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# An Investigation of Dissonance in Telework Frequency

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# An Investigation of Dissonance in Telework Frequency

**by**

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## Abstract


### An Investigation of Dissonance in Telework Frequency

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The remote work arrangement trend engendered by the pandemic continues to be prevalent today in most work sectors. But some employers have reverted to an all in-person office workday system recently, with no allowance for remote work despite their employees' desire for such flexibility. At the same time, some employees may prefer more office-based workdays than what their employer is able to offer today based on office rotation schemes and office downsizing. The challenge to find a harmonious balance between employee and employer preferences and perceptions regarding telework raises the issue of telework frequency dissonance (TFD). The purpose of this study is to investigate this pandemic-induced TFD. The data for our study is derived from the third wave of the COVID Future Panel Survey which was deployed across the United States in the Fall of 2021. The survey includes information regarding employees' existing telework frequency (ETF) and ideal telework frequency (ITF). These two dimensions are jointly modeled as a function of socioeconomic and demographic explanatory variables. The findings from this study provide important insights regarding how best to balance employee and employer preferences regarding work arrangements. Given the important effects of work

arrangements on commute and non-commute travel, the findings from our study should help inform land use and travel models regarding predicting our transportation future.

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# Chapter 1: Introduction

The outbreak of COVID-19 has led to many challenges and changes to our society, including a significant shift in workplace locations. At the start of the pandemic, most employees were forced to work remotely from home as a result of lockdowns and social distancing measures as a means to contain the spread of the virus. Many individuals who never worked from home before experienced this new work modality, while those who were able to telework only for a few days a month before the pandemic experienced more remote work from home and other non-office locations. At the same time, because of the increased remote work during the pandemic, many employers also witnessed benefits, such as lower real estate and operating costs (Sweet and Scott, 2022; Boland et al., 2020; Türkes and Vuta, 2022).

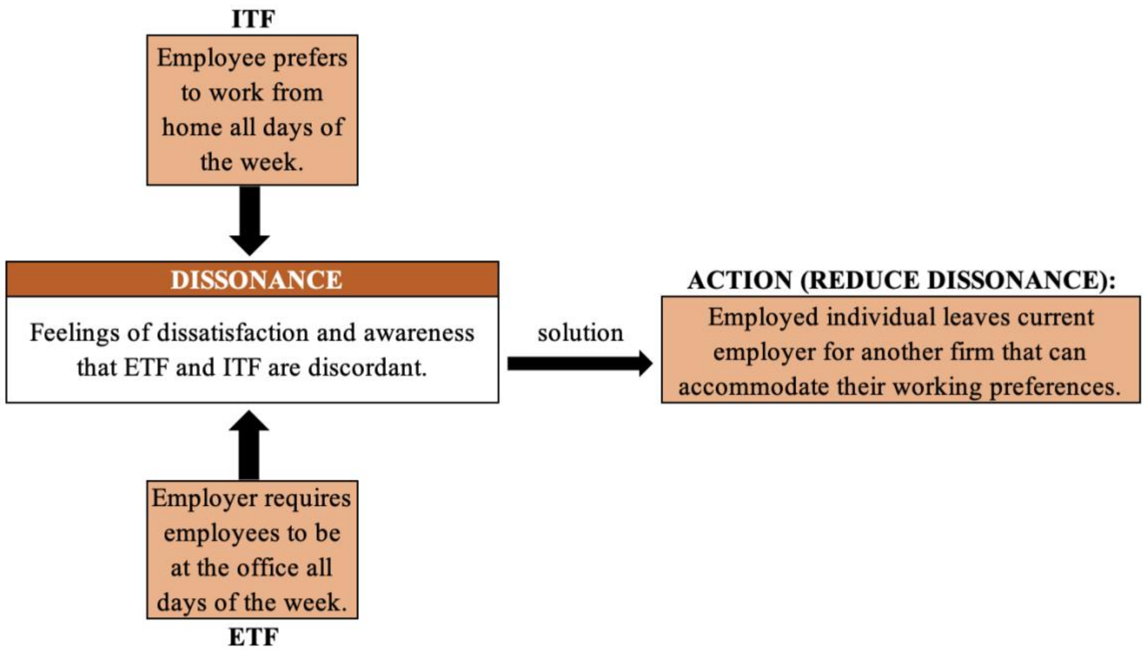
The remote work arrangement trend engendered by the pandemic continues to be prevalent even after wide dissemination of COVID vaccinations and other drug treatments, due to a number of employee- and employer-related reasons. From an employee perspective, for many workers, remote work (which we will also refer to as telework, and which was predominantly from home) offers a level of flexibility that increases their work-life balance (Sweet and Scott, 2022), enhances mental well-being and happiness (Owl Labs, 2021), reduces financial cost-outlays of working from the office (for example, investment in clothing/attire and formal day care facilities for children; see Thompson et al., 2022 and Bjursell et al., 2021), and lowers time/emotional stress (for instance, due to the long and tiresome commutes; see Nguyen, 2021). Besides, the newfound flexibility to telework caused by the pandemic, and the pandemic itself, encouraged many employees to move farther away from their offices to less dense and remote residential locations for reasons that ranged from reducing in-person contact to saving on housing costs to enjoying more desirable housing attributes (Caldarola and Sorrell, 2022). For such individuals, the resulting increased distances between their homes and regular office locations naturally heightens the preference for remote work. Also, individuals who added new family members during the pandemic, and became accustomed to telework during the pandemic, are naturally going to be reticent to return back to the work office on a regular basis (especially on a full-time basis, even if that was the norm for their jobs before the pandemic). More generally, telework has been known to provide employees with a higher level of autonomy (associated with freedom, independence, and ability to make decisions) on how job-related tasks are completed, which, in turn, elevates job satisfaction for most individuals (see Allen et al., 2015). From an employer perspective, many employers downsized office space or completely abandoned physical offices to save on real-estate costs and other unnecessary business expenses during the pandemic (see Boland et al., 2020 and Türkes and Vuta, 2022). A study by Owl Labs (2021) found that 22% of employers have closed the office, 22% have reduced office space, and 18% have implemented hot desking since the start of the pandemic. This was particularly the case for small (1 to 50 employees) and large employers (more than 10,000 employees), though a third of medium-sized employers (500 to 1,000 employees) also reduced their office space. The resulting cost savings to employers have been palpable and clearly offer a substantial incentive for such employers to continue to retain telework policies either partially or fully. Besides, during a period dubbed in the popular press as the era of the "great resignation", employers have become increasingly aware of the need to continue to provide work flexibility as a means to attract new employees and retain experienced employees (Dua et al., 2022; Mission Square Research Institute, 2022).

While telework is still deeply entrenched in the work arrangements of most employees, the fact that the worst of the pandemic is in the rear-view mirror has led to an increasing chorus of employer voices starting to express concerns about continuing with extensive telework arrangements. These employers are worried about the inability to maintain a distinctive brand of corporate culture and high productivity/performance levels, as well as the potential deleterious effects of the lack of in-person collaborations for community and team building. In fact, a study conducted after the widespread availability of vaccines in Spring 2021 (for ease, we will refer to this period after Spring 2021 as the post-COVID period) determined that 68% of company executives prefer their employees to return to office-based work at least three days a week to maintain their distinctive brand of corporate culture. Additionally, 65% of company executives believe that office-based work is imperative for increasing employee productivity levels. Further, over half of the executives believe that employee collaboration is an important component of office-based work as it provides meeting spaces for clients and facilitates team building (PWC, 2021). A number of employers also see office-based work as an essential ingredient for mentoring young and new employees. As a result, several employers have explicitly declared that the telework wave brought on during the height of the pandemic will not constitute a new normal and have strongly encouraged office-based work, either on all days of the week or with limited flexibility to work remotely. The net result of this is a move toward workplace hybridization, splitting the work week between working in-person and remotely, which is ostensibly a happy medium between employer and employee preferences.

Yet, for many employees, their current and future expected work arrangement may still be influenced by employer pressure/expectation to be at the office, due to job security concerns (especially so amidst an economic outlook that is not necessarily one of optimism). For instance, a survey of US workers conducted in July 2022 indicated that 62% believed they were more productive when working remotely, but about half of them also felt that upper management viewed those coming into the office on a regular basis as being "harder working and more trustworthy" (Owl Labs, 2022). Also, about half of the respondents to the survey were worried that not going into the office often would make them less visible (not just literally, but also from a career advancement perspective) to upper management. Such feelings, justified or not, would imply that employees might go into the office more days than if the choice were completely left to themselves. Of course, it is also possible that some individuals may prefer more office workdays (due to a need for more professional-social interactions and a perceived higher productivity level at the office with fewer distractions) than what their employer may be able to offer based on office rotation schemes and office downsizing, but the general trend is that such employees constitute a very small fraction of all employees.

The discussion above brings up the issue of *telework dissonance* – that is, the potential disconnect between the existing telework arrangements of employees (as influenced, in large part, by employer preferences/requirements) and what employees would prefer if the choice were totally up to them. According to Festinger (1975), "dissonance" and "consonance" refer to the relations that exist between pairs of "elements", wherein the elements refer to beliefs/attitudes (BA) on the one hand and actual behavior (AB) on the other. Festinger proposed that dissonance arises when BA and AB are in opposition, while consonance arises when BA and AB are in alignment. Individuals feel uncomfortable and psychologically stressed when in a state of dissonance and so strive toward consonance. Further, when in a state of dissonance, individuals, even if not completely able to bridge the dissonance gap, will do all it takes to at least avoid situations and information that increases the dissonance gap. This fits in well with the issue of telework frequency dissonance (TFD), with the two elements representing the existing telework frequency (ETF) and the ideal telework frequency (ITF) of an employee. Then, fitting neatly within Festinger's cognitive dissonance theory, empirical studies have shown that employees who feel pressure to work from their office more often than their ideal (that is, ETF<ITF, because of a formal requirement of their employer, or the pressure they perceive from their employer, or other reasons) appear to manifest their TFD-related stress and discomfort through lower levels of work engagement/well-being and higher levels of burnout (Wigert, 2022; Alrawadieh and Dincer, 2021). Additionally, earlier studies provide credence to the notion that individuals seek to reduce TFD and certainly avoid situations that increase it. This can be through increasing EFT to get closer to ITF by pursuing alternative positions with the current employer (even if at the expense of a pay cut), or leaving the company to seek jobs elsewhere, or dropping out entirely from the labor force (Dowling et al., 2022). An extreme situation of dissonance is illustrated in Figure 1, where the employee would like to work full time from home, while the employer requires the employee to be at the work office every work day. The resulting dissonance leads the individual to leave the current employer for another firm. Alternatively, employees may reduce TFD by modifying (decreasing) ITF to bring it closer to ETF, for example, by convincing oneself that the ITF is simply not appropriate for the job, and one must be more reasonable in the ITF expectation, or moving closer to the office that can then reduce ITF to match more closely to the ETF (see Asmussen et al., 2023a). As already indicated, some employees may also want to come into the office more often than possible (that is, ETF>ITF), but we expect the segment of employees falling in this category to be very small (as we will also note later in our study).

**Figure 1**: Example of an Extreme Case of Telework Frequency Dissonance (TFD)




In this thesis, we take a deep dive into the issue of TFD. The data for our study is gathered through the COVID Future Panel Survey Wave 3, which was deployed across the United States in October-November 2021 (Salon et al., 2022). The survey data includes information on ETF and ITF. Both these dimensions are collected in six ordinal telework categories in the survey. These two dimensions are modeled jointly in a bivariate ordered-response probit (BORP) system to recognize that unobserved individual factors that elevate ETF may also lead to the individual planning to telework more in their ideal choice situation. A novel and elegant heterogeneous thresholding mechanism, which we have not seen proposed in the econometric literature, is employed within the context of the BORP system to (a) recognize that many individuals may in fact be in consonance (ITF=ETF), and (b) identify who such individuals are likely to be and the teleworking frequency level at which their consonance exists. The findings from this study provide important insights regarding how best to balance employee and employer preferences to improve overall workplace and life satisfaction. Additionally, this study contributes to future transportation and land-use modeling that needs to explicitly account for remote work preferences and arrangements.

The rest of the thesis is organized as follows. Chapter 2 provides a brief overview of previous literature that is relevant to understanding workplace location dissonance. Chapter 3 describes the survey data, sample description statistics, and the analytic framework. Chapter 4 presents the model estimation results and goodness of fit measures. Chapter 5 discusses policy implications. Finally, Chapter 6 concludes the thesis with a summary description and future research directions.

# Chapter 2: Literature Review

The literature on ETF, investigated based on revealed preference survey data, and the literature on ITF, examined based on stated preference/intention survey data, has a long history that can be categorized in terms of time of survey administration into three distinct periods: (i) *Before* COVID, (ii) *During* COVID, and (iii) *Post* COVID. However, given the objective of the current study, and the substantially COVID-altered work landscape, our literature review will focus on the *Post* COVID period. Good reviews of studies examining ITF and ETF in the Before COVID and During COVID periods are available in Singh et al. (2013), Shabanpour et al. (2018), Cerqueira et al. (2020), Hensher et al. (2021), Sweet and Scott (2022), Asgari et al. (2023), and Asmussen et al. (2023a), among many other studies.

