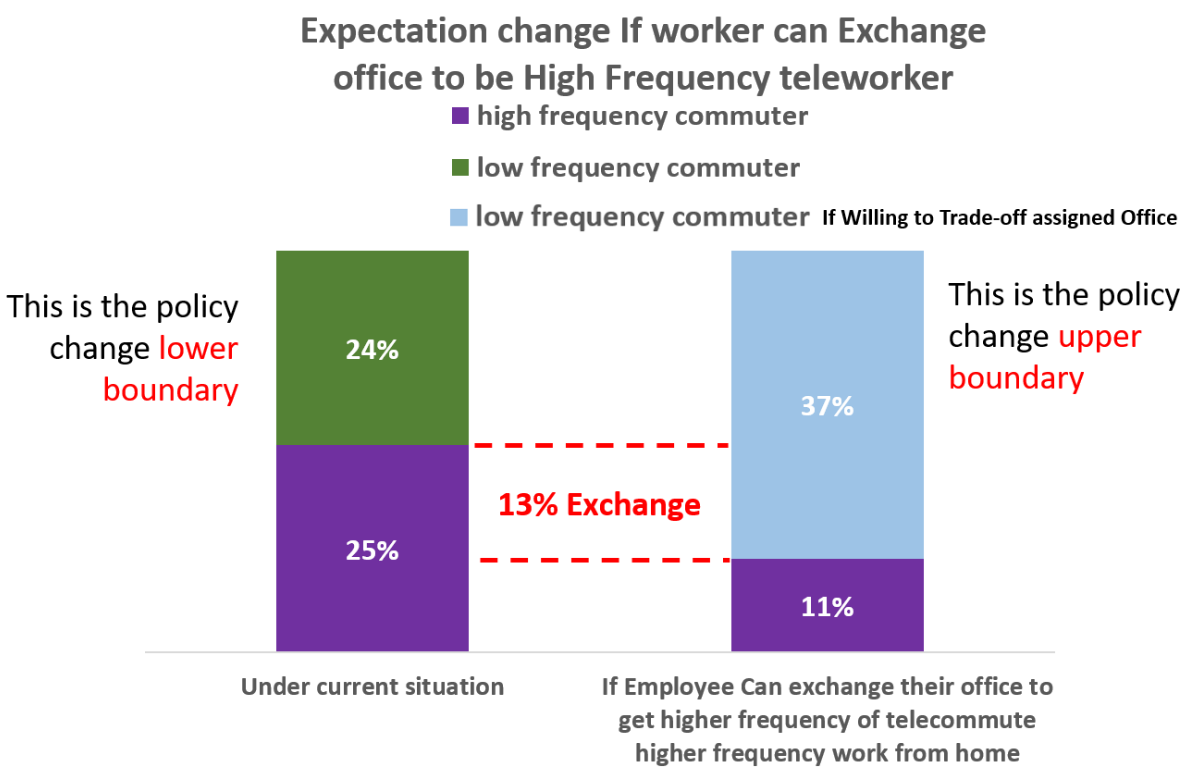

Figure 6.11 – Expectation change based on workspace trade

Analyzing the impact of a policy that offers workers the option to exchange their dedicated workspace at their employer's location for increased telecommuting reveals noteworthy class-specific dynamics. The policy scenario posits that by relinquishing their assigned office—a tangible asset at the workplace—employees could benefit from a higher frequency of remote work.

Overall, the data suggests a significant inclination toward accepting this trade-off, with the proportion of workers classified as low-frequency commuters (as depicted by the blue bar) rising from 24% to 37%. This represents a 13% potential increase in high-frequency telecommuting, which we can regard as the policy change's upper boundary.