## 2.1 Post-COVID Existing Telework Frequency (ETF)

A distinguishing feature of post-COVID studies relative to the Before-COVID studies is the surge in the number of studies that consider not only telework adoption (whether an individual teleworks at all or not over a given time period, such as a week or a month), but also telework frequency over a given time period. Examples of such studies include Zhang et al., 2020, Hensher et al., 2021, Mohammadi et al., 2022, Yamashita et al., 2022, Ton et al., 2022, and Asmussen et al., 2023a. These studies adopt a variety of methodological frameworks to relate demographic and work-related variables to telework frequency, ranging from simple descriptive analysis (Yamashita et al., 2022) to multivariate econometric methods such as ordinal or count or joint discrete-count-nominal models (Shabanpour et al., 2018; Zhang et al., 2020; Heiden et al., 2021; Hensher et al., 2021; Ton et al., 2022; Dua et al., 2022; Asmussen et al., 2023a). The results from these studies generally suggest three main categories of variables that influence ETF: (1)

individual and household demographics, (2) job-related characteristics (including employer size), and (3) residential attributes. Within the category of individual and household demographics, the studies indicate that, in general, women (especially single women with children), young individuals, those with a high formal education degree attainment, and those in households with a higher number of motorized vehicles and with high incomes are more likely to telework than their peers. Of course, the results are not always consistent across studies. For example, Sweet and Scott (2022) and Tahlyan et al. (2022b) find that it is the middle-aged individuals who are most likely to telework, not the youngest segment of the working population, as has been reported in much of the literature. In the category of job-related characteristics, results generally suggest that those in non-essential occupation sectors (such as in professional, management, and technical jobs as opposed to in manufacturing, trade, construction, healthcare, and retail), part-time and self-employed workers, those residing far from their office locations, and those working in small-sized firms tend to telework more than other individuals (see, for example, Sweet and Scott (2022), Asgari et al. (2023), Caldarola and Sorrell (2022), and Haider and Anwar (2023)). Finally, in the category of residential attributes, those residing in high-density urban areas and those who live closer to non-work and leisure activity opportunities have been found to be more frequent teleworkers (see Haider and Anwar (2023) and Tahlyan et al. (2022a)).

### 2.2 POST-COVID IDEAL TELEWORK FREQUENCY (ITF)

Several recent studies have examined an outcome that gets close to ITF. A good review of such studies is available in Asmussen et al. (2023b). For example, Nayak and Pandit (2021) and Jain et al. (2022) study an employee's stated intention to telework based on a direct question regarding stated intent in a future when "travel and other restrictions would be withdrawn after the elimination or control of the pandemic" (Nayak and Pandit) or the virus is "gone" (Jain et al., 2022). Specifically, Nayak and Pandit elicit a binary response to whether the employee would be willing to telework in the future, while Jain et al. pose a question related to how much more likely (as collected on a seven-point Likert scale) would the respondent be to telework in the future compared to pre-COVID times. These studies are likely to capture what respondents expect or might be willing to do, given the COVID-related telework experience. The studies of Asgari et al. (2023), Appel-Meulenbroek (AM) et al. (2022), and Asmussen et al. (2023b), on the other hand, get even closer to the ITF concept by eliciting the preferred telework arrangement in a future where telework arrangements can be freely chosen by the respondent. The Asgari et al. study modeled the preferred telework frequency from home as elicited from respondents in a post-pandemic landscape, using an ordinal five-point Likert scale ranging from "never" to "daily or almost daily". They used the telework frequency before the pandemic as an exogenous variable, and did not consider potential unobserved correlation effects between pre-pandemic teleworking and preferred telework frequency in a post-pandemic situation. Among their results was that attitudes formed during the pandemic, such as productivity change due to pandemic-spurred teleworking, appeared to shape preferred telework in a post-COVID landscape more so than demographic factors. Within the group of limited demographic factors they tested, those with lower formal degrees (professional/associate degrees) and low-income individuals desired higher levels of telecommuting in the future. Also, as expected, individuals preferred more teleworking in the future than in the pre-pandemic state.

The AM et al. and Asmussen et al. studies use stated choice experiments with specific design attributes to elicit telework preferences, rather than using a direct stated intention question. In particular, AM et al. use a day as the analysis unit, and present work environment attributes (such as noise levels, openness, space size, and crowdedness) and work activity day type attributes (whether the day will be with unplanned meetings and relatively little concentrated individual desk time, or the day will be with few unplanned meetings and concentrated individual desk time, or a hybrid of the two) in their experiments. They then elicit the preferred telework choice during the day (as a result, AM examine an outcome that is closer to what may be labeled as "ideal telework adoption", not ITF). Asmussen et al. (2023b) investigate individual desires (by way of frequencies) for teleworking by presenting respondents with, among other attributes, work environment (measures of distraction and crowding levels), commute times to the work office and a third workplace, and work timing flexibility. They then ask respondents to imagine they had 22 workdays in the month and allocate those days to telework from home, telework from a non-home location, and work from the office in response. Both these studies highlight the importance of work environment attributes, such as crowdedness and noise, in the choice of where to work from. Other results are similar to those of ETF studies of the previous section, indicating higher ITF among (a) single young women with young children and those in households with high incomes (in the category of individual/household demographics), (b) those in non-essential occupation sectors, part-time and self-employed workers, and those residing far from their office location (in the category of job-related factors), and (c) those residing in dense urban areas (in the category of residence attributes).

### 2.3 The Sweet and Scott (2022) Study

The studies of the previous two sections examine either post-COVID ETF or some measure of post-COVID ITF, but do not examine both ETF and ITF simultaneously. The study that comes closest to the current research is that of Sweet and Scott (2022), who use data collected through a survey administered in fall 2021 across six different metropolitan areas in Canada. The survey elicited information on telework frequency at different points in time, including in fall 2021 (that is, ETF in our terminology) and a post-COVID ideal state (that is ITF). ETF was specifically defined as remote workdays from home over the past month, obtained in the five ordinal categories of 0 days, a few days in the month, 1-2 days per week, 3-4 days per week, and 5 days or more in the week. The ITF question was only asked of those who teleworked at least a few days based on the ETF response, assuming that those who responded with an ETF of “0 days per month” would have an ITF of “0 days per month”. The same five ordinal categories as for ETF were used to elicit ITF responses. The study descriptively examined aggregate differences between ETF and ITF, and then followed that up with independent ordered response models for each of ETF and ITF. The ETF (ITF) percentages from their study are as follows: 0 days – 54.1% (54.8%), a few days in the month – 4.1% (5.5%), 1-2 days per week – 10.8% (7.9%), 3-4 days per week – 9.1% (13.4%), and 5 days or more per week – 22% (18.4%). Interestingly, these descriptive statistics suggest that the aggregate levels of ETF and ITF are quite similar, though they do not provide the ETF-ITF differences (and therefore the TFD) at the individual level. The independent ordered-response models for ETF and ITF also are surprisingly similar in results, though again these models do not provide TFD at the individual level. Overall, the results indicate that middle-aged individuals, women working full-time and men working part-time, employees with high formal education degrees (especially if working full-time), full-time workers with children in the household, part-time workers without children in the household, those from high income households, and individuals in non-essential occupation sectors had both higher ETF and ITF, though the differences based on all of the variables just identified were more moderate for ITF than for ETF. In the current thesis, we use similar data as collected by Sweet and Scott, but analyze the data more rigorously and study the bivariate distribution of ETF and ITF to identify TFD at the individual level and as a function of a host of exogenous variables. We also study ETF and ITF for US workers rather than for Canadian workers.

### 2.4 The Current Thesis in Context

In the current thesis, we contribute to the teleworking literature in multiple ways. First, we examine the extent of the gulf between what workers would ideally like to do by way of teleworking frequency relative to what they expect to do "once society reaches a post-COVID new normal." The intensity of the gulf between ETF and ITF (that is, TFD) can provide a good indication to employers of the types of employees who may have the most TFD, which employers can use for future corporate policy planning, and recruitment strategies. Further, our analysis helps inform employers and land-use-transportation professionals to plan appropriately for the future. Through an enhanced understanding of the work arrangements desired by the workforce (as denoted by the ideal desired telework frequency of employees), employers can design customized telework policies and programs. Second, to our knowledge, the current study is the first to investigate the pandemic-induced dissonance and consonance from a telework context. Previous literature has focused on applying cognitive dissonance theory in other fields such as waste management (Arriagada et al., 2022), workplace organizations (Zou et al., 2020; Oduh, 2016), and kinesiology (Cooper and Feldman, 2020). Within the transportation field, the theory of cognitive dissonance has been applied to mode choice and residential location choices (see for example, De Vos (2018) and De Vos and Singleton (2020)). However, to our knowledge, this social psychology theory has not been applied to telework choices. The application of this theory can help inform ways to reduce stress in the US workforce and reduce the high job quit rate that has been prevalent in the aftermath of the pandemic

(Barrero et al., 2021). Third, we consider a suite of individual/household demographics, job-related characteristics, and residential attributes in our analysis. In addition to including the attributes identified above, we also consider multi-way interactions among these attributes to examine, for example, gendered lifecycle effects. Fourth, we use a novel bivariate ordered-response probit model to study potential TFD effects. In particular, we structure our model to immediately identify those with high/low TFD, while also explicitly recognizing that there is likely to be a sizeable share of workers who are in a consonance state. In this regard, our methodology allows us to estimate the share of individuals in a state of consonance and dissonance, as well as the expected telework frequency level of consonance and the intensity of dissonance. We also recognize the potential presence of common unobserved individual factors that may simultaneously affect ETF and ITF and allow the intensity of any such common unobserved effects to vary across individuals. Finally, we translate our estimation results to quantify an individual's 1) probability of being in consonance, 2) preferred monthly teleworking consonance levels, 3) probability of being in dissonance, and 4) dissonance intensity.

# Chapter 3: Methodology

## 3.1 Survey Overview

Data for this study are derived from Wave 3 of a COVID Future Panel Survey (CFPS) deployed across the United States and collected in October-November 2021. Only data from the Wave 3 survey were utilized for the purpose of this study, and the analysis is limited to the 1,292 employed individuals. After filtering and screening records with missing data, the final sample comprised 1,239 workers. Complete details about the survey and longitudinal data set may be found in Chauhan et al (2021).

The CFPS collected information on household and individual socio-economic and demographic characteristics, along with information on travel behavior and preferences relating to teleworking, online learning, and lifestyle attitudes. Pertinent to this study, the survey elicited information from two questions related to ETF and ITF. To be precise, the ideal telework frequency (ITF) is collected in response to the question "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?" The existing telework frequency (ETF), as used in this thesis, actually refers to the expectation for telework frequency from home once society reaches a post-COVID normal.[1] Both of the ETF and ITF dimensions were

[1]We use the expected telework frequency "once society reaches a post-COVID new normal" as the measure of the actual telework behavior of an employee down the road (assuming the employee sticks with the employer). While the worst of the pandemic was in the rear view mirror by fall 2021, many employers still had not had the time to gear up to provide/develop a clear framework for employee telework policies. Besides, the Omicron variant was still lingering around the time, and led to another round of safety measures in late fall 2021. Thus, many employees were aware that their existing telework behavior in fall 2021 was not what should be expected down the road, as also clearly indicated by Mohammadi et al. (2022) and Appel-Meulenbroek et al. (2022). Further, in the context of the focus of this paper on telework frequency dissonance, the gulf between the expected telework frequency down the road and the ideal telework frequency down the road is what should matter in the minds of employees. However, for ease of interpretation and understanding, and also to avoid any confusion with the alternative statistical interpretation of the label "expected telework frequency", in this thesis, we use the terminology "existing telework frequency" (ETF) to refer to the expected (in the future) telework frequency. This important point should be kept in mind in all future invocations of the label "existing" telework frequency in the current thesis. Also, in the context of ETF, for ease in presentation and conciseness, we will use crisp sentences

collected in six ordinal telework categories in the survey: (1) never telework, (2) a few times a year, (3) a few times a month, (4) once a week, (5) a few times a week, and (6) every day of the week.

## 3.2 SAMPLE DESCRIPTION

### 3.2.1 Exogenous Variables

Table 1 shows sample socio-economic and demographic characteristics for the analysis sample of this study. Women are over-represented in the sample at 60.8%, as U.S. worker statistics (see U.S. Bureau of Labor Statistics, 2022b) indicate that about 46.8% are women. A vast majority of respondents are between the ages of 30 to 49 (44.5%) and 50 to 64 (34.3%). Given the fact that this is a sample of workers, it is not surprising that over three-quarters of the respondents had a bachelor's degree or higher. Similarly, it is not surprising that 31.7% of respondents are from households with an annual income between $50,000 to $99,999 followed by about a quarter of individuals from households with an annual income between $100,000 to $149,999. About two-fifths of respondents live in a two-person household, while a little shy of a quarter of respondents live in a household with 4 or more individuals. The sample shows a mean of 2.5 individuals per household, which is exactly the same as the mean number of individuals per household in 2022 in the entire U.S. population.[2] 70.2% of respondents do not have a child (in the age group of 0-17 years) in the household, which is similar to the 71.3% of adults in the overall U.S. population living without children, as per the Census Bureau statistics of 2017 (U.S. Census Bureau, 2017). With regards to household vehicle ownership, a majority of

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such as "About 28% of individuals never telework" as though it were a statistic referring to existing teleworking arrangements, rather than the technically correct "About 28% of individuals expect never to be teleworking once society reaches a post-COVID new normal"

[2] see https://www.statista.com/bstatistics/183648/average-size-of-households-in-the-us/, accessed May 19, 2023

households have less vehicles than household members (80%). Overall, it should be noted that an apples-to-apples comparison of the individual/household level demographic characteristics from our sample with the Census Bureau data is not possible, because the latter database does not distinguish between employed and non-employed individuals.