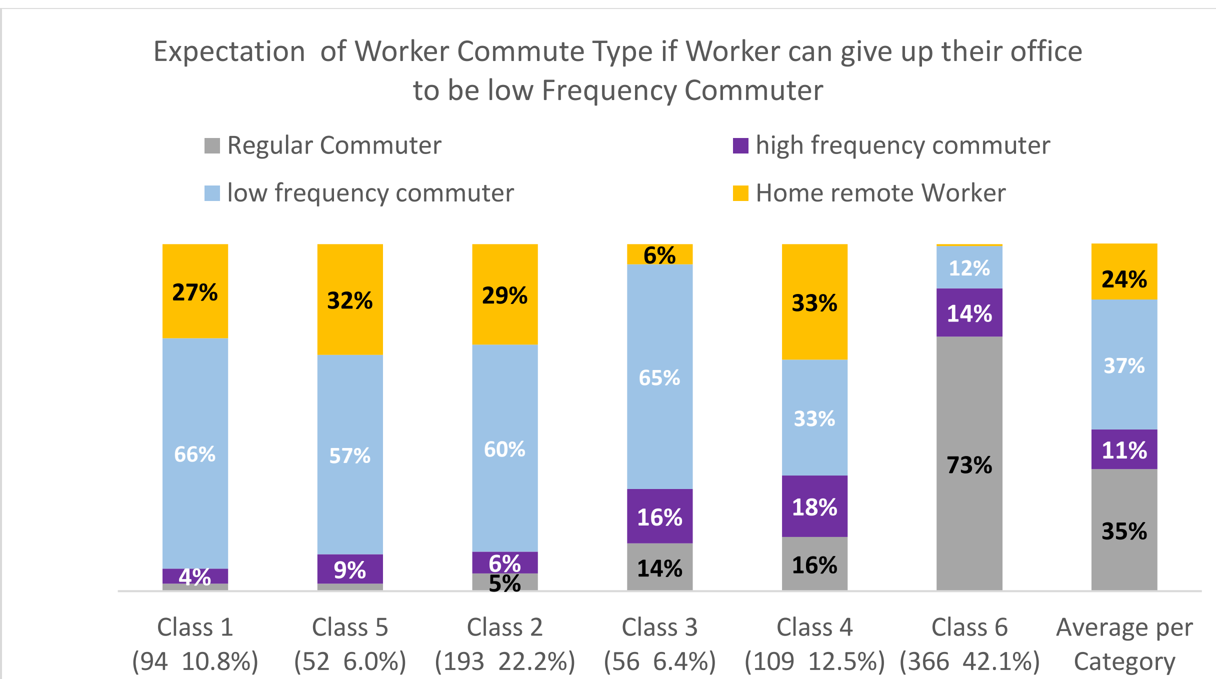

Figure 6.12 – Commute type expectation after workspace exchange by class

Delving into the specifics, 52% of workers report having a personal assigned office. When prompted with the hypothetical of giving up this personal workspace in exchange for more frequent telecommuting—defined as several times a week—a 13% shift is observed. This indicates that a notable portion of the workforce values the flexibility of telecommuting over the permanence of a personal office and suggests a willingness to adapt to new work arrangements that prioritize telecommuting.

However, this 13% exchange rate does not uniformly align across all data points, hinting at complex underlying factors influencing these decisions. The variation could be attributed to different classes' unique circumstances or possibly to disparities in how questions were administered across the survey waves. Some of the incongruence may also stem from missing data, particularly regarding the assigned office question, where not all respondents provided an answer.

It's crucial to consider that the two sets of questions serve distinct purposes within the survey. The first set was directed at all employed individuals, including those who were employed pre-pandemic, while the follow-up question regarding the willingness to give up assigned offices targeted only current employees. This methodological distinction may necessitate a recalibration of the figures to account for non-responses and the specific subset of the workforce being surveyed.

In summary, the data analysis uncovers a palpable readiness among workers to embrace more flexible telecommuting options, even at the cost of their personal workspace. This readiness varies by class and is subject to the nuances of survey methodology and participant response rates. Understanding these subtleties is crucial for policymakers aiming to craft effective telecommuting policies that reflect the preferences and needs of the contemporary workforce.

6.8 Insight of Workplace

The figure presents a policy scenario examining the willingness of employees across different classes to trade their assigned office or workspace for the option to telecommute more frequently. The green solid line represents the percentage of employees in each class who report having an assigned office or workspace. The blue dashed line indicates the proportion of those employees who would be willing to exchange their assigned space for a higher frequency of telecommuting.

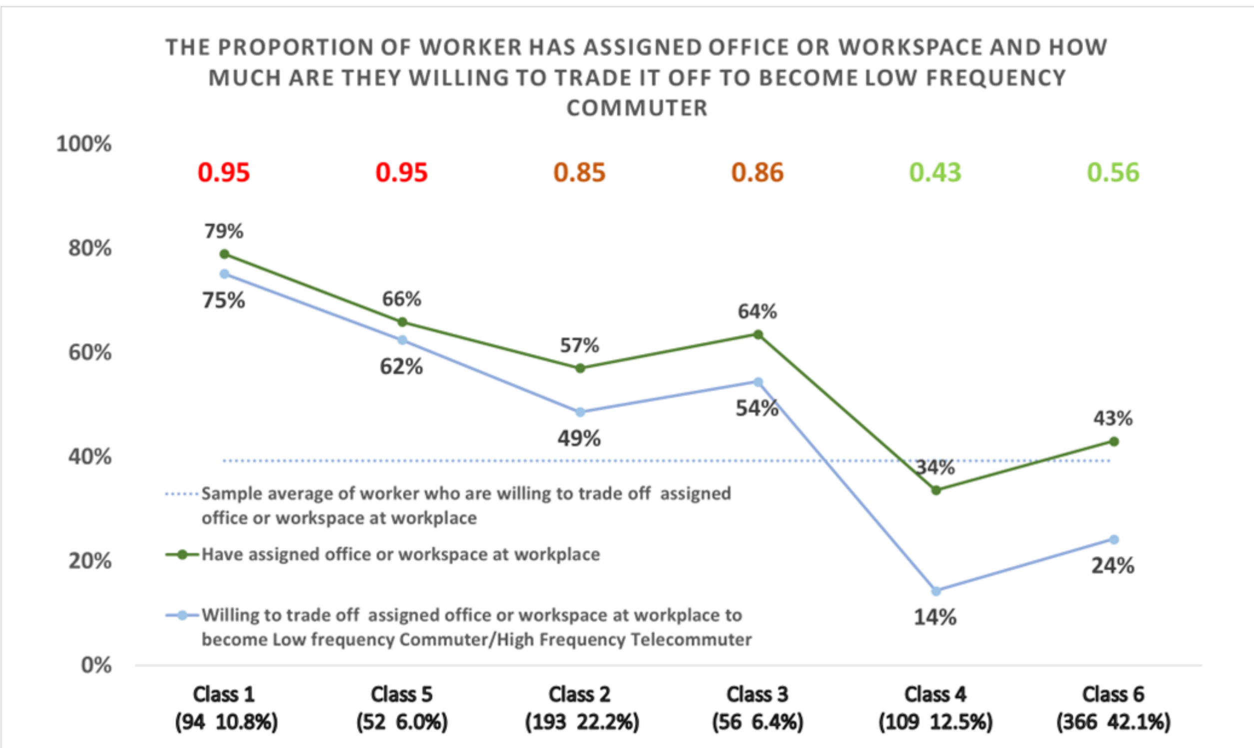

Figure 6.13 – Willingness to trade office space to commute less

Upon analyzing the data, we observe a significant variance among the classes. On top of the figure is the proportion of workers in each class willing to trade-off office to exchange higher telecommute frequencies.

For classes 1 and 5, an overwhelming majority as 95%, in classes 2 and 3 around 85% of those with assigned offices are open to trading their office for more telecommuting opportunities. This high willingness to trade suggests that employees in these classes may not deem a fixed workplace as essential for their productivity or job satisfaction.

Conversely, class 4 and 6 display lower percentages of employees with assigned offices, and correspondingly, a smaller proportion of these workers are willing to make the trade for more telecommuting. Notably, only 14% in class 4 and 24% in class 6 show willingness to exchange their office space, indicating that the office holds more significance for these workers, or they may have less flexibility in their roles.

This figure is crucial as it raises additional questions about the value and necessity of a dedicated workspace for employees. It suggests that workplace attachment and the need for a physical office may vary significantly by class, which could inform future workplace policies. For example, employees in classes 1, 2, 3 and 5 who predominantly have assigned offices, are considerably more open to relinquishing their physical workspaces in favor of more flexible telecommuting options, these results indicate that the necessity of personal office space could be a significant factor in policy development.

The trend among large tech companies to move away from centralized offices and the impact on office space rental markets over recent years echo these findings. From an employee's perspective, there appears to be a perceived advantage in having the option to telecommute more frequently.