In terms of job-related characteristics, approximately 81% of respondents are full-time employees, which aligns with the proportion of full-time employees in the U.S. as of 2022 (84%) (see U.S. Bureau of Labor Statistics, 2022a). It should be noted that the survey did not define the number of working hours required for an employee to be considered full-time, while the U.S. Census Bureau considered a full-time employee as one who works 35 hours or more per week. A majority of respondents indicate that they work in an occupation that is business-related (61.5%). Meanwhile, the medical (11.4%), transportation (6.1%), and sales/retail services (5.6%) are also reasonably well represented. These percentages align fairly well with the U.S. working population, based on the U.S. Bureau of Labor Statistics (2022b). Most respondents report that they drive a private vehicle to get to work (81%), which is largely aligned with the 77% use of private vehicles for the commute as documented by the Bureau of Transportation Statistics (2021). With regard to one-way home-to-work (commute) distance, a majority of individuals either travel 11.00 to 30.99 miles (36.6%) or 0.00 to 5.99 miles (35.4%). A vast majority of respondents (65.8%) indicate that there are at least one hundred employees at their workplace, with the remaining employees split about evenly between small-sized (1 to 9 workers) and medium-sized employers. Overall, our sample is reasonably aligned with worker characteristics of the U.S. population.

In terms of residential characteristics, more than half of the respondents live in an urban area (46%) or suburban area (42.6%). This seems to align relatively closely with the 80% of the U.S. population residing outside a rural area in 2020 (U.S. Census Bureau, 2020). A vast majority reside in a stand-alone housing unit (66.4%) and 68.0% indicate that they own their housing unit. The housing ownership rate matches closely with the 66% ownership percentage in the U.S. Census Bureau (2023) statistics.

Finally, a majority of respondents are from the Western region of the U.S. (41.6%) which is a clear over-representation of that geographic region (according to the U.S. Census Bureau statistics from 2022, 24% of the U.S. population resides in the Western region). In fact, Arizona and California alone comprise 28% of the sample. Further, we see that the Northeast (13%) and Midwest (21%) regions fairly align with the U.S. Census (i.e., 17% of population in the Northeast and 21% in the Midwest). Meanwhile, the Southern region (24%) is under-represented (38% of the U.S. population reside in the South, according to Census data).[3]

[3] The U.S. Census Bureau groups all 50 states into four distinct regions (Midwest, Northeast, South, and West) based on their geographic proximity (see U.S. Census Bureau, 2021).

**Table 1**: Sample Descriptive Statistics of Exogenous Variables

| Variable | Count | % |
|---|---|---|
| ***Individual-Level Characteristics*** | | |
| **Gender** | | |
| Male | 486 | 39.20% |
| Female | 753 | 60.80% |
| **Age** | | |
| 18 to 24 | 58 | 4.70% |
| 25 to 29 | 87 | 7.00% |
| 30 to 39 | 292 | 23.60% |
| 40 to 49 | 259 | 20.90% |
| 50 to 64 | 425 | 34.30% |
| 65 or older | 118 | 9.50% |
| **Education Level** | | |
| Highschool | 69 | 5.60% |
| Some College | 232 | 18.70% |
| Bachelor's Degree | 486 | 39.20% |
| Graduate Degree | 452 | 36.50% |
| ***Household Characteristics*** | | |
| **Income** | | |
| < $50,000 | 253 | 20.40% |
| $50,000 to $99,999 | 393 | 31.70% |
| $100,000 to $149,999 | 303 | 24.50% |
| ≥ $150,000 | 290 | 23.40% |
| **Household Size** | | |
| 1 | 235 | 19.00% |
| 2 | 490 | 39.50% |
| 3 | 223 | 18.00% |
| ≥ 4 | 291 | 23.50% |
| **Presence of Children (Including Ages)** | | |
| No Children | 870 | 70.20% |
| 0 to 4* | 108 | 8.70% |
| 5 to 12 | 210 | 16.90% |
| 13 to 17 | 181 | 14.60% |
| ***Household Characteristics (continued)*** | | |
| **Vehicles / Person / Household** | | |
| More Vehicles than Household Members | 248 | 20.00% |
| Less Vehicles than Household Members | 991 | 80.00% |
| ***Job-Related Characteristics*** | | |
| **Employment Status** | | |
| Employed Full-time | 1004 | 81.00% |
| Employed Part-time | 235 | 19.00% |
| **Occupation / Industry Type** | | |
| Business-Related | 762 | 61.50% |
| Education | 57 | 4.60% |
| Manufacturing/Construction | 28 | 2.30% |
| Medical | 141 | 11.40% |
| Professional, Managerial, or Technical | 64 | 5.20% |
| Public Administration | 41 | 3.30% |
| Sales/Retail Service | 70 | 5.60% |
| Transportation | 76 | 6.10% |
| **Mode to Work** | | |
| Private Vehicle | 999 | 80.60% |
| Public Transit | 140 | 11.30% |
| Bicycle/Scooter | 53 | 4.30% |
| Walk | 36 | 2.90% |
| Work From Home | 11 | 0.90% |
| **Distance to Work** | | |
| 0.00 to 5.99 miles | 438 | 35.40% |
| 6.00 to 10.99 miles | 262 | 21.10% |
| 11.00 to 30.99 miles | 454 | 36.60% |
| ≥ 31.00 miles | 85 | 6.90% |
| ***Job-Related Characteristics (continued)*** | | |
| **Employer Size** | | |
| 1 to 9 Workers | 188 | 15.20% |
| 10 to 99 Workers | 236 | 19.00% |
| ≥100 Workers | 815 | 65.80% |
| ***Residential Characteristics*** | | |
| **Land-Use Type** | | |
| Rural | 141 | 11.40% |
| Suburban | 528 | 42.60% |
| Urban | 570 | 46.00% |
| **Tenure** | | |
| Rent | 352 | 28.40% |
| Own | 887 | 71.60% |
| **Residential Type** | | |
| Non-Standalone Home/Apartment | 416 | 33.60% |
| Standalone Home | 823 | 66.40% |
| ***Built Environment Characteristics*** | | |
| **Census Bureau-Designated Regions** | | |
| Midwest | 262 | 21.10% |
| Northeast | 161 | 13.00% |
| South | 301 | 24.30% |
| West | 515 | 41.60% |
| **States** | | |
| Arizona | 172 | 13.90% |
| California | 170 | 13.70% |
| Other | 897 | 72.40% |

***** 368 households have children in them. The “Presence of Children” categories do not add up to this number because some households have children in multiple age groups

### 3.2.2 Sample Descriptive Statistics of ETF, ITF, and TFD

Table 2 presents a detailed description of the endogenous variables of interest. Note that both ETF and ITF are not revealed behaviors, so there is no way to compare these with numbers from the Census Bureau or elsewhere. The first part of Table 2 provides descriptive statistics of ETF and ITF. In terms of ETF, about 28% of individuals indicate that they never telecommute, while about a quarter telework every day of the week. The highest percentage of respondents telework a few times per week at 30.1%, and the overall percentage of hybrid workers (working both from home and office) is at 47.5%. The shift toward higher levels of telework desire is noticeable when comparing the ITF numbers with the ETF numbers, with only 4.8% of respondents indicating they would never telework in their ideal scenario and 44.6% indicating they would telework every day. Interestingly, the percentage who indicate teleworking a few times per week remains stable at about 30% across both ETF and ITF, as does the percentage who desire a hybrid work arrangement (which goes up a little from 47.5% to 50.6%). The ITF numbers from Table 2 may be compared with those from Sweet and Scott's (2022) study from Canada, where more than half (54.8%) indicate that they would never telework in their ideal scenario and less than one-fifth (18.4%) indicate they would telework every day. Clearly, US workers appear to be much more desirous of teleworking than their Canadian counterparts.

The first part of the table, while providing overall ETF and ITF split statistics, does not provide information on the movement from specific ETF levels to specific ITF levels, which is the basis of consonance versus dissonance. The second part of the table displays this joint distribution of ETF and ITF. The diagonal of this matrix represents the number and percentage of individuals that experience consonance (these are the bolded cells in the table). The upper non-diagonal elements of the matrix represent individuals that experience dissonance and prefer to telework more than they currently are, while the lower non-diagonal elements represent individuals that experience dissonance and prefer to telework less than they currently are. Looking at the diagonal of the matrix, it is clear that those who currently never telework are the least likely to be in a state of consonance with only 15.7% stating that their current “never telework” state is what they would like in their ideal scenario. On the other side, those who currently telework everyday have the highest level of consonance, with 90% stating that that is also their ideal state. The move from lower levels of current telework levels to higher desired telework levels is quite clear in the loading of the respondents in the upper non-diagonal rather than the lower non-diagonal. To see this even more clearly, the third part of the table displays the proportions of individuals that experience dissonance and consonance. More than half of individuals (50.4%) experience dissonance and prefer more telework than their current arrangement, while a sizeable percentage of close to half (46.3%) experience consonance. A very small percentage of individuals experience dissonance and prefer less telework work than their current arrangement (3.3%).

**Table 2**: Descriptive Characteristics of Endogenous Work Arrangement Variables

| | **Existing Telework Frequency (ETF)** | | **Ideal Telework Frequency (ITF)** | |
|---|---|---|---|---|
| | Count | % | Count | % |
| Never | 351 | 28.3 | 59 | 4.8 |
| A few times/year | 40 | 3.2 | 57 | 4.6 |
| A few times/month | 92 | 7.5 | 113 | 9.1 |
| Once/week | 83 | 6.7 | 82 | 6.6 |
| A few times/week | 373 | 30.1 | 376 | 30.3 |
| Every day | 300 | 24.2 | 552 | 44.6 |
| Total | 1239 | 100.0 | 1239 | 100.0 |

**ETF Versus ITF**

| **ETF** | **ITF** | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Never | | A few times/ year | | A few times/ month | | Once/ week | | A few times/ week | | Every day | | Total |
| | Count | % | Count | % | Count | % | Count | % | Count | % | Count | % | % |
| Never | **55** | 15.7 | 32 | 9.1 | 50 | 14.2 | 49 | 14.0 | 146 | 41.6 | 19 | 5.4 | 100.0 |
| A few times/year | 1 | 2.5 | **19** | 47.5 | 7 | 17.5 | 0 | 0.0 | 5 | 12.5 | 8 | 20.0 | 100.0 |
| A few times/month | 1 | 1.1 | 2 | 2.2 | **48** | 52.2 | 9 | 9.8 | 16 | 17.4 | 16 | 17.4 | 100.0 |
| Once/week | 0 | 0.0 | 1 | 1.2 | 3 | 3.6 | **22** | 26.5 | 28 | 33.7 | 29 | 34.9 | 100.0 |
| A few times/week | 1 | 0.3 | 1 | 0.3 | 0 | 0.0 | 1 | 0.3 | **160** | 42.9 | 210 | 56.3 | 100.0 |
| Every day | 1 | 0.3 | 2 | 0.7 | 5 | 1.7 | 1 | 0.3 | 21 | 7.0 | **270** | 90.0 | 100.0 |

| **Does the Individual Experience Dissonance?** | Count | % |
|---|---|---|
| Yes & individual would prefer to work from home LESS than they do right now | 41 | 3.3 |
| Yes & individual would prefer to work from home MORE than they do right now | 624 | 50.4 |
| No (individual experiences consonance) | 574 | 46.3 |
| Total | 1239 | 100.0 |

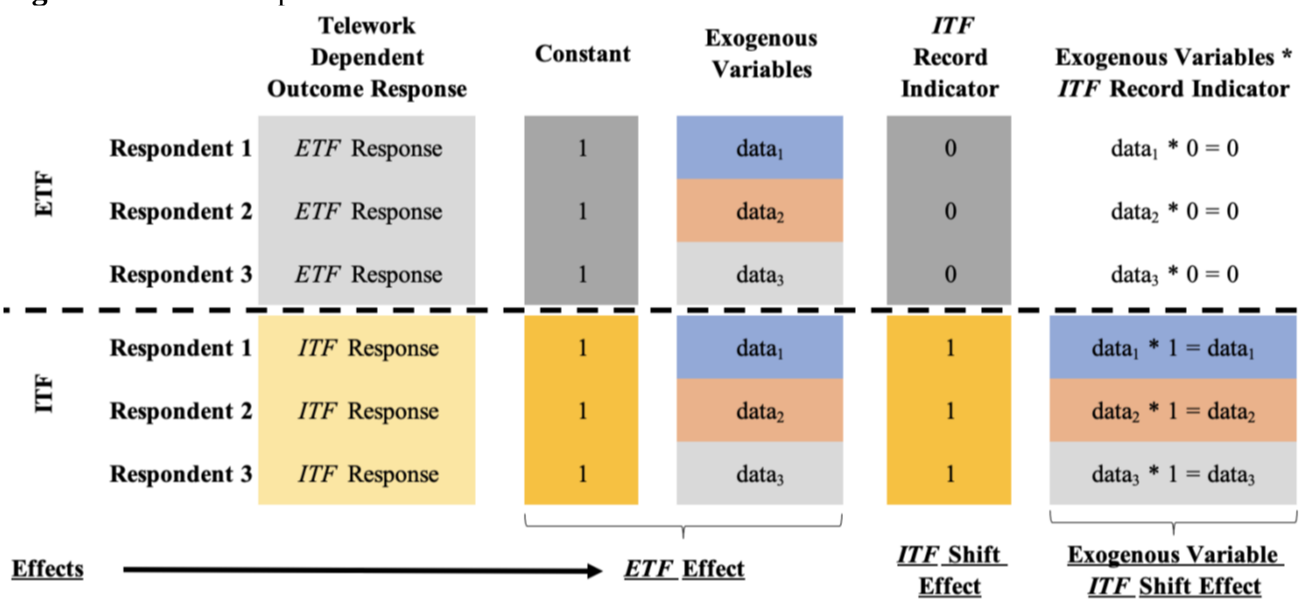
## 3.3 Modeling Framework

### 3.3.1 Analytic Framework

The exogeneous variables in our model include individual and household demographics, job-related characteristics, and residential attributes, based on the findings from the earlier literature. The two endogenous outcomes of interest constitute ETF and ITF. In our analysis, consistent with the ordinal capture of telework levels for ETF and ITF in the survey, we use an ordered-response modeling mechanism for each of ETF and ITF (in such a mechanism, the telework frequency ordinal outcome is viewed as originating from an underlying latent propensity variable extending over the real line, and whose horizontal partitioning through appropriately spaced thresholds maps into the observed outcome; see McKelvey and Zavoina, 1975 and Bhat and Koppelman, 1993). But, unlike in Sweet and Scott (2022), ETF and ITF are not modeled independently but as a joint bivariate system with correlated effects that recognizes the potential presence of correlated unobserved individual-specific effects. We also accommodate for heterogeneity across individuals in the extent of these unobserved effects by allowing the correlation in the bivariate system to vary as a function of observed individual characteristics. Allowing for such correlation, and the heterogeneity across individuals in this correlation, enables us to better tease out the extent of "true" telework frequency dissonance (TFD) in the population. For example, if, as we expect, there is a high level of positive correlation among the ETF and ITF ordinal levels (for example, because introverted individuals may have high levels of both ETF and ITF), this positive association would get incorrectly captured as lower dissonance levels than actuality. On the other hand, by controlling for unobserved effects, we disentangle "true" dissonance levels from spurious levels.

Next, to capture the "true" dissonance levels, and the variation in these levels across individuals, we introduce two sets of additional effects. First, we capture the effect of an exogenous variable on the latent propensity underlying the ITF outcome as a "shift effect" from the effect of the variable on the latent propensity underlying ETF latent propensity. Combined with a separate set of thresholds for each of ETF and ITF, this would capture the overall higher levels of ITF observed in the data relative to ETF, as well as allow differential propensity shifts in ITF (relative to ETF) for different individuals. This first set of additional effects (over and beyond the bivariate ordered-response structure with individual-varying correlation) is achieved through a data set up mechanism during estimation. Specifically, we stack the dataset in a configuration as depicted in Figure 2. For each respondent, there is a pair of records – one corresponding to ETF and a second corresponding to ITF. The ETF outcomes for all individuals are first stacked up in the top row panel labeled "ETF", followed by ITF outcomes in the bottom row panel labeled "ITF". Next, there is a constant followed by a set of exogenous variables, all of which take the same set of values for each individual across the ETF and ITF panels (labeled as $\text{data}_1$ for the first individual, $\text{data}_2$ for the second individual, and so on). This is followed by an "ITF record" indicator that takes a value of 1 if a row record corresponds to the ITF dimension and 0 otherwise. Finally, the dataset has an interaction element, corresponding to interaction terms between the exogenous variables and the "ITF record" indicator. Essentially, this configuration allows the estimation of a model system that is capable of revealing three types of effects, as identified at the bottom of the figure – (1) an ETF effect corresponding to the column labeled at the top as "constant" and "exogenous variables", (2) a generic ITF shift effect (from the ETF effect) corresponding to the column labeled at the top as "ITF record indicator", and (3) an exogenous variable ITF shift effect from the ETF effect, corresponding to the column labeled at the top as "exogenous variables*ITF record indicator. It should be noted that the ETF effects and ITF shift effects for the constant or any exogenous variable may manifest themselves in different forms. Both the ETF effect and the ITF shift effect may be positive, or both effects may be negative, or they may be of opposite sign; by algebraically adding the two effects, it will be possible to determine the overall effect of the exogenous variable on the ITF latent propensity underlying the ITF outcomes. Also, if an exogenous variable shows up as an ETF effect with no shift effect, that implies that the effect of the exogenous variable is the same across ETF and ITF. On the other hand, if an exogenous variable only has a shift effect and no ETF effect, it implies that the variable does not have an impact for ETF outcome but has an impact on the ITF outcome.

**Figure 2**: Data Set-Up

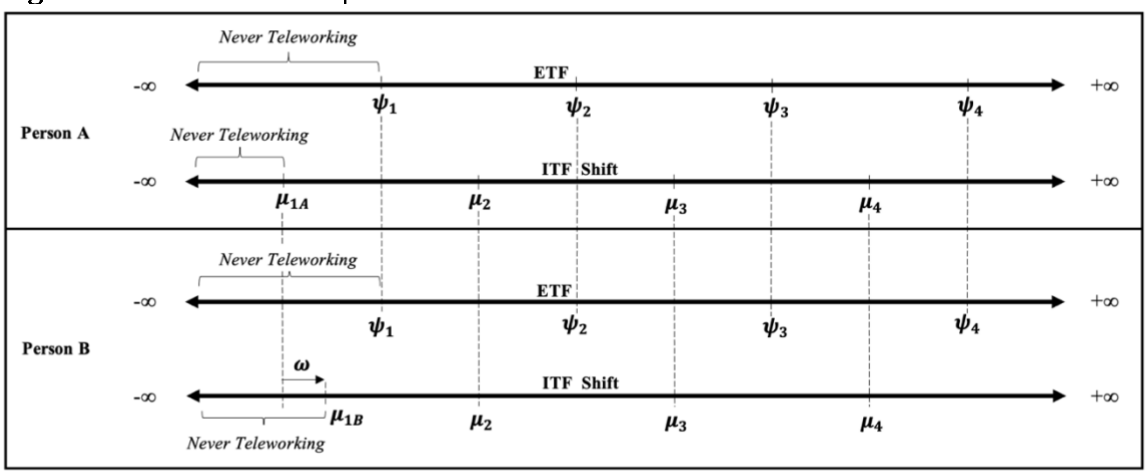



The first set of additional effects just discussed above would still not adequately capture the substantial consonance effects (and the variation in the consonance effects based on ETF outcomes) as observed from the descriptive statistics of the previous section. That is, the ITF ordered-response component can reflect the aggregate ITF counts on the right side of the first (top) part of Table 2 well, but will not be able to capture the bivariate clustering representing consonance (even after allowing for unobserved correlation between ITF and ETF). For example, of the 59 respondents having an ITF of "never teleworking", 55 respondents also have an ETF of "never teleworking". A simple bivariate ordered-response model will not capture such consonance-based clustering across the two outcomes. To accommodate such bivariate consonance effects, we introduce a second set of additional ETF outcome-specific shifter effects for the ITF thresholds, in an innovative (and, to our knowledge, first extension of ordered-response modeling) methodology. To visually illustrate our thresholding innovation, we provide a simple example in Figure 3 for the case of a person A with an ETF that is not "never teleworking" (top panel) and for a person B with an ETF of "never teleworking" (bottom panel). The underlying propensities for ETF and ITF are shown by the horizontal lines, which are allowed to be correlated as shown by the curved double arrow between the horizontal lines. The thresholds for the ITF propensity (the $\psi$ thresholds in Figure 3) are shown to be generally toward the left of those for the ETF propensity (the $\mu$ thresholds), because of the loading of ITF toward higher levels of teleworking (the gap between thresholds corresponding to each teleworking level is an indicator of the size of each teleworking level). Then, for the person B with an ETF of "never teleworking" (but not for person A), we introduce a shift effect for the first ITF threshold toward the right, increasing the bivariate consonance for the combination corresponding to ETF "never teleworking" and ITF "never teleworking". This shift effect shown in Figure 3 as $\omega_1$ can be a constant shift effect across all individuals who never telework, or can be further extended to be a function of individual characteristics. A positive effect of an exogenous variable would then imply that individuals with that corresponding exogenous variable characteristic are more likely to be concordant than other individuals for that particular teleworking level. Similar shift effects, as shown for the ETF of “never teleworking” in Figure 3, are then introduced specific to the upper threshold of each ITF level if the corresponding ETF level is chosen. For ease in specification testing, the exogenous variable effects on the upper ITF threshold shifts (based on corresponding choice of ETF level) are themselves introduced as uniform shifts across all teleworking levels (overall characteristics of concordant individuals), and then secondary shifts from these uniform shifts are captured specific to each teleworking level (characteristics of individuals that make them particularly concordant or not for specific telework levels). Of course, all these shifts should still ensure the increasing nature of the thresholds from the lowest to the highest, which can be ensured through appropriate parameterization of the thresholds. Also, important to note is that introducing ETF outcome-specific shifter effects for the ITF thresholds does not introduce any endogeneity bias, because the potential endogeneity of ETF to ITF is already captured through the unobserved correlation effects.

Along the same lines as discussed above, the second set of additional ETF-outcome specific shifter effects for the ITF thresholds can also accommodate for specific cross ETF-ITF combination levels (that is ETF level ≠ ITF level) that are seldom likely to occur. As an example, of the 351 respondents who have an ETF level of “never”, only 19 have an ITF level of “everyday”. If such kinds of infrequent combinations are not explicitly accounted for, it could inflate levels of estimated discordance. Again, such situations can be accommodated by shifting appropriate thresholds based on the observed ETF level. In our empirical analysis, our many specification tests for such cross ETF-ITF threshold adjustments indicated only the need for two such (only) constant adjustments, one corresponding to the ETF level of “never” and the ITF level of “a few days/week”, and another corresponding to the ETF level of “never” and the ITF level of “everyday”. As such, these cross ETF-ITF threshold adjustments do not have the same behavioral appeal as do the ETF-ITF threshold adjustments for accommodating high consonance levels, and so it is gratifying to note that we needed only two such simple adjustments in our empirical analysis. In the rest of this methodology chapter, and in the discussion of our results, we will not pay much attention to such cross ETF-ITF threshold adjustments.

The analysis framework above represents an elegant structure that, while accounting for associations due to unobserved correlation effects between ETF and ITF, also immediately and simultaneously is able to identify the characteristics of individuals who are concordant/discordant, as well as provide the predicted teleworking levels of concordant individuals as well as the ETF-ITF bivariate combination levels for discordant individuals.