Future surveys should be designed to gain a deeper understanding of employees' dependencies on their workplace. Traditional models assume a default of commuting to a central location for work; however, in a potential shift towards hybrid arrangements, factors such as in-person collaboration and the need for collegial contact must be re-evaluated. Understanding these dynamics is essential for developing flexible work policies that align with evolving employee preferences and needs.

6.9 Summary

The discussion has centered on the analysis of telecommuting preferences and the potential for policy interventions to influence these preferences across different socio-economic classes. The data indicates significant class-based disparities in both the current ability to telecommute and the willingness to embrace higher frequencies of telecommuting if given the opportunity.

Class 3 has been identified as particularly responsive to the prospect of increased telecommuting opportunities, displaying a notable willingness to transition to high-frequency telecommuting. This is contrasted by classes 4 and 6, which exhibit less inclination to relinquish their physical workspaces for remote work. Interestingly, classes 1, 5, and 2, which have a high proportion of workers with assigned offices, show a substantial readiness to trade their dedicated workspaces for the ability to telecommute more often.

This exploration reveals that personal office space is variably valued across classes, which could reflect differences in job functions, the nature of work, or the perceived benefits of telecommuting. The data suggests a broader trend of employees valuing flexibility and the option to work remotely, a sentiment echoed by the evolving policies of large tech companies and shifts in the office rental market.

Future research should delve deeper into the nuances of workplace attachment and the role of physical office space in productivity and job satisfaction. Surveys should be carefully designed to minimize framing biases and more accurately capture the trade-offs employees are willing to make. Further studies should also consider the impact of hybrid work arrangements on collaboration and in-person interactions, adapting traditional employment models to reflect these preferences.

In conclusion, the data points toward a future where flexible telecommuting policies could play a significant role in shaping the workforce. A nuanced understanding of employees' preferences and the factors influencing their willingness to telecommute is crucial for developing policies that support a balanced and equitable transition to more adaptable work arrangements.

CHAPTER 7

CONCLUSION

7.1 Contributions

7.1.1 Abstracting Telecommuting as an Activity

This research introduces a novel conceptualization of telecommuting, treating it not merely as a work arrangement, but as an activity characterized by both supply and demand dynamics. This reconceptualization is necessitated by the observed dramatic shift in telecommuting rates – from 7.9% to 28% – indicating a profound transformation in workforce behaviors. Traditional models prove inadequate in capturing this seismic shift. Consequently, this study proposes an updated theoretical framework and modeling approach, designed to accurately reflect the current realities of workforce dynamics.

7.1.2 Defining and Incorporating Teleworking Capability

A unique aspect of this research is the introduction and definition of 'teleworking capability' – a concept that extends beyond the conventional understanding of telecommuting. This notion encapsulates the nature of work, emphasizing the relevance of individual skills and educational backgrounds, as well as the broader impacts on organizational structures and the economy at large. This concept of teleworking capability underscores the need for a societal focus on adapting to the evolving nature of work, particularly in the context of increasing telecommuting trends.

7.1.3 Methodological Innovation in Modeling Telecommuting

In addition to the conceptual contributions, this research introduces a significant methodological innovation in modeling telecommuting, particularly relevant during the pandemic period. This methodology provides a nuanced approach to identifying indicators and framing modeling efforts, specifically tailored to the unique circumstances of the pandemic. It is crucial to note that this methodology is not intended for direct application in regional models. Instead, it serves as a sophisticated classification system, utilizing Latent Class Analysis (LCA) to categorize individuals based on their commuting patterns. This is followed by further modeling processes to achieve more detailed and realistic distributions of commuter types.

7.1.4 Application in Policy and Planning Contexts

The methodology delineated in this research is instrumental in identifying key factors for future studies, which hold significant relevance for policy objectives, particularly in light of the observed outcomes and demographic disparities. This approach offers a path forward for planners and policymakers, providing insights that are pivotal for advancing socio-technological and economic goals while simultaneously achieving environmental benefits. The methodology does not advocate for a straightforward application but rather emphasizes a deeper understanding and adaptation for specific contexts.

Ultimately, this research contributes to a broader discourse on how best to integrate telecommuting into our evolving societal framework, providing valuable guidance for future modeling efforts and policy considerations. The findings and methodologies presented herein underscore the potential for leveraging telecommuting to achieve sustainable and equitable outcomes in urban and regional planning.