**Figure 3**: ETF Outcome-Specific ITF Threshold Shifts




### 3.3.2 Methodology

Let $q$ ($q = 1,2,...,Q$) be an index for the individual, $k$ be the index for the ordinal ETF level ($k$=1,2,…,6 as shown in Figure 3), and $j$ be the index for the ordinal ITF level ($j$=1,2,…,6). Define underlying latent propensities $y_{q1}^*$ (for ETF propensity) and $y_{q2}^*$ (for ITF propensity) as follows:

$$
\begin{aligned}
&y_{q1}^{*} = \boldsymbol{\alpha}'\mathbf{w}_q + \varepsilon_{q1};\; y_{q1} = k \;\; if \;\; \psi_{k-1} \le y_{q1}^{*} \le \psi_k \\
&y_{q2}^{*} = (\boldsymbol{\alpha}' + \boldsymbol{\delta}')\mathbf{w}_q + \varepsilon_{q2};\; y_{q2} = j \;\; if \;\; \mu_{q,j-1} \le y_{q2}^{*} \le \mu_{q,j}
\end{aligned} \tag{1}
$$

where $\mathbf{w}_q$ is an $H \times 1$ vector of exogenous variables (without a constant) that enters both the underlying preference equations (i.e., $y_{q1}^{*}$ and $y_{q2}^{*}$). $\boldsymbol{\alpha}$ represents the corresponding parameter vector of dimension $H \times 1$ of exogenous variable effects on ETF propensity $y_{q1}^{*}$ (the ETF effect). $\boldsymbol{\delta}$ (a vector of dimension $H \times 1$)) corresponds to the vector of first ITF shift effects mentioned in the previous section, interpreted as the differential influence of exogenous variables on ITF propensity relative to ETF propensity. The latent propensities $y_{q1}^{*}$ and $y_{q2}^{*}$ are mapped to the observed ordinal levels of ETF (i.e., $y_{q1}$) and ITF (i.e., $y_{q2}$) through elements of a threshold vector $\boldsymbol{\psi} = \{\psi_1, \psi_2, ..., \psi_5\}$ (for ETF) and $\boldsymbol{\mu}_q = \{\mu_{q1}, \mu_{q2}, ..., \mu_{q5}\}$ (for ITF). The elements of each threshold vector are in strictly ascending order for each individual *q*, with the convention that $\psi_0 = -\infty$ and $\psi_6 = +\infty$, and $\mu_{q0} = -\infty$ and $\mu_{q6} = +\infty$ for all *q*. The stochastic components (i.e., $\varepsilon_{q1}$ and $\varepsilon_{q2}$ in the above propensity equations (Equation 1) are assumed to follow a bivariate normal distribution ($\boldsymbol{\varepsilon}_q = \{\varepsilon_{q1}, \varepsilon_{q2}\}' \sim BVN(\mathbf{0}, \boldsymbol{\Omega}_q)$). Note that the diagonal elements in $\boldsymbol{\Omega}_q$ are fixed to 1 for identification purposes, and therefore $\boldsymbol{\Omega}_q$ corresponds to a correlation matrix $\boldsymbol{\Omega}_q = \begin{bmatrix} 1 & \rho_q \\ \rho_q & 1 \end{bmatrix}$ with $-1 \le \rho_q \le 1$. To capture heterogeneity across individuals in the correlation, we reparametrize $\rho_q$ using exogenous variables specific to the decision maker as $\rho_q = \dfrac{1 - \exp(\boldsymbol{\theta}'\mathbf{z_q})}{1 + \exp(\boldsymbol{\theta}'\mathbf{z_q})}$, where $\mathbf{z_q}$ is an $M \times 1$ vector of individual-specific exogenous variables (including a constant), and $\boldsymbol{\theta}$ being the corresponding $M \times 1$ vector of parameters. Note that, in the above parameterization, a positive parameter in $\boldsymbol{\theta}$ for a specific exogenous variable implies that individuals with characteristics corresponding to that variable have a lower correlation between ETF and ITF, while a negative parameter implies the reverse.

Finally, we capture the sizeable concordance observed through the second set of ETF outcome-specific shifter effects of the ITF thresholds as follows:

$$\mu_{q,j} = \tilde{\mu}_j + \left[\Delta_j + \left(\boldsymbol{\lambda}' + \boldsymbol{\tau}'_j\right)\mathbf{s}_q\right]\left(I_{q,k,j=k}\right) \tag{2}$$

where $\mu_{q,j}$ is the adjusted upper bound ITF threshold for individual *q* for the *j*th outcome level, $\tilde{\mu}_j$ is the corresponding unadjusted upper bound ITF threshold for the *j*th outcome level, and $\Delta_j$ is a constant consonance shift effect for ITF level *j*. For future reference, define $\boldsymbol{\Delta} = (\Delta_1, \Delta_2, ..., \Delta_5)'$. $\mathbf{s}_q$ is a set of individual-specific exogenous variables, $\boldsymbol{\lambda}$ and $\boldsymbol{\tau}_j$ represent coefficient vectors, and $\left(I_{q,k,j=k}\right)$ is an indicator variable that takes a value of 1 if individual *q* is observed to choose ETF level *k* <u>and</u> ITF level *j* is equal to ETF level *k*, and zero otherwise. Any element in $\mathbf{s}_q$ with a significant corresponding positive element in $\boldsymbol{\lambda}$ points to an individual-related trait that elevates consonance (without being specific to any particular ITF level *j*), while a negative element points to an individual-specific effect that depresses consonance. We will refer to elements of $\boldsymbol{\lambda}$ as "generic consonance shift effects". Then, any element in $\mathbf{s}_q$ with a significant corresponding element in $\boldsymbol{\tau}_j$ represents an individual-related trait that modifies the level of the generic individual consonance for the specific ordinal level *j*. We will refer to elements of $\boldsymbol{\tau}_j$ as "outcome-specific consonance shift effects". To ensure the strict ascending order of $\mu_{q,j}$ (that is, $\mu_{q,1} < \mu_{q,2} < \ldots < \mu_{q,5}$ for every individual *q*), the shifts (i.e., $\left[\Delta_j + \left(\boldsymbol{\lambda}' + \boldsymbol{\tau}'_j\right)\mathbf{s}_q\right]\left(I_{q,k,j=k}\right)$) corresponding to an ITF level *j* were also added to all subsequent thresholds $\tilde{\mu}_{q,r} : r > j; r \le 5$ such that the new adjusted threshold $\mu_{q,j}$ do not overlap with other subsequent thresholds.[4]

The parameters to be estimated in the above bivariate ordered probit model may be collected into a vector as follows: $\boldsymbol{\gamma} = (\boldsymbol{\alpha}', \boldsymbol{\delta}', \boldsymbol{\theta}', \boldsymbol{\psi}', \tilde{\boldsymbol{\mu}}', \boldsymbol{\Delta}', \boldsymbol{\lambda}', \boldsymbol{\tau}')'$, where $\boldsymbol{\tau} = (\boldsymbol{\tau}_1', \boldsymbol{\tau}_2', ..., \boldsymbol{\tau}_5')'$. and $\tilde{\boldsymbol{\mu}} = \{\tilde{\mu}_1, \tilde{\mu}_2, ..., \tilde{\mu}_5\}$. Then, the probability that individual *q* will have an ETF level of *k* and an ITF level of *j* may be written as follows:

$$
\begin{aligned}
P(y_{q1} = k, y_{q2} = j) &= \int_{\varepsilon_{q,1} = \psi_{k-1} - \boldsymbol{\alpha}'\mathbf{w}_q}^{\varepsilon_{q,1} = \psi_k - \boldsymbol{\alpha}'\mathbf{w}_q} \int_{\varepsilon_{q,2} = \mu_{q,j-1} - (\boldsymbol{\alpha}' + \boldsymbol{\delta}')\mathbf{w}_q}^{\varepsilon_{q,2} = \mu_{q,j} - (\boldsymbol{\alpha}' + \boldsymbol{\delta}')\mathbf{w}_q} f_{\boldsymbol{\varepsilon}_q}(\mathbf{0}, \boldsymbol{\Omega}_q) d\boldsymbol{\varepsilon}_q \\
&\quad \Big[ \Phi_2\left(b_{q,k}, c_{q,j}, \rho_q\right) - \Phi_2\left(b_{q,k}, c_{q,j-1}, \rho_q\right) \\
&\quad - \Phi_2\left(b_{q,k-1}, c_{q,j}, \rho_q\right) + \Phi_2\left(b_{q,k-1}, c_{q,j-1}, \rho_q\right) \Big]
\end{aligned} \tag{3}
$$

where $b_{q,k} = \psi_k - \boldsymbol{\alpha}'\mathbf{w}_q$, $c_{q,j} = \mu_{q,j} - (\boldsymbol{\alpha}' + \boldsymbol{\delta}')\mathbf{w}_q$, and $\Phi_2$ is the bivariate cumulative normal distribution function. To write the likelihood function, define $I_q(k, j)$ as a binary indicator variable that takes the value of 1 if individual has an ETF level of *k* and ITF level of *j*. Then, the likelihood function for individual *q* may be written as:

$$
L_q(\boldsymbol{\gamma}) = \prod_{k=1}^{K} \prod_{j=1}^{J} \left[ P(y_{q1} = k, y_{q2} = j) \right]^{I_q(k,j)} \tag{4}
$$

This likelihood function entails the computation of bivariate normal cumulative distribution functions, which is easily achieved. The estimation was undertaken using

[4] Despite the above-adopted additive specification, there could be situations when adjusted thresholds can overlap with the unadjusted thresholds, particularly when the shifts are highly negative. In such situations, it is advisable to adopt a second level exponential parameterization of these shifts (see for example, Eluru et al., 2008, Balusu et al., 2018) to avoid violation of the non-decreasing property of the thresholds. However, in our empirical case, since the shifts were corresponding to consonance behavior that were mostly positive, we did not require any additional parameterization.

libraries and routines written by the research team in the GAUSS matrix programming language (Aptech, 2022).

# Chapter 4: Model Estimation Results

The final model specification was developed through a systematic method of testing several functional forms and combinations of explanatory variables, while removing statistically insignificant ones to develop a parsimonious specification. All explanatory variables are available in the data in categorical/bracketed form, except for age which was collected as a continuous variable. The categorical/bracketed variables were considered as dummy variables in the most disaggregate form available, and progressively combined based on statistical tests to yield parsimonious specifications. The age variable was tested in linear form as well as non-linear dummy variable forms in different brackets (for the latter, again starting in disaggregate brackets with adequate number of observations, and then progressively combining into larger brackets). The non-linear dummy variable form clearly outperformed the linear form in terms of data fit, and is the retained form for age.

In the model estimation process, we used a t-statistic threshold of 1.00 to retain variables (corresponding to a 0.32 level of significance or 68% confidence level), because of the moderate-sized sample used in the analysis and the potential for such included variables to guide future investigations with larger sample sizes.

The model results are presented by variable within each broad group going down the rows of Table 3. The results for exogenous variable effects on ETF propensity and ITF propensity shift effects are first presented, with the former effects identified by the label "ETF" in parenthesis, and the latter effects identified by the label "ITF shift" (these correspond to $\boldsymbol{\alpha}$ and $\boldsymbol{\delta}$ parameters). Note that any variable in the table with the label of "ETF" (with no additional label of "ITF shift") has the same effect on both ETF and ITF propensity. Any variable with the label of "ETF" as well as "ITF shift" has an effect on ETF propensity given by the coefficient labeled "ETF", and an effect on ITF propensity given by the sum of the coefficients labeled "ETF" and "ITF shift". Next, in our results discussion, the threshold parameters are presented, starting with the fixed ETF threshold elements of $\boldsymbol{\psi}$ and the ITF unadjusted threshold value elements embedded in $\tilde{\boldsymbol{\mu}}_{\cdot}$, followed by the constant consonance shift effects (the elements of the $\boldsymbol{\Delta}$ vector), the generic consonance shift effects of the $\boldsymbol{\lambda}$ vector, the outcome-specific consonance shift effects of $\boldsymbol{\tau}_j$, and the cross ETF-ITF threshold adjustments. Finally, the correlation parameter results are listed, corresponding to the $\boldsymbol{\theta}$ vector.

**Table 3**: Estimates of Exogeneous Variables on ETF and ITF

| **Exogeneous Variables (Base Category - Frequency)** | **ETF and ITF** | |
|---|---|---|
| | Coeff. | t-stat |
| ***Individual-Level Characteristics*** | | |
| **Gendered Lifecycle and Employment Status Variables** | | |
| Single Individual (ETF) | 0.174 | 1.97 |
| Single Female (ETF) | 0.094 | 1.55 |
| Employed Part-time * Male (ETF) | 0.220 | 1.52 |
| Single Individual (ITF Shift) | -0.289 | -2.23 |
| Employed Part-time * Male (ITF Shift) | -0.335 | -1.71 |
| **Age (18 to 24 years old)** | | |
| 25 to 29 (ETF) | -- | -- |
| 30 to 39 (ETF) | -- | -- |
| 40 to 64 (ETF) | -0.141 | -2.22 |
| 65 or Older (ETF) | -0.208 | -1.96 |
| 25 to 29 (ITF Shift) | -0.287 | -2.04 |
| **Education (High School or Some College)** | | |
| Bachelor or Graduate Degree (ETF) | 0.201 | 2.63 |
| Bachelor or Graduate Degree (ITF Shift) | -0.223 | -2.03 |
| ***Household Characteristics*** | | |
| **Income (≥ $150,000)** | | |
| < $50,000 (ETF) | -0.705 | -6.30 |
| $50,000 to $99,9999 (ETF) | -0.442 | -4.56 |
| $100,000 to $149,999 (ETF) | -0.328 | -3.29 |
| $50,000 to $99,999 (ITF Shift) | 0.216 | 1.85 |

**Table 3**: Estimates of Exogeneous Variables on ETF and ITF (continued)

| Exogeneous Variables (Base Category - Frequency) | ETF and ITF | |
|---|---|---|
| | Coeff. | t-stat |
| **Vehicles / Person / Household (Scarcity or Equilibrium of Vehicles)** | | |
| More Vehicles than Household Members (Surplus of Vehicles) (ETF) | -0.12 | -1.44 |
| More Vehicles than Household Members (Surplus of Vehicles (ITF Shift) | 0.214 | 1.91 |
| ***Job-Related Characteristics*** | | |
| **Occupation (Public Administration, Services/Retail Service, Transportation, Business-Related)** | | |
| Education (ETF) | -0.349 | -2.9 |
| Manufacturing/Construction (ETF) | -0.421 | -2.59 |
| Medical (ETF) | -0.424 | -4.48 |
| Professional, Managerial, or Technical (ETF) | 0.55 | 4.11 |
| Medical (ITF Shift) | 0.272 | 1.86 |
| **Employer Size (≥ 100 Workers)** | | |
| 1 to 9 Workers (ETF) | 0.42 | 4.67 |
| 10 to 99 Workers (ETF) | -0.191 | -2.36 |
| 1 to 9 Workers (ITF Shift) | -0.34 | -2.41 |
| ***Residential Characteristics*** | | |
| **Distance to Work (≥ 31 miles)** | | |
| 0.00 to 5.99 miles (ETF) | -0.132 | -1.08 |
| 6.00 to 10.99 miles (ETF) | -0.441 | -3.21 |
| 11.00 to 30.99 miles (ETF) | -0.441 | -3.41 |
| 6.00 to 10.99 miles (ITF Shift) | 0.355 | 2.99 |
| 11.00 to 30.99 miles (ITF Shift) | 0.348 | 3.37 |
| **Neighborhood Density (Suburban or Urban)** | | |
| Rural (ITF Shift) | 0.215 | 1.89 |
| **States by Census Bureau-Designated Regions (Northeast, Midwest, South)** | | |
| All states in the west besides Arizona and California (ETF) | 0.152 | 2.13 |
| **Housing Tenure (Own)** | | |
| Rent (ETF) | -0.063 | -1.03 |

**Table 3**: Estimates of Exogeneous Variables on ETF and ITF (continued)

| Exogeneous Variables (Base Category - Frequency) | ETF and ITF | |
|---|---|---|
| | Coeff. | t-stat |
| ***Thresholds*** | | |
| **ETF Thresholds (** $\psi$ vector) | | |
| 1\|2 | -1.187 | -7.28 |
| 2\|3 | -1.083 | -6.63 |
| 3\|4 | -0.860 | -5.29 |
| 4\|5 | -0.669 | -4.12 |
| 5\|6 | 0.206 | 1.28 |
| **Unadjusted ITF Thresholds** ($\tilde{\mu}$ vector) | | |
| 1\|2 | -3.068 | -12.37 |
| 2\|3 | -2.736 | -11.46 |
| 3\|4 | -2.351 | -10.10 |
| 4\|5 | -2.220 | -9.58 |
| 5\|6 | -1.506 | -6.67 |
| **Constant Consonance Shifts in ITF** ($\Delta$ vector) | | |
| 1\|2 Consonance Shift | 1.194 | 4.67 |
| 2\|3 Consonance Shift | 2.068 | 8.07 |
| 3\|4 Consonance Shift | 1.939 | 8.58 |
| 4\|5 Consonance Shift | 1.272 | 6.54 |
| 5\|6 Consonance Shift | 1.017 | 7.15 |
| **Generic Consonance Shifts in ITF** ($\lambda$ vector) | | |
| **Income (between $50,000 and $149,999)** | | |
| < $50,000 | -0.664 | -4.14 |
| ≥ $150,000 | 0.346 | 2.43 |
| **Employer Size (≥ 100 workers)** | | |
| 10 to 99 Workers | -0.150 | -1.32 |
| **Outcome-Specific Consonance Shifts in ITF** ($\tau_j$ vector) | | |
| **Household Size (Two or More Individuals)** | | |
| One Individual * EVERDAY TELEWORK | -0.735 | -2.03 |
| **Income (between $50,000 and $149,999)** | | |
| < $50,000 * NEVER TELEWORK | 0.436 | 2.26 |

**Table 3**: Estimates of Exogeneous Variables on ETF and ITF (continued)

| Exogeneous Variables (Base Category - Frequency) | ETF and ITF | |
|---|---|---|
| | Coeff. | t-stat |
| **Employer Size (≥ 100 workers)** | | |
| 1 to 9 Workers * EVERDAY TELEWORK | 0.359 | 1.42 |
| **Cross ETF-ITF Threshold Adjustments** | | |
| "Never" ETF to "2-3 times a week" ITF | 0.229 | 3.66 |
| "Never" ETF to "Everyday" ITF | 1.055 | 7.01 |
| ***Correlations*** ( $\theta$ vector) | | |
| **Age (18 to 64 years old)** | | |
| 65 or Older | -0.671 | -2.26 |
| **Income (<$100,000 or ≥ $150,000)** | | |
| $100,000 to $149,999 | 0.345 | 1.81 |
| **Household Size (Two or more individuals)** | | |
| One Individual | -0.291 | -1.15 |
| **Constant** | -0.499 | -2.24 |

## 4.1 ETF PROPENSITY AND ITF PROPENSITY SHIFT PARAMETER ESTIMATES

### 4.1.1 Individual/Household Demographics

The gendered lifecycle variable effects in Table 3 indicate that individuals who live alone have a higher ETF propensity than other individuals. This maybe a consequence of single individuals self-selecting themselves into jobs that provide more autonomy and time flexibility. Single individuals also may have fewer distractions at home (i.e., no roommates, children, significant other, and parents) and so may welcome teleworking opportunities (see Zhang et al., 2020). Interestingly, while many earlier studies before COVID have reported a lower propensity of telework among single women relative to single men (Popuri and Bhat, 2003; Tomei, 2021), our results show a more nuanced picture. In particular, the results for the gender effects need to be considered together with those for the employment status (part-time versus full-time) variable because of the interaction effect between gender and employment status. Thus, though employment status is technically a job-related characteristic, we include it as an individual demographic variable in Table 3. Overall, single women working full-time have a higher ETF propensity relative to (single and non-single) men employed full-time, but men (single and non-single) employed part-time have a higher ETF propensity relative to women regardless of whether the woman is single or not and regardless of whether the woman is part-time or full-time employed. This clearly suggests, as in Sweet and Scott (2022) and aligned with Ono and Mori (2021), a gendering of telework particularly for part-time employees, possibly attributable to employer-related pressure felt by women part-time workers (but not men part-time workers) to show up regularly at the work office. Our analysis did not reveal any statistically significant variations in ETF inclination between men and women if not single and working full-time. The results also point to young children in the household having the expected effect of increased telework proclivity to better balance work and life outside of work (see Barrero et al., 2021 and Vilhelmson and Thulin, 2016). Besides, teleworking could also be a means for parents of young children, as they become more aware of life responsibilities, to save commuting and work apparel costs. However, there is no gendered effect of young children; that is, we did not find any statistically significant difference in teleworking predisposition between men and women when young children are present, suggesting that the prolonged at-home lockdown period during the pandemic may have reduced traditional gender inequalities in housework and child-rearing. Another intriguing result pertaining to the ideal teleworking frequency (ITF) is that single individuals and men working part-time would rather have a lower telework frequency in their ideal state (that is, a lower ITF) than their existing telework frequency (that is, ETF; see the negative coefficient on the single individual (ITF shift effect) and the employed part-time*male (ITF shift effect)). This may be a reflection of how the pandemic has impacted perceptions of teleworking. While COVID may have opened teleworking doors for many non-single individuals and for men working part-time (as a means to a good work-life balance), it appears to have had the opposite effect on single individuals who were locked down in their homes with few people to interact with. This may explain the desire among single individuals to return to regular day-to-day at-work socialization, even if at the expense of a reduction in socialization outside the work place.

The age effects in Table 3 reveal that individuals aged 40 years and older have a lower ETF propensity than individuals aged 18 to 39 years old, with no difference in ETF propensity among individuals under 40 years (unlike Sweet and Scott, 2022, we did not find any difference in the age effects between part-time and full-time employees, nor did we find any age-gender interaction effects as has been observed in many earlier studies; see, for example, Sener and Bhat, 2011). Further, individuals aged 65 years and older have the lowest ETF propensity. These results may be explained by the different network correlates of socialization between young and older adults (Green et al., 2001). While younger adults generally revel in the size of their social networks outside their workplace and look to balance work and play (PWC, 2021; Asdecker, 2022), older adults typically view their workplace as one of the primary (if not the primary) location of social networking (Tahlyan et al., 2022a and Asmussen et al., 2023b). Further, older individuals stick to life rhythms and are resistant to change (Duque et al., 2019). Thus, being accustomed to in-person workdays before the pandemic, older workers are less likely to prefer teleworking arrangements (Asmussen et al., 2023b). Additionally, challenges that arise with technology-use during teleworking may also discourage teleworking among older workers (Tahlyan et al., 2022b). However, it appears that, in their ideal work arrangements, younger individuals in the age group of 25-29 years would prefer to telework less than their ETF, to the point that their ITF propensity is actually lower than their older peers. There is a suggestion here that the pandemic, while opening up teleworking opportunities, has also led to a felt need among younger workers for more in-person mentorship and professional networking opportunities for career advancement (Bucknell University, 2021; Tahlyan et al., 2022b). However, this holds only for the older young adults in the age group of 25-29 years, not to the youngest of adults in the age group of 18-24 years.

Similar to the case of younger workers, the results show a higher ETF among individuals with a bachelor or graduate degree than among individuals with some college or high school education, a result presumably of high-level knowledge jobs generally being more conducive to teleworking arrangements (Sener and Bhat, 2011; Dua et al., 2022; Rembert et al., 2021; Marshall et al., 2021; López-Igual and Rodríguez-Modroño, 2020). In addition, individuals with higher levels of formal education typically have a negotiating advantage in the marketplace (Zhang et al., 2020), which may be contributing to the higher ETF propensity. However, as in the case of young workers, those with higher formal degrees would actually like to telework less than their existing arrangement, to the point where there is no difference in ITF based on education (note that the effect of bachelor and graduate degree education is almost zero (=0.201-0.223) on ITF). This is likely because workers with a higher level of formal education may have become saturated with telework over the course of the pandemic and after, and therefore would like to go into the work office more often (Asgari et al., 2023).

Among household demographics, clearly individuals from lower income households have a lower ETF predisposition than those from higher income households, as evidenced in the highest negative value for the lowest income bracket and progressively decreasing (but still negative) coefficients for other income brackets (with the highest income bracket being the base category). These findings align with the previous literature, and may be ascribed to more options for telework, and more negotiating power to telework in the market place, for individuals with high income earning potential (see for example Tahlyan et al., 2022b, Asmussen et al., 2023b, He and Hu, 2015). However, workers with a household income of $50,000 to $99,999 prefer to telework more in their ideal situation than their existing telework arrangement. Effectively, then, as for ETF propensity, employees from the lowest household income bracket continue to indicate the lowest ITF propensity, and those from the highest household income bracket continue to express the highest ITF propensity, but there is little difference in ITF propensity between the two middle income brackets of $50,000-$99,999 (ITF propensity effect of -0.226 = -0.442+0.216) and $100,000-$149,999 (-0.328).

With regard to household vehicle availability effects, households with more vehicles than household members (i.e., with a surplus of vehicles) have a lower ETF propensity relative to households with the same number or less vehicles than household members, a result consistent with the findings from Sweet and Scott (2022). In an ideal situation, though, this telework propensity difference based on vehicle availability becomes statistically insignificant (the vehicle availability effect on ITF propensity is +0.094 (0.214-0.120) with a corresponding t-statistic of only 0.67). Overall, it appears that many of the individual/household demographic effects are tempered in their effects on ITF propensity relative to their effects on ETF propensity, suggesting that the pandemic has opened up telework possibility in the minds of individuals from all demographic segments of society.

### 4.1.2 Job-Related Characteristics

Within the set of job characteristics, the occupation effects are consistent with expectations, with those in frontline occupations (education, manufacturing/construction, and medical sectors) exhibiting a lower ETF propensity, and those in the professional, managerial, and technical professions exhibiting a higher ETF propensity, relative to those in public administration, services/retail, transportation, and business-related sectors (Astroza et al., 2020; Dey et al., 2020; López-Igual and Rodríguez-Modroño, 2020). These differential teleworking intensities across sectors carry over to ITF propensity too, except that individuals in the medical profession (i.e., first responders and other healthcare workers) would prefer to telework more than their existing telework arrangement (based on the positive coefficient for the medical sector corresponding to the ITF shift effect). The uptake of telemedicine during COVID appears to have tempered the perception among medical employees that they must go into the work office routinely to pursue their job effectively, thus fueling a desire for more telework (Wosik et al., 2020).

Also, in the set of job characteristics, individuals employed in small-sized firms (1 to 9 workers) have the highest ETF propensity, while those in mid-sized firms (10 to 99 workers) have the lowest ETF propensity. Zhang et al. (2020) and Haider and Anwar (2023) similarly find that those employed in smaller and larger firms have more teleworking opportunities than those in mid-sized firms. The higher ETF propensity of employees of small-sized firms gets tempered in the context of ITF propensity, to the point that there is no difference between those employed in small-sized or large-sized firms. That is, employees in small-sized firms desire less teleworking than currently, perhaps because their current teleworking arrangement is dictated by lack of office space and not reflective of their ideal preference.