7.2 Limitations of the Current Study

7.2.1 Model Design Limitation

The model's design does not accommodate the reflection of activity changes.

The prevailing regional model operates on an activity-based framework, yet it incorporates elements of a tour-based design. This model systematically organizes tour patterns based on predefined role choices: work, school, both, other, and none. Each role is associated with distinct tour patterns nested within it. These tour pattern proportions are meticulously adhered to during the model's process of estimating the final pattern decisions. To illustrate, the California Statewide Travel Demand Model (CSTDM) reveals that, in the 2012 California Household Travel Survey, 33.4% of all tours were categorized as work tours. This specific proportion is not only replicated in future scenario projections to align with survey results but also plays a crucial role in the model's calibration, given its multinomial logistic regression design.

Moreover, within the framework of a typical workday pattern (specifically for those identified as workers), tours are defined through multiple dimensions: the Work Tours and Time Periods, the Number of Diversion Stops on Work Tour, and the Complexity and Number of Nonwork Tours. These dimensions are articulated by Cambridge Systematics Inc. in their 2014 report (Part 2 of 3). Each of these dimensions has a fixed proportion, directly derived from historical survey data, and these proportions are intended to be preserved in future estimations. As a result, the tour pattern is intrinsically linked to the survey data. However, significant changes in activities, such as the substitution of commuting with telecommuting, render the old survey results obsolete. To adapt to such shifts in activity patterns, irrespective of the situation, the implementation of a new survey becomes imperative.

7.2.2 Survey Data Limitation

7.2.2.1 Limited Insight from the Current Survey

The survey utilized in this study, namely the ASU COVID future survey, offers limited insights into commute status and falls short in providing a comprehensive understanding of travel patterns. This limitation restricts the study's analysis to merely identifying commute statuses, without the capacity to trace and analyze subsequent travel patterns of commuters or telecommuters. Future research endeavors should aim to integrate these detailed travel patterns into the analytical framework. The need to categorize emerging patterns as either telecommuter or commuter types remains, but with a renewed emphasis on the commuting aspect. This focus is critical, as the primary objective of the model is to estimate the number of people engaged in commuting activities, a fundamental aspect of this study's design.

7.2.2.2 Impact on Policy Analysis and Definition Limitations

A significant limitation of the survey is its inadequacy in influencing policy changes. The survey currently does not permit a redefinition of the 'home remote worker' classification, as this designation is tied to a variable distinct from the queries related to telecommunication preferences. Consequently, it is not feasible to categorize individuals who express a desire to telecommute daily as definitive telecommuters. This is primarily because telecommuting and commuting can occur concurrently, even within the same day, making a clear-cut classification based on the survey responses unfeasible and potentially misleading.

7.2.2.3 Absence of Detailed Travel Patterns and Employer Information

The study's focus on behavioral changes in telecommunication is hindered by the lack of detailed travel schedules and patterns in the survey data. This gap significantly reduces the potential benefits that could be derived from an Activity-Based Model (ABM). Future research should address this by incorporating more comprehensive data, particularly those elements relevant to metropolitan planning organizations (MPOs), such as workspace environment, work flexibility, and the ability to work remotely.

Assessment of Policy Impacts and Home Remote Work: The current survey data inadequately captures the nuances required for assessing policy impacts, particularly concerning the classification of home remote workers. The transition between frequent and infrequent commuters is feasible within the data; however, the survey's approach to defining home remote workers, based on expected travel modes, falls short in the context of policy analysis.

Lack of Employer-Side Information: A critical gap in the survey is the complete absence of employer-side information. This missing dimension limits the study’s ability to fully comprehend and analyze the dynamics of telecommuting and its implications on both individual and organizational levels.

In summary, this excerpt critically examines the limitations of the survey data used in the study, highlighting its constraints in adequately capturing commute statuses, travel patterns, and employer perspectives. These limitations underscore the need for more comprehensive data collection and analysis in future research to enhance the understanding and modeling of telecommuting behavior.

7.3 Future work suggestion

Continued refinement and validation of the model with new survey and in different contexts will enhance its applicability and accuracy.