### 4.1.3 Residential Attributes

The residential attributes that turned out to be statistically significant in our specification include residential location (characterized by distance to the work office, density type of neighborhood in the three categories of urban, suburban, and rural, and U.S. state of residence), and housing tenure. The distance to work effects reveal a higher ETF propensity among those with a commute distance of 31.00 miles or longer relative to those with shorter commute distances. Also of note is that individuals commuting between 6.00-30.99 miles are less likely to telework relative to those with a commute distance of shorter than six miles. That is, teleworkers appear to be clustered in the relatively low commute distance range and the high commute distance range, and least in the middle commute distance range in a U-shaped pattern. The telework clustering at the low commute distance end may be a reflection of a conscious effort on the part of those who like to socialize beyond work but also at work to locate themselves close to the office. The telework clustering at the high commute distance range is consistent with that observed in the earlier literature (Ravalet and Rérat, 2019; Cerqueira et al., 2020; Melo and de Abreu e Silva, 2017; He and Hu, 2015). As interesting is that individuals in the middle commute distance range of 6.00-30.99 miles, who have the lowest ETF propensity, would like to telework more in their ideal state. In fact, the commute distance effect literally vanishes in the context of ITF propensity for distances below 31 miles, with only those with extreme commutes (≥ 31.00 miles) having a uniformly higher ITF propensity than other individuals (notice that the 6.00-10.99 miles distance effect on ITF propensity is -0.441+0.355=-0.086, and the 11.00-30.99 miles distance effect on ITF propensity is -0.441+0.348 =-0.093, while the 0.00-5.99 miles distance effect on ITF propensity remains at -0.132; all these three distance effects are about the same and are not statistically significant even at the 20% level of significance). We considered interaction effects for the commute distance effect based on density type of living for both ETF and ITF propensities, but these did not turn out to be statistically significant.

In terms of a density main effect, the results show that individuals living in a rural area prefer to telework more than their existing telework arrangement. This is consistent with previous research that has determined that many teleworkers have moved to a remote residential location after the onset of the pandemic (Caldarola and Sorrell, 2022; Cerqueira et al., 2020). Therefore, it makes sense that these workers would prefer even more telework than their current remote work arrangement as a result of a longer commute distance to work.

The other residential location attribute effects are uniform and remain unchanged between the ETF and ITF propensities. These reveal that telework propensity is higher for individuals who (a) live in states in the west besides Arizona and California, and (b) own a home rather than rent a home. The higher ETF propensity in the western part of the U.S. (excluding Arizona and California) should be interpreted simply as an overall adjustment term to accommodate for a whole set of unobserved spatial factors, though Ozimek and Carlson (2022) also find that telework is less frequent in the Midwest and Southern regions of the U.S. The latter result related to housing tenure may be explained by more privacy and fewer distractions when in an own home rather than in a rented home. Also, we found substantial correlation between housing tenure and dwelling type, with those owning a home almost always living in a private standalone home, while those renting a home residing in a condominium/apartment complex. Thus, we did not include the dwelling unit type as another explanatory variable in addition to housing tenure. But given this correlation, it gives further reinforcement for the elevated privacy/less distraction justification for the lower telework propensity among those who rent a home (see also Zhang et al., 2020; Caldarola and Sorrell, 2022).

### 4.2 Dissonance and Consonance Parameter Estimates on Threshold Values

The second row panel of Table 3 presents the threshold values and the many shifts in these values. The ETF thresholds (elements of the $\boldsymbol{\psi}$ vector) and the unadjusted ITF thresholds (elements of the $\tilde{\boldsymbol{\mu}}$ vector) do not have any substantive interpretations, but simply adjust to provide the best mapping between the underlying latent ETF/ITF propensities and the actual observed bivariate ETF/ITF ordinal outcomes of individuals, after accommodating all other model effects.

The constant consonance shift effects refer to elements of the $\boldsymbol{\Delta}$ vector, and represent shifters of ITF thresholds after accounting for individual characteristics that lead to consonance of ETF and ITF. The magnitudes of these constant consonance shift effects, like the unadjusted ITF thresholds, do not have any substantive interpretation. But all these effects are positive, indicative of clear consonance effects at play (as discussed earlier in Chapter 3.2.2, more than 46 percent of the individuals in our sample demonstrated consonant behavior).

The next set of generic consonance shift effects in Table 3 refer to the elements of the $\boldsymbol{\lambda}$ vector. The results indicate, very intuitively, that individuals with an annual household income of less than $50,000 are least likely to have consonance, while those in the highest household annual income bracket of 150K or more have the highest consonance level. Typically, individuals with less income earnings have the lowest bargaining ability in the marketplace (Asmussen et al., 2023b). Also, individuals who work at a medium-sized company (10 to 99 workers) are more likely to experience dissonance than those who work at a small or large-sized company. Typically, relatively small- or larger-sized firms have more flexibility, which enables their employees to telework according to their preferences (see Zhang et al., 2020 and Lister and Harnish, 2011).

The outcome-specific consonance shift effects, corresponding to the vector $\boldsymbol{\tau}_j$, are listed next in the table. While the generic consonance shift effects account for demographic effects generic to all telework frequency levels, the outcome-specific consonance shift effects capture individuals who are consonant based on specific telework frequency levels. The results reveal that single individuals have the least consonance (the most dissonance) in terms of telework every day. This effect reinforces the earlier finding that single individuals would rather have a lower telework frequency in their ideal state than their existing telework frequency, but indicates that this effect is particularly acute for those currently teleworking every day. That is, single individuals currently teleworking everyday appear to want to be in the work office at least on some days of the week. In contrast, individuals in the lowest household income bracket (who display the most dissonance across all telework frequency levels because of a lack of bargaining ability) have that dissonance level tempered some in the lowest level of telework, as indicated by the positive coefficient on the "<50,000*Never Telework" variable. Again, this is rather intuitive, given that individuals in the lowest income group would be cognizant of the relatively essential nature of their occupations, and may have come to terms somewhat with never being able to telework. Further, the results point to a high level of consonance among those working in small firms of 1-9 workers, in terms of their specific preference to telework every day. This may seem to be inconsistent with the earlier finding that employees in small-sized firms desire less teleworking than currently, but the takeaway is that, among employees in small-sized firms, those currently teleworking everyday are happy continuing to do so. However, employees in small-sized firms who are currently teleworking at other teleworking levels would rather do less teleworking.

Finally, to accommodate ETF-ITF combinations that are unlikely to occur, we include cross ETF-ITF threshold adjustments, as explained in Chapter 3.3.1. The two that turned out statistically significant correspond to the "Never ETF/2-3 times ITF" and "Never ETF/everyday ITF" combinations. The observed positive effect on the ITF thresholds pushes the thresholds toward the right. The net effect is to mimic the observed outcome combinations in the sample. This is particularly discernible for the large positive shift of the lower bound of the "Everyday ITF" threshold for those who have "Never ETF" as their outcome. This adjustment has the effect of substantially reducing the "Never ETF/Everyday ITF" combination to fit the very low percentage of individuals with "Never ETF" who desire "Everyday ITF" (see Table 1), so that such infrequent combinations do not unduly corrupt dissonance estimation levels.

### 4.3 CORRELATION TERMS

The penultimate row panel of Table 3 presents the estimates corresponding to the vector $\boldsymbol{\theta}$ embedded in the correlation function (see Chapter 3.3.2). The constant value of -0.499 indicates that the correlation between the ETF and ITF propensities for the base individual (that is, an individual who is 18-64 years of age, in the less than 100K or 150K or more household annual income range, and with two or more individuals in the household) is +0.244 with a t-statistic of 2.33. This significant correlation indicates the presence of several unobserved factors that influence both current as well as preferred telework frequency in the same direction. Explicitly incorporating the correlation is important to maintain the strict jointness of the ETF and ITF outcomes, since current telework frequency is used as an "endogenous" explanatory variable in the thresholds of ITF propensity. The other sociodemographic effects modify the correlation intensity. Specifically, a higher correlation between ITF and ETF propensity is observed for older individuals (i.e., 65 and above) and individuals belonging to single households, as compared to all others sub-segments in the population (thus, for example, the estimates in the table indicate that the correlation rises to a value of 0.526 for older individuals in households with at least one additional individual and with an income of less than 100K or 150K or more). In contrast, individuals from medium income households have lower correlations relative to individuals from households belonging to other income categories.

### 4.4 Model Goodness of Fit

The goodness of fit measures for the developed model are presented in two forms – (a) Likelihood based goodness of fit measures, and (b) non-likelihood-based goodness of fit measures. We first discuss the likelihood-based data measures.

#### 4.4.1 Likelihood Based Goodness of Fit Measures

As shown in Table 4, the log-likelihood at convergence and the constants-only predictive log-likelihood estimates are sufficient to assess fit. Through the log-likelihood ratio, the results indicate that the model with the sociodemographic attributes in the specification describe the telecommuting behavior better than the constants-only model at any reasonable significance level.

**Table 4**: Disaggregate Data Fit Measures

| Metric | Proposed Model |
|---|---|
| Log-Likelihood at Convergence | -3038.11 |
| Number of Parameters | 60 |
| Constants-Only Predictive Log-Likelihood | -3305.60 |
| Number of Parameters for Constants-Only Model | 10 |
| Log-Likelihood Ratio | 534.97 |
| Likelihood Ratio Test | $LR = 534.97 > \chi^2{}_{(50,0.01)} = 29.71$ |

#### 4.4.2 Non-Likelihood Based Goodness of Fit Measures

To further supplement the likelihood-based data fit measures (reported in Table 4), we evaluate the disaggregate level joint distribution for the entire sample. Further, the joint distribution is aggregated to arrive at the predicted distribution of the "existing" and "ideal" telecommuting frequencies in the estimation sample. Notably, due to our moderately sized sample, we undertook an in-sample evaluation rather than a more traditional hold-out sample validation. The predicted in-sample ETF and ITF are reported in Table 5. Clearly, the developed model is able to replicate the sample trends fairly accurately.

For instance, the in-sample predictions, specifically those across the diagonal (i.e., the count of individuals who experience consonance), align very closely with the in-sample descriptive statistics shown in Table 2. If anything, the predictions are slightly over-estimated for “a few times/year”, “a few times/month”, “once/week”, “a few times/week”, and “every day” but not significantly so. The predictions for the marginals of the ETF align exactly for the “never” and “a few times/year” in-sample descriptive statistics. The “a few times/month” and “once/week” frequencies are slightly over-represented in the ETF predictions, while the “a few times/week” and “every day” frequencies are slightly under-represented. Meanwhile, the predictions for the marginals of ITF align exactly for the “a few times/year” in-sample descriptive statistic. The predictions are slightly over-estimated for the “a few times/month”, “once/week”, and “a few times/week” frequencies in the ITF predictions, while the “never” and “every day” frequencies are under-estimated.

**Table 5**: Predicted Frequency Within Each ETF and ITF Category

| ETF | ITF | | | | | | | | | | | | ETF Marginal | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Never | | A Few Times/ Year | | A Few Times/ Month | | Once/Week | | A Few Times/Week | | Every Day | | | |
| | Count | % | Count | % | Count | % | Count | % | Count | % | Count | % | Count | % |
| Never | **54** | 15.4% | 32 | 9.1% | 47 | 13.4% | 49 | 14.0% | 148 | 42.2% | 21 | 6.0% | 351 | 100.0% |
| A few Times/Year | 0 | 0.0% | **20** | 50.0% | 6 | 15.0% | 2 | 5.0% | 8 | 20.0% | 4 | 10.0% | 40 | 100.0% |
| A Few Times/Month | 1 | 1.0% | 1 | 1.0% | **54** | 56.3% | 5 | 5.2% | 21 | 21.9% | 14 | 14.6% | 96 | 100.0% |
| Once/Week | 1 | 1.2% | 1 | 1.2% | 2 | 2.3% | **27** | 31.4% | 24 | 27.9% | 31 | 36.0% | 86 | 100.0% |
| A Few Times/Week | 2 | 0.5% | 2 | 0.5% | 6 | 1.6% | 3 | 0.8% | **163** | 44.2% | 193 | 52.3% | 369 | 100.0% |
| Every Day | 0 | 0.0% | 1 | 0.3% | 2 | 0.7% | 1 | 0.3% | 18 | 6.1% | **275** | 92.6% | 297 | 100.0% |
| **ITF Marginal** | 58 | 4.7% | 57 | 4.6% | 117 | 9.4% | 87 | 7.0% | 382 | 30.8% | 538 | 43.4% | 1239 | 100.0% |

# Chapter 5: Implications

The estimation results in the previous chapter do not provide information on the actual effects of the variables on ETF and ITF. In fact, even the directionality of the effect of a variable on the underlying propensity does not provide a sense of how the variable may actually impact ETF and ITF. Besides, with the unobserved individual-specific correlation and ITF shifter effects based on the endogenous ETF levels, and because of the non-linear nature of the model, the consonance and dissonance effects will vary across individuals. But our model can provide the joint probability of any combination of the ETF and ITF outcomes, and therefore the consonance/dissonance intensities, given a specific combination of the many exogenous variables. But the number of combinations of exogenous variables is over 86,000. So, we provide the teleworking consonance/dissonance levels for each exogenous variable separately by holding all other exogenous variables fixed at those in the sample. Specifically, for each exogenous variable, we consider all sample individuals to be at each specific state of the exogenous variable. For example, we consider all individuals to be renting their homes, compute the teleworking consonance/dissonance levels for each individual, and take an average across all individuals. Next, we consider all individuals to be owning their homes, again compute the teleworking consonance/dissonance levels of reach individual, and take an average.

The approach to estimate the individual-level teleworking consonance/dissonance levels itself still entails 36 ETF-ITF combinations. To simplify the presentation, cardinal values are assigned to each of the ETF and ITF ordinal levels. The cardinal value assignments on a per month basis are as follows: (1) Never = 0 instances per month, (2) A few times/year = 0.25 instances per month, (3) A few times/month = 2 instances per month, (4) once/week = 4 instances per month, (5) a few times/week = 10 instances per month, and (6) Everyday = 22 instances per month. Based on these assignments, let the cardinal value assignment corresponding to ETF level *k* be and using the notation $g_k$, and let the cardinal value assignment corresponding to ITF level *j* be $h_j$. Then, using the same notations for ETF and ITF levels as in Chapter 3.2.2, we can compute the following attributes characterizing teleworking consonance/dissonance attributes for individual *q*:

(1) Probability of being in consonance: $\text{Prob}(con_q) = \sum_{k=1}^{6} P(y_{q1} = k, y_{q2} = k)$ (5)

(2) Preferred monthly teleworking consonance level: $\sum_{k=1}^{6} g_k \times P(y_{q1} = k, y_{q2} = k)$ (6)

(3) Probability of being in dissonance: $\text{Prob}(dis_q) = 1 - \text{Prob}(con_q)$ (7)

(4) Dissonance intensity: $\sum_{k=1}^{6} \sum_{j \neq k} (h_j - g_k) \times P(y_{q1} = k, y_{q2} = j).$ (8)

The results of the above analysis are presented in Table 6, which generally follows the discussion in Chapter 4, though we are better able to discern the extent of consonance/dissonance for each group of individuals. Thus, for example, the table indicates that about 44% of men who have a partner and are employed full-time are content with their ETF (i.e., they experience consonance). Additionally, for these individuals who experience consonance, their number of telework days per month, on average, is 5.8 days (another way to interpret this is that, to keep such individuals happy, they should be allowed to telework, on average, 5.8 days per month). On the other hand, about 56% of men who have a partner and are employed full-time are not happy with their ETF (i.e., they experience dissonance). Further, we see that their dissonance intensity (4.9 days) is the highest among the gendered lifecycle and employment status variable categories, tied with full-time employed women who live with a partner. Given that almost all individuals prefer more ITF than ETF, this dissonance intensity of 4.9 days implies that men with a partner and employed full time are teleworking only one day a month (5.9-4.9) (equivalent, roughly to a few times per month based on our cardinal assignment), while they would actually like to be teleworking 5.9 days a month (between once/week to a few times/week based on our cardinal assignment). Other entries in Table 6 may be similarly interpreted.

**Table 6**: Estimate of ETF and ITF Shift Effects on Telework Frequency Dissonance and Consonance

| | **Consonance State** | | **Dissonance State** | |
|---|---|---|---|---|
| | **Share** | **Preferred Telework Monthly Consonance Level (Days)** | **Share** | **Dissonance Intensity (Days)** |
| ***Individual-Level Characteristics*** | | | | |
| **Gendered Lifecycle and Employment Status Variables** | | | | |
| Full-time Employed Males with Partner | 43.9% | 5.8 | 56.1% | 4.8 |
| Full-time Employed Males without Partner | 54.3% | 7.5 | 45.7% | 3.9 |
| Full-time Employed Females with Partner | 43.9% | 5.8 | 56.1% | 4.8 |
| Full-time Employed Females without Partner | 55.1% | 8.0 | 44.9% | 4.0 |
| Part-time Employed Males with Partner | 51.3% | 7.1 | 48.7% | 3.5 |
| Part-time Employed Males without Partner | 62.7% | 9.1 | 37.3% | 2.7 |
| Part-time Employed Females with Partner | 43.9% | 5.8 | 56.1% | 4.8 |
| Part-time Employed Female without Partner | 55.1% | 8.0 | 44.9% | 4.0 |
| **Age** | | | | |
| 18 to 24 | 46.5% | 6.8 | 53.5% | 4.9 |
| 25 to 29 | 51.2% | 6.9 | 48.8% | 3.5 |
| 30 to 39 | 46.5% | 6.8 | 53.5% | 4.9 |
| 40 to 64 | 48.9% | 6.9 | 51.1% | 4.2 |
| 65 or Older | 54.2% | 7.2 | 45.8% | 3.7 |

**Table 6**: Estimate of ETF and ITF Shift Effects on Telework Frequency Dissonance and Consonance (continued)

| | **Consonance State** | | **Dissonance State** | |
|---|---|---|---|---|
| | **Share** | **Preferred Telework Monthly Consonance Level (Days)** | **Share** | **Dissonance Intensity (Days)** |
| **Education** | | | | |
| High School or Some College | 41.9% | 5.3 | 58.1% | 5.2 |
| Bachelor or Graduate Degree | 47.7% | 6.6 | 52.3% | 4.4 |
| ***Household Characteristics*** | | | | |
| **Income** | | | | |
| < \$50,000 | 29.0% | 3.7 | 71.0% | 6.5 |
| \$50,000 to \$99,999 | 43.6% | 5.8 | 56.4% | 5.1 |
| \$100,000 to \$149,999 | 46.8% | 6.3 | 53.2% | 4.4 |
| ≥ \$150,000 | 60.6% | 9.1 | 39.4% | 3.4 |
| **Vehicles / Person / Household** | | | | |
| Scarcity or Equilibrium of Vehicles | 47.4% | 6.5 | 52.6% | 4.5 |
| Surplus of Vehicles | 42.4% | 5.7 | 57.6% | 5.3 |
| ***Job-Related Characteristics*** | | | | |
| **Occupation** | | | | |
| Public Administration, Services/Retail Service, Transportation, and Business-Related | 47.0% | 6.5 | 53.0% | 4.6 |
| Education | 45.1% | 4.6 | 54.9% | 3.9 |
| Manufacturing/ Construction | 45.0% | 4.3 | 55.0% | 3.8 |
| Medical | 39.0% | 4.2 | 61.0% | 5.1 |
| Professional, Managerial, or Technical | 55.1% | 10.2 | 44.9% | 4.8 |

**Table 6**: Estimate of ETF and ITF Shift Effects on Telework Frequency Dissonance and Consonance (continued)

| | **Consonance State** | | **Dissonance State** | |
|---|---|---|---|---|
| | **Share** | **Preferred Telework Monthly Consonance Level (Days)** | **Share** | **Dissonance Intensity (Days)** |
| **Employer Size** | | | | |
| 1 to 9 Workers | 54.4% | 8.5 | 45.6% | 3.5 |
| 10 to 99 Workers | 40.9% | 5.0 | 59.1% | 5.1 |
| ≥ 100 Workers | 46.1% | 6.2 | 53.9% | 4.8 |
| ***Residential Characteristics*** | | | | |
| **Distance to Work** | | | | |
| 0.00 to 5.99 miles | 51.5% | 7.4 | 48.5% | 3.9 |
| 6.00 to 10.99 miles | 42.3% | 5.4 | 57.7% | 5.1 |
| 11.00 to 30.99 miles | 42.5% | 5.4 | 57.5% | 5.1 |
| ≥ 31 miles | 53.0% | 8.2 | 47.0% | 4.0 |
| **Neighborhood Density** | | | | |
| Suburban and Urban | 46.8% | 6.3 | 53.2% | 4.5 |
| Rural | 42.8% | 6.2 | 57.2% | 5.5 |
| **States by Census Bureau-Designated Regions (Northeast, Midwest, South)** | | | | |
| States in the Northeast, Midwest, South and Arizona and California | 46.2% | 6.2 | 53.8% | 4.6 |
| All states in the west besides Arizona and California | 47.6% | 7.1 | 52.4% | 4.8 |
| **Housing Tenure** | | | | |
| Own | 46.5% | 6.4 | 53.5% | 4.7 |
| Rent | 46.0% | 6.0 | 54.0% | 4.6 |

The results from Table 6 provide several important insights, a few of which are briefly discussed here. First, individuals experiencing the highest levels of dissonance include full-time employed men with a partner, full-time/part-time employed women with a partner, young adults, and those with the lowest formal education level and in the lowest household income bracket. These findings represent challenges faced by the segments of employees who already struggle with work-life balance issues and/or are poorly resourced.

Employers can help address this equity divide by fostering programs to enhance telework capabilities, work-life balance, and overall quality of life and mental health. Also, targeted social events, and entrusting young employees with work that they find meaningful, may help young individuals feel less dissonance. It is also likely that lower-income and lower-education employees reside in homes that may not be large enough to afford a dedicated workspace or high speed connectivity. Thus, in cases where the occupation does allow some level of teleworking, employers may want to provide a third workplace option (close to employee residences) and support (financial, technical, and material) for in-home high speed internet connectivity and equipment (devices and accessories). Of course, our results also provide important insights regarding the characteristics of employees who experience telework consonance, which employers should find useful in their recruitment practices. Second, employees in the medical profession have the highest dissonance intensity of all occupations. Employers should be aware that these are the individuals who will experience stress and job dissatisfaction as a result of their work situation. The extreme pandemic-induced workload, coupled with the realization that telemedicine constitutes an effective alternative for delivering medical care (at least in some instances), may be fueling a desire for more telework among medical workers (Wosik et al., 2020). Employers in the medical profession, and more broadly across all occupation sectors, can enhance support for workers in these frontline occupations by increasing the use of remote communication systems to accomplish tasks. Third, from a travel demand standpoint, the impacts of telework on commute vehicle miles of travel (VMT) and non-work VMT has been of substantial interest for decades (see Asmussen et al., 2023b for a recent and detailed review of this literature). Teleworkers are associated with longer commute distances, live in more remote residential locations, and also have more VMT for non-work trips compared to non-teleworkers (Zhu and Mason, 2014). On the last point, studies investigating travel demand in the aftermath of the pandemic have found that the number of non-work trips gradually increased as the pandemic evolved (McNally et al., 2023 and Yang and Lewis, 2023). Meanwhile, the number of non-work trips linked to work trips decreased. Also, the fewer work trips during the pandemic resulted in a reduction in peak period traffic, especially in the morning peak hours (Rafiq et al., 2022). In general, we know that the pandemic altered individuals travel behavior and patterns. Therefore, it is of interest to investigate the intensity of VMT changes for work and non-work, as well as peak period traffic flow changes, that would accrue if employment policies enabled employees to pursue their ITF state. Such an effort, which we leave for future studies, should provide useful insights at the interface of societal quality of life, mental wellness, and travel demand management and land use policies.

# Chapter 6: Conclusion

In this thesis, we have examined the COVID-19 induced telework frequency dissonance (TFD) of workers by investigating workers' existing telework frequency (ETF) versus their ideal telework frequency (ITF). Our approach is grounded within Festinger's influential social psychology theory on cognitive dissonance. This theory is used to explain the potential disconnect between the existing telework arrangements of employees (as influenced, in large part, by employer preferences/requirements) and what employees would prefer if the choice were totally up to them. The study employed a bivariate ordered response probit (BORP) system to jointly model an individual's ETF and ITF, while also recognizing that unobserved individual factors that elevate ETF may also lead to the individual planning to telework more in their ideal choice situation. A novel and elegant heterogeneous thresholding mechanism, which we have not seen proposed in the econometric literature, is employed within the context of the BORP system to (a) recognize that many individuals may in fact be in consonance (ITF=ETF), (b) identify individual groups that are likely to be more in consonance than other groups, and the teleworking frequency level at which their consonance exists, and (c) identify groups particularly likely to be in state of dissonance and the intensity of the dissonance. The data used for the analysis is derived from the COVID Future Panel Survey Wave 3, deployed across the United States in October and November of 2021. The findings from the study provide important insights regarding how best to balance employee and employer preferences regarding work arrangements. Given the important effects of work arrangements on commute and non-commute travel, the findings from our study should help inform land use and travel models regarding predicting our transportation future.

Of course, there are many directions for further research. First, our study only considered a single telework location possibility – from home. However, Asmussen et al. (2023a and 2023b) note the importance today of considering a third workplace location for telework to obtain a better understanding of telework effects on commute VMT. Second, our sample was dominated by individuals who experience dissonance in the direction of preferring to telework more than their ETF, with only about 3% experiencing dissonance in the opposite direction of preferring to telework less than their ETF. Previous surveys suggest that there is a sizeable segment of employees that is unhappy with certain aspects of telework (e.g., social isolation, greater distractions at home, limited access to resources, blurring of the boundary between work and personal life, and reduced opportunities for career progression). Future studies with richer data should provide more insights on dissonance going both ways. Finally, it would be beneficial and useful to include psycho-social personality traits and attitudinal factors (such as an individual's green-lifestyle propensity, introverted/extroverted behaviors, productivity levels, and technological savviness) that may affect teleworking desires.

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