This framework could be borrowed but my suggestion is that in the future, people's preference and observed proportion of the telecommute type may continue to change. Mostly, I think we need to better understand the motivations of companies and employees to offer and accept work from home options so that we can survey this newly prevalent work pattern.

We need more information about the workplace. Currently, the connection between a worker's capability (their ability to work remotely) and opportunity (permission to work remotely) plays a significant role in determining the outcomes of telecommuting. Yet, for a more precise understanding of workers' telecommuting and commuting behaviors, direct information from surveys detailing actual work schedules and explicitly indicating commuting status is crucial. Additionally, a deeper insight into work flexibility is required, including the extent of colleague support needed by the worker and the level of support they are expected to provide in return. Understanding the role that the physical workplace plays in the worker's job is also essential to fully grasp the dynamics of telecommuting and commuting.

It is critically important to elucidate the dynamics between telecommuting and commuting, particularly in terms of how and when individuals transition between these modes, the timing of these shifts, and the patterns of hybrid commuting that combine both elements. To achieve a comprehensive understanding, future surveys should be designed to specifically explore telecommuting as an integral part of overall travel behavior, capturing the nuances of these evolving work and travel patterns.

The model’s adaptability to policy changes is a crucial strength, yet it demands ongoing updates and recalibrations to stay relevant in the evolving socio-economic landscapes shaped by events like the COVID-19 pandemic.

McNally's in-depth study reveals that in the United States, the pandemic led to a significant decrease in work-related trips but an increase in non-work trips. This change resulted in an overall increase in the total number of trips and Passenger Miles Traveled (PMT), despite a 13% reduction in Vehicle Miles Traveled (VMT) in 2020 compared to 2019, as per Federal Highway Administration data (McNally, M. G., Rafiq, R., & Uddin, M. Y. S., 2023). These trends suggest a shift from work-related tours to activities of a different nature, indicating changing travel patterns in society. Moreover, the pandemic era witnessed a remarkable surge in e-commerce and associated delivery trips. E-commerce sales in the U.S. soared by 43% in 2020, and this pattern was reflected globally, with a notable increase in consumer e-commerce deliveries. The shift towards online shopping and home delivery services was further substantiated by studies showing most U.S. households turning to online grocery shopping, often for the first time. This sustained trend towards e-commerce and delivery services persisted into 2021, even as pandemic restrictions eased. These insights are vital for transportation planning, particularly for California’s Metropolitan Planning Organizations (MPOs), which need to integrate such behavioral shifts into their Sustainable Community Strategies to meet greenhouse gas reduction targets. Most MPOs are implementing work-from-home policies, but the long-term viability of these policies needs more empirical evidence. The challenge in policy testing lies in isolating specific impacts, such as the effect of telecommute frequency, from the broader spectrum of human activities that co-occur in real-world scenarios. The pandemic period serves as a case study where, despite widespread telecommuting, the overall alteration in human activities complicates the assessment of telecommuting's isolated effects.

7.4 Conclusion

Reflecting on Methodological Contributions and Applications

This research presents a methodological framework designed to identify critical indicators and frame a comprehensive modeling effort, particularly relevant in the context of the COVID-19 pandemic. It is imperative to recognize that this methodology, primarily utilizing Latent Class Analysis (LCA) to categorize individuals based on their commuting behavior, is not a standalone model for direct application in regional planning. Instead, it serves as a sophisticated approach to classify and understand commuter types, facilitating subsequent models that yield realistic and detailed distributions of commuting patterns.

Implications for Policy and Planning

While the methodology itself is not intended for immediate application in regional models, it distinctly highlights key areas for future research, crucial for achieving policy objectives. The outcomes of this research, particularly the demographic differences observed, underscore the importance of these factors in policy development and planning. This research contributes significantly to the discourse on telecommuting and commuting, providing planners and policymakers with a robust framework to better understand and adapt to evolving socioecological and economic conditions.

Envisioning the Future of Socioecological and Economic Progress

In conclusion, the implications of this study extend beyond academic discourse, offering tangible opportunities for planners and policymakers. By embracing the insights and methodologies presented, there is potential for significant advancements in our socioecological and economic landscape, especially in the context of environmental stewardship. The research thus stands as a testament to the evolving nature of work and commute behaviors, urging a continuous and adaptive approach in policy making and urban planning to align with these changes.

